

EVALUATION OF DIGITAL X-RAY DETECTORS FOR MEDICAL IMAGING APPLICATIONS

By

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I, Anastasios Konstantinidis confirm that the work presented in this thesis is my own.
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Abstract

Digital x-ray detectors are now the detector of choice in many X-ray examinations. They have been accepted into clinical practice over the past decade but there are still ongoing developments in the technology. Complementary metal oxide semiconductor (CMOS) active pixel sensors (APS) are a novel digital technology that offers advantages compared to some of the more established approaches (charge-coupled devices (CCD), thin film transistor arrays (TFT) and CMOS passive pixel sensors (PPS)). This thesis looks at the performance of these new sensors and attempts to identify their role in future medical imaging applications.

Standard electro-optical and x-ray performance evaluations of two novel CMOS APS, namely the Large Area Sensor (LAS) and Dexela CMOS x-ray detector, are presented. The evaluation was made in terms of the photon transfer curve (PTC), the modulation transfer function (MTF), the normalized noise power spectrum (NNPS) and the resultant detective quantum efficiency (DQE). Modifications were introduced to extend the standard methods to overcome technical limitations. The performance of these detectors was compared to three commercial systems (Remote RadEye HR (CMOS APS), Hamamatsu C9732DK (CMOS PPS) and Anrad SMAM (a-Se TFT)) at beam qualities (28 kV for mammography and 52 kV and 74 kV for general radiography) based on the IEC standards. Both the LAS and Dexela CMOS detectors demonstrate enhanced performance. The effect of the CMOS APS inherent nonlinearity on the x-ray performance was also evaluated.

Finally, the measured performance parameters were used to simulate images for different mammographic imaging tasks in order to establish possible areas of application for the new sensors. Two software phantoms (one representing a 3-D breast and the other the CDMAM test tool) were used to simulate a range of mammographic conditions. The results show that both novel CMOS APS detectors offer high image quality compared to the commercial detector systems.

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List of Abbreviations

Al	Aluminium
APS	Active Pixel Sensor
a-Se	Amorphous Selenium
a-Si:H	Amorphous Silicon
CB-CT	Cone Beam Computed Tomography
CCD	Charge-Coupled Device
CDMAM	Contrast-Detail MAMography phantom
CMOS	Complementary Metal Oxide Semiconductor
CR	Computed Radiography
CsI:TI	Thallium-activated Cesium Iodide
DAK	Detector Air Kerma
DICOM	Digital Imaging and Communications in Medicine
DN	Digital Number
DR	Digital Radiography
DQE	Detective Quantum Efficiency
EAE	Energy Absorption Efficiency
ESAK	Entrance Surface Air Kerma
ESF	Edge Spread Function
FFT	Fast Fourier Transform
FOP	Fibre Optic Plate
FPN	Fixed Pattern Noise
Gd₂O₂S:Tb	Terbium-doped Gadolinium Oxysulfide
HFW	High Full Well
HVL	Half-Value Layer
IQF	Image Quality Figure

IEC	International Electrotechnical Commission
K_a	Air Kerma
Kerma	Kinetic Energy Released per unit MAss
LAS	Large Area Sensor
LED	Light Emitting Diode
LFW	Low Full Well
LSF	Line Spread Function
MGD	Mean Glandular Dose
MV	Mean-Variance
NLC	Nonlinear Compensation
NNPS	Normalized Noise Power Spectrum
QDE	Quantum Detection Efficiency
pMTF	Presampling Modulation Transfer Function
PTC	Photon Transfer Curve
PPS	Passive Pixel Sensor
PSF	Point Spread Function
rms	Root Mean Square
RQA	Radiation beam Quality
Rh	Rhodium
SDD	Source to Detector Distance
SOD	Source to Object Distance
SF	Screen-Film
SNR	Signal-to-Noise Ratio
STP	Signal Transfer Property
TASMIP	Tungsten Anode Spectral Model using Interpolating Polynomials
TFT	Thin Film Transistor
W	Tungsten

Chapter 1

1 Medical x-ray imaging using digital detectors

1.1 Overview of chapter

In this chapter the basic concepts of medical image quality and digital detectors are described. Furthermore, the physical aspects of the investigated x-ray detectors are presented. For clarity reasons, the detector itself will be referred to as a digital sensor and the system as a digital detector. This separation is common in the literature and it is based on “the sensitivity to optical photons” and “the detection of x-ray photons”.

1.2 Background and motivation of the current work

The purpose of medical x-ray imaging is to provide information about specific aspects of body structure or function. The quality of a medical image needs to be sufficient enough to provide the required information for each task. The image quality depends on the properties of the object imaged, the imaging system (i.e. the hardware) and the x-ray imaging technique used (Bourne, 2010). The parts of the human body that are usually imaged are breast, chest, teeth and extremities. The hardware aspects that affect the image quality are the x-ray anode and filtration, tube voltage, radiation dose, scatter and the x-ray detector (Yaffe *et al.*, 2008 and Uffmann and Schaefer-Prokop, 2009). Finally, the imaging technique can be either a well established one, such as mammography, general radiography, computed tomography (CT) and fluoroscopy, or an advanced one such as tomosynthesis, contrast enhanced dual energy or temporal subtraction, cone beam (CB) CT, etc.

The most important factors that affect the image quality are contrast, spatial resolution and noise. They are related factors and affect each other in complex ways. All of them need to reach sufficient levels for each task to get meaningful images. The contrast represents the magnitude of the measured signal differences between the object

of interest and the surrounding background and contains the diagnostic information in medical imaging. It depends on the inherent contrast and the detector contrast. The spatial resolution describes the ability of a detector to represent distinct anatomic features within the imaged object. It is affected by the geometry of the system and the blurring and sampling (or pixel) pitch of the x-ray detector. The noise expresses systematic and random variations superimposed on the “true” measured signal, arising from the x-ray photons which are information carriers and the x-ray detector (Lança and Silva, 2009 and Bourne, 2010). These three factors and the relationship between them are quantitatively described by the contrast-to-noise ratio (CNR), signal-to-noise ratio (SNR), dynamic range, modulation transfer function (MTF), noise power spectrum (NPS) and detective quantum efficiency (DQE) parameters. The CNR represents the relationship between contrast and noise in an image for large scale objects (Lança and Silva, 2009). Correspondingly, SNR expresses the ratio between signal and noise in large scale objects. The dynamic range represents the range of incident dose which the detector can accommodate and convert to imaged signal. It is defined by the ratio of the maximum and minimum detector signal and is an indicator of the contrast limits (Cowen *et al.*, 2008). The MTF shows the ability of the detector to reproduce image contrast from subject contrast at various spatial frequencies, i.e. it represents the relationship between contrast and spatial resolution (Dainty and Shaw, 1974, Cunningham, 2000 and Cowen *et al.*, 2008). The NPS expresses the distribution of the image noise, which is defined in terms of variance, at the various spatial frequency components of the image (Dainty and Shaw, 1974 and Cunningham, 2000). The combination of SNR, MTF and NPS determines the DQE which represents the ability to visualize object details of a certain size and contrast (contrast-detail resolution). In other words, DQE provides a measure of the SNR transfer from the input to the output of a detector as a function of frequency (Dainty and Shaw, 1974, Cunningham, 2000, Bick and Diekmann, 2007 and Veldkamp *et al.*, 2009). By definition, the DQE of a digital detector should be dose independent, i.e. demonstrate a quantum limited behaviour. However, the actual DQE performance is sometimes dose dependent in the presence of detector noise (electronic noise) or nonlinearity. Further details about this are given in section 2.4.5. The first two parameters (CNR and SNR) can be calculated from imaged objects, while the dynamic range, MTF, NPS and DQE comprise the physical

parameters of the detector and are calculated using electro-optical and x-ray performance evaluation methods.

In this study the performance of two novel digital x-ray detectors, based upon complementary metal oxide semiconductor (CMOS) active pixel sensor (APS) technology, was investigated. The performance of these detectors was compared to three commercial systems in terms of physical characteristics and evaluation of the image quality. The physical performance is better described by the DQE than the MTF parameter, because the former takes into account the SNR, contrast and noise of the detector (Shaw *et al.*, 2004). A system with a higher DQE will reach the same contrast-detail resolution at a lower dose or higher contrast-detail resolution at the same dose level compared to another system with a lower DQE (Dainty and Shaw, 1974, Cunningham, 2000, Samei *et al.*, 2004, Bick and Diekmann, 2007). On the other hand, CNR is a more useful measure of image quality than SNR because the actual information content of a medical image depends on contrast (Bourne, 2010). Since the x-ray photons are information carriers, the noise effect is expected to decrease with the increase of the dose level (Cunningham, 2000). However, because ionizing radiation is carcinogenic it is desirable to keep the radiation dose to patients as low as reasonably achievable (ALARA), with the required image quality to provide an accurate diagnosis (Huda *et al.*, 2003, Schaefer-Prokop *et al.*, 2008, Yaffe *et al.*, 2008 and Uffmann and Schaefer-Prokop, 2009). Therefore, DQE and CNR parameters need to be relatively high at low dose levels.

As mentioned above, extracting information by the observer is the most important task in x-ray imaging. Objective x-ray performance evaluation of an x-ray detector (MTF, NNPS and DQE) allows a quantitative comparison between different radiographic systems. However, it does not involve the radiologists, the technicians or the patients, i.e. the subjective evaluation. Since the image quality is task dependent (ICRU Report No. 54, 1996) we cannot easily predict whether it is more strongly affected by the spatial resolution (MTF) or the noise (NPS) parameters. In particular, a study demonstrated that the MTF had a stronger effect on the detectability of lung nodules than the NPS (Saunders *et al.*, 2004). On the other hand, other studies showed that the NPS had stronger effect on the visual grading analysis (VGA) of anatomic structures (Tingberg *et al.*, 2002) or the detectability of microcalcifications in digital mammography (Saunders *et al.*, 2007). Furthermore, even when a system has superior

signal and noise transfer characteristics compared to another, the quantitative difference in terms of image quality is unknown (Saunders and Samei, 2003). For this reason, the experimentally measured performance parameters (MTF, NPS and SNR) were used with software phantoms to simulate images in mammographic conditions. More specifically, two software phantoms (one representing a 3-D breast and the other the CDMAM test tool) were employed for the simulation. The first one was used at four different thickness/glandularity combinations to compare the image quality performance of the detectors at different parenchymal densities. The comparison was made in terms of CNR between simulated microcalcifications and the adjacent background. However, CNR does not give sufficient information on the perceptibility of details of different size and contrast. Therefore, the second phantom (CDMAM 3.4 test tool) was used for a contrast-detail analysis of small thickness and low contrast objects. The second analysis was made using an automated scoring software tool (CDCOM) and published data were used (Young *et al.*, 2008 and van Engen *et al.*, 2010) to predict the respective human readings. Although all the above methods cannot be used to directly predict the clinical image quality, they provide useful information for the performance comparison of digital detectors. The current study focuses on image quality in mammography. However, the observed relationship between the physical parameters and the corresponding image quality allows us to predict the performance of the detectors for a broader range of x-ray imaging applications.

1.3 Digital detectors for medical x-ray imaging

X-ray photons were discovered by Wilhelm Conrad Roentgen in 1895. Shortly after this discovery radiographic films were developed to detect x-rays based on the screen–film (SF) combination (Weil, 1938 and Kim *et al.*, 2008). It consists of a phosphor screen (or scintillator) which converts the x-ray photons to visible light (optical) photons and a radiographic emulsion. The film grains in the emulsion layers of the film absorb the energy of the optical photons during the exposure and using chemical processing an analog image is created (Williams *et al.*, 2007). When a high amount of x-ray photons is absorbed in the scintillator, a respective high amount of optical photons exposes the film grains, leading to higher optical density of the exposed grains which corresponds to a dark analog image after film processing. The relationship between the optical density and the number of absorbed x-rays is not linear over the range of the

created signal (Johns and Cunningham, 1983). The main limitation of the SF radiography is that the acquisition, display and storage of the analog image are not separable. Other drawbacks of this technology are the small exposure latitude (dynamic range), the need of chemical exposure to create the analog image, inefficient mechanical handling, no instantaneous access to the analog images, the film is fragile and it cannot be duplicated without quality loss and high costs for film materials and work. Also, there is a compromise between the spatial resolution and the detection efficiency of the x-ray image, because the scintillator needs to be thin to reduce the blurring from the lateral diffusion of optical photons created inside the scintillating material. However, the thin scintillator results in low detection of x-ray photons and requires increased amount of x-rays (radiation dose) to achieve the desired image quality. There is another trade-off between the dynamic range and the contrast resolution, because to have a high contrast resolution the dynamic range has to be small (Muller, 1999 and Williams *et al.*, 2007). Nevertheless, SF radiography has been used for many years mainly due to high spatial resolution, consistency of image appearance and the experience of radiologists, medical physicists and technologists in utilizing this technology in an optimal way (Williams *et al.*, 2007).

To overcome the limitations of analog imagers, digital detectors have been developed over the past 40 years. They are constructed to offer independent acquisition, display and storage of the images allowing for separate optimization of each of the three steps. Therefore, better image quality in terms of increased dynamic range, increased display contrast, higher detection efficiency and lower noise compared to SF technology has been achieved over the years. The increased image quality permits lower doses to patients. Another advantage is the acceleration of the patient throughput in terms of less data typing, no need for chemical processing, shorter time from the acquisition to the radiographic image and no cassette manipulation in some cases. Finally, digital images can be easily transmitted to and from remote places for consultation, review or interpretation (Muller, 1999, Kotter and Langer 2002 and Williams *et al.*, 2007). The main limitations of digital detectors are higher initial cost, the fact that a number of radiologists, medical physicists and technologists are not familiar with electronic image display and with online softcopy reading and the lack of consistent feedback from radiologists to radiographers about the use of optimal acquisition parameters (Williams *et al.*, 2007). Also, another parameter that can limit the acceptance of digital detectors is

the sampling in both the spatial and intensity dimensions. In the spatial dimension, the analog signal is averaged over picture elements (pixels) which are spaced at equal intervals over the area of the image. In the intensity dimension, the analog signal is binned into one of a finite number of discrete digital levels. The number of these levels is usually a power of 2 and it depends on the bit-depth of the analog-to-digital converter (ADC) used to digitize the analog image. In other words, if the bit-depth of the ADC is 12, there are 2^{12} (0-4095) discrete digital values over the analog signal amplitude range. Digital x-ray detectors typically employ 12 to 14 bits ADCs. Therefore, information can be lost if the dimensions of a fine detail in the image (such as microcalcifications) are smaller than the pixel area (or pitch) and from intermediate intensities and variations on a sub pixel scale lost in the digitization process (quantization error) (Yaffe and Rowlands, 1997 and Bruijns *et al.*, 2000).

All digital detectors produce an output signal in the form of a digital number (DN) which represents the integrated amount of x-ray photons or energy absorbed in a given pixel over a specific exposure time. There are two main categories of digital detectors, the computed radiography (CR) and the digital radiography (DR) systems. The CR or storage phosphor radiography (SPR) system is the first digital radiography system introduced to the market by Fuji in the early 1980s (Sonoda *et al.*, 1983). It uses a photostimulable (or storage) phosphor that stores the image information from the absorbed x-rays as a latent image. The latent image is a distribution of electron charges trapped in meta-stable energy level (f-centres). Then the phosphor is exposed to the light (photon energy) of a red or near infrared laser beam, which causes the electrons to fall back to their original energy state with subsequent light (blue-green or ultraviolet) emission. Finally, the photostimulated luminescence pattern is collected by a photomultiplier tube (PMT) or from an array of photodiodes. This luminescence pattern is proportional to the absorbed intensity. However, it is logarithmically (or square root) amplified in order to compress the dynamic range of the analog signal to preserve digitisation accuracy over the finite number of discrete digital levels resulted from 12 to 14-bit ADCs used in digital radiography (Kotter and Langer, 2002, Williams *et al.*, 2007, Kim *et al.*, 2008 and Doyle, 2008). CR technology is typically a cassette-based system analogous to that used in SF radiography. Therefore, it normally requires human intervention to transfer the storage phosphor cassette from behind the patient to the laser scanning beam. This two step process may reduce both image quality and system

efficiency due to the introduction of noise. However, recent commercial products of CR technology do not need human intervention because they are constructed in such a way to automatically move the phosphor plate to the laser scanner or that the laser scanning occurs with the phosphor plate in the imaging location (Yorkston, 2007). The main advantages of CR technology are that they are well-established, robust, relatively inexpensive and have good reproducibility (Kotter and Langer, 2002, Schaefer-Prokop, 2003, Williams *et al.*, 2007 and Kim *et al.*, 2008). Also, the photostimulated phosphor plates are reusable, have linear response over a wide range of x-ray intensities and are completely erased by exposure to a uniform stimulating laser beam. Finally, CR detectors can be combined with existing x-ray systems (modality), while DR units are often sold as complete systems (i.e. x-ray source and detector together). However, a problem of the CR system is the loss of the spatial resolution due to the scatter of the stimulating beam from the phosphor material. A second possible limitation of this technology is the reduction of the DQE at higher spatial frequencies due to secondary quantum sink introduced from the mechanically complex readout system. Secondary quantum sink arise from a lack of gain at a given conversion stage. A mechanically complex system may not transfer sufficient information carriers (e.g. light photons coupled via a lens) and hence generate a secondary sink (Yaffe and Rowlands, 1997). The newer DR technology was developed to improve the image quality, leading to the potential for dose reduction. DR systems demonstrate higher DQE and this can be used either to reduce the acquisition dose or to increase the SNR at the same dose (Schaefer-Prokop, 2003). The term DR is used to describe digital x-ray imaging system that converts the absorbed x-ray energy to digital images directly, without the need of further processing as in SF and typical CR technologies. They do not require any mechanical motion to achieve the output digital image. Both DR and CR are digital radiographic systems and the different names are given to separate the two technologies. However, some new CR systems are automated (cassetteless), while some DR systems are integrated to a cassette-based x-ray system. Therefore, a distinction based on cassette versus cassetteless operation would be more accurate. The current DR and CR terms are kept for historical nomenclature reasons (Kotter and Langer, 2002, Williams *et al.*, 2007 and Kim *et al.*, 2008).

The DR systems are further separated to direct and indirect conversion detectors. The terms direct and indirect refer to the technology used to convert the input x-rays to

the output electron charge created in each pixel. Direct refers to the conversion of x-rays to electron-hole pairs directly and the subsequent charge collection from individual pixel electrodes. Indirect refers to the conversion of x-rays to secondary information carriers, such as light photons from the scintillator, before conversion of these secondary carriers to charge (Yaffe and Rowlands, 1997, Kotter and Langer, 2002, Williams *et al.*, 2007 and Yorkston, 2007). The direct conversion detectors usually consist of amorphous selenium (a-Se) photoconductors and thin film transistor (TFT) technology to read the charge signal. The TFT detectors are also used as active matrix flat panel imagers (AMFPI) or flat panel detectors. The a-Se TFT detectors offer high spatial resolution and high x-ray absorption efficiency at low energies. However, the increased resolution of the photoconductor can introduce signal and noise aliasing which affects the high spatial frequency contents of the clinical image (Yaffe and Rowlands, 1997, Kotter and Langer, 2002 and Yorkston, 2007). The indirect conversion detectors usually combine scintillators (such as CsI:Tl or Gd₂O₂S:Tb) coupled to secondary quantum detectors comprised of hydrogenated amorphous silicon (a-Si:H) TFT, charge-coupled devices (CCD) or complementary metal oxide semiconductors (CMOS) sensors. The indirect conversion detectors present poorer resolution due to the light diffusion inside the scintillator. However, they offer higher detection efficiency at higher frequencies (higher DQE) because the aliasing noise is smaller (Samei, 2003b and Marshall, 2000a). Direct a-Se detectors are mainly used in mammography due to the relatively low Z (34) and the K-absorption edge at 12.7 keV. On the other hand, the indirect detectors can be used in both mammography and higher energy applications such as general radiography, due to the increased Z and absorption edge of the scintillating elements (55 and 36.0 keV for Cs, 53 and 33.2 keV for I and 64 and 50.2 keV for Gd) (Yaffe and Rowlands, 1997 and Yorkston, 2007). Finally, the a-Se detector at low exposures (less than 30 μ Gy) demonstrates low DQE values. This happens because a) Se makes less efficient use of the absorbed x-rays (i.e. to produce an electron-hole pair using a 27 kV Mo/Mo spectrum, 64 eV are required for Se operated at 10 V/ μ m, while less than 25 eV are needed for the CsI/Si combination) and b) the effect of electronic noise is higher on smaller pixel sizes (Shaw *et al.*, 2004).

The a-Si:H TFT detectors include a P-I-N junction a-Si:H photodiode inside each pixel which converts the optical photons from the scintillator to electron charge and stores that charge on the photodiode capacitance. Then, the TFT transistor inside each

pixel allows the charge to be read out for each row of the active area. Therefore, an entire row of the detector array is read out simultaneously and the signal is read on lines for each column via a charge amplifier. Then the amplified column signals are multiplexed and digitized. This method allows fast detector readout (Yaffe and Rowlands, 1997). Also, the flat panel detectors are radiation hard and can consist of very large areas of up to $43 \times 43 \text{ cm}^2$ for general radiography applications (Kotter and Langer, 2002). However, flat panel detectors have low DQE at low exposure levels (Zhao and Rowlands, 1997, Siewerdsen *et al.*, 1997 and Antonuk *et al.*, 2000), caused by high read noise due to the use of passive pixels (Busse *et al.*, 2002, Jee *et al.* 2003 and Scheffer, 2007). Finally, the flat panel detectors at high frame rates show an excess of image lag, ghosting and baseline drifts (Siewerdsen and Jaffray, 1999, Bloomquist *et al.*, 2006 and Korthout *et al.*, 2009). On the other hand, the CCD detector was developed in 1970 with a completely different readout method (Boyle and Smith, 1970). It consists of an array of metal-oxide-semiconductor (MOS) capacitors, which are formed from the deposition of a series of electrodes (“gates”) on a semiconductor substrate. By applying voltages to the gates, the material below the gates is depleted and forms charge storage “wells”. Each well corresponds to the pixel. The storage charge is created from photoelectric absorption of optical photons. When proper voltage differences are applied on the gates the charge is transferred from well to well under the gates. The charge is shifted out of the array via vertical and horizontal charge coupling, converted to voltage via a simple follower amplifier and then serially read out and converted to DN via an ADC. (Yaffe and Rowlands, 1997 and El Gamal and Eltoukhy, 2005). The CCD technology was the most prevalent in the market of digital imaging for more than 25 years due to its high performance. It has high sensitivity due to high fill factor (the ratio of the light sensitive area to the total area of a pixel) and quantum efficiency (i.e. number of photon-generated electrons per impinging optical photons), thus leading to very small pixels (down to $15 \text{ }\mu\text{m}$ for video applications). The fill factor of the interframe transfer CCDs is 100% because their operation does not require extra electronics per pixel. The respective fill factor of the interline transfer CCDs is slightly lower. Also, CCDs illustrate very low noise because the charge transfer is passive and it does not introduce temporal noise. The read noise of commercial CCDs is around 10-20 e^- r.m.s. Additionally, they do not suffer from pixel-to-pixel and column-to-column fixed pattern noise (FPN). Finally, they appear to have high dynamic range and image

quality in terms of SNR (Fish and Yadid-Pecht, 2004, Bigas *et al.*, 2005 and El Gamal and Eltoukhy, 2005). CCDs were introduced in digital radiography in 1987 (Nelson, 1987) due to the high spatial resolution capability, wide dynamic range and linear response. For medical applications the pixel pitch of the CCD is in the range of 25-100 μm to get the desired full well capacity (Yaffe and Rowlands, 1997). A main disadvantage of the CCDs is that the production cost is high, which limits their active area to 2-5 cm^2 . Therefore, it is often necessary to demagnify the image from the scintillator to allow coverage of the required x-ray field size in the patient. There are three ways to demagnifying the light signal: using optical lens coupling or fibre optic coupling or electron-optic coupling (Yaffe and Rowlands, 1997). However, this demagnification stage increases the chance of a quantum sink occurring by imposing stricter requirements on light propagation in order to keep image quality within acceptable levels. Furthermore, CCDs are serial devices, which means that the entire signal has to pass through the same sense node before being read out, leading to high read noise at high frame rates. This limits the use of CCDs to applications requiring a high frame rate such as tomosynthesis, CT and fluoroscopy (Janesick, 2002). Additionally, they require high power due to the need for high-rate and high-voltage clocks to transfer the charge efficiently (El Gamal and Eltoukhy, 2005). Finally, CCDs are susceptible to radiation damage (Janesick, 2001).

CMOS image sensors first appeared in 1967 having the architecture of passive pixel sensors (PPS) (Weckler, 1967 and Dyck and Weckler, 1968). However, in the middle 1990s CMOS sensors re-emerged in the market as an alternative to CCDs due to the development of active pixel sensors (APS) and their consequent advantages and high performance (Mendis *et al.*, 1994). By adding a buffer per pixel as a source follower, the signal is transferred onto a common readout bus as a voltage rather than as a charge. This modification, known as APS technology, improves the sensor's SNR and readout speed. The main advantages of CMOS sensors over CCD and TFT technology are the low cost with low power consumption, radiation tolerance (Said *et al.*, 2001 and Bogaerts *et al.*, 2003), very fast image acquisition due to random pixel addressing capability (Fossum, 1997 and Krymski, 2003) and low read noise at high frame rates due to column parallel read out (Janesick, 2002). Also, stitching and tiling technologies can be used to obtain large area sensors suitable for x-ray applications (Scheffer, 2007, Korthout *et al.* 2009 and Reshef *et al.*, 2009). Finally, the CMOS APS features lower

read noise than PPS (Bohndiek *et al.*, 2008b and Elbakri *et al.*, 2009). In the following sections the pixel architecture and readout methods of CMOS APS, CMOS PPS and a-Se TFT technologies are described as they are employed in the current study.

1.4 CMOS Sensors

1.4.1 CMOS Active Pixel Sensors (APS)

The simplest (three transistor (3T)) APS pixel usually contains one photodiode and at least 3 MOSFETs: a) a reset (R), b) a source follower (SF) and c) a row select (RS) MOSFET (Fossum, 1997, Janesick *et al.*, 2003b, El Gamal and Eltoukhy, 2005, Hoffman *et al.*, 2005). Figure 1.1 shows a schematic of a 3T APS incorporating a silicon photodiode for optical photons detection (El Gamal and Eltoukhy, 2005).

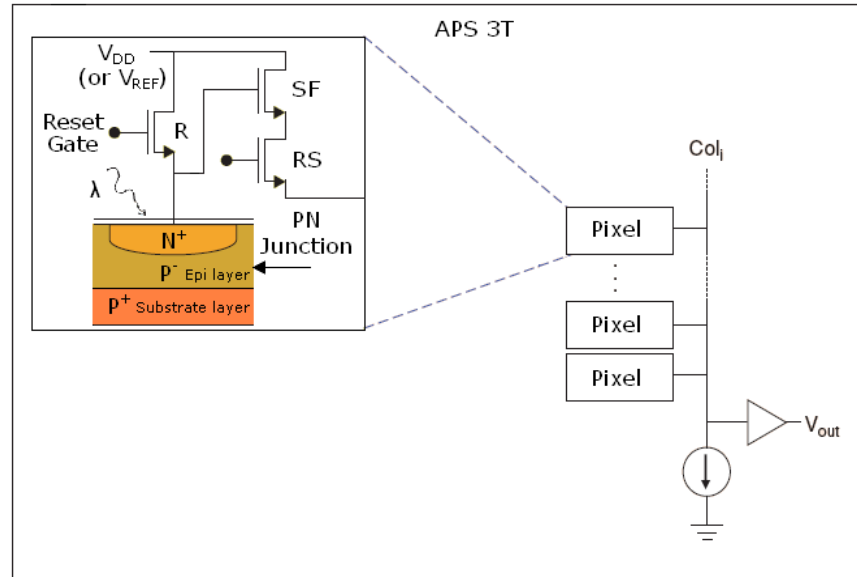


Figure 1.1: A schematic of a 3T APS pixel and readout architecture

Each pixel behaves as an individual sensor element, the operation of which is separated into three phases: reset, integration and readout.

During the reset phase, a positive voltage, V_{Reset} , is applied at the reset gate, allowing the supplied reference voltage, V_{DD} , to pass through and recharge the photodiode to a fixed reference level. There are two main types of reset, depending on the voltages applied at the drain and the gate of the reset transistor: ‘soft’ and ‘hard’ reset (Pain *et al.*, 2003a, Janesick and Putnam, 2003a). The ‘soft’ reset corresponds to the condition where the gate-to-drain voltage of the reset transistor is less than the

threshold voltage of the transistor. In this state, charge from the sense node can thermally cross the reset gate barrier to the V_{DD} drain region. As charge escapes, the sense-node voltage increases and results in a signal variation with time at the output of the source follower. On the other hand, the reset is termed ‘hard’ when the gate-to-drain voltage on the reset transistor exceeds its threshold voltage, yielding steady state operation. In other words, the ‘hard’ reset eliminates the field that would cause electrons to leave the sense node. ‘Soft’ reset results in a high saturation level and low read noise at the cost of image lag and low-illumination nonlinearity, while ‘hard’ reset shows no image lag and greater linearity, at the expense of increased noise and reduced saturation level.

The integration phase is the period in which the signal is measured. V_{Reset} drops from a positive voltage and the reset MOSFET stops conducting. The silicon photodiode is sensitive to light in the spectral range of 200-1200 nm, which extends from UV through the visible to near IR. Usually, it consists of a P-N junction, i.e. a N^+ well and a P^- epitaxial layer, which is reversed biased. Therefore, a depletion region is created and the photodiode acts as a semiconductor. An additional P^+ substrate layer exists for mechanical support. When an optical photon interacts with the photodiode it creates an electron-hole pair inside the epitaxial layer. Electrons diffuse until they experience the electric field of the P-N junction and are collected from the N^+ well (or ‘sense node’). An electron charge is created between the sense node and the P^- epitaxial layer, related to the number of interacting photons. During the integration time (T_{int}) the photodiode behaves as a capacitor and the variation of the sense node capacitance C_{SN} with charge level is described as (Janesick, 2007):

$$C_{SN}(V_{SN}) = q \frac{dS(e^-)}{dV_{SN}} \quad (1.1)$$

where $S(e^-)$ is the sense node charge (number of accumulated electrons), V_{SN} is the sense node voltage and q is the electron charge (1.6×10^{-19} C). Integrating Eq. (1.1) with respect to V_{SN} yields:

$$S(e^-) = \frac{1}{q} \int_{V_{SN}}^{V_{REF}} C_{SN}(V_{SN}) dV_{SN} \quad (1.2)$$

where V_{REF} is the reference voltage on the sense node after its reset. The integration results in a signal charge $S(e^-)$ and the respective voltage $S(V_{SN})$ which is negatively related to V_{REF} because the photodiode is reverse biased. Therefore, the sense node voltage discharges as:

$$V_{SN} = V_{REF} - S(V_{SN}) \quad (1.3).$$

After the integration period's completion, signal S is measured at the input of the source follower as a decrease of either the electron charge or the V_{REF} . Figure 1.2 shows the variation of the signal voltage $S(V_{SN})$ during a given integration time. The source follower acts as a buffer, allowing only the input voltage V_{ISF} to pass through. Therefore, the signal passes to the next stage, the readout column bus, as a voltage only.

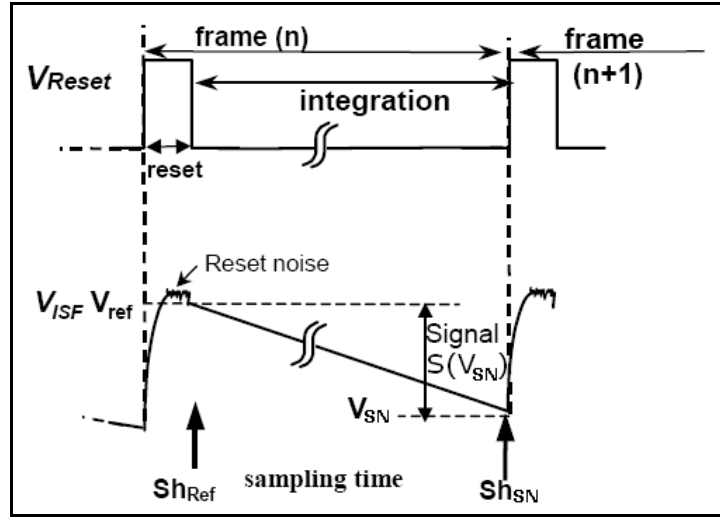


Figure 1.2: Signal voltage measurement within the integration time (Magnan, 2003)

Readout phase follows the integration phase. The row select MOSFET switches on, enabling the buffered signal voltage to be presented to the column bus in order to be measured from the imager. Progressive scan readout mode is the most common readout mechanism in CMOS APS. This mode incorporates the rolling shutter method (Fish and Yadid-Pecht, 2004, Turchetta R. *et al.*, 2004, Hoffman *et al.*, 2005). The rows of pixels in the image sensor are reset in a sequence, starting at the top of the image and proceeding row by row until the bottom. When this reset process has moved down in the image for a given number of lines, the readout process begins. The number of lines defines the integration time. The read out process occurs in exactly the same mode and at the same speed as the reset process. Figure 1.3 represents the rolling shutter

principle. Finally, from the column bus, the signal voltage passes through column parallel amplifiers and ADC, where it is converted to DN and passes off chip (Fossum, 1997).

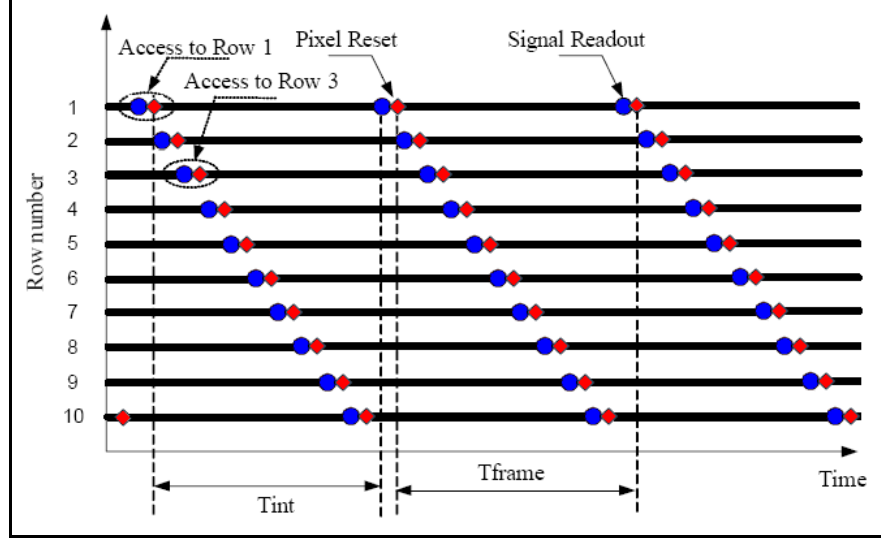


Figure 1.3: Rolling readout method of the photodiode APS (Fish and Yadid-Pecht, 2004).

CMOS APS sensors offer low noise and fast readout of the signal at the cost of adding more transistors in the pixel which leads to smaller fill factor, smaller quantum efficiency and decreased sensitivity. These parameters prevent the construction of very small pixels (i.e. smaller than 25-50 μm).

1.4.2 CMOS Passive Pixels Sensors (PPS)

The typical PPS pixel consists of a photodiode and just one transistor (RS). Therefore, it has very high fill factor and quantum efficiency leading to high sensitivity and the ability to construct small pixels, similar to a CCD. The current structure of the PPS has not been further developed since its first conception in 1967 (Weckler, 1967 and Dyck and Weckler, 1968). A reference voltage V_{REF} is used to reset the photodiode to reverse bias. After the reset the RS MOSFET transistor, which acts as a switch, is opened for the period of integration time. During the integration time, the photodiode discharges at a rate proportional to the intensity of the input optical photons (photosignal). Then the RS switch closes to reset the photodiode once more and proportional current flows via the resistance and capacitance of the vertical column bus. As discussed in the previous section, this current is created due to the voltage difference

between V_{REF} and the photodiode (sense node) voltage V_{SN} . The total charge that flows to reset the photodiode is equal to the charge created during the integration time (Fish and Yadid-Pecht, 2004 and El Gamal and Eltoukhy, 2005). Figure 1.4 shows the architecture of a 1T PPS (El Gamal and Eltoukhy, 2005).

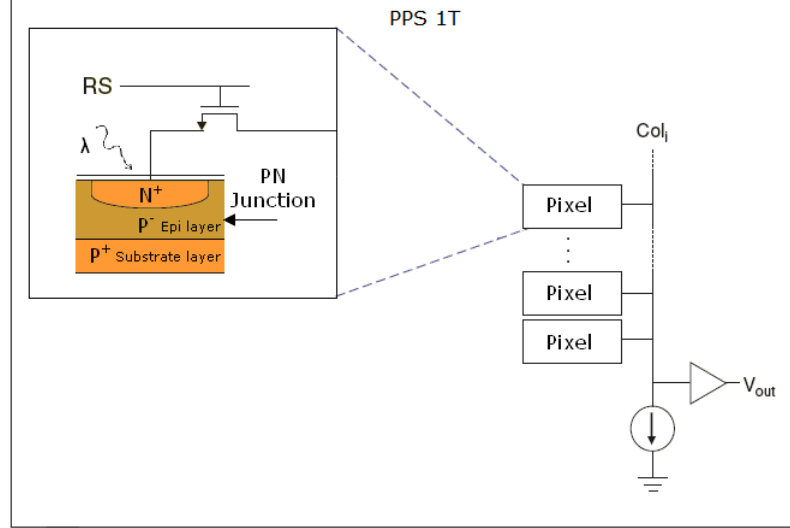


Figure 1.4: A schematic of a 1T PPS pixel and readout architecture

However, the pixel architecture of the PPS results in major problems due to its large capacitance loads. The column bus is directly connected to the photodiode during readout, therefore the RC time constant is very high and the readout is slow. Also, the PPS readout noise is relatively high, i.e. around $250 e^-$ r.m.s.. Therefore CMOS PPS appear to have limited scalability, i.e. they do not scale well to larger array sizes or faster pixel readout rates. Also, column-wise fixed pattern noise (FPN) appears due to different gains of the amplifiers on the bottom of each different readout column (Fish and Yadid-Pecht, 2004, El Gamal and Eltoukhy, 2005 and Fossum, 1997).

1.5 Direct conversion TFT detectors

Direct conversion detectors consist of photoconductors and TFT transistors for the readout of the signal. The photoconductor absorbs the x-ray photons, generates free electron-hole pairs proportional to the intensity of the incident x-rays and collects them at the electrodes. The most developed photoconductor for x-ray applications is amorphous selenium (a-Se). It offers high x-ray absorption at low energies (K-absorption edge at 12.7 keV) and a very high spatial resolution. The amorphous state makes possible the preservation of uniform imaging characteristics over large areas

(Yaffe and Rowlands, 1997, Kotter and Langer, 2002, Que and Rowlands, 1995). The first medical application of a-Se was in 1973 (Boag, 1973) where a toner read out the latent charge image created on the surface of an a-Se plate. During the following years several developers used a-Se based detectors for analog and digital radiography. In 1992 Zhao and Rowlands introduced the a-Se TFT combination for radiography and fluoroscopy (Zhao and Rowlands, 1992, Zhao and Rowlands, 1995). In the following years Lee *et al.* (1996) studied the performance parameters (resolution, dynamic range and sensitivity) of a-Se TFT detectors for radiography. The potential advantages of this technology are high image quality, real-time readout and compact size.

The structure and readout technology of a-Se TFT detectors is shown in Figure 1.5. When x-ray photons hit the detector, their energy is absorbed by the a-Se layer and electron-hole pairs are created respectively. This created charge is drawn by the electric field applied between the top and charge collection electrodes. The latter is constructed inside each pixel, collects the created charge and leads it to the pixel capacitance (i.e. self-capacitance and integrated storage capacitance). Both charge collection electrode and storage capacitor are connected to the TFT switch inside each pixel. The TFT switch is controlled from the gate row line and for specific integration time allows the transfer of the charge from the pixel capacitors to the readout columns. Then the charge is collected and amplified by an amplifier on each column and the data for an entire row is multiplexed out and digitized. The sequence is repeated row by row (Yaffe and Rowlands, 1997).

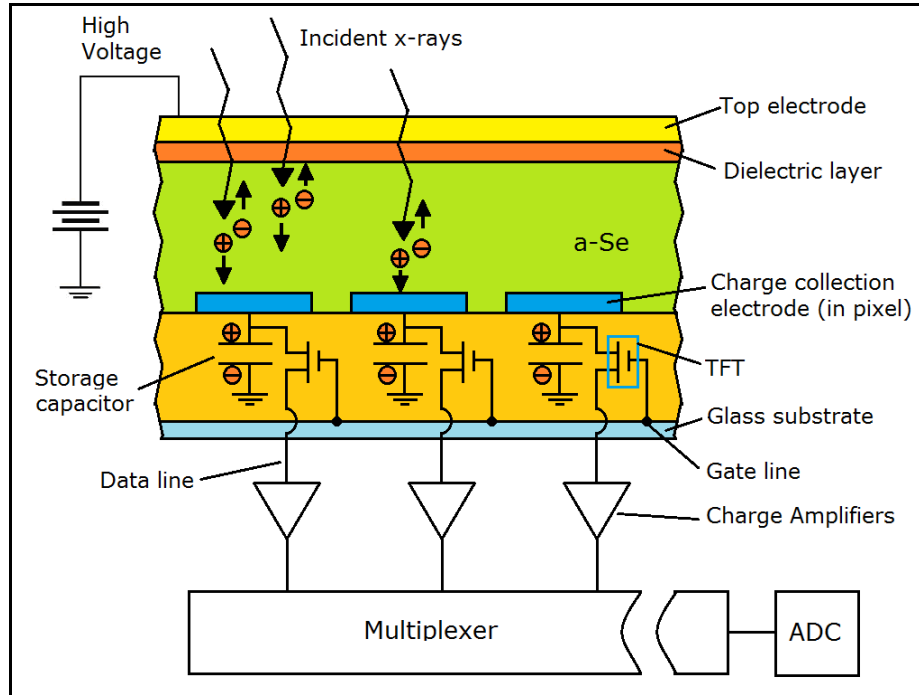


Figure 1.5: Layered structure and readout architecture for a direct-conversion (a-Se) TFT detector

The thickness of the a-Se layer must be adequate to achieve high x-ray detection efficiency. However the overall detection efficiency of the system may be decreased for very high a-Se thicknesses, because the charge carriers (i.e. the electron-hole pairs) may recombine or be absorbed by the a-Se layer itself. In this case the number of charges arriving at the charge collection electrode decreases. Therefore, for general radiography applications the typical thickness of the a-Se layer is around 500 μm , while for lower x-ray energy applications such as mammography the thickness is around 250 μm . It is observed that the thickness of the a-Se layer can be increased without sacrificing the spatial resolution which is the usual case in scintillators. General radiography a-Se flat panel detectors usually employ 140 μm square pixels, while the full-field digital mammography detectors are constructed with ~ 70 μm square pixel pitch (Yaffe and Rowlands, 1997, Lee *et al.*, 1996, Kim *et al.*, 2008).

1.6 Digital detectors under investigation

Five digital detectors are investigated in this thesis. Three of them are CMOS APS (LAS, Dexela CMOS x-ray detector and Remote RadEye HR), one is CMOS PPS (Hamamatsu C9732DK) and one is direct conversion (a-Se) TFT (Anrad SMAM). A complete electro-optical and x-ray performance characterization of the novel detectors

(LAS and Dexela CMOS x-ray detector) is carried out in this study. The x-ray performance of these two detectors was compared with that of the three commercial detectors (Hamamatsu C9732DK, Anrad SMAM, Remote RadEye HR) developed for medical x-ray imaging applications.

1.6.1 Large Area Sensor (LAS)

The LAS CMOS APS was designed and manufactured for scientific applications and in particular under x-ray conditions by the MI-3 consortium (Allinson *et al.*, 2009, Multidimensional Integrated Intelligent Imaging, 2008). This collaboration was created in 2004 under the RC-UK Basic Technology Programme and involved 11 research centres (including UCL) all over the UK. The aim of this consortium was to develop CMOS APS for a broad range of scientific applications (Cabello *et al.*, 2007, Olivo *et al.*, 2007, Bohndiek *et al.*, 2008b, Osmond *et al.*, 2008). LAS sensor contains 1350 x 1350 pixels at 40 μm pitch, resulting in a photodiode area of 5.4 x 5.4 cm^2 . A standard CMOS reticle or photomask, which is the glass mask containing the design patterns, is limited in size to approximately 2 x 2 cm^2 . Therefore, stitching technology (Hoffman *et al.*, 2005, Scheffer, 2007, Korthout *et al.*, 2009, Reshef *et al.*, 2009) is used to combine 5 x 5 sub-stitched areas, each one containing 270 x 270 pixels. A dedicated differential analogue output for every section of 135 columns exists to connect to a 14-bit ADC. ADCs are incorporated into an additional stack board on which LAS is connected. A preliminary investigation (Bohndiek *et al.*, 2009) resulted in read noise (r.m.s.) of 62 e^- , full well capacity equal to 61.3 x 10³ e^- and dynamic range of 60.3 dB. However, these results are affected by the presence of electromagnetic interference (EMI) in the readout electronics. Studies presented in section 3.2.1 of this thesis, isolated the effect of the EMI on the above performance parameters (Konstantinidis *et al.*, 2010 and Zin *et al.* 2010).

It may be seen from Figure 1.6 that each pixel contains 9 MOSFETs (9T APS), i.e. 6 extra transistors are included in order to define 'regions of reset' (RORs) with the ability for three different integration times. It was found that this method can increase the dynamic range (i.e. avoid saturation) within the RORs, which is one of the main demands in x-ray diffraction applications.

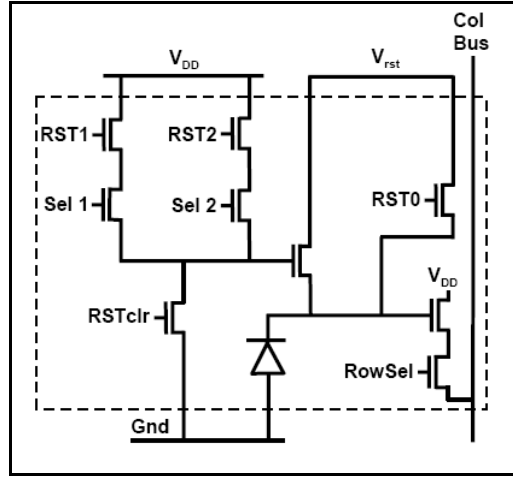


Figure 1.6: LAS pixel layout incorporating 9T. RST0, RST1 and RST2 refer to the three different reset levels that may be applied to each pixel. (Bohndiek, 2008c)

By default, RST0 level (high gate voltage for given number of delay lines) is applied to all pixels in a row, when the rolling shutter first passes. Sel 1 and Sel 2 act as switches for a given window (both rows and columns can be addressed). If one of them (or both) is enabled, the respective gate voltage (RST1 and/or RST2), which is high for extra lines of delay, increases the reset time of each pixel within the given ROI. Therefore, as the reset time increases, the integration time decreases. The maximum frame rate of the whole area is 20.7 fps. Using a given frame rate, the integration time of each ROR can be defined. The maximum integration time of the whole area is 2.4s. The minimum integration time within the ROR, which can be used in combination with this, is 37.4 μ s. These extremes define a nominal dynamic range of at least 96 dB. The pixel fill factor for LAS is 73 % (Bohndiek *et al.*, 2009).

1.6.2 Hamamatsu C9732DK

Hamamatsu C9732DK is a PPS CMOS x-ray detector designed for mammography. It consists of 2400 x 2400 pixels at 50 μ m pitch, corresponding to an active (photodiode) area of 12 x 12 cm². The vertical dimension consists of 15 stitched periphery blocks, each one containing 2400 x 160 pixels. Each block is connected to a dedicated 14-bit ADC. The number of active pixels is 2368 x 2400. The nominal read noise (r.m.s.) is 1250 e⁻ and the saturation charge is 6.4 x 10⁶ e⁻, leading to 74 dB dynamic range. The minimum frame rate of the whole area is 0.95 fps while the maximum one is 1 fps (Hamamatsu, 2008a). At slow read out rates the electronic noise (i.e. read noise and dark current) “fills up” the pixels array. Therefore, it determines the

minimum frame rate. The pixel fill factor for this detector is 79 % (Hamamatsu, 2008b), due to the absence of the extra transistors used in APS technology.

1.6.3 Dexela CMOS x-ray detector

The Dexela flat panel CMOS x-ray detector is an APS based on a 3T-pixel architecture. Each pixel contains 3 transistors (reset, source follower and row select), and a pinned photodiode to increase the photo-responsivity (and thus the quantum efficiency) and decrease dark current and read noise (Fossum, 1997 and El Gamal and Eltoukhy, 2005). Each pixel contains an option for switching the full well capacity between two separate levels, high full well (HFW) and low full well (LFW) modes (Figure 1.7). The typical fill factor of this detector is around 84 %.

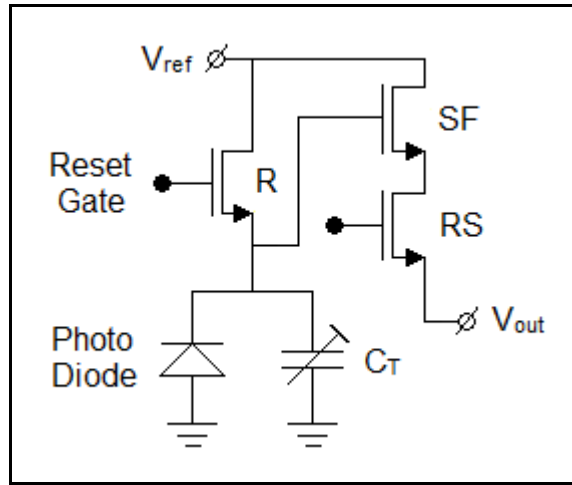


Figure 1.7: Pixel architecture of Dexela's x-ray detector.

The full well capacity switch is operated globally across the whole active area. The LFW mode allows achieving low noise during binned mode read-out and increasing the sensitivity of the detector at low Air Kerma (K_a) levels. This mode trades off full well capacity with sensitivity. The expected nominal read noise (r.m.s.) is around 309 e^- and 106 e^- for HFW and LFW modes respectively. The nominal saturation charge (or full well capacity) is $1.4 \times 10^6 e^-$ and $0.4 \times 10^6 e^-$, leading to 73.1 dB and 70.1 dB for HFW and LFW modes respectively (Dexela, 2011). The typical photodiode area of a single detector module at full resolution (pixel pitch equal to 74.8 μm) is 1944 x 1536 pixels, i.e. 14.5 x 11.5 cm^2 . The respective number of active pixels is 1934 x 1536 pixels. The vertical dimension consists of 6 stitched periphery blocks (Hoffman *et al.*, 2005, Scheffer, 2007, Korthout *et al.*, 2009, Reshef *et al.*, 2009). Each block is connected to a dedicated 14-bit ADC. A detector with reduced dimensions (11.5 x 6.5 cm^2) is also

available for small field mammography and cone beam computed tomography (CB-CT) applications. The tiling technology allows a combination of the above detectors modules to obtain fields of view suitable for a variety of medical applications. The largest detector currently available is obtained by tiling 2x2 modules for an overall area of $29 \times 23 \text{ cm}^2$, and is intended for use in mammography, breast tomosynthesis, breast CT, CB-CT and fluoroscopy. The binning mode capability allows a trade-off between spatial and temporal resolutions. The $75 \text{ }\mu\text{m}$ pixel resolution allows a frame rate of 26 fps, while the $300 \text{ }\mu\text{m}$ resolution (4x4 binning mode) corresponds to a maximum rate of 86 fps, enabling dynamic applications.

1.6.4 Anrad SMAM

The Anrad SMAM is a direct conversion a-Se flat panel imager designed for screening mammography. The thickness of the a-Se is $200 \text{ }\mu\text{m}$. The total area of the detector is $17.3 \times 24 \text{ cm}^2$ (2032×2817 pixels) with a pixel pitch of $85 \text{ }\mu\text{m}$. The number of active pixels is 2016×2816 (Tousignant *et al.*, 2007). The maximum frame rate is around 0.7 fps (Anrad, 2004). Another digital detector is developed from Anrad (LMAM detector) with similar properties compared to the SMAM. The main difference between the two detectors is that LMAM is designed mainly for breast tomosynthesis and dual energy, so it has slightly higher active area ($24 \times 30 \text{ cm}^2$), higher maximum fps (0.8 fps in screening mode and 2.5 fps in tomosynthesis mode) and higher SNR performance at low K_a levels. However, as the pixel pitch of both detectors is the same, identical presampling MTF (pMTF) curves are expected. This direct conversion detector is expected to present high resolution, limited mainly from the pixel size (Bissonnette *et al.*, 2005 and Tousignant *et al.*, 2007). The read noise of this detector is around $5200 \text{ e}^- \text{ r.m.s.}$, the full well capacity is around $15 \times 10^6 \text{ e}^-$ and the resulted dynamic range is 69.2 dB. The geometric fill factor of this detector is 70 %. Finally, the total ADC bit-depth is 16 bits but 13 bits are used due to limitations of the chip in the screening mode (Boissonneault, 2010).

1.6.5 Remote RadEye HR

The Remote RadEye HR sensor manufactured by Rad-icon Imaging Corp. (USA) is a 1200×1600 pixel CMOS photodiode array with an active area of $2.7 \times 3.6 \text{ cm}^2$ and a pixel pitch of $22.5 \text{ }\mu\text{m}$. It is designed for high-resolution radiation imaging in the energy

range from 10 to 90 kV (Rad-icon Imaging Corp., 2005a). The nominal conversion gain of the detector is 60 e⁻/DN with a high gain option (2x) available. The nominal read noise (r.m.s.) is less than 120 e⁻ and the dynamic range is 72 dB. Therefore, the calculated saturation charge is less than 480 x 10³ e⁻. The maximum frame rate is around 0.5 fps and the nominal average dark current is 3000 e⁻/s (i.e. 7 pA/cm²) at 23 °C (Rad-icon Imaging Corp., 2005b). A one meter shielded cable is included to connect the sensor head to the electronics module, where the analog video signal is processed, digitized using 12-bit ADCs and transferred to a PC.

1.7 Scintillators

Scintillators or phosphor screens are used to convert x-rays to photons within the visible wavelength (400-700 nm). They are coupled to indirect conversion sensors. The most important parameters of a scintillator are the ability to detect the x-ray photons and their energy, the number of created optical photons per unit of absorbed energy (light yield) and the spectral matching between the emitted optical photons and the light sensitivity of the digital sensor. The first parameter is described by the quantum detection efficiency (QDE) and the energy absorption efficiency (EAE). The QDE (η_q) corresponds to the ratio of the absorbed over the incident x-ray photons. It depends on the attenuation coefficient and the thickness of the scintillating material. For polyenergetic spectra used in x-ray imaging applications the QDE is given by the following formula (Boone, 2000):

$$\eta_q = \frac{\int_0^{E_0} \Phi_0(E)(1 - e^{-\mu_{tot,t}(E)w_0})dE}{\int_0^{E_0} \Phi_0(E)dE} \quad (1.4)$$

where $\Phi_0(E)$ is the x-ray spectrum or photon fluence (x-rays/mm²), incident on the scintillator, $\mu_{tot,t}(E)$ is the x-ray total linear attenuation coefficient of the scintillator (in cm⁻¹) (Hubbel and Seltzer, 1995) and w_0 is the thickness of the scintillator (in cm). The term $(1 - e^{-\mu_{tot,t}(E)w_0})$ expresses the monoenergetic QDE and is weighted at each energy by the x-ray spectrum shape. However, scintillators are energy integrating detectors, therefore the EAE parameter is used to describe the fraction of incident energy absorbed locally at the points of x-ray interaction within the scintillator. It depends on the amount

of energy absorbed in the scintillator per absorbed x-ray, the photons attenuated in the scintillator and the amount of incident energy. It is given by the following formula (Boone, 2000):

$$\eta_E = \frac{\int_0^{E_0} \Phi_0(E) E \left(\frac{\mu_{tot,en}(E)}{\mu_{tot,t}(E)} \right) (1 - e^{-\mu_{tot,t}(E)w_0}) dE}{\int_0^{E_0} \Phi_0(E) E dE} \quad (1.5)$$

where $\mu_{tot,en}(E)$ is the total linear energy absorption coefficient of the scintillator. It includes all mechanisms of energy deposition locally at the point of x-ray interaction within the scintillator. The dependence of EAE on the amount of energy absorbed in the scintillator per attenuated x-ray photon is expressed by the ratio of the linear energy absorption coefficient to the linear attenuation coefficient $(\mu_{tot,en}(E)/\mu_{tot,t}(E))$. The former describes the probability per cm of matter that the energy deposited per incident x-ray photon is absorbed in the scintillator, while the latter represents the probability that the incident photon interacts with the material. For energies above the K-edges, $\mu_{tot,en}(E)$ considers that the energy of any K-fluorescence photon generated escapes the scintillator (or photoconductor), while $\mu_{tot,t}(E)$ represents the increased probability that both the incident and K-fluorescence x-ray photons will be attenuated. Therefore, their ratio drops at the K-absorption edges. In truth, an amount of energy from K-fluorescence photons is re-absorbed within the scintillator (or photoconductor), but despite this EAE is considered to provide a suitable representation of the signal detection efficiency in energy integrating detectors (Boone, 2000). In other words, the EAE is expected to give an upper limit to the DQE (i.e. the DQE(0)) of energy integrating detectors. This is true for energies up to the K-edge of the x-ray detecting material. For higher energies the assumption that all the K-fluorescence photons escape the x-ray detecting material severely underestimates the EAE values. This can be observed in Table 3.7 where for low energies the EAE results are slightly lower than the QDE (i.e. in the range of 0.06-0.08). However, in the case that the average energy of the spectrum is above the K-edge the EAE values much lower compared to the QDE (in the range of 0.35-0.40 for energies slightly higher than the K-edge). A similar behaviour is observed in Marshall (2009b) study where the difference between the EAE and QDE is around 0.06 at low energies and 0.32 at higher ones. A Monte Carlo study can give a

more precise representation of the signal detection efficiency by calculating the actual ratio of the reabsorbed K-fluorescence x-ray photons (Liaparinos *et al.*, 2007). For a quick estimation of the expected DQE(0) one can probably use the EAE values at lower energies and the QDE values at higher ones.

The light yield is expressed in photons per MeV of absorbed radiation energy and is of the order of magnitude of 10^4 photons per MeV for most scintillators (van Eijk, 2003). Scintillators with high light yield may result in higher detector's output signal (in DN), which makes them suitable for low exposure applications such as breast tomosynthesis, CT, fluoroscopy, etc. Finally, the spectral matching is expressed from the matching factor (Giakoumakis, 1991) which shows the ratio of the emitted light spectrum which overlaps with the spectral sensitivity (or interacting quantum efficiency) of the digital sensor. The interacting quantum efficiency of the sensor represents the fraction of the visible photons interacting with the sensor with respect to the number of visible photons incident on the sensor. Most scintillators used in medical x-ray imaging emit light spectra with maximum peak in the range 450-550 nm (green light), therefore the sensitivity of the sensor needs to be high within this range.

In this thesis two scintillating materials were coupled to the indirect detection digital sensors to constitute x-ray detectors. A structured Thallium-activated Cesium Iodide (CsI:Tl) scintillator was coupled to LAS, Hamamatsu C9732DK and Dexela CMOS x-ray detector and a Terbium-doped Gadolinium Oxysulfide ($\text{Gd}_2\text{O}_2\text{S:Tb}$) granular scintillator was coupled to Remote RadEye HR. The term structured CsI:Tl refers to high-density fibres of this scintillator with a structure resulting from growth on a specially designed substrate (Nagarkar, 1995). This scintillating material is grown in preferential microstructured columns (5-10 μm diameter), which reduces the width of the point spread function (PSF), resulting in superior spatial resolution compared to bulk or polycrystalline (granular) scintillators. Therefore, it preserves good spatial resolution also at the increased layer thickness required to have sufficient x-ray stopping power (Nagarkar *et al.*, 1998). Both scintillators present a very high light yield (around 66000 optical photons/MeV for CsI:Tl and almost 60000 optical photons/MeV for $\text{Gd}_2\text{O}_2\text{S:Tb}$) and similar light spectra (emission maximum at 550 nm for CsI:Tl and 545 nm for $\text{Gd}_2\text{O}_2\text{S:Tb}$) (van Eijk, 2002).

LAS was coupled to structured CsI:Tl scintillator 150 μm thick grown on a 3 mm thick etched fibre optic plate (FOP). The FOP between the scintillator and the sensor's

surface is used to eliminate the direct absorption of x-rays in the Si layer of solid states detectors. According to Flynn *et al.* (1996) a directly detected x-ray produces large charge, in the order of $4,700\text{ e}^-$ for a 17 keV x-ray absorbed in Si. Hence, about 200 x-rays can saturate an imager with a 1 million e^- full well capacity and result in significant quantum noise. A silicone coupling gel (Gruner *et al.*, 2002) was used to match the refractive indices of the FOP and the detector surface preventing losses that would occur at an air gap. The thickness of this coupling layer is crucial: too thin and air bubbles will exist; too thick and optical spreading between adjacent pixels will be high (Arvanitis *et al.*, 2007a). A syringe was used to apply Visilox V-711 silicone grease to the detector surface ensuring even coverage. Hamamatsu C9732DK was coupled to a structured CsI:Tl 160 μm thick (Hamamatsu, 2010). The manufacturers did not provide any further information about the coupling. However, Elbakri *et al.* (2009) mentioned that structured CsI:Tl scintillators were directly deposited onto two similar Hamamatsu sensors. This implies no use of FOP or coupling gel. In the case of the Dexela and RadEye detectors, the scintillator was directly deposited on a FOP which was attached to the sensor. Hence, no information about the coupling gel was available. The Dexela CMOS sensor was optically coupled to two different structured CsI:Tl scintillators to test the effect of the scintillator on the output SNR of the detector. A thinner (150 μm) scintillator resulted in better performance in mammographic conditions, while a thicker one (600 μm) showed best results at higher energies (sections 3.3.8 and 3.3.9). The scintillator was mechanically supported by using a thin polyurethane foam layer for compression from the graphite cover. Finally, a $\text{Gd}_2\text{O}_2\text{S:Tb}$ granular scintillator 85 μm thick (Min-R 2190) was directly deposited on a FOP attached to the Remote RadEye HR sensor (Cho *et al.*, 2008). Again, a thin polyurethane foam layer was used to mechanically support the scintillator.

1.8 Image simulation

To simulate the detector's effect on ideal input images, signal and noise modification routines were developed based on Saunders and Samei (2003) study. To apply the former routine, two-dimensional (2-D) pMTF matrix is extracted from the experimentally measured 1-D pMTF values. This matrix is multiplied with the 2-D Fourier transform of the input image to simulate the blurring. Then the restored image is sampled to form the pixels of the digital image. Therefore, the signal modification

routine results in blurred and sampled image. To implement the noise modification routine, the square root of the measured 2-D NNPS matrix is multiplied with the Fourier transform of a white Gaussian noise image. The restored image contains the noise correlation described by the NNPS. Then it is scaled based on the experimentally measured mean-variance relationship and added on the blurred and sampled image to form the final simulated image. In this thesis the signal modification routine was slightly adapted to simulate anisotropic signal transfer behaviour. Furthermore, a different sampling method was used in order to avoid the sinc correction. Finally, the sampling method was modified in Anrad and Dexela detectors to get a ratio equal to a full integer number and a half, because the “analog” pitch of the ideal image was 10 μm and the pixel pitches of the detectors were 75 and 85 μm respectively. Further details about the simulation algorithm are given in Chapter 4. Each detector modifies in a different way the same input data and the simulation was used to predict the resultant image quality of the investigated detectors. Furthermore, the simulation allowed the examination of two combinations of the spatial resolution of one detector with the noise characteristics of another detector in terms of contrast-detail analysis. Two types of ideal software phantoms were used to compare the response of the detectors in a range of mammographic conditions. The first category of phantoms represented 3-D breasts of different thicknesses and glandularity. Each breast phantom contained 6 microcalcifications in order to evaluate their visibility in terms of the contrast to noise ratio. The second phantom was a CDMAM test tool, i.e. it contained gold disks at different thickness and diameter in order to define the effect of the detector on the threshold contrast. Further details about the digital phantoms are given in Chapter 5.

1.9 Image quality evaluation

1.9.1 Rose theory and signal detectability

According to the theory developed by Rose the detectability of a flat-topped and sharp-edge object of area A against a uniform background is given by the following equation (Rose, 1948 and Burgess, 1999):

$$SNR_{Rose} = C\sqrt{A\langle n_b \rangle} \quad (1.6)$$

where C is the signal contrast, i.e. the difference in signal between the object and the background divided by the signal of the background, and $\langle n_b \rangle$ represents the x-ray photons per unit area for the background. For linear (or linearized) and quantum limited x-ray detectors, Marshall (2009a) demonstrated that the above equation can be expressed as follows:

$$SNR_{Rose} = C \frac{m_b}{\sigma} = \frac{|m_o - m_b|}{\sigma} \quad (1.7)$$

where m is the mean pixel value (or digital number - DN), σ is the noise of the image and the subscripts b and o correspond to background and object respectively. In x-ray imaging applications the parameters contrast-to-noise ratio (CNR) or signal-difference-to-noise ratio (SDNR) are used to quantify the detectability of certain objects against the background. For instance, in mammography the object often corresponds to microcalcifications (μ Cs), while the background is the adipose/glandular tissue. However, the definition of the noise is different in several studies. In particular, Huda *et al.* (2003), Bernhardt *et al.* (2006), Bertolini *et al.* (2010), Desai *et al.* (2010) and Singh *et al.* (2010) took into account only the background noise. On the other hand, van Engen *et al.* (2006), Toroi *et al.* (2007), Gennaro *et al.* (2008), Alsager *et al.* (2008) and Marshall (2009a) used the combined object-background noise. Since there is not a formal separation between CNR and SDNR in the literature and the interpretation of noise depends solely on the researcher's definition, the parameters CNR and SDNR were calculated as follows in this study:

$$CNR = \frac{m_o - m_b}{\sqrt{\frac{\sigma_o^2 + \sigma_b^2}{2}}} \quad (1.8)$$

$$SDNR = \frac{m_o - m_b}{\sigma_b} \quad (1.9).$$

In other words, the parameter CNR was used to express the ratio of the signal contrast to the combined noise and the SDNR to take into account only the background noise. Both parameters were employed to quantitatively compare the performance detectability of the investigated digital detectors on digital mammograms (see section 5.2.2).

1.9.2 Contrast-detail analysis

According to the European Guidelines for quality control in digital mammography, mammographic image quality is expressed in terms of threshold contrast visibility using clinical exposure settings (van Engen *et al.*, 2006, Young *et al.*, 2006a, Young *et al.*, 2006b and Young *et al.*, 2008). The threshold contrast is defined as the lowest contrast value for which the objects are visible (Wagner and Frey, 1995). The contrast-detail mammography (CDMAM) phantom is commonly used for the contrast-detail analysis (Thomas *et al.*, 2005). In this study a slightly modified version of the Artinis CDMAM 3.4 Phantom (Bijkerk *et al.*, 2000) is used to compare the ability of the investigated digital systems to detect very low contrast and very small details. Figure 1.8 shows a photograph of the CDMAM 3.4 phantom. The phantom consists of a 16 cm x 24 cm x 0.5 mm aluminum plate with 205 square cells that are arranged in 16 rows and 16 columns. Each cell contains two identical gold disks of given thickness and diameter. One is placed at the centre and the other is located in a randomly chosen corner (eccentric disk). Both disk diameter and thickness decrease logarithmically to cover a range of object diameters from 2.00 to 0.06 mm in each column and thicknesses between 2.00 and 0.03 mm in each row respectively. Both ranges are selected to simulate the respective size and contrast ranges for microcalcifications. The CDMAM phantom is used to determine the contrast limit (threshold contrast) or threshold gold thickness for a given disk diameter that corresponds to successful observation of the eccentric disk location. The Al base is attached to a polymethyl methacrylate (PMMA or plexiglas) cover 5 mm thick. To simulate the detectability of microcalcifications, the details have to be imaged on a background object with a thickness close (in terms of attenuation) to a typical compressed breast. Hence, the CDMAM phantom is usually inserted between two PMMA plates of 20 mm thickness each (Grosjean and Muller, 2006, Segui and Zhao, 2006, Young *et al.*, 2006a and van Engen *et al.*, 2010). This combination under a 28 kV Mo/Mo radiation beam corresponds to a total attenuation approximately equal to 50 mm PMMA, which has been shown to be equivalent to breasts of typical composition with a compressed thickness of 6 cm (Dance *et al.*, 2000 and Dance *et al.*, 2009)

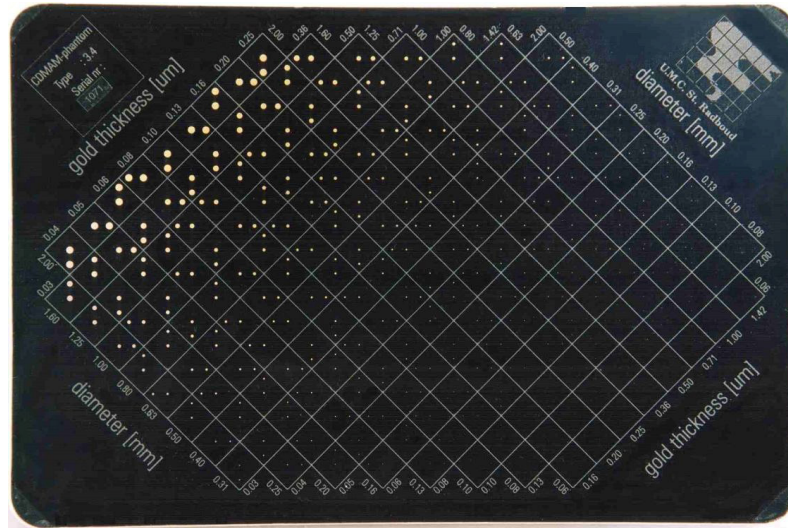


Figure 1.8: Image of a CDMAM 3.4 phantom from Artinis Medical Systems, Netherlands

The evaluation of the CDMAM test object is usually based on reading of CDMAM radiographs by human observers. To implement this, contrast-detail measurements rely on a large number of observer readings. However, this procedure suffers from three main drawbacks: a) the presence of significant inter-observer error decreases the reliability and confidence in the measurements, b) the evaluation may be biased from memory effects in the human observer because it is practically focused to a specific number of cells and c) it is time consuming (Young *et al.*, 2006a, Young *et al.*, 2006b, Young *et al.*, 2008, Prieto *et al.*, 2009 and Singh *et al.*, 2010). A couple of studies suggested solutions to eliminate the memory effect by rotating the eccentric disc inside each cell (Rivetti *et al.*, 2006 and Prieto *et al.*, 2008). However, the other two limitations still exist. Hence, automatic scoring softwares for the evaluation of the CDMAM phantom were developed by Karssemeijer and Thijssen (1996), Yip *et al.* (2009) and Prieto *et al.* (2009) to provide a reliable and less time consuming alternative to human readout. The first software was further developed by Veldkamp *et al.* (2003) and Visser and Karssemeijer (2008) to create the *CDCOM* software tool. *CDCOM* is widely accepted by researchers and the scientific community and is supported by the European Reference Organisation for Quality Assured Breast Screening and Diagnostic Services (EUREF). In this study the freeware *CDCOM v1.5.2* software tool was used for automated readout of CDMAM 3.4 images and was downloaded from the EUREF website (Visser and Karssemeijer, 2008).

Briefly, the *CDCOM* determines the position, orientation and scale of the phantom and it constructs templates of the disk objects in each of the four corners of each cell. Then, it selects the cell corners in which the disks are most likely to be located using the ideal observer model. Finally, it checks if it has selected the corner where a disk is actually present. By applying the program to a number of CDMAM phantom images and calculating the probability of detection for each cell, contrast-detail curves can be calculated (Karssemeijer and Thijssen, 1996). While any number of CDMAM images can be used for the extraction of the contrast-detail curves the *CDCOM* manual suggests the use of at least eight images (Visser and Karssemeijer, 2008). However, the *CDCOM* program does not combine the data from more than one image or determine the threshold contrast. Instead, it provides two output files, one with results for the eccentric disks and the other with results for the centre disks. The data is in a form of a 16x16 matrix, where 1 is a correctly located disk, 2 is an incorrectly located disk and -1 is a cell that is not in the phantom. Further analysis needs to be done from the user. The manual suggests the combination of the two output files and refers to the procedure described by Karssemeijer and Thijssen (1996) and Veldkamp *et al.* (2003). In each of the resulted 16 matrices the incorrectly located disk is set equal to zero in order to allow the calculation of an average matrix that shows the proportion of correctly identified discs for each detail diameter and thickness. The following figure shows an example of the average detection matrix showing the proportion of correctly detected disks created from eight CDMAM images using LAS at 59 μGy DAK (Air Kerma at detector input plane).

		Disk thickness (μm)															
		0.03	0.04	0.05	0.06	0.08	0.1	0.13	0.16	0.2	0.25	0.36	0.5	0.71	1	1.42	2
Disk diameter (mm)	2		0.81	0.75	0.94	0.94	1	1	1	1	1						
	1.6	0.44	0.25	0.75	0.94	0.94	1	1	0.56	1	0.5	1					
	1.25	0.38	0.56	0.63	0.44	0.94	1	1	1	1	1	1	1				
	1	0.31	0.5	0.5	0.69	0.75	0.94	1	1	1	1	1	1	1			
	0.8	0.44	0.38	0.5	0.5	0.5	0.69	0.88	1	1	1	1	1	1	1		
	0.63	0.25	0.31	0.19	0.63	0.44	0.69	0.88	0.75	1	1	1	1	1	1	1	
	0.5	0.56	0.38	0.44	0.5	0.5	0.69	0.63	0.75	0.88	0.88	1	1	1	1	1	1
	0.4	0.31	0.25	0.44	0.25	0.38	0.31	0.75	0.81	0.75	1	1	1	1	1	1	1
	0.31	0.25	0.56	0.25	0.5	0.38	0.13	0.38	0.44	0.75	0.69	1	1	1	1	1	1
	0.25		0.25	0.25	0.31	0.31	0.19	0.25	0.56	0.63	0.38	0.81	1	1	1	1	1
	0.2			0.19	0.44	0.38	0.25	0.38	0.44	0.38	0.56	0.56	0.56	1	1	1	1
	0.16				0.25	0.38	0.31	0.19	0.56	0.38	0.31	0.44	0.56	0.63	1	1	1
	0.13					0.38	0.06	0.25	0.5	0.44	0.31	0.38	0.63	0.63	0.75	1	1
	0.1						0.25	0.19	0.31	0.25	0.19	0.13	0.44	0.31	0.31	0.44	0.81
	0.08							0.19	0.44	0.38	0.38	0.25	0.31	0.19	0.31	0.56	0.63
	0.06								0.38	0.19	0.44	0.19	0.38	0.63	0.25	0.31	

Figure 1.9: Example of the original average detection matrix over 16 *CDCOM* matrices

From the above matrix it can be seen that the maximum probability of detection $p(t)$ equals to 1, while the minimum $p(t)$ (i.e. 0.19) is close to the theoretical value of 0.25 which corresponds to a random guessing of the eccentric disk corner. The small deviations from the minimum theoretical value are probably introduced from the *CDCOM* software. Therefore, a detection rate of $p(t)=0.625$ represents the mid-point between these two extremes and defines the threshold between correct and wrong indications. The disc thickness and the associated contrast that correspond to this value are called threshold thickness (t_T) and threshold contrast (C_T) respectively. The relationship between contrast and thickness is given by $C(t)=100 \cdot (1-e^{-\mu t})$ (%), where μ is the linear attenuation coefficient of gold ($\mu=0.145 \text{ } \mu\text{m}^{-1}$ in this study). This relationship is extracted from the contrast equation $\Delta I/I = \log_e(\psi_o/\psi_b)$ where ψ_o is the target energy flux and ψ_b is the background energy flux (Wagner and Frey, 1995). To determine the threshold gold thickness for a given disk diameter a psychometric curve is fitted to the data (Karssemeijer and Thijssen, 1996 and Veldkamp *et al.*, 2003):

$$p(t) = \frac{0.75}{1 + e^{-f(C(t)-C_T)}} + 0.25 \quad (1.10)$$

where $C(t)$ is the logarithm of signal contrast according to Webers law (i.e. the relationship between stimulus and perception is logarithmic; Falmagne, 1987) and f is a free parameter to be fitted. According to Verbrugge (2007) the above formula can be simplified to a more practical function:

$$p(t) = \frac{0.75}{1 + e^{-f(\frac{t}{t_T})}} + 0.25 \quad (1.11).$$

In this study the latter equation was fitted by means of nonlinear least mean squares procedure using custom built software written in MATLAB version 7.10 (The MathWorks, Natick, MA, USA) to define the threshold thickness and its uncertainty (expressed by the 95 % confidence level). The calculated threshold contrast can be further fitted using a third order polynomial function to obtain a contrast-detail curve (Young *et al.*, 2006b and Young *et al.*, 2008):

$$C_T = a + b \cdot x^{-1} + c \cdot x^{-2} + c \cdot x^{-3} \quad (1.12)$$

where x is the disc diameter (mm) and a , b , c and d are coefficients adjusted to achieve a least squares fit. Young et al. (2006b) compared four methods to extract the contrast-detail curve from the *CDCOM* results matrix. Briefly, *method A* uses a simple thresholding technique by applying a nearest neighbour correction (NNC) on each individual matrix prior the calculation of the average matrix with proportion correctly detected disks (Figure 1.9). This method is similar to the human observer scoring. *Method B* is the already described one, i.e. it fits the psychometric curve to the original data of the average detection matrix. *Method C* applies a simple smoothing algorithm on the average detection matrix and then a linear interpolation to determine the threshold contrast. Finally, *method D* which is the combination of the above two methods, applies the psychometric curve fit on the smoothed data of the average detection matrix. It was found that the most reproducible method of all was *method D*. Hence, the average detection matrix is smoothed by convolving each cell with the following smoothing mask (SM):

$$SM = \frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 1 & 4 & 1 \\ 1 & 2 & 1 \end{bmatrix} \quad (1.13)$$

Figure 1.10 shows the smoothed version of the original detection matrix presented in Figure 1.9.

		Disk thickness (μm)															
		0.03	0.04	0.05	0.06	0.08	0.1	0.13	0.16	0.2	0.25	0.36	0.5	0.71	1	1.42	2
Disk diameter (mm)	2		0.64	0.77	0.89	0.95	0.98	0.96	0.93	0.92	0.9						
	1.6	0.44	0.53	0.68	0.82	0.92	0.98	0.95	0.89	0.88	0.87	0.91					
	1.25	0.41	0.48	0.59	0.69	0.85	0.96	0.97	0.95	0.94	0.94	0.97	1				
	1	0.4	0.46	0.53	0.61	0.73	0.87	0.96	0.99	1	1	1	1	1			
	0.8	0.37	0.39	0.45	0.53	0.61	0.74	0.88	0.95	0.98	1	1	1	1	1		
	0.63	0.36	0.35	0.39	0.48	0.55	0.66	0.78	0.85	0.93	0.98	0.99	1	1	1	1	
	0.5	0.39	0.36	0.39	0.44	0.49	0.59	0.7	0.78	0.86	0.94	0.98	1	1	1	1	1
	0.4	0.36	0.37	0.38	0.39	0.39	0.44	0.58	0.7	0.79	0.89	0.97	1	1	1	1	1
	0.31	0.33	0.35	0.35	0.36	0.32	0.29	0.41	0.57	0.67	0.76	0.9	0.99	1	1	1	1
	0.25		0.3	0.3	0.34	0.32	0.26	0.33	0.48	0.55	0.6	0.75	0.89	0.97	1	1	1
	0.2			0.27	0.33	0.33	0.29	0.34	0.43	0.46	0.48	0.58	0.71	0.87	0.98	1	1
	0.16				0.32	0.33	0.27	0.31	0.42	0.42	0.4	0.46	0.58	0.74	0.9	0.98	1
	0.13					0.29	0.23	0.27	0.38	0.38	0.32	0.38	0.5	0.59	0.7	0.84	0.92
	0.1						0.21	0.25	0.33	0.33	0.27	0.29	0.37	0.4	0.45	0.61	0.74
	0.08							0.27	0.33	0.33	0.3	0.28	0.31	0.33	0.35	0.47	0.6
	0.06								0.33	0.33	0.32	0.3	0.35	0.4	0.35	0.38	

Figure 1.10: Example of the smoothed average detection matrix over 16 *CDCOM* matrices

In this study the contrast-detail curves were calculated between details of size 0.1 and 1.0 mm based on Young *et al.* (2006) observations. They found out that *CDCOM*

could not effectively locate the discs for detail diameters of less than 0.1 mm, while it can easily locate almost all the discs for large diameters.

It is known that the results of the *CDCOM* software are different compared to the results from human observers (Visser and Karssemeijer, 2008). For this reason, Young *et al.* (2008) investigated the relationship between human and computer readouts. More specifically, they compared the threshold contrast results extracted from observers from three diagnostic centres (Guildford, Nijmegen and Leuven) to the respective ones calculated using *CDCOM*. Furthermore, they applied four different detection methods by smoothing or not the detection matrix data before fitting the psychometric curve and by using or not the contrast-detail curve fitted values (Eq. (1.12)) instead of raw values. They found out that the correlation between the results of the automated process and the human readings follows a power function of the following form:

$$TC_{human} = a(TC_{CDCOM})^n \quad (1.14)$$

where a and n are coefficients to be fitted using the least squares approximation. They applied this type of function to minimize confusions by differences between the readers at the three centres. However, they found out that the studied correlations were slightly different for different diagnostic centres and the detection methods applied on the *CDCOM* results. Van Engen *et al.* (2010) combined all the data from the three diagnostic centres and they provided average factors equal to $a=1.17$ and $n=0.888$ using the aforementioned detection method D (i.e. smoothing the original data and then applying the psychometric curve fit to determine the threshold contrast for each detail diameter). Finally, they suggested that the resulting predicted human readout threshold contrast should be fitted using Eq. (1.12) and checked against the limiting values for human readout as published in the European Guidelines (van Engen *et al.*, 2006).

Finally, an overall image quality index of a detector can be extracted from the contrast-detail analysis by means of the image quality figure (IQF). It is the sum of the products of the diameters of each of the smallest scored objects and their respective threshold thickness (Zoetelief *et al.*, 1993 and Thomas *et al.*, 2005). Oberhofer *et al.* (2008 and 2010) introduced the inverse IQF (IQF_{inv}) as follows:

$$IQF_{inv} = \frac{100}{\sum_{i=1}^{16} D_i \cdot t_{T,i}} \quad (1.15)$$

where D_i is the disk diameter, $t_{T,i}$ is the threshold thickness and i the diameter. In our case i varied from 1 to 11 due to the selected range of disk diameters, i.e. 0.1-10 mm. They found a linear correlation between this parameter and CNR over a wide range of exposures. They described this parameter as an objective and absolute measure of image quality, suitable for comparing different digital detectors. Hence, in this thesis the overall contrast-detail performance of the detectors was compared using the IQF_{inv} parameter.

1.10 Summary and structure of the rest of this thesis

This chapter presents the aim of the thesis and the technology of the digital detectors commonly used in medical x-ray imaging. Also, it introduces the role of the scintillators in the detection of x-rays. Furthermore, it describes in detail the image quality metrics used to evaluate the simulated images. Further details about the performance evaluation of the detectors, simulation process and software phantoms are presented in the following chapters. Figure 1.11 shows photographs of the used sensors/detectors.

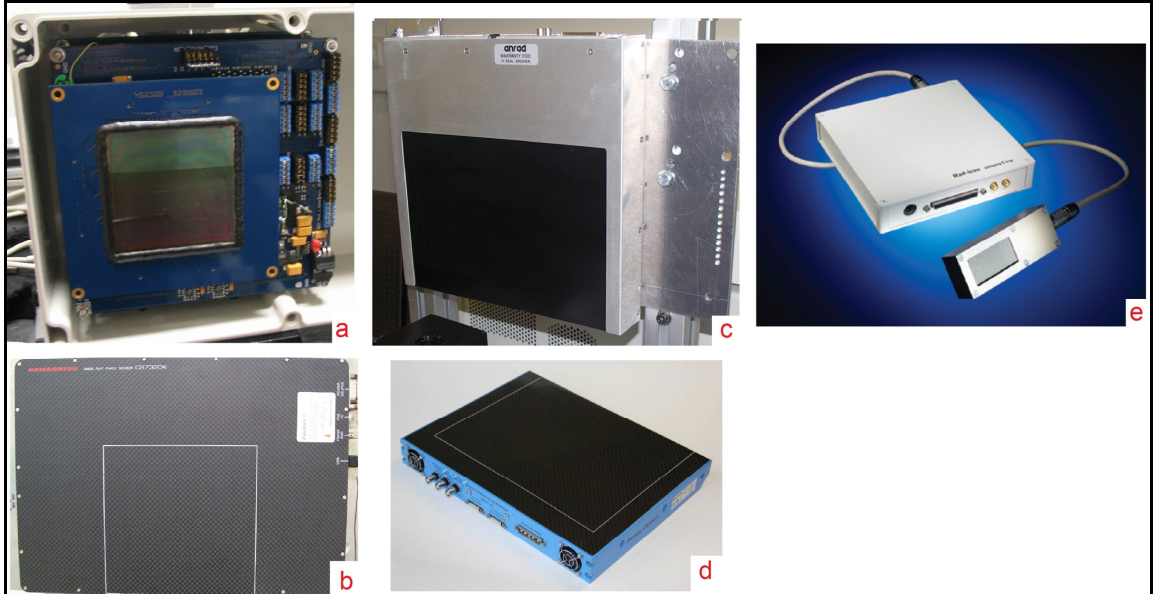


Figure 1.11: Photographs of a) LAS sensor, b) Hamamatsu C9732DK detector, c) Anrad SMAM detector, d) Dexela CB 2923 detector and e) Remote RadEye HR detector

Table 1.1 shows the design specifications of the five digital x-ray detectors which are evaluated in this study, i.e. their expected performance based on their design. In this table some of the differences between the imaging technologies are observed. For instance, the flat panel and CMOS PPS technologies demonstrate higher read noise and lower achievable frame rate compared to the CMOS APS technology. The actual performance of any sensor inevitably depends on the conditions under which it is operated and the data acquisition system used to retrieve data from it. Finally, the calculation of the performance parameters of LAS was affected by the EMI (Bohndiek *et al.*, 2009).

Table 1.1: Nominal design specifications of the digital detectors under investigation

Parameter	LAS	Hamamatsu C9732DK	Dexela CMOS x-ray detector	Anrad SMAM	Remote RadEye HR
Technology	CMOS APS	CMOS PPS	CMOS APS	a-Se TFT	CMOS APS
Pixel size (μm)	40	50	74.8	85	22.5
Photodiode area (cm^2)	5.4 x 5.4	12 x 12	14.5 x 11.5	17.3 x 24	2.7 x 3.6
Number of pixels	1350 x 1350	2400 x 2400	1944 x 1536	2032 x 2817	1200 x 1600
Number of active pixels	1350 x 1350	2368 x 2340	1934 x 1536	2016 x 2816	1200 x 1600
ADC bit depth (bit)	14	14	14	13	12
Read noise (r.m.s.) (e^-)	62	1250	309 (HFW) 126 (LFW)	5200	< 120
Full well capacity (e^-)	61.3×10^3	6.4×10^6	1.4×10^6 (HFW) 0.4×10^6 (LFW)	15×10^6	$< 0.48 \times 10^6$
Dynamic range (dB)	60.3	74	73.1 (HFW) 70.1 (LFW)	69.2	72
Resolution (lp/mm)	12.5	10	6.7	5.9	22.2
Max frame rate (fps)	20.7	1	26	0.7	0.5
Fill factor (%)	73	79	84	70	80
x-ray detecting material / thickness (μm)	CsI:Tl / 150	CsI:Tl / 150	CsI:Tl / 150 and 600	a-Se / 200	Gd ₂ O ₂ S:Tb / 85

The remainder of the thesis is organized as follows:

- Chapter 2 describes the methodology used to apply the electro-optical and x-ray performance evaluation of digital x-ray detectors.
- Chapter 3 presents the experimental results of the performance evaluation.
- Chapter 4 describes the aim and methodology used for the image simulation based on the experimentally measured physical performance parameters.

- Chapter 5 compares the resultant image quality of the simulated images.
- Chapter 6 summarizes the finding of this work and suggests suitable x-ray applications for the investigated detectors.

Chapter 2

2 Objective performance evaluation of the x-ray detectors

2.1 Overview of chapter

In this chapter the theory of the electro-optical and x-ray performance evaluations is described. Both of them depend on the relationship between the signal and the noise, i.e. the SNR. Additionally, the origin of the noise sources and their effect on the input signal are studied. The performance parameters of the sensor are extracted using electro-optical evaluation by employing the photon transfer curve (PTC), the mean-variance (MV) or the nonlinear compensation (NLC) methods. The x-ray performance evaluation of the x-ray detector is made by calculating the presampling modulation transfer function (pMTF), the noise power spectrum (NPS) and the resultant detective quantum efficiency (DQE).

2.2 Parameters that affect the signal

During the creation of the digital image, from the detection of the optical or x-ray photons to the formation of the respective DN, there are several parameters that cause either overestimation or underestimation of the signal level. These parameters are noise from the x-ray photons to the readout electronics, electromagnetic interference from external sources and the nonlinearity of the CMOS APS. For a proper evaluation of the detector performance the effect of these parameters has to be assessed. A brief description of each of them is given in the following subsections.

2.2.1 Detector noise sources

The detector noise sources are primary quantum noise, excess Poisson noise, secondary quantum noise, structure noise, aliasing and additive electronic noise which

includes the read noise and the dark current (Granfors and Aufrichtig, 2000, Evans *et al.*, 2002 and Mackenzie and Honey, 2007).

The primary quantum noise (σ_Q) source is related to the Poisson distribution of the number of x-ray photons absorbed by the x-ray detecting material (i.e. either the scintillator or the photoconductor). Due to the Poisson statistics this noise is given by $\sigma_Q = \sqrt{N}$ where N is the input signal represented by the number of x-ray photons incident (per unit area) on the detector. In the electro-optical evaluation literature the primary quantum noise is referred to as shot noise (Janesick, 2007). In this case, it arises from the Poisson variation in the rate of optical photon arrival at the sensor. Knowing that one visible photon creates one electron-hole pair and assuming a unity quantum yield (the number of electrons generated, collected and transferred per interacting photon), the uncertainty in the collected charge in any pixel becomes

$$\sigma_{Shot}(e^-) = \sqrt{S(e^-)} \quad (2.1)$$

where $S(e^-)$ is the signal in electrons. This formula is fundamental for the electro-optical performance evaluation of the linear sensors (see sections 2.3.3 and 2.3.4).

The Poisson excess noise is a result of variations in the number of secondary quanta detected per primary quanta absorption. Therefore, this is the ratio between excess noise (σ_{ex}) and the primary quantum noise. These variations are described by the Swank factor and the Lubberts effect (Granfors and Aufrichtig, 2000, Lubberts, 1968 and Swank, 1973). The Swank factor is related to the fact that different absorbed x-ray photons produce different amounts of signal. It includes effects due to the polychromatic x-ray spectra used for imaging and due to the statistical variation in the signal produced by different x-rays of the same energy. Similarly to the Swank factor, the Lubberts effect describes the noise caused by different photons producing signals with different PSF. However, the Lubberts effect is smaller in structured CsI scintillator compared to a conventional one with similar x-ray absorption due to the light guidance.

The secondary quantum noise (σ_{SQ}) is also Poisson noise and occurs at each stage of the imaging chain where the secondary quanta (e.g., light photons, electrical charge) are converted. The level of this noise depends on the conversion efficiency of the scintillator (i.e. number of optical photons per absorbed energy), the fraction of light

escaping from the scintillator, the coupling efficiency of the optical arrangement between the scintillator and the digital sensor and the quantum efficiency of the digital sensor for the emitted light spectrum. According to Cunningham (2000) this noise is negligible when the equivalent number of quanta at each spatial frequency for each stage is greater than ten, i.e. an effective system gain of greater than 100 at all stages is necessary. The term quantum sink describes the stage that this criterion is not met and where significant secondary quantum noise will occur.

The structure (σ_s) or fixed pattern noise (FPN) describes the spatially fixed variations in the gain across the detector, i.e. variations in the amount of output signal for a given input quantity. The sources of structure noise in the detector include phosphor screen granularity, variations in FOP transmission and variation in sensitivity between the digital sensor pixel elements. Part of the normal clinical imaging procedure with these units is the use of flat-field image correction to remove the effects of structure noise. It has a fixed spatial pattern from frame to frame. The FPN of the sensor is related to pixel-to-pixel and column-to-column non uniformities, due to differences in sensitivity and the transistor's gain inside each pixel and differences in the gain of columns amplifiers, respectively. The magnitude of the FPN is assumed to be proportional to the signal level. In normal clinical imaging procedure with digital detector the FPN noise is removed by flat-field image correction methods, either by normalizing with the flat-field image or by logarithmic subtraction of the flat-field image (Evans *et al.*, 2002). In the electro-optical performance evaluation of the sensor the FPN is removed by subtracting two consecutive frames at the same illumination level, because the read and shot noises are temporal while FPN is spatial (see section 2.3.3). Finally, in the x-ray performance evaluation of the detector the FPN is usually removed by normalizing with the flat-field image (see section 3.3.3).

According to the sampling theory when the image contains frequencies higher than the Nyquist frequency aliasing occurs. The Nyquist frequency (F_{Nyq}) is defined as $F_{Nyq} = 1/(2 \cdot \Delta x)$ where Δx is the pixel pitch in mm. In the case of aliasing, the frequency spectrum of the image beyond Nyquist Frequency is mirrored (folded) about this value, added to the spectrum of their counterpart frequencies below the Nyquist frequency and becoming indistinguishable from them (Dobbins III, 1995, Rowlands *et al.*, 2000a, Evans *et al.*, 2003, Mackenzie and Honey, 2007 and Monnin *et al.*, 2007).

The aliasing noise may affect both the signal and noise transfer (MTF and NPS respectively; section 2.4). It has a strong effect on direct conversion flat panel detectors (a-Se TFT) and is almost negligible on scintillator-based detectors because the blur of the scintillator acts as a filter which reduces the MTF and NPS above the Nyquist frequency.

Additive electronic noise (σ_{el}) is introduced by electronic components in the system, such as the read noise and dark current, that are present even in the complete absence of external signal. Read noise is mainly due to on-chip transistors and amplifier noises, but can also include any other noise sources independent of the signal level. The dark current corresponds to thermally generated charge carriers inside the photodiode. The additive electronic noise affects the signal at low exposure levels used in applications such as fluoroscopy. At higher signal levels it has almost negligible effect.

Summarizing, the electro-optical performance evaluation decomposes the main noise sources of the sensor: shot, read and fixed pattern noise, while the x-ray performance evaluation takes into account the total noise of the digital detector which can be described as follows (Evans *et al.*, 2002, Mackenzie and Honey, 2007):

$$\sigma_{total}^2 = \sigma_Q^2 + \sigma_{ex}^2 + \sigma_{SQ}^2 + \sigma_S^2 + \sigma_{el}^2 \quad (2.2)$$

The total noise of the digital detector is further described in section 2.4.4 that analyses the NPS.

2.2.2 Electromagnetic Interference

A periodic noise pattern may occur if the imaging system (the acquisition or networking hardware) is subject to electromagnetic interference (EMI) of a periodic nature. EMI is disturbance that affects an electrical circuit due to either conduction or radiation emitted from an external electrical source or magnetic induction between two circuits (Carr, 2000). This noise results in one or more sinusoidal patterns superimposed on the image, having specific period and phase relationships (Al Hudhud and Turner, 2005, Ji *et al.*, 2007b, Russ, 2007 and Aizenberg and Butakoff, 2008). The origin of the noise may be internal (the digital sensor itself or the DAQ) or external (any other electric circuit beyond the acquisition system, e.g. x-ray tubes, power supplies, computers, etc.). In the case of LAS, periodic noise was found when a specific version

(namely 2nd generation) of the electronics stack board was used. The periodic noise is concealed by FPN on a single frame and therefore it is not directly visible. However, the periodic noise affected the evaluation of the performance parameters of this sensor, because according to the photon transfer method two consecutive frames are subtracted to remove the FPN (see section 2.3.3). Therefore, the periodic noise appears and is amplified by a factor $\sqrt{2}$ because it is uncorrelated. Further details about the extraction of this factor are given in section 3.3.3. This combination both amplifies and reveals the periodic pattern on a difference image.

Several hardware methods for reducing periodic noise were tested during this thesis, including a) the use of a common power supply and/or ground between the sensor and the FPGA which connects the sensor to the PC, b) the use of a Faraday cage to electrically isolate various parts of the imaging system, and c) testing the imaging system in various places to see if it is affected by external electrical sources. None of these solutions reduced or changed the periodic noise pattern. This is an indication that the noise had an internal origin. According to the manufacturers of the sensor's readout electronics (Aspect Systems GmbH, Dresden, Germany), this periodic pattern is likely to be due to unfiltered EMI noise arising from the switch mode voltage regulator within the DAQ system (it generates a -5V supply for the output amplifiers). In this case, software solutions can be used to reduce the noise off line. Periodic noise can be reduced by filtering either in the spatial (Ji *et al.*, 2004, Ji *et al.*, 2006, Ji *et al.*, 2007a and Ji *et al.*, 2007b) or in the frequency domain (Parker, 1997, Aizenberg and Butakoff, 2002, Gonzalez *et al.*, 2004, Al Hudhud and Turner, 2005, Russ, 2007, Sonka *et al.*, 2007, Gonzalez and Woods, 2008 and Aizenberg and Butakoff, 2008). The former has been achieved using a soft morphological filter (SMF) which is an extension of standard morphological operators, i.e. it uses the "substitution" strategy that replaces the value of the central pixel by a value calculated from the pixels within a local window according to a certain rule. This type of filtration is less computationally time-consuming because it does not require the transformation between the spatial and frequency domains and the noise peak detection and filtering procedure. However, it appears to be less effective in the elimination of low frequency periodic noise, as it was found to be the case in the current work. Moreover, it entails poor detail preservation according to a comparison made in terms of peak signal-to-noise ratio (PSNR) (Ji *et al.*, 2006, Ji *et al.*, 2007a and

Ji *et al.*, 2007b). Therefore, a more effective approach in this case is to eliminate the periodic noise in the frequency domain.

The periodic noise pattern appears as one or more cross-shaped spikes in the frequency domain. These crosses result from the convolution of a frequency spike due to periodic noise with the Fourier transform of the windowing function representing the finite size of the difference image. There are three main categories of frequency domain filters suggested in the literature: band-reject (Gonzalez and Woods, 2008), notch-reject (Gonzalez *et al.*, 2004, Al Hudhud and Turner, 2005, Russ, 2007, Sonka *et al.*, 2007, Gonzalez and Woods, 2008, Aizenberg and Butakoff, 2008) and frequency median filters (Aizenberg and Butakoff, 2002, Al Hudhud and Turner, 2005). In two dimensions, band-reject filters attenuate a frequency band which is circularly symmetric around the origin (zero frequency or DC component) in the frequency domain. Notch-reject filters attenuate a small region of frequencies around a central frequency. Finally, median filters replace the value of either the central pixel (Aizenberg and Butakoff, 2002) or to the neighbourhood of peaks (Al Hudhud and Turner, 2005) by the median value calculated from the pixels within a local window. Band-reject filters are not appropriate for filtering specific spikes, as their effect would extend to a broader frequency range, therefore having a more significant impact on the signal. The suggested median filters would only remove the central points in the cross-shaped spike, and would therefore either leave adjacent excessive values unaffected, thus resulting in insufficient removal of the EMI noise (Aizenberg and Butakoff, 2002), or smear the entire area around it, thus affecting a wider part of the useful signal (Al Hudhud and Turner, 2005). On this basis, cross-shaped notch-reject filters can be considered the most appropriate to remove the specific spikes, since they precisely target the artifact while causing a minimum modification of the useful frequencies.

A novel study was made to remove the periodic noise during the electro-optical evaluation of LAS (Konstantinidis *et al.*, 2010). This method is described in detail in section 3.2.1. Briefly, it applies and compares three different cross-shaped notch-reject filters on the frequency domain to remove the spikes that correspond to the periodic pattern. The selection of the shape of filters was made to precisely target the artifact while causing a minimum modification of the useful frequencies. The filtering was applied to a central ROI of LAS assuming that it corresponds to the average performance of the sensor. Another study applied the filtration algorithm on different

ROIs over the sensor to compare the effect of the stitching on the performance of LAS (Zin *et al.*, 2010).

2.2.3 Inherent nonlinearity of CMOS sensors

Digital sensors and mainly CMOS APS suffer from inherent nonlinearity. As it is discussed in section 2.3.4, nonlinearity may affect the measurement of the sensor's conversion gain and therefore the calculation of the sensor performance parameters. Also, it may affect the calculation of the x-ray performance parameters (section 3.3.11). This problem arises from two sources (Janesick *et al.*, 2006 and Janesick, 2007):

- 1) Sensitivity (V/e^-) nonlinearity: takes place at the charge-to-voltage conversion. This is expressed from the term inside the brackets. In the CMOS sensors case, this drawback occurs because the sensor photodiode is an element of the sense node and the capacitance inside each pixel changes during charge integration. The variation of the sense node capacitance with charge level is described in Eq. (1.1). It may be observed that the photodiode capacitance increases and consequently the sense node sensitivity (V/e^-) decreases as a function of the signal level $S(e^-)$ (Janesick, 2002).
- 2) Gain (V/V) nonlinearity: arises from any amplifier in the readout chain, i.e. it affects the voltage that corresponds to the input signal. In the case of CMOS APS, this parameter is more prominent due to the additive nonlinearity of the source follower inside each pixel.

V/V nonlinearity can be well controlled to less than 1% over a sensor's dynamic range. Therefore, it is usually ignored. V/e^- nonlinearity for CCD is usually negligible ($< 0.2\%$) because charge-to-voltage conversion takes place at a common sense node for which a good linearity is achieved. On the other hand, V/e^- nonlinearity may be significant for CMOS sensors, exceeding 200 % in some cases, because the capacitance varies with the number of accumulated electrons inside each pixel (Janesick, 2007). The V/e^- nonlinearity results in reduction of both the signal and the noise at high illumination levels. However, the signal to noise ratio (SNR) improves because the reduction on the noise is higher. This happens because the signal voltage is inversely proportional to C_{SN} , while the r.m.s. noise voltage is inversely proportional to C_{SN}^2 (Tian *et al.*, 2001).

2.3 Sensor performance evaluation

The performance parameters of the sensor itself are measured through optical characterisation, i.e. using light photons in the visible wavelength. The parameters commonly referred to the literature are the conversion gain, decomposition of the three main noise sources (read, shot and fixed pattern noise), linearity, full well capacity, dynamic range and quantum efficiency of the sensor at a given wavelength.

2.3.1 Methods used for the calculation of the conversion gain

Digital sensors with various specifications are manufactured by many different industries. In order to compare the performance of different sensors, their properties should be expressed in absolute units of electrons, rather than in relative DN, which is the output of an ADC. Sensor conversion gain connects the above two quantities. It is defined as the number of electrons per digital number K (e^-/DN) or G (DN/e^-) = K^{-1} depending on the application. Janesick in the 1980s developed the ‘photon transfer’ technique for CCDs, incorporating the ‘photon transfer curve’ (PTC) (Janesick *et al.*, 1987). This early approximation of photon transfer removes the fixed pattern noise from the read & shot noise and calculates the gain as a constant from the medium signal level, where the read noise is considered negligible. Using the photon transfer technique, one can extract, in addition to the camera gain, a number of fundamental parameters of a digital sensor, such as linearity, read & shot noise decomposition from FPN, signal to noise ratio, full well capacity, dynamic range, dark current and quantum efficiency at specific wavelengths (Janesick, 2001). Also, in the 1980s the ‘mean-variance’ technique, using the same origin and assumptions, was developed for CCD’s gain constant calculation (Mortara and Fowler, 1981 and Sims and Denton, 1987). Using this method, it is possible to extract all the above parameters, except noise decomposition as a function of the signal. Holdsworth *et al.* (1990) described the full derivation of the mean-variance technique using statistical analysis of the observed signal. They observed nonlinearity at lower signal level, which they attributed to V/V nonlinearity. However, they ignored this nonlinearity by calculating the gain from zero signal level until near saturation point. Stark *et al.* (1992) assumed that Janesick’s early technique was not accurate because read noise may still exist at medium signal level until early saturation. Instead, they presented a new approximation on the calculation of the already known mean-variance method and they were able to calculate the gain from

lower signal levels, where shot noise is not dominant. This calculation method is complicated and it is evident from the literature that it has not been adopted by CCD researchers. After the broad development of CMOS APS in the early 1990s (Mendis *et al.*, 1994), researchers started characterizing these digital imagers. Beecken and Fossum (1996) determined the accuracy of the conversion gain using the mean-variance technique for both CCD and APS imagers. However, CCD technology was still dominant and Janesick republished the gain calculation of CCD using the early defined photon transfer method (Janesick, 1997 and Janesick, 2001). This method does not take into consideration the very small ($<0.1\%$) V/V nonlinearity of CCD. However, it is considered the standard method used to characterise and optimize scientific CCD imagers. Additionally, EMVA Standard 1288 (2005) recommends this method for digital cameras, i.e. for both CCD and CMOS. In 2002 Janesick published a performance comparison between CCD and CMOS APS (Janesick, 2002). Due to the high V/e^- nonlinearity of APS at higher signal levels, Janesick redefined the gain extraction from the PTC for this particular type of sensor. He decomposed the read from the shot noise, and calculated the gain constant from lower signal levels. Due to the decreased sense node sensitivity (V/e^-), he calculated a higher gain constant from signal levels prior saturation. He used the lower gain constant for read noise calculation and the higher one for the full well capacity. Nevertheless, this approximation leads to overestimation of the sensor's performance. Also, he presented for the first time a nonlinearity corrected PTC. However, he did not extract any performance parameter from this curve. In the following year, Reibel *et al.* (2003) made an extended approach to Janesick's early photon transfer method. They calculated the contribution of the pattern noise (FPN and photon response non uniformity) and the observed nonlinearities (V/V nonlinearity and nonlinearity due to saturation) into the CCD's overall noise. They also came to the conclusion that this method could be applied to CMOS imagers. However, this was not the case because they had not taken into account APS's V/e^- nonlinearity. Helmers and Schellenberg (2003) adopted the standard photon transfer method for CCDs, while for CMOS they developed a power function which approximates the characteristic curve. Therefore, they calculated the gain from the non-linear fitting of this curve. The accuracy of this method depends on how precisely their function describes the PTC. Pain and Hancock (2003b) developed the 'nonlinear estimation' method (NLE) in order to accurately estimate the quantum efficiency,

conversion gain and noise in CMOS imagers. NLE method takes into account both V/V and V/e^- nonlinearities. They compared NLE with the standard mean-variance method by means of the conversion gain and quantum efficiency of the sensor. In contrast to mean-variance, the NLE method provides illumination invariant quantum efficiency which is the case on a digital imager. Recently, Janesick (Janesick *et al.*, 2006 and Janesick, 2007) developed the ‘nonlinear compensation’ (NLC) method in order to cope with both APS nonlinearity sources. NLC method is an extension of the photon transfer method. It decomposes the constant gain obtained from PTC into a signal and a noise gains which are related to the signal level. This method is more precise than photon transfer and mean-variance methods at higher signal levels. In 2008, Bohndiek (Bohndiek *et al.*, 2008a and Bohndiek, 2008c) compared the mean-variance, photon transfer, NLE and NLC methods by means of the performance parameters of Vanilla APS. The gain from the first two methods was extracted from low signal level, where V/e^- nonlinearity is not obvious. However, these two methods did not correctly calculate read noise and full well capacity. Both NLE and NLC methods were found to solve this problem, thus they can be performed for APSs. Additionally, Bohndiek calculated the performance parameters of LAS, using photon transfer and NLC methods (Bohndiek, 2008c). Table 2.1 illustrates a synopsis of the above optical characterisation studies listed in chronological order.

Table 2.1: Studies related to optical characterisation of digital sensors. MV: mean-variance, PTC: photon transfer curve, NLC: nonlinear compensation, NLE: nonlinear estimation, QE: quantum efficiency, FW: full well capacity and FPN: fixed pattern noise

Reference	Method	Sensor	Nonlinearity referred	Parameters calculated	Comments
Mortara and Fowler (1981)	MV	CCD	No	conversion gain, read noise, SNR	Introduction of MV method
Janesick <i>et al.</i> (1987)	early PTC	CCD	No	conversion gain, read noise, QE	Early PTC for CCD only
Sims and Denton (1987)	MV	CCD	No	conversion gain, read noise, QE	MV for CCD based on Mortara (1981)
Holdsworth <i>et al.</i> (1990)	MV	CCD	V/V (ignored)	conversion gain, noise (various sources), QE	Analytical derivation of MV formula
Stark <i>et al.</i> (1992)	MV (PTC)	CCD	No	conversion gain, read noise, SNR	Complicated MV extraction in order to correct early PTC
Beecken and Fossum (1996)	MV	CCD & CMOS	No	conversion gain and its accuracy	Standard statistical theory is used
Janesick (1997)	early PTC	CCD	V/V (ignored)	conversion gain, read noise, FPN, QE, FW, dynamic range, linearity, SNR	Application of early PTC to extract more parameters of CCD
Janesick (2001)	early PTC	CCD	V/V (ignored)	conversion gain and its accuracy, read noise, FPN, QE, FW, dynamic range, linearity, SNR, node sensitivity	Synopsis and description of early PTC method
Janesick (2002)	PTC	CMOS (CCD)	V/e ⁻	conversion gain, read noise, FPN, QE, FW, dynamic range, linearity, SNR, sense node sensitivity	Redefinition of PTC method to be applied for CMOS
Reibel <i>et al.</i> (2003)	Extended PTC	CCD (CMOS)	V/V	conversion gain, read noise, pattern noises, linearity, nonlinearity contribution	This method cannot be applied for CMOS sensors
Helmers and Schellenberg (2003)	Modified PTC (for CMOS)	CCD & CMOS	V/e ⁻	conversion gain, FPN, SNR, sensitivity, dark current	The accuracy of this method is not well defined
Pain and Hancock (2003b)	MV, NLE	CMOS	V/V & V/e ⁻ depending on the method	conversion gain, quantum efficiency, reset & downstream noises	NLE can be applied for CMOS sensors instead of MV
EMVA Standard 1288 (2005)	PTC	CCD & CMOS	V/V & V/e ⁻	describes how to calculate all parameters referred on Janesick (2001)	They preferred a well defined and widespread method
Janesick <i>et al.</i> (2006)	NLC	CMOS	V/V & V/e ⁻	conversion gain, signal and noise gains, read noise, linearity	Introduction of NLC to take into account CMOS nonlinearity
Janesick (2007)	MV, PTC, NLC	CCD & CMOS	V/V & V/e ⁻ depending on the method	conversion gain and its accuracy, signal and noise gains, read noise, FPN, QE, FW, dynamic range, linearity, dark current	Synopsis of NLC and comparison with PTC
Bohndiek <i>et al.</i> (2008)	MV, PTC, NLC, NLE	CMOS APS	V/V & V/e ⁻ depending on the method	conversion gain, signal and noise gains, read noise, FPN, QE, FW, dynamic range, linearity, dark current	Comparison between the 4 methods: NLC and NLE can be applied for CMOS

It can be observed that all the above optical characterization methods are applied to CCD or CMOS sensors. To the best of my knowledge they are not used for the performance evaluation of the flat panel detectors. First of all, they cannot be applied on direct conversion flat panel imagers (such as a-Se TFT) because they are sensitive to visible photons of short wavelength only (Cowen *et al.*, 2008). However, they are not applied to indirect conversion detectors (such as a-Si:H TFT) as well. This happens probably due to the fact that the number of the created electrons depends on the electric field applied on the photodiode. As mentioned in the following sections (2.3.2 to 2.3.4) both PTC and MV methods are applied assuming unity quantum yield, i.e. the number of created electrons is equal to the number of impinging optical photons. Instead, in an a-Se TFT study (Zhao and Rowlands, 1995) the shot noise was calculated based on the square root of the number of x-rays attenuated by the a-Se layer, assuming quantum limited behaviour. On the other hand, the read noise in many studies was calculated based on the nominal characteristics of the electronics (Zhao and Rowlands, 1995, Antonuk *et al.*, 2000, Hunt *et al.*, 2002, Zhao *et al.*, 2005 and Sultana *et al.*, 2008).

2.3.2 Linear sensor response – Mean-Variance analysis (MV)

Mean-variance analysis has been used for many years for CCDs' conversion gain calculation (Mortara and Fowler, 1981, Sims and Denton, 1987 and Holdsworth *et al.*, 1990). According to the detailed description of Holdsworth *et al.* (1990), for a linear sensor with constant conversion gain, an input signal of P_I interacting optical photons produce an output signal S given by

$$S(DN) = G(DN / e^-) P_I = \frac{P_I}{K(e^- / DN)} \quad (2.3)$$

where $G(DN/e^-)$ is the sensor conversion gain. Assuming unity quantum yield, a similar formula can be applied related to the number of signal electrons (Bohndiek *et al.*, 2008a). Applying the Burgess's variance theorem (van der Ziel, 1976) on Eq. (2.3) the variance in the mean output signal is

$$\sigma_S^2 = \bar{G}^2 \sigma_{P_I}^2 + \bar{P}_I \sigma_G^2 \quad (2.4)$$

where $\bar{G}$ and $\bar{P}_I$ are the mean values of gain and signal electrons correspondingly, σ_G^2 and $\sigma_{P_I}^2$ are their respective variances. The interacting optical photons, P_I , are assumed to be governed by Poisson statistics ($\sigma_{P_I}^2 = \bar{P}_I$), therefore

$$\sigma_S^2 = \bar{G}^2 \bar{P}_I + \bar{P}_I \sigma_G^2 \quad (2.5).$$

Eq. (2.3) shows $\bar{P}_I = \bar{S} / \bar{G}$, and substitution into Eq. (2.5) gives

$$\sigma_S^2 = \bar{G} \bar{S} \left[1 + \left(\frac{\sigma_G}{\bar{G}} \right)^2 \right] \quad (2.6).$$

If the variance in gain is very small in relation to the mean gain, the above equation may be simplified to $\sigma_S^2 = \bar{G} \bar{S}$. In a real system, signal independent read noise is present, thus the total noise variance is given by

$$\sigma_S^2 = \bar{G} \bar{S} + \sigma_R^2 \quad (2.7)$$

where σ_R^2 represents the read noise.

Plotting σ_S^2 vs $\bar{S}(DN)$ corresponds to a mean-variance graph. Figure 2.1 shows the theoretical mean-variance expression for a linear sensor on a linear plot because the variance scales linearly with the average DN. The slope of this graph provides $G(DN/e^-)$, while the intercept σ_R^2 . Therefore, the sensor conversion gain $K(e^-/DN)$ can be extracted from this curve.

The data for the mean-variance graph are determined from N frames measured at a number of illumination levels between dark and saturation. Pain and Hancock (2003b) describe the required formulas:

$$\bar{S}_{l,m} = \frac{\sum_n S_{l,m,n}}{N} \quad ; \quad \bar{S} = \frac{\sum_{l,m} \bar{S}_{l,m}}{LM} \quad (2.8)$$

$$\sigma_{l,m}^2 = \frac{\sum_n S_{l,m,n}^2}{N} - \left[\bar{S}_{l,m} \right]^2 \quad ; \quad \sigma_S^2 = \frac{\sum_{l,m} \sigma_{l,m}^2}{LM} \quad (2.9)$$

where $\bar{S}$ represents the average temporal mean signal and σ_s^2 represents the average temporal noise. The temporal average (over N frames) accounts for pixel variations in time, while the spatial average (over L rows times M columns) accounts for variations across the array. The dark offset level, S_D , should be calculated by applying Eq. (2.8) to a set of N frames recorded without illumination.

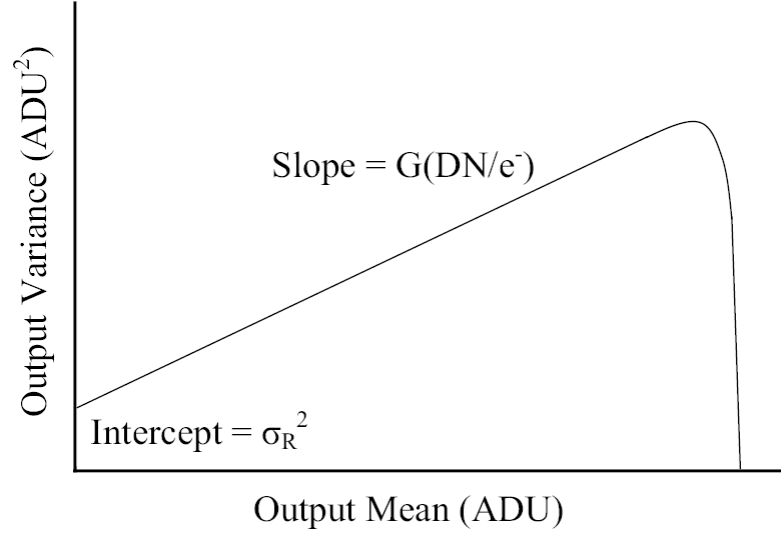


Figure 2.1: Mean-variance graph showing the theoretical expression for a linear sensor.

The noise increases linearly with signal up to a saturation point. (Bohndiek, 2008a)

2.3.3 Linear sensor response – Photon Transfer Curve (PTC)

The conversion gain of the sensor may also be calculated from the photon transfer technique (Janesick, 2001 and Janesick, 2007). Considering uncorrelated noise sources, the standard propagation of errors formula can be applied on Eq.(2.3) to determine the variance of the signal

$$\sigma_s^2(DN^2) = \left[\frac{\partial S(DN)}{\partial P_t} \right]^2 \sigma_{P_t}^2 + \left[\frac{\partial S(DN)}{\partial K(e^- / DN)} \right]^2 \sigma_K^2 ((e^- / DN)^2) + \sigma_R^2(DN^2) \quad (2.10).$$

Read noise is added in quadrature because, as mentioned above, it exists in real systems. Performing the differentiation yields

$$\sigma_s^2(DN^2) = \left[\frac{1}{K(e^- / DN)} \right]^2 \sigma_{P_I}^2 + \left[\frac{-P_I}{K(e^- / DN)^2} \right]^2 \sigma_K^2((e^- / DN)^2) + \sigma_R^2(DN^2) \quad (2.11).$$

In the case that a sufficient number of pixels are sampled, the variance of the gain is assumed negligible, i.e. $\sigma_K^2((e^- / DN)^2) = 0$. As mentioned above (section 2.2.1), the interacting optical photons are considered to have Poisson distribution, i.e. $\sigma_{P_I}^2 = P_I$. Therefore, Eq. (2.11) reduces to

$$\sigma_s^2(DN^2) = \left[\frac{I}{K(e^- / DN)} \right]^2 P_I + \sigma_R^2(DN^2) \quad (2.12).$$

Substituting Eq. (2.3) into Eq. (2.12) and solving for $K(e^- / DN)$ gives

$$K(e^- / DN) = \frac{S(DN)}{\sigma_s^2(DN^2) - \sigma_R^2(DN^2)} \quad (2.13)$$

where σ_R^2 is the signal-independent read noise, σ_s^2 is the signal dependent noise of an image at signal level $S(DN)$. The difference $\sigma_s^2 - \sigma_R^2$ defines the signal shot noise, σ_{Shot}^2 . Therefore, the gain may be calculated from the slope of the PTC, which is the logarithmic (in order to cover the large dynamic range of the CMOS APS) plot of the r.m.s. signal noise of the sensor, σ_s , against the average sensor signal, $\overline{S(DN)}$.

An ideal PTC response from a sensor is illustrated in Figure 2.2. This response contains the three main noise sources of a digital sensor: the read, shot and fixed pattern noise (see section 2.2.1). It can be observed that each noise is dominant at different signal levels. In order to obtain this curve, the sensor needs to be uniformly illuminated at different levels of light, i.e. to capture flat images.

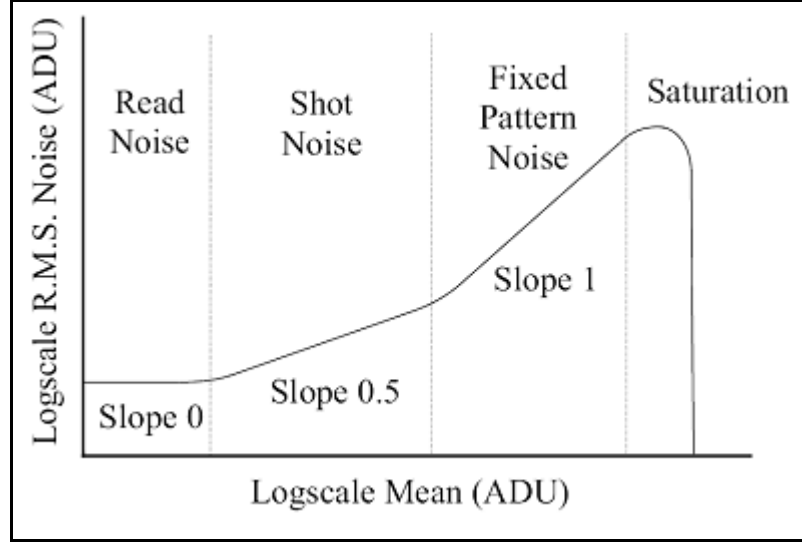


Figure 2.2: Ideal total noise Photon Transfer Curve. The three noise regimes prior saturation are indicated (Janesick, 2007).

The first regime, read noise, is constant because it is signal-independent. It is dominant at low signal levels because it represents the random noise measured under totally dark conditions. As the illumination increases, shot noise of the signal becomes dominant. According to Eq. (2.1) the r.m.s. shot noise is related to the square root of the signal. In a logarithmic plot, this yields a line of slope 0.5. The third regime is associated with FPN. At this level, a gradient of 1 is observed because signal and FPN scale together. Finally, saturation occurs when the area of pixels enters the full well regime. At this level any additional signal spills over into surrounding pixels resulting in noise averaging.

All noise sources apart from shot noise (i.e. read and fixed pattern noise) have to be removed to get data available for the extraction of the gain $K(e^- / DN)$. The FPN is removed by subtracting two consecutive frames at the same illumination level. In order to calculate this, the frame mean $\overline{S_K}$ for $k=A$ and $k=B$ (where A and B are the consecutive frames), the corrected mean $\overline{S}$ of the frame difference (by subtracting the background level) and the temporal signal noise, σ_S^2 , are calculated using the following formulas (Bohndiek *et al.*, 2008a and Bohndiek, 2008c):

$$\overline{S_K} = \frac{1}{LM} \sum_{l,m} S_{l,m}^k \quad (2.14),$$

$$\bar{S} = \frac{1}{2} [\bar{S}_A + \bar{S}_B] - \bar{S}_D \quad (2.15),$$

$$\sigma_S^2 = \frac{1}{2(N-1)} \sum_{l,m} \left[(S_{l,m}^A - \bar{S}_A) - (S_{l,m}^B - \bar{S}_B) \right]^2 \quad (2.16).$$

Read noise is subtracted from the outcome of Eq. (2.16) to define the shot noise at each illumination level. The division by a factor of 2 in Eq. (2.16) is used to compensate for the additive uncorrelated noise arising from the subtraction. Further details about this are given in section 3.3.3. After the removal of read and FPN noise, PTC is defined by plotting the r.m.s. shot noise, σ_{Shot} , against the average signal, $\bar{S}$, at each illumination level.

In order to extract the gain from the PTC, linear regression fit is applied on the linear part of the sensor's response. This fit has the form of $y = mx + c$ on a logarithmic scale. In order to calculate the gain $K(e^- / DN)$ on a decimal scale, the following calculation is done (Bohndiek *et al.*, 2008a and Bohndiek, 2008c)

$$K = 10^{\frac{c}{m}} \quad (2.17).$$

The uncertainty on the conversion gain is calculated from the uncertainties on the slope m and intercept c using propagation of errors.

2.3.4 Nonlinear sensor response – Nonlinear Compensation method (NLC)

Mean-variance and photon transfer methods have been applied under a number of assumptions (Bohndiek, 2008c):

1. The sensor output signal is linear with illumination, therefore both V/V and V/e⁻ nonlinearities are ignored.
2. Fluctuations in the number of interacting photons are described by a Poisson distribution.
3. Interacting photons are converted to signal electrons in the pixel with quantum yield equal to unity.
4. The variance in the conversion gain σ_K^2 is negligible.

5. In order to extract the photon transfer formula, the noise sources in the sensor are uncorrelated.

The above assumptions often hold in CCD and CMOS PPS sensors, however the linearity assumption cannot hold for the CMOS APS, due to the V/e^- nonlinearity. Therefore, the conversion gain derived by the above two methods can be in severe error. In order to cope with nonlinearity, the above linear methods are applied to the ‘linear region’ of the APS sensor. Mean-variance method is applied to data having a very small fraction of nonlinearity ($< 5\%$), while photon transfer method is applied to ‘linearized’ (logarithmically transformed) data having a slope very close to 0.5 inside the shot noise region. However, this slope may deviate significantly from 0.5 if any nonlinearity exists. The V/e^- nonlinearity results in a slope less than 0.5 as the illumination increases because it improves the SNR (see section 2.2.3).

In order to cope with both nonlinearities, Janesick (Janesick *et al.*, 2006 and Janesick, 2007) instead of using a single and constant gain $K(e^- / DN)$, decomposed it into a signal gain $S(e^- / DN)$ and a noise gain $N(e^- / DN)$, which are related to the signal level. Signal gain is employed to determine signal related performance parameters, such as charge capacity (signal e^-), dark current, full well capacity, quantum efficiency, nonlinearity, etc. On the other hand, noise gain is used for the calculation of sense node capacitance and noise related parameters, such as read noise, shot noise, FPN, etc.

At low illumination levels, V/e^- nonlinearity is not significant (because C_{SN} variation is not appreciable) therefore $K(e^- / DN) = S(e^- / DN) = N(e^- / DN)$. Thus, using the signal conversion gain at low illumination levels the signal in absolute units, $S_1(e^-)$, is calculated for the first illumination level. Based on accurate knowledge of the illumination level at specific integration time or the integration time at specific illumination level, ‘n’ and assuming that the signal is proportional to this level, $S_n(e^-)$ can be calculated in proportion to $S_1(e^-)$. At each level ‘n’ the signal $S_n(e^-)$ can be divided by the respective sensor output $S_n(DN)$. Therefore, signal gain $S(e^- / DN)$ is determined as a function of illumination.

Correspondingly, noise conversion gain $N(e^- / DN)$ is extracted from the shot noise relation

$$N(e^- / DN) = \frac{\sqrt{S(e^-)}}{\sigma_{Shot}(DN)} \quad (2.18).$$

Figure 2.3 shows an example of the NLC method outcome. The representation of signal and noise gains is useful in terms of separating V/V and V/e⁻ nonlinearities. V/V nonlinearity is present when both signal and noise gains change simultaneously at low signal levels. V/e⁻ nonlinearity exists when the two gains increase and diverge at higher signal levels. This divergence occurs because the calculation of signal gain takes the sense node capacitance change more into consideration.

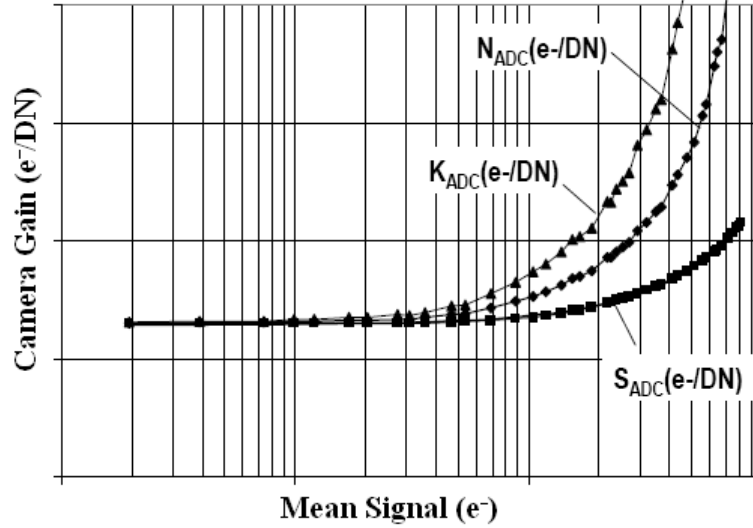


Figure 2.3: Comparison between the ‘linear’ conversion gain $K(e^- / DN)$ and signal $S(e^- / DN)$ and noise $N(e^- / DN)$ gains extracted from NLC (Janesick, 2007).

2.3.5 Performance parameters extracted from optical evaluation

After the gain determination from the above methods, the performance parameters of the digital sensor can be calculated in absolute values. This study presents some of the LAS and Dexela sensors performance parameters measured through optical characterisation. These parameters are the decomposition of the three main noise sources (read, shot and fixed pattern noise), full well capacity, dynamic range and dark current. The full well capacity shows the maximum electron charge that the photodiode’s sense node inside each pixel can hold. After this charge level saturation occurs. It is calculated from the product of the signal level at which the maximum

variance occurs (without subtracting the dark level) times the conversion gain, i.e. $FW(e^-) = S(e^- / DN) S_{\max}(DN)$. The dynamic range of a sensor is defined by the largest possible signal divided by the smallest possible signal it can generate. The largest possible signal corresponds to the full well capacity of the pixel. The lowest signal is the noise level when the sensor is not exposed to any light, i.e. the read noise. The dynamic range is expressed in decibels (dB) by $DR(e^-) = 20 \log(FW(e^-) / \sigma_R(e^-))$. Finally, the dark current is calculated from the slope of the graph of the output signal in e^- versus the integration time, expressed in units of current per area (pA/cm^2).

2.4 Physical characteristics of the x-ray detector

The performance parameters of an x-ray detector are described in both spatial and frequency domain. Usually the signal transfer property (STP), the presampling modulation transfer function (pMTF), the normalized noise power spectrum (NNPS) and detective quantum efficiency (DQE) are sufficient to describe the signal and noise properties of the x-ray detector. The STP shows the response of the detector to the input signal. The MTF describes the contrast reduction of different spatial frequencies that compose the image and the NPS describes the frequency components of the noise. Finally, the DQE shows the ability of the detector to transfer the squared SNR from the input stage to the output stage.

2.4.1 Signal and noise transfer

The analysis of digital detectors is based on the linear systems theory to describe the signal and noise transfer from the input to the output. This theory assumes that the digital detector is linear and shift invariant. A linear detector transfers the input signal linearly, i.e. the output is proportional to the input throughout the dynamic range of the detector. Most DR systems are considered linear. The CR detectors are non linear due to the logarithmic or square-root output but they are linearisable through the use of mathematical transformations. The response of a digital detector is tested for linearity from the STP curve which is the representation of the output DN as a function of the input DAK. Also, the slope of the STP gives useful information about the sensitivity of the digital detector. It is a combination of the x-ray detection efficiency (QDE or EAE), the light yield of the scintillator, the quantum efficiency and the conversion gain, i.e. the

relationship between the created e^- and the output DN. For each detector the average output signal was calculated from 5 flat frames for each DAK level over the array used for the NPS calculation. A digital system is considered shift invariant when its response to an input signal is the same at all locations relative to the pixel matrix. The output of a linear and shift invariant detector in response to any input signal is the convolution of the input with the PSF of the system which corresponds to the 2-D resolution. However, no digital system is completely linear and shift invariant because of the aliasing arising from the discrete nature of the pixels. Therefore, the output of an undersampled system will depend at the same degree on the position of the input signal (Dobbins III, 1995, Cunningham and Shaw, 1999 and Cunningham, 2000).

Since both the signal and noise transfer are spatially correlated to some degree (i.e. are not the same at all frequencies) a frequency domain response characterisation is more useful than a spatial one. The Fourier transform provides the way to move between spatial and frequency domains, giving the same information in two different ways. The Fourier transform of an image shows the composition of its content at each spatial frequency. Also, the convolution in one domain corresponds to multiplication in the other. Therefore, using the Fourier transform the same information can be easier interpreted in one or the other domain. The STP is calculated in spatial domain, while the MTF, NPS and DQE are calculated in frequency domain.

2.4.2 Presampling Modulation Transfer Function (pMTF)

The modulation transfer function describes the contrast reduction of different spatial frequencies that compose the image and it is used to quantify the resolution of an imaging system. It shows how well an input signal is transferred to the output at each spatial frequency. Two methods are developed to measure the MTF of an x-ray imager: the slit method to calculate the line spread function (LSF) and the edge method to calculate the edge spread function (ESF) which is the integral of the LSF. Both methods were first developed to evaluate analog x-ray detectors (Tatian, 1965, Rossmann and Sanderson, 1968, Lubberts, 1969 and Smith, 1972) and then applied to digital radiography (Judy, 1976, Giger and Doi, 1984a, Fujita *et al.*, 1992, Boone and Seibert, 1994, Samei *et al.*, 1998 and Buhr *et al.*, 2003). The LSF is the response of the imager to a test device with a very narrow slit. Then the modulus of the Fourier transform of the LSF (normalized to one at zero frequency) corresponds to the MTF. On the other

hand, the ESF is the response of the detector to a straight edge test device. Correspondingly, the ESF is differentiated to calculate the LSF which results in the MTF. According to the literature, the edge method is cost-effective and not very sensitive to physical defects, scattered radiation and misalignments of the test device (Samei *et al.*, 1998 and Samei *et al.*, 2006). Also, it provides accurate results even at low frequencies (below the Nyquist) which are of interest in determination of the DQE and the NPS (Cunningham and Reid, 1992, Samei *et al.*, 1998 and Samei *et al.*, 2006).

The resolution of two digital detectors can be compared only in terms of the pMTF which describes the system's response up to, but not including, the stage of sampling by the pixel matrix. However, the total MTF of a digital detector includes both the "presampling" and the "digital" component. The pMTF includes the image blurring from geometric considerations (focal spot blurring), the scintillator blurring in case of indirect conversion detectors and the aperture function of the detector which corresponds to the shape and size of the active response area of the pixel. The geometric blur from the focal spot has to be eliminated because it depends on the geometry of image acquisition rather than an intrinsic property of the detector itself. This is done by placing the test object directly on the detector's surface to eliminate any magnification which introduces the geometric blurring. The digital MTF includes both the blurring described from the pMTF and the sampling function. It is given from the convolution between the pMTF and the Fourier transform of the sampling function (i.e. the comb function). It shows the response of the system to a delta function comprising equal amounts of all frequencies. It is calculated from the Fourier transform of the output of a system which has a delta function in input normalized to unity at zero frequency. On the other hand, the pMTF is the response of a system at all frequencies to a sinusoidal signal s with frequency value (u, v) . It is expressed from the following formula (Dobbins III, 2000):

$$pMTF(u, v) = \frac{|FT_{out}(u, v)|}{|FT_{in}(u, v)|} \quad (2.19)$$

where FT is the Fourier transform of the input signal s . In analog imagers there is only pMTF due to the absence of sampling. In digital systems with no aliasing due to oversampling the digital MTF and the pMTF are the same. However, if there is any aliasing due to undersampling, the two MTFs are different at frequencies affected from

the overlap of adjacent FT replications. The digital MTF is higher at these frequencies because it contains the response of the system at these frequencies plus the overlapping aliased information from frequencies higher than the Nyquist frequency. On the other hand, the pMTF of an undersampled digital detector contains replicated but not overlapped values. The digital MTF cannot be used for the comparison of two digital detectors because 1) it does not describe the amplitude of a sinusoidal signal passed by the system and 2) it is phase dependent due to the overlapping aliased frequency components which introduces spatial invariance. The latter violates the linear-systems approach which describes the detector as linear and shift invariant (Dobbins III, 1995 and Dobbins III, 2000).

As mentioned before, the pMTF includes the image blurring from geometric considerations, the scintillator blurring in case of indirect conversion detectors and the aperture function of the detector which expresses the effect of the pixel pitch Δx . In the case that the focal spot and the scintillator blurring are insignificant the pMTF is limited only by the nominal pixel area. For an ideal square pixel detector that collects all of the charge created from x-ray absorptions occurring in the nominal pixel area (i.e. fill factor = 100%) the ideal maximum pMTF equals to the modulus of the sinc function which is the Fourier transform of the aperture function (Yaffe and Rowlands, 1997 and Samei and Flynn, 2003c). The sinc function is expressed as

$$\text{sinc}(\pi \Delta x f) = \frac{\sin(\pi \Delta x f)}{\pi \Delta x f} \quad (2.20)$$

and is around 0.64 at F_{Nyq} and its first zero appears at the sampling frequency (i.e. the double of F_{Nyq}). The pMTF of the indirect conversion detectors is much lower than the respective sinc function due to the scintillator blurring. On the other hand, the direct conversion detectors pMTF appear very close to the sinc function. However, the sinc function performance implies strong aliasing.

In practice, most of the digital detectors (including the indirect conversion ones) allow some aliasing due to design compromises. Therefore, the MTF of these detectors is not zero after the Nyquist frequency. All frequencies beyond the Nyquist frequency are aliased in the output image, i.e. the amplitude of the aliased frequency components of the MTF is folded back to their counterpart frequencies prior to Nyquist frequency. Therefore, the frequencies of interest for the determination of the pMTF are from zero

up to the Nyquist frequency. To define precisely the pMTF without aliasing in this frequency range, a finer sampling (oversampling) has to be used. This oversampling is achieved by using slightly tilted slit (Fujita *et al.*, 1992) or edge test object (Samei *et al.*, 1998) with respect to the pixel array. This angulated orientation results in an increase in the sampling interval proportional to the reciprocal of the tangent of the angle. However, there is a trade-off between high sampling frequency and low statistical uncertainty. If the angle is very small the oversampling frequency will be very high. On the other hand, relatively large angle results in a larger number of ESFs / LSFs that can be averaged, resulting in lower uncertainty. Usually both requirements are fulfilled by choosing an angle that ensures a sampling distance at least five times smaller than the original sampling of the detector (pixel pitch) (B  th, 2003a). The following section describes the oversampled ESF method used in this thesis to calculate the pMTF.

2.4.3 Oversampled Edge Spread Function (ESF) to calculate the pMTF

For the determination of the MTF, the edge technique (Samei and Flynn, 2002) was used according to the IEC standard (IEC 62220-1, 2003 and IEC 62220-1-2, 2007) based on the Buhr *et al.* (2003) algorithm. An opaque, polished edge test object (W foil, 1 mm thick, 99.95 % pure (Alfa Aesar)) was placed at a shallow angle α (1.5  -3  ) with respect to the detector pixel rows and columns. The position and angulation of the edge within each image was estimated using the linear regression technique (Greer and van Doorn, 2000 and Price *et al.*, 2008). Then a standard gain and offset correction formula (i.e. normalization with the flat-field image) was applied to remove the structure noise:

$$\overline{I_{cor1}}(x, y) = \frac{\overline{I_{raw}}(x, y) - \overline{I_D}(x, y)}{\overline{I_F}(x, y) - \overline{I_D}(x, y)} \cdot \left(\overline{I_F}(x, y) - \overline{I_D}(x, y) \right) \quad (2.21)$$

where $\overline{I_{raw}}(x, y)$ is the average raw edge image, $\overline{I_F}(x, y)$ is the average flat image at the same irradiation conditions and integration time and $\overline{I_D}(x, y)$ is the average dark image at the same integration time. All images are averaged over 10 frames to reduce the random noise components. A second order polynomial fit correction was applied on the gain and offset corrected edge test images to remove low frequency (background) trends arising from the x-ray field's non-uniformity (e.g. from the heel effect, etc.) that

could increase the MTF at low frequencies (IEC 62220-1, 2003 and IEC 62220-1-2, 2007). The background removal was applied from the following formula:

$$\overline{I_{cor2}}(x, y) = \frac{\overline{I_{cor1}}(x, y)}{S(x, y)} \cdot \text{Avg}\{S(x, y)\} \quad (2.22)$$

where $S(x, y)$ is the second order polynomial fit of the average flat image $\overline{I_F}(x, y)$. Figure 2.4 shows a created $S(x, y)$ image in 3-D (a) and 2-D (b) representation respectively.

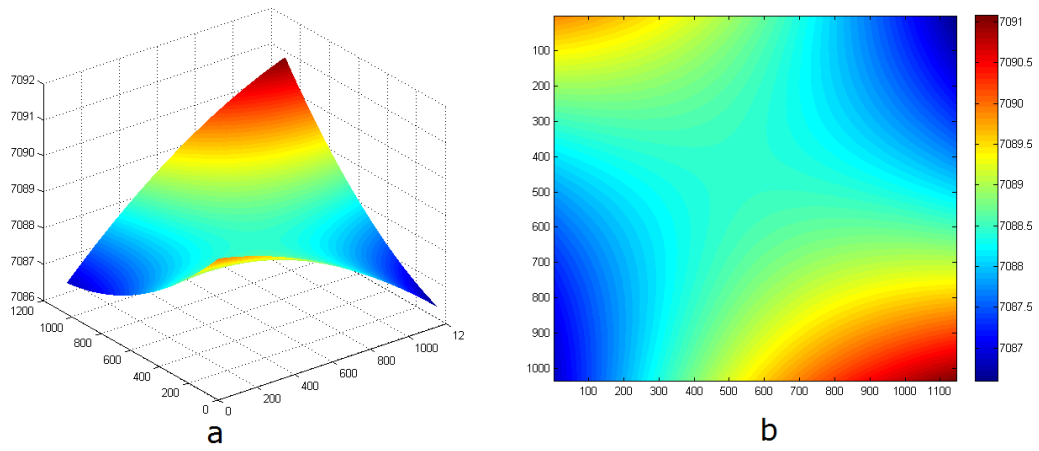


Figure 2.4: Representation of a created $S(x, y)$ image in 3-D (a) and 2-D (b)

The pixel values of the corrected data of seven consecutive lines (i.e. rows or columns depending on the edge's orientation) across the edge were then used to generate seven oversampled edge profiles (or ESF). More than one ESFs have been generated to reduce the statistical noise. An ESF was selected as the reference one, and the remaining six shifted laterally until the position overlapping most closely to the reference one was reached. Two methods can be applied to optimize this lateral shift. The first one is to compare the correlation coefficient between each shifted ESF at each line and the reference one, and select the line where the maximum correlation is achieved. However, this method can be affected by defective pixels or lines leading to erroneous shifts. The second method uses the formula $N = \text{round}(1/\tan \alpha)$ to calculate the number N of lines necessary for the edge to shift laterally by 1 pixel (Buhr *et al.*, 2003, IEC 62220-1, 2003 and IEC 62220-1-2, 2007). Both methods were tested in each case, and the one providing the highest correlation between the shifted ESF curves was used to calculate the average oversampled ESF. The sampling distance in the

oversampled ESF is assumed to be constant, and is given by the pixel pitch Δx divided by N , i.e. $\text{ESF}(x_n)$ with $x_n = \Delta x/N$. The oversampled ESF was then differentiated to get the oversampled LSF. Figure 2.5 shows an example of the various steps of the MTF calculation for the Dexela detector from the oversampled ESFs to the presampling MTF.

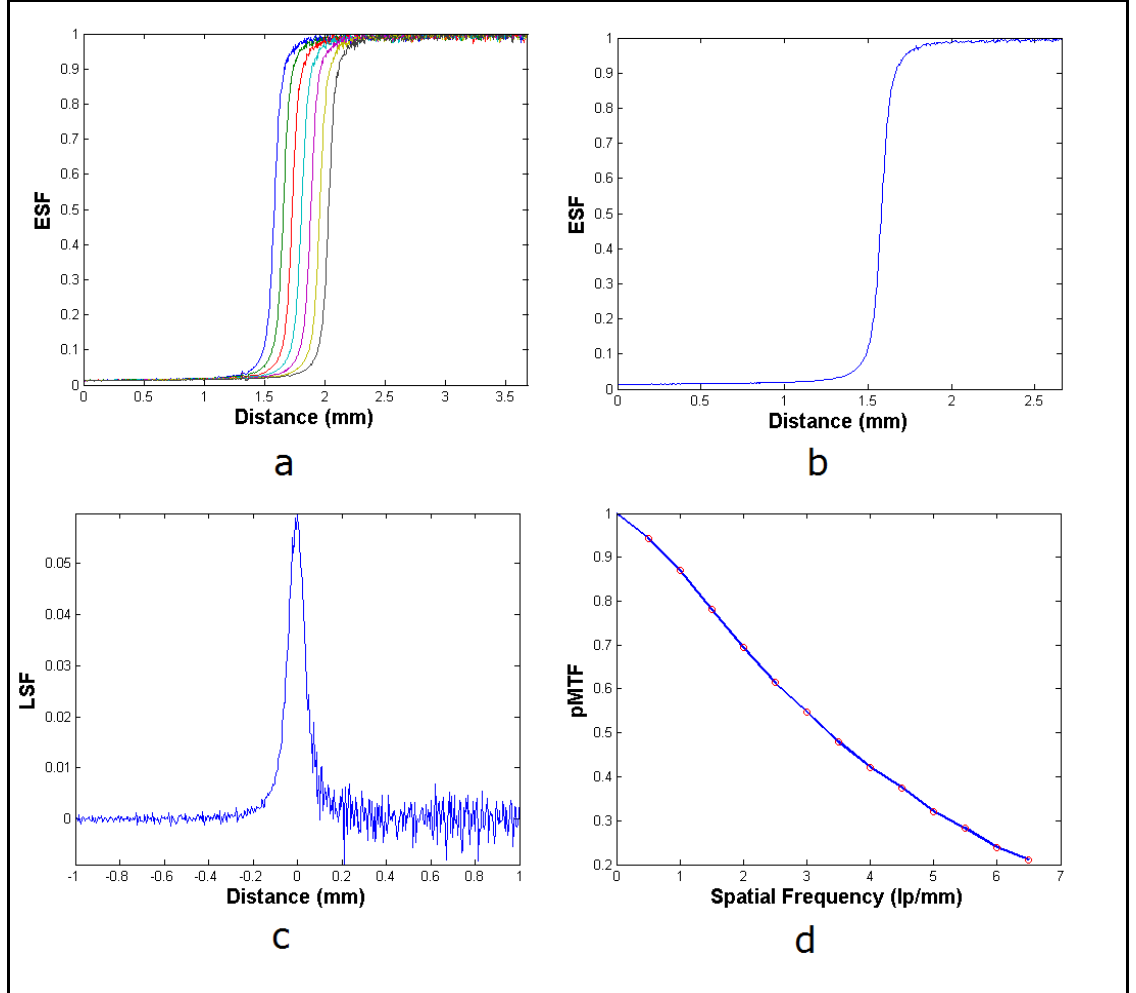


Figure 2.5: A representation of the MTF calculation process - a) oversampled ESFs, b) average oversampled ESF, c) oversampled LSF and 4) presampling MTF

The MTF was obtained from the modulus of the fast Fourier transform (FFT) of the oversampled LSF. The MTF was normalized to one at zero frequency, and then calculated until the Nyquist frequency (F_{Nyq}) to avoid noise aliasing effects, leading to presampling MTF (pMTF). In accordance with the IEC standard, the horizontal and vertical pMTFs have been calculated by binning the data points in a frequency interval f_{int} ($f - f_{\text{int}} \leq f \leq f + f_{\text{int}}$) around the spatial frequencies from 0.5 to F_{Nyq} with an interval of

0.5 lp/mm. f_{int} is obtained as $0.01/\Delta x(\text{mm})$. Finally, the average (over the edge's orientation) pMTF was calculated.

It should be noted that the extracted length of the ESF used for the pMTF calculation was different for each detector due to the different pixel area. It was 3.2 cm for LAS, 3.5 cm for the Hamamatsu detector, 6 cm for the Dexela detector, 6.8 cm for the Anrad detector and 2.3 cm for the RadEye detector. The length of the ESF affects the pMTF. Small ESFs correspond to overestimation of the pMTF at low frequencies and underestimation at high frequencies. The presence of low frequency (background) trends reduces the pMTF at frequencies lower than 0.5 lp/mm causing a low frequency drop in the pMTF. However, at higher frequencies the pMTF is not affected. It was found that the pMTF of the Anrad detector changed by 1 % within one month. Also, the pMTF of the RadEye detector change by 2.5 % within a period of four months. The pMTF values were calculated at around half of the saturation level on the open field. This corresponds to a range of 30 (for LAS and Dexela in the LFW mode detectors) to 180 $\mu\text{Gy DAK}$ (for the Hamamatsu detector) at 28 kV, 7 to 15 $\mu\text{Gy DAK}$ at 52 kV and 9 to 24 $\mu\text{Gy DAK}$ at 74 kV respectively.

2.4.4 Noise Power Spectrum (NPS)

The noise power spectrum (NPS) describes the spectral decomposition of the noise variance in an image as a function of spatial frequency. The aliasing problems that exist in the interpretation of the MTF in a digital system also apply in the interpretation of the NPS. Unfortunately, we cannot measure directly the presampling NPS using fine sampling techniques as we can do for the presampling MTF calculation, so the noise is undersampled in almost every digital system. Therefore, according to the sampling theorem if the image contains frequencies higher than the Nyquist frequency then aliasing occurs. In practice, it is not possible to measure the presampling NPS because the analog image contains all noise frequencies simultaneously, including those above the Nyquist frequency. So, for any system the digital NPS consisting of the full complement of input frequencies is the only NPS that we can measure (Dobbins III, 1995).

As mentioned in section 2.2.1 the noise of a digital x-ray detector consists of quantum, excess, secondary quantum, structure, additive electronic and aliasing

components. Therefore Eq. (2.2) can be rewritten in terms of the total presampling normalized NPS (NNPS) as follows (Mackenzie and Honey, 2007):

$$NNPS_{pre}(f) = NNPS_Q(f) + NNPS_{ex}(f) + NNPS_{sQ}(f) + NNPS_s(f) + NNPS_{el}(f) \quad (2.23)$$

The NNPS is normalized to the NPS at zero frequency. Further details about this are given later in this section. Evans *et al.* (2002) presented a similar formula assuming that the structure and additive electronic noise components are independent of the spatial frequency f . However, Mackenzie and Honey (2007) showed that both noise sources depend on the spatial frequency. Both studies, based on Giger *et al.* (1984b) analysis, relate the presampling NNPS to the analog NNPS ($NNPS_a(f)$) by multiplying with the sinc function which is the Fourier transform of the aperture function that corresponds to the pixel pitch Δx :

$$NNPS_{pre}(f) = NNPS_a(f) |\sin c(\pi \Delta x f)|^2 \quad (2.24)$$

Therefore, Eq (2.23) can be rewritten as follows:

$$NNPS_{pre}(f) = \frac{pMTF^2(f)}{\eta Q} + \frac{n_{ex} pMTF^2(f)}{\eta Q} + \frac{|\sin c(\pi \Delta x f)|^2}{\eta \tilde{g} Q} + N_s(f) + \frac{N_{el}(f)}{(\eta \tilde{g} Q)^2} \quad (2.25)$$

where η is the fraction of x-rays absorbed in the scintillator/photoconductor (also known as QDE), Q is the number of x-ray photons impinging on the detector per unit area, n_{ex} is the Poisson excess noise, $\tilde{g}$ is the average system gain, i.e. the produced e⁻ in the photodiode per absorbed x-rays, N_s is structure noise (or FPN) and N_{el} is the additive electronic noise. Next, according to Giger *et al.* (1984b) and Dobbins III (1995) studies the digital sampling corresponds to the multiplication of the noise data by a sampling comb function, $\Delta x III(x; \Delta x)$ in the spatial domain. Both studies are based on the sampling theory described in Bracewell (1978). The above product in frequency space corresponds to the convolution of the $NNPS_{pre}$ with the Fourier transform of the comb function. Therefore, the digital NNPS is given by the following formula (Evans *et al.*, 2002)

$$NNPS_{dig}(f) = NNPS_{pre}(f) * III(f; \frac{1}{\Delta x}) \quad (2.26).$$

This convolution produces replications of the noise spectrum in the frequency domain, at interval of $1/\Delta x$ which is double the Nyquist frequency (F_{Nyq} ; see section 2.2.1). Hence, $NNPS_{pre}(f)$ which extend to frequencies beyond the Nyquist frequency will be aliased to lower frequencies as follows:

$$NNPS_{dig}(f) = NNPS_{pre}(f) + NNPS_{pre}(2F_{Nyq} - f) \quad (2.27)$$

for frequencies in the range 0 to F_{Nyq} . This short description of the NNPS explains about the aliasing of the noise due to sampling. Further details about the sampling and the comb function are given in section 4.3.

The noise is calculated from flat field images. A novel gain and offset correction algorithm was applied to the flat images to remove the dark offset and minimize gain variations between different pixels (structure noise). The structure (or FPN) noise is correlated noise and needs to be removed to improve the SNR of the detector. The suggested correction algorithm is described in detail in section 3.3.3 after the full explanation of the NPS and DQE calculations and their physical meaning. After the removal of the structure noise and assuming that the electronic noise is small compared to the quantum noise, the NNPS is an inverse function of the ηQ product (see Eq. (2.25)).

Following the correction of the raw flat images, the NPS was calculated by applying a 2-D algorithm to a corrected flat field image according to the IEC standard. First, overlapping regions of interest (ROI) of 256×256 pixels were taken from a central area of the image. At least four million independent image pixels are required for an accuracy of the 2-D NPS of 5 % (IEC 62220-1, 2003 and IEC 62220-1-2, 2007), and therefore a number of flat field images sufficient to meet this criterion was used. Each captured image was corrected for the presence of background trends (such as heel effect) by fitting a second order polynomial and subtracting the fitted 2-D function $S(x, y)$ from the flat field image $I(x, y)$. This second order polynomial de-trending corrected the NPS at frequencies lower than 1 lp/mm. The average 2-D NPS has been calculated

by applying the following formula [Dobbins III, 2000, IEC 62220-1, 2003 and IEC 62220-1-2, 2007]:

$$NPS(u,v) = \frac{\Delta x \cdot \Delta y}{M \cdot N_x \cdot N_y} \sum_{m=1}^M |FFT\{I(x_i, y_i) - S(x_i, y_i)\}|^2 \quad (2.28)$$

where u and v are the spatial frequencies corresponding to x and y , Δx and Δy are the x and y pixel pitches, N_x and N_y express the ROI size in pixels in the x and y directions (256 according to the IEC), M is the number of ROIs used in the ensemble average. Figure 2.6 shows an example of 2-D NPS extracted from Hamamatsu detector at 120.5 μ Gy DAK, on a logarithmic greyscale to enhance the visibility of low contrast-details (Gonzalez and Woods, 2008). Also, in this figure the 1-D thick slices to calculate the horizontal and vertical 1-D NPS are shown.

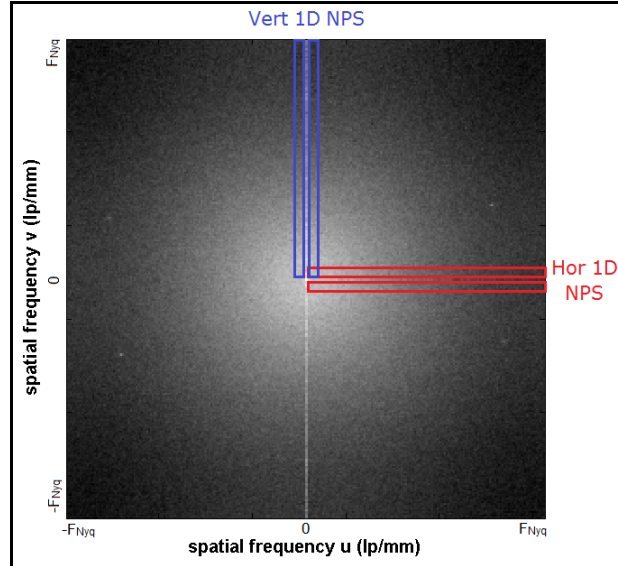


Figure 2.6: An example of 2-D NPS with 1-D cuts for the horizontal and vertical 1-D NPS

In order to use the NPS for the DQE calculation, 1-D profiles were extracted from the 2-D NPS. Data from seven rows or columns on both sides of the corresponding axis (a total of 14), omitting the axis itself, were averaged, resulting in the horizontal and vertical 1-D NPS. The axes were omitted because they are susceptible to any remnant column- or row-wise FPN on the flat field images. In other words, in the presence of horizontal or vertical structure noise, the NPS has an unusually large value along the u and v axes which is not representative of stochastic noise. Therefore, it is not representative of the 1-D NPS (or NNPS) to include the artificially high noise of the

axes themselves, because those values are not reflective of the NPS in the great majority of frequency space (Dobbins III, 2000). Each data point was associated with a specific spatial frequency by means of the formula $f = \sqrt{u^2 + v^2}$. As done when calculating the pMTF, smoothing was obtained by averaging the data points within the 14 rows and columns that fall in a frequency interval of f_{int} around the spatial frequencies from 0.5 to F_{Nyq} with an interval of 0.5 lp/mm (IEC 62220-1, 2003 and IEC 62220-1-2, 2007). The horizontal and vertical $NPS(f)$ were then divided by the $(large\ area\ signal)^2$ to obtain the normalized NPS (NNPS), expressed in terms of relative input exposure fluctuation (Dainty and Shaw, 1974 and Dobbins III, 2000). The term “large area signal” corresponds to the mean DN in the image for each particular dose and can be obtained from the STP (after offset and gain corrections). The mean DN corresponds to the NPS at zero frequency, i.e. $NPS(0)$. This normalization is made in accordance to the normalization of the pMTF at zero frequency, because the DQE shows the difference in the efficiency of the signal (pMTF) and noise (NNPS) transfers. Finally, the horizontal and vertical 1-D NNPS were combined to calculate the average 1-D NNPS. Figure 2.7 shows an example of horizontal and vertical 1-D NNPS cuts extracted from the 2-D matrix.

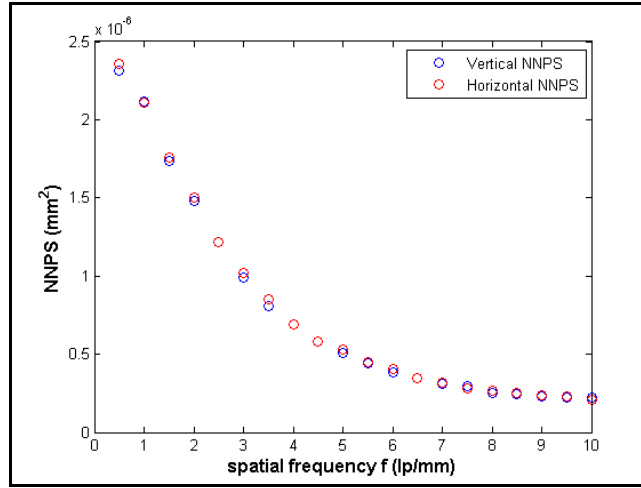


Figure 2.7: Horizontal and vertical NNPS extracted from the 2-D NPS

According to Saunders *et. al* (2005) the relationship between the image r.m.s. variance in spatial domain and the 2-D NNPS is given by the following formula:

$$\sigma^2 = \frac{\langle I \rangle^2 \cdot \sum_{u,v} NNPS(u,v)}{N_x N_y \cdot \Delta x \Delta y} \quad (2.29)$$

where u and v are the spatial frequencies corresponding to the x and y directions, Δx and Δy are the x and y pixel pitches (in mm), N_x and N_y express the respective ROI size in pixels and $\langle I \rangle$ corresponds to the average pixel value of the image (in DN).

2.4.5 Detective Quantum Efficiency (DQE)

The DQE shows the ability of the detector to transfer the SNR from its input to the output. It expresses the fraction of input x-ray quanta used to create an image at each spatial frequency and describes the ability of a particular system to effectively use the available input quanta. Practically, it is calculated from the following formula (Cunningham, 2000, IEC 62220-1, 2003 and IEC 62220-1-2, 2007):

$$DQE(f) = \frac{SNR_{out}^2}{SNR_{in}^2} = \frac{MTF^2(f)}{\frac{\Phi}{K_a} \cdot K_a \cdot NNPS(f)} \quad (2.30)$$

The IEC standard assumes that an ideal detector behaves as an ideal photon counter (Samei and Flynn, 2002). Therefore, the fluence per exposure ratio Φ/K_a for each beam quality was calculated according to the following formula (Johns and Cunningham, 1983, Boone, 1998, Cunningham, 2000 and Samei and M. Flynn, 2002):

$$\frac{\Phi}{K_a} = \int_0^{kV} \Phi_{norm}(E) \cdot \frac{W \cdot Q}{\left(\frac{\mu_{en}(E)}{\rho}\right)_{air} \cdot E \cdot e \cdot 10^8} dE \quad (2.31)$$

where $\Phi_{norm}(E)$ is the normalized spectrum, W is the work function of air (33.97 keV), Q is the charge liberated in air by one R (2.58×10^{-4} C/kg/R) and e is the electron charge (1.6022×10^{-19} C). The current system consists of an energy integrating detector, so an energy-weighted calculation of the Φ/K_a would be more realistic. However, Samei and Flynn (2002) showed that for 70 kV (W/Al anode/filtration combination) with additional 19 mm Al, which is close to the radiation beam quality RQA5 (70 kV (W/Al) with additional 21 mm Al (IEC 62220-1, 2003)), the difference between the energy-weighted and photon-counting approximations is less than 3%. This difference is even smaller for lower kV spectra.

The product $(\Phi/K_a) \cdot K_a$ corresponds to the SNR_{in}^2 input due to the Poisson distribution of the input quanta. Therefore, the SNR_{out}^2 output is calculated from the ratio

between MTF^2 and NNPS. An ideal imaging system would be characterized by a DQE equal to one at all spatial frequencies. In practice, there is always a departure from this behavior and the DQE decreases gradually with increasing spatial frequencies. This occurs due to the increased effect of the noise as a function of spatial frequency (Williams *et al.*, 2007). As done when calculating the pMTF and NNPS, the DQE is presented at spatial frequencies from 0.5 to F_{Nyq} with an interval of 0.5 lp/mm according to the IEC standard (IEC 62220-1, 2003 and IEC 62220-1-2, 2007). Note that the average of the pMTF and NNPS data into 0.5 lp/mm spatial frequency bins allows easier visualization of the DQE results because it smoothes the pMTF curve and reduces the influence of the spikes frequently seen in the NNPS. Also, the DQE at zero frequency is excluded because low-frequency artifacts (such as the background trends, etc.) result in unusually high NNPS at zero frequency which leads to underestimation of DQE. Therefore, it is hard to distinguish between low-frequency artifacts and low-frequency stochastic noise. As mentioned in section 2.4.4 detrending may be used to reduce the low-frequency trends. However, it does not change the mean value, i.e. the central point on the 2-D NNPS array and it does not completely remove the excessively large values along the u and v axes (Dobbins III, 2000).

At low DAK levels the electronic noise (read noise and dark current) is comparable to the signal produced from the x-ray quanta, and may therefore have a strong effect on the overall noise (NNPS) decreasing the DQE. At this signal level the system is defined as electronic noise limited. As the DAK level increases, this effect decreases and the DQE increases. Finally, at high signal levels this effect is negligible and the DQE reaches a maximum. At this level the system is quantum limited, as only the quantum noise affects its performance. According to Saunders *et al.* (2005), for a linear and quantum limited detector the product of NNPS and DAK should remain constant. Eq. (2.20) shows that this results in constant DQE. One of the few cases in which the DQE may decrease at high signal levels is when there is a substantial level of FPN, the amplitude of which increases linearly with the signal, and therefore becomes predominant at high dose (Monnin *et al.*, 2007). However, appropriate gain and offset correction algorithm is normally sufficient to eliminate this effect. The combination of Eq. (2.25) and (2.30) result to the following equation (Evans *et al.*, 2002):

$$DQE(f) = \frac{\eta}{I + n_{ex} + \frac{1}{\tilde{g}pMTF^2(f)}(1 + \eta\tilde{g}QN_s(f) + \frac{N_{el}(f)}{\eta\tilde{g}Q})} \quad (2.32)$$

which shows the dependency of the DQE on the various parameters. Each parameter presented in this formula is described in Eq. (2.25). According to Evans *et al.* (2002) the zero frequency DQE of a linear and quantum limited detector can be approximated by

$$DQE(0) = \frac{\eta}{I + n_{ex} + (1/\tilde{g})} \quad (2.33)$$

which shows that when n_{ex} and the $(1/\tilde{g})$ are very small, the difference of the DQE can be estimated from the variation of the η (QDE). The QDE depends on the beam quality which is a function of the anode material, the maximum energy of the spectrum which is defined by the tube voltage (kV) and the additional filtration. Several investigators studied the relationship between the beam quality and the DQE (Tapiovaara and Wagner, 1985, Cahn *et al.*, 1999, Fetterly and Hangiandreou, 2001 and Suryanarayanan *et al.*, 2003). Marshall (2009b) based on the aforementioned studies (Fetterly and Hangiandreou, 2001, Evans *et al.*, 2002, Suryanarayanan *et al.*, 2003 and Mackenzie and Honey, 2007) demonstrated experimentally that 11% and 27% reductions in the QDE resulted in subsequent reductions of 8% and 22% in the DQE of a-Se TFT and CsI-based a-Si:H TFT detectors respectively.

Finally, the presence of V/e^- nonlinearity on the CMOS sensors may increase the DQE at high signal levels even if the sensor is quantum limited. This happens because the nonlinearity has a stronger effect on the noise rather than on the signal which results in improved SNR (see section 2.2.3; Tian *et al.*, 2001).

2.5 Summary

In this chapter the theoretical framework of signal and noise transfer of digital x-ray detectors has been presented. Within this framework a complete x-ray and electro-optical performance evaluation of the detectors can be performed. The PTC and MV methods are presented for the electro-optical performance evaluation of a linear sensor. On the other hand, the NLC method is presented in the case of a nonlinear sensor, such

as CMOS APS. The standard x-ray performance evaluation parameters of a digital detector (i.e. MTF, NPS and DQE) are also presented.

Chapter 3

3 Empirical performance evaluation of the imagers

3.1 Overview of chapter

In this chapter the electro-optical performance evaluation of the two novel CMOS APS employed in this study is presented. The electro-optical performance of the sensors has been measured in terms of read noise, shot noise, full well capacity, dynamic range and dark current. A novel method is suggested to reduce the periodic pattern that affects the evaluation of the performance parameters in the presence of the EMI noise. Also, the x-ray performance parameters (MTF, NNPS and DQE) of the five available digital x-ray detectors are presented using four beam qualities, two for mammography and two for general radiography. Furthermore, a preliminary study on the performance of Dexela's detector under dynamic imaging conditions is carried out. This chapter also includes a suggested method that requires a minimum number of reference frames for the calculation of the NNPS. Finally, the effect of the digital detector's inherent nonlinearity on the DQE is presented as well.

3.2 Electro-optical evaluation of the sensors

Due to technical difficulties (the Hamamatsu detector was sealed, the Anrad a-Se is insensitive to light and the RadEye appeared to have nonlinear behaviour at low signal levels) it was decided to focus the electro-optical evaluation on the LAS and Dexela detectors only instead of trying to find time-consuming solutions for the well established commercial ones. LAS suffered from EMI noise when a specific version (namely 2nd generation) of electronics stack board was employed for the electro-optical performance characterization. However, this version was the only one available at the time and a software solution was developed to facilitate this. A novel solution was

applied to remove the periodic noise related to the EMI during the electro-optical evaluation of LAS (Konstantinidis *et al.*, 2010). This method was applied first on a central ROI of LAS assuming that it corresponds to the average performance of the sensor. Another study applied the filtration algorithm on different ROIs over the sensor to compare the effect of the stitching on the performance of LAS (Zin *et al.*, 2010).

3.2.1 LAS sensor – EMI noise reduction algorithm

The difference image between 2 flat images used for the electro-optical evaluation of LAS is affected by the EMI noise. Figure 3.1a shows a difference image of a central ROI (250x125 pixels) of LAS. The periodic pattern from the EMI noise emerged because the FPN is removed. The standard deviation of this pattern corresponds to the read and shot noise combination of the sensor at a particular signal level. Therefore, the periodic pattern needs to be removed in order to calculate the real performance parameters of the sensor. Figure 3.1b shows the modulus of the Fourier transform of the difference image shown in Figure 3.1a, where three pairs of spikes can be seen. Analyzing this specific spectrum it is found that the main spike (the one with the highest spectral magnitude, i.e. the higher contribution on the periodic pattern—located at the top left and bottom right areas) corresponds to 7.4 lp/mm at 20° orientation, while the other two spikes correspond to 4.1 lp/mm at 15° and 12.3 lp/mm at 115°. It was observed that the main spike is usually located within a specific frequency and phase range. However, the number and the location of the other spikes were found to change. In addition to the spikes, the central three columns have a high magnitude, which corresponds to a combination of row-wise sinusoidal patterns in the difference image. This pattern is believed to be quasi-periodic noise, which is the combination of more than one periodic patterns (Aizenberg and Butakoff, 2008). The spectrum is displayed on a logarithmic greyscale to enhance the visibility of low contrast-details (Gonzalez, 2008).

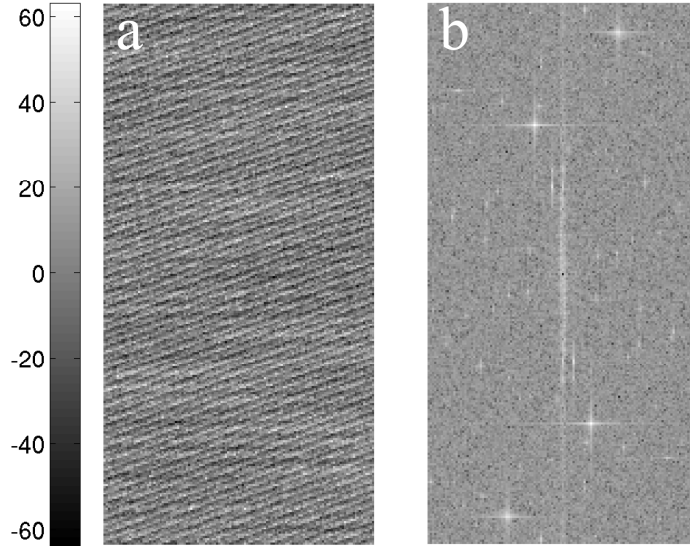


Figure 3.1 a) High magnitude periodic pattern, superimposed on a difference image, b) the respective Fourier spectrum represented on logarithmic scale ($\log(I+|\tilde{I}|)$), where $|\tilde{I}|$ is the magnitude of the Fourier transform).

As mentioned in section 2.2.2 cross-shaped notch-reject filters were applied to reduce the periodic pattern and at the same time cause the minimum modification of the useful frequencies. However, before the application of the notch-reject filter the noise spikes must be located because it was observed that the position, number and intensity of these spikes is not constant in the case of LAS. Therefore, the location of the noise spikes was performed using the so called “top-hat” filter (Russ, 2007), defined by a mask comprised of two regions of pixels as depicted in Figure 3.2 (which shows the specific mask employed in this work). The mask may take various shapes, however it usually has a central, simply connected region called the crown, and a surrounding region of pixels called the brim. For reasons of brevity, the crown and brim are denoted as sets of pixels $C=\{(i,j)\}$ and $B=\{(i,j)\}$ respectively.

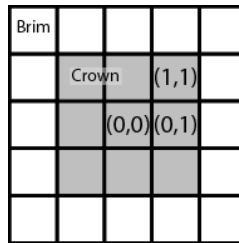


Figure 3.2: Topology of top-hat filter demonstrating the crown (shaded) and brim regions

For each pixel (i,j) in the Fourier spectrum $\tilde{I}(i,j)$ the filter is applied by first evaluating one of the metrics f_1 and f_2 defined as

$$f_1(i, j) = \left| \tilde{I}(i, j) \right| - \max_{(i, j) \in B} \left| \tilde{I}(i + \bar{i}, j + \bar{j}) \right| \quad (3.1)$$

$$f_2(i, j) = \max_{(i, j) \in C} \left| \tilde{I}(i + \bar{i}, j + \bar{j}) \right| - \max_{(i, j) \in B} \left| \tilde{I}(i + \bar{i}, j + \bar{j}) \right| \quad (3.2)$$

In the case where the above functions refer to pixels located outside the Fourier spectrum, these are omitted from the calculation. A peak is detected when one of the chosen metrics exceeds a threshold. After a series of preliminary tests were carried out, it was observed that a threshold value of 30000 DN effectively detects the spikes.

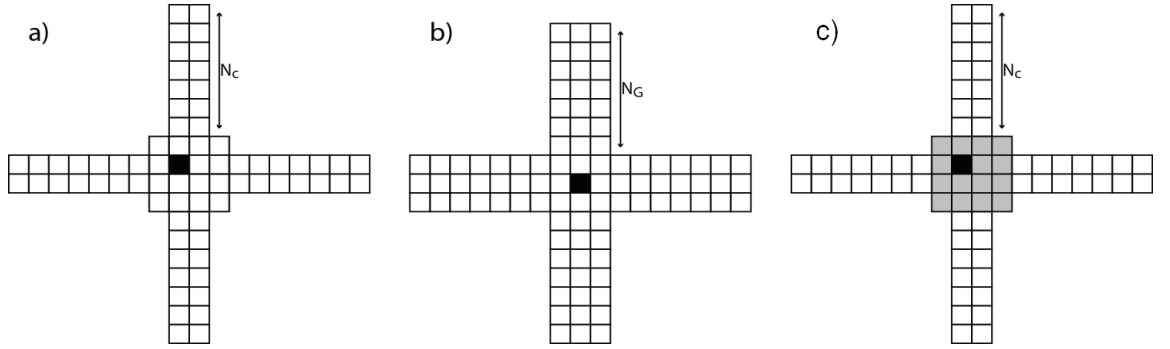


Figure 3.3: Topology used to define masks for the brick wall (a), Gaussian (b) and interpolation (c) type filters. The mask origins are depicted by a solid black pixel

Three types of notch-reject filters were considered: “brick wall”, “Gaussian” and “interpolation”. When applying the brick wall filter, the mask shown in Figure 3.3a is positioned with its origin in the pixel corresponding to the peak. Then all pixels in the spectrum covered by the brick wall mask are set to zero. In Figure 3.3a, N_c is the half width of the mask with the central shaded square region excluded. The value of N_c is chosen to be 0, 8 or 16 depending upon the position of the peak and the boundary of the frequency domain and taking into account that the maximum width of crosses due to EMI found in our case was 30 pixels. When applying a Gaussian type filter, the mask shown in Figure 3.3b is positioned with its origin covering the pixel where the peak is detected. Then each pixel in the spectrum covered by the mask is multiplied by the value

$$H(i, j) = 1 - \exp \left(- \left(\frac{i - i_0}{\sigma} \right)^2 - \left(\frac{j - j_0}{\sigma} \right)^2 \right) \quad (3.3)$$

where (i_0, j_0) is the pixel where the peak is detected and σ controls the width of the Gaussian profile. Sigma was calculated such that $H(i_0 + N_G + 1, j_0)$ took the value 0.7

which was judged to be adequate to reduce the values at the edges of the cross shape. For this filter, N_G is the half width of the mask cross section with the central 3x3 pixel region excluded. N_G took a value of 9 or 14 pixels correspondingly to N_c . Note that although other filter profiles, for example Butterworth (Gonzalez, 2008), could be used here, it was found that their use yielded no significant difference from the simpler Gaussian profile.

The third type of filter was an interpolation filter which is similar to the brick wall filter. This filter employs the mask depicted in Figure 3.3c. Instead of replacing covered pixels of the Fourier spectrum with 0, it replaces the central shaded region with a fifth of the average of all pixels covered by the brim of the top-hat mask. Pixels covered by the cross section of the mask in Figure 3.3a are replaced by a value equal to one third that of their adjacent pixel in the Fourier spectrum. It was found that these parameters were sufficient for the reduction of the noise spikes. The aforementioned threshold used for the identification of the spikes was the same for all filters. The widths of the filtering masks have been chosen on the basis of the ROI dimensions (250 x 125 pixels). This happens because the Fourier transform of the windowing function, which results in the cross shape of the spikes, represents the size of the used ROI (section 2.2.2). Therefore, the detection and proposed filtering methods used can be considered as semi-automatic.

The three notch-reject filters were used to reduce the detected spikes in the Fourier spectrum. Correspondingly, they reduced the periodic noise in the restored image, obtained via the inverse Fourier transform. Figure 3.4 shows an example of the way each filter modified the above difference image. The application of cross shaped notch-reject filters to remove pure periodic noise in the frequency domain is the novel aspect of this work. Doing this reduces the amount of information discarded through filtering compared with using circularly symmetric filters used in Russ (2007), Sonka *et al.* (2007) and Aizenberg and Butakoff (2008). As mentioned above, this is due to the similarity between the shape of the artifact that we want to remove and the shape of the filter itself (in the Fourier space).

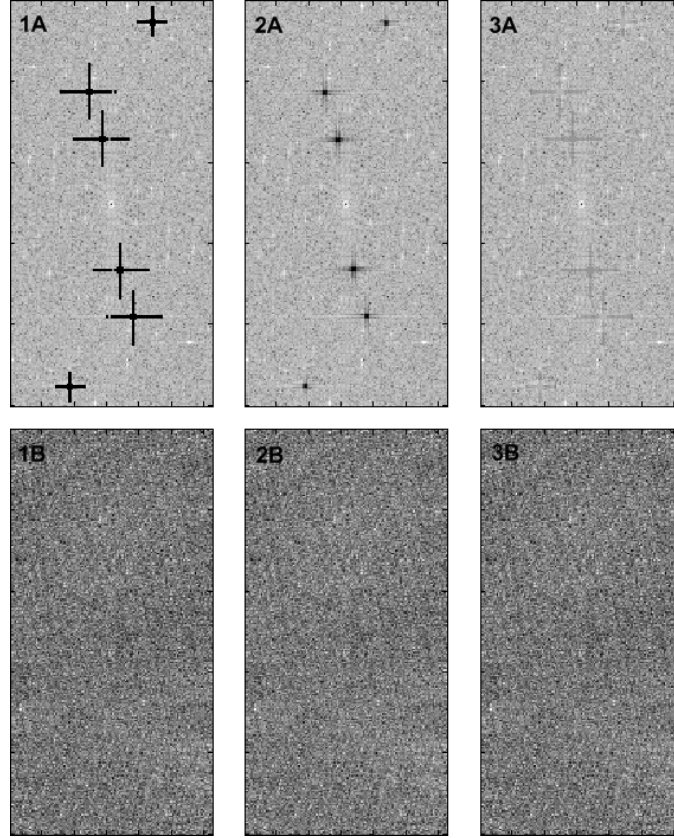


Figure 3.4: Images 1A, 2A and 3A show the effect of the brick wall, Gaussian and interpolation notch-reject filters on the Fourier transform of the images. Images 1B, 2B and 3B show the effect of the same filters on the direct space images following inverse Fourier transformation. The corresponding uncorrected image is shown in Figure 3.1.

The central three columns of the Fourier spectrum have been replaced with an interpolation of the adjacent columns in order to eliminate the row-wise pattern. However, a central region of 4x4 pixels was kept the same in order to preserve the origin (i.e. the zero frequency) of the Fourier spectrum. These low-frequency spectral coefficients make a significant contribution to the signal energy, and their change may lead to an undesirable distortion of the image (Aizenberg and Butakoff, 2008). In order to save computational time, the top-hat filter was scanned only on half of the spectrum. When a spike was detected, the filter was applied also to the symmetric (conjugate) point of the spectrum (Al Hudhud and Turner, 2005). The above 3 filters have been applied to the difference image to reduce the effect of periodic noise on the performance parameters extracted through photon transfer and nonlinear compensation methods. It has been found that reducing the periodic noise does not affect the average value of the difference image, since the spikes were filtered away from the origin of the Fourier

spectrum. However, the standard deviation of the difference image decreases, indicating a reduced overall noise level.

3.2.2 LAS sensor – experimental setup

The experimental procedure that was used is described in Bohndiek *et al.* (2008a). Two white diffusion sheets with 25 % and 87 % attenuation (Lee filters, white 129 ¼ and 129), were coupled to a narrowband light emitting diode (LED) with an emission spectrum centred around 520 nm. The LED was connected to a DC power supply (Agilent E3646A) to provide constant illumination at a given voltage. The light intensity was varied by changing the voltage applied to the LED. The total distance between the LED and the sensor was 67.8 cm, yielding a light non-uniformity of less than 4 % across the region of analysis. The light non-uniformity has been measured using a calibrated photodiode (Hamamatsu S1336-5BQ) placed in the position of the sensor prior to data acquisition and read out via a high voltage source-measure unit (Keithley 237) connected to a PC. The setup used for the electro-optical evaluation of LAS sensor is shown in Figure 3.5. The LAS stack board was attached to a plastic support box.

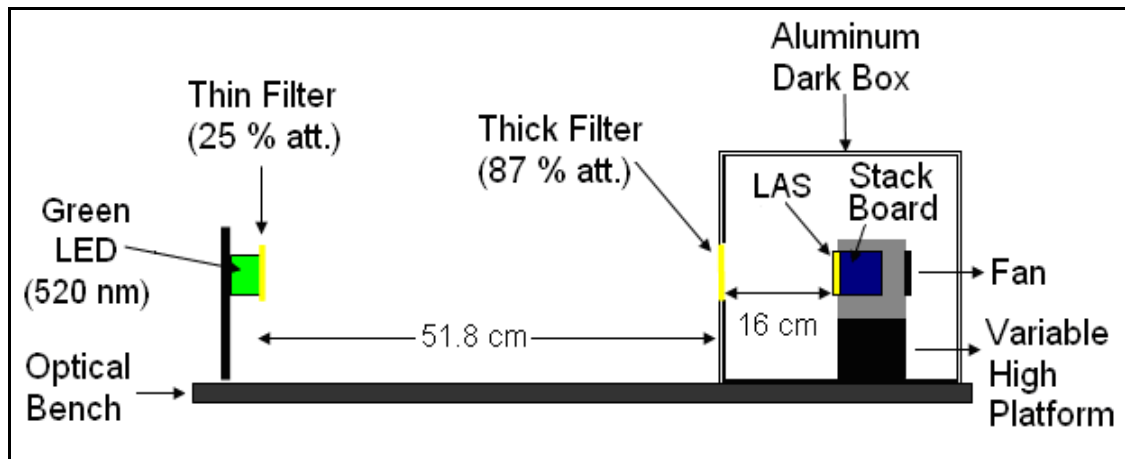


Figure 3.5: Experimental setup for the electro-optical evaluation of LAS sensor

The LAS sensor was warmed up for half an hour before the measurements in order to have stable response. During the measurements, hard reset was used for the LAS sensor because it shows a greater linearity than soft reset (see section 1.4.1). The whole frame was read out having an integration time of 0.1 sec., which enabled accommodating almost the entire intensity range of the LED as input signal. The LAS sensor and its stack board, which incorporates 10 ADCs and readout electronics, were

placed inside an aluminum light tight box in order to eliminate additional background signal. Furthermore, the measurements took place inside a dark room. The stack board was connected to a dedicated P160 expansion board, via a high performance 120 way Samtec cable. The expansion board was connected to a Xilinx FPGA board. An external power supply (TTi / Dual Output) provided the required voltage input to the stack board, while a 12 V DC power supply was connected to the FPGA and to a fan which attached to the back side of the stack board for cooling. The FPGA was connected to a Windows desktop PC via a fibre optic cable, transferring a 14-bit digitized image. LabVIEW software was used to capture images and simultaneously drive the illumination levels via the Agilent E3646A power supply. 110 illumination levels were used and for each level 90 frames were captured for analysis.

A central ROI of 250x125 pixels was analyzed from the captured frames per each illumination level. The dimensions of the ROI have been chosen in order to fit within one of the 50 different areas of the sensor, and simultaneously provide a sufficient accuracy on the results. These frames have been analysed using custom built software written in MATLAB version 7.6 (The MathWorks, Natick, MA, USA) which extracts the photon transfer curve and reduces the periodic noise. For the NLC method, the mean and gain extracted from the photon transfer method have been combined with the illumination input, in order to calculate signal and noise gains separately. The illumination input has been measured using the aforementioned photodiode, placed in the position of the central ROI prior to data acquisition.

3.2.3 LAS sensor – results and discussion

The PTC resulting from the data suffering from EMI noise is shown in Figure 3.6. This figure shows both read & shot noise and shot noise curves as a function of the signal. Only the latter is used for extracting the gain. The shot noise curve shows a high amount of fluctuations at lower illumination levels, due to the periodic noise. This curve is useful for the extraction of the signal and noise gains obtained with the NLC method. The data points used for this extraction were within a signal range of 240 to 740 DN, because in this region shot noise is dominant and the V/e^- nonlinearity may be neglected. The slope of these points, after logarithmic transformation, is compatible with the theoretical value of 0.5 (0.49 ± 0.01).

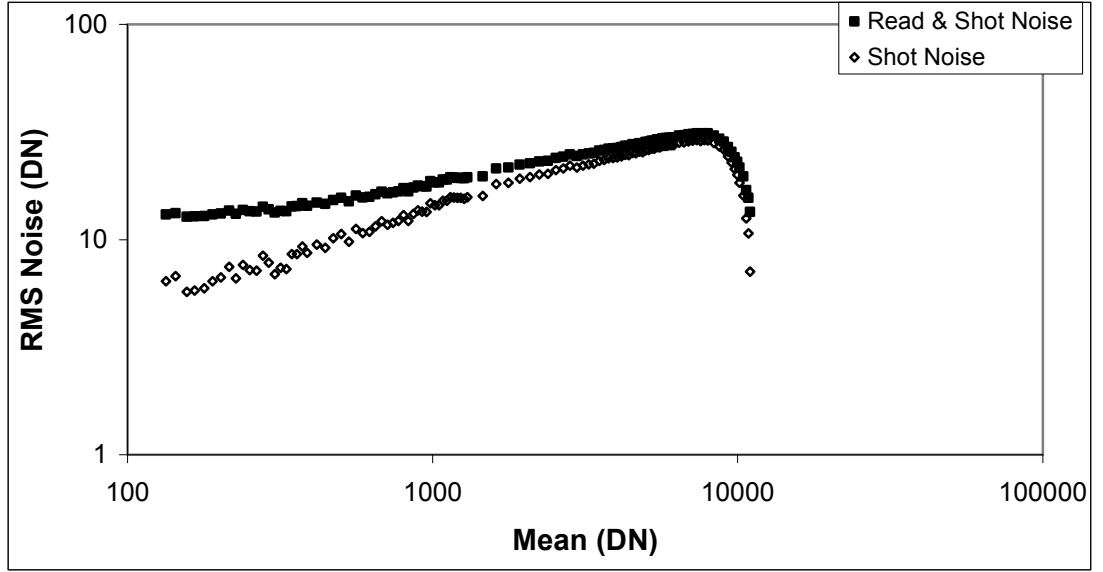


Figure 3.6: Read and shot noise photon transfer curve of the data suffering from EMI.

Figure 3.7 shows the photon transfer curve extracted from the data after removal of EMI by means of the brick wall filter. It is observed that the fluctuations on the lower signal levels are less prominent compared to the unfiltered data. For these filtered data, the slope of the logarithmically transformed curve used for the gains extraction had a value of 0.474 ± 0.003 , over the aforementioned signal range.

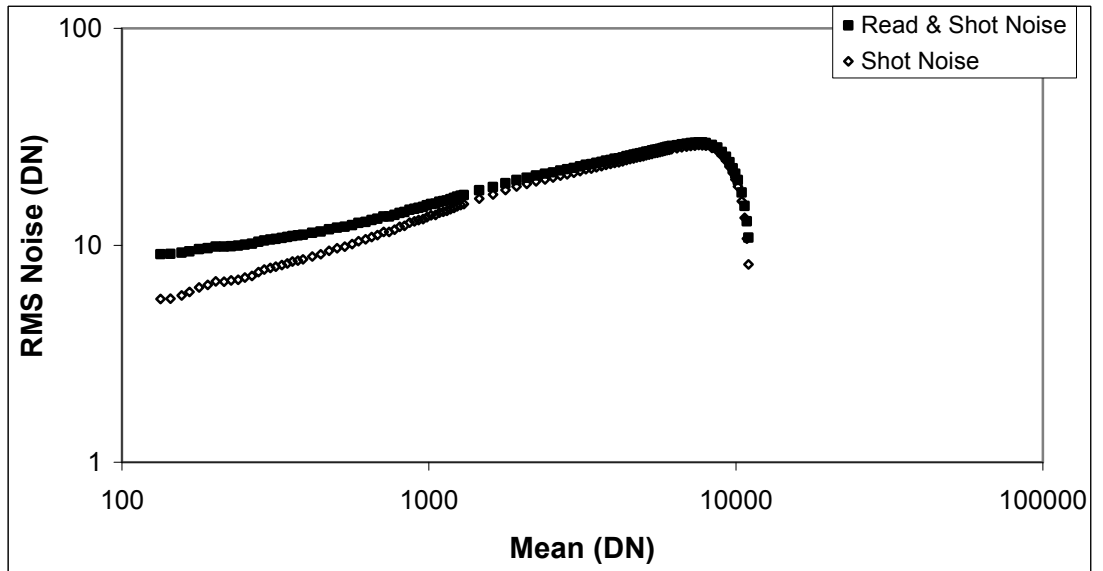


Figure 3.7: Read and shot noise PTC of the reduced EMI noise data (brick wall notch reject filter).

A comparison between PTCs before and after EMI suppression with the different filters is shown in Figure 3.8. To better demonstrate the agreement between results obtained with the three different filters, the correlation coefficients between the three

possible couples of curves (i.e. 1 with 2, 2 with 3 and 1 with 3) were calculated and they were all found to be equal to 1. On the other hand, the correlation coefficient between the curve obtained through filtering with the first (brick wall) filter and the unfiltered one was 0.986 for the points used for the gain extraction, and 0.997 for the higher signal points. This demonstrates that the EMI noise has a stronger effect on lower signal levels, because it has fixed amplitude.

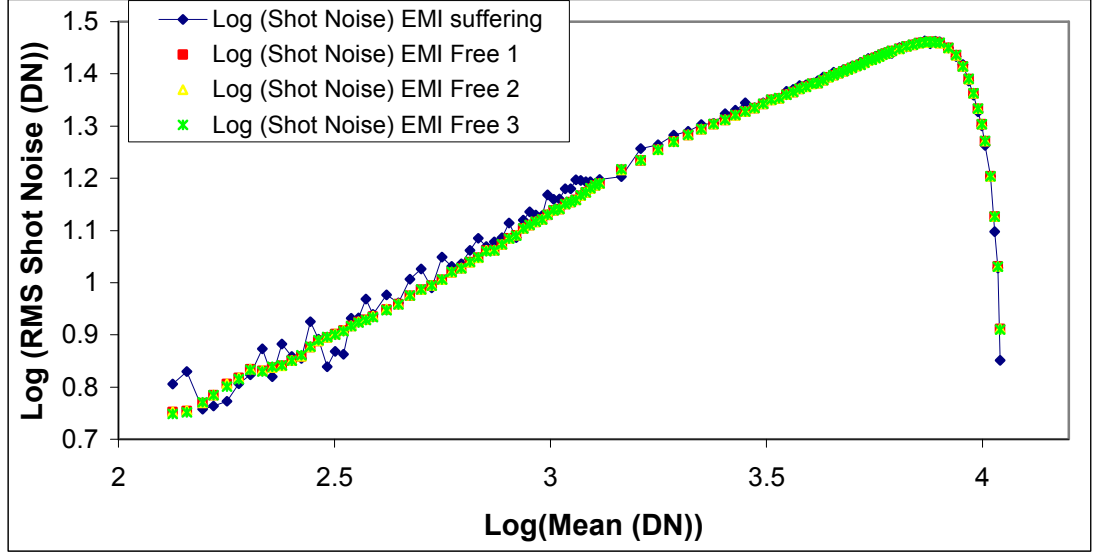


Figure 3.8: EMI noise suffering PTC compared to EMI noise reduced PTCs using all three filters. Numbers 1,2 and 3 are referring to the brick wall, Gaussian and interpolation notch-reject filters. It can be seen that all filters reduce in a similar way response's fluctuations caused from EMI noise.

Figure 3.9 shows the NLC method applied to data suffering from EMI noise. It can be seen that both signal and noise gains change as a function of the signal, rather than being a constant (as the photon transfer method would assume). Both V/V and V/e^- nonlinearities were found to be present for the LAS sensor. Signal and noise gains are decreasing at lower levels, indicating the presence of V/V nonlinearity. After 8500 e^- , signal and noise gains start to diverge significantly, showing V/e^- nonlinearity.

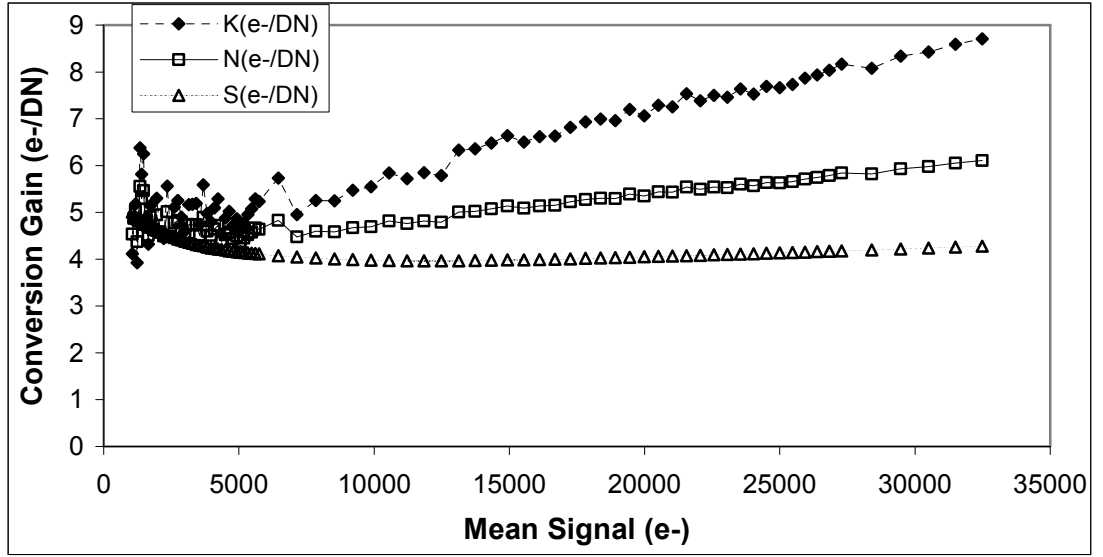


Figure 3.9: NLC method applied on data suffering from EMI noise. A large amount of fluctuations is seen, mainly on lower signal levels.

For reasons of brevity, Figure 3.10 shows the respective NLC results applied to data processed with the third filter only. It can be observed that the fluctuations on the lower signal gains are less obvious, because of the reduced effect of EMI noise.

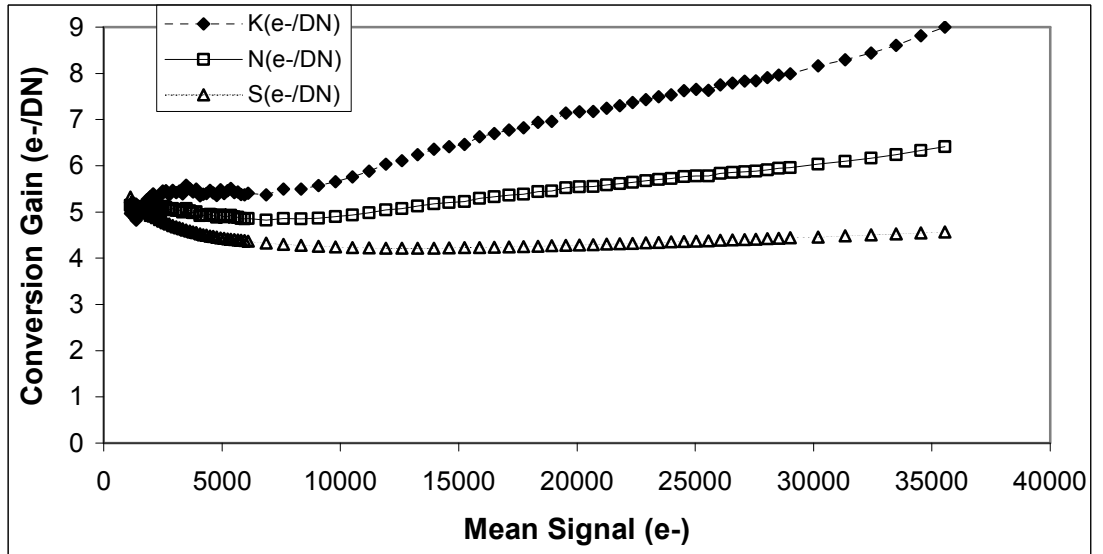


Figure 3.10: NLC method applied on reduced EMI noise data using the Gaussian notch-reject filter

The performance parameters, extracted from both filtered and unfiltered data, are shown in Table 3.1. Signal gain was used for the full well capacity calculation, i.e. $FW(e^-) = S(e^- / DN) S_{\max}(DN)$ where $S_{\max}(DN)$ is the signal level corresponding to the maximum variance. Noise gain was used for the read noise extraction. Therefore,

the following table shows the values of the signal gain at full well capacity level and the respective noise gain at dark level. The signal gain can be used to characterise the sensor. Using this method, the difference on the signal gain between unfiltered and filtered data was relatively small (approximately 5 %). Correspondingly, the difference on the noise gain was found to be almost 13 %. The filtered data result in a low read noise (42 % difference compared to unfiltered data), due to the low temporal r.m.s. of the dark image. A full well capacity of around 52×10^3 electrons was found for the filtered data, which is close to the value extracted from unfiltered data (7 % difference). Finally, the dynamic range of the filtered data is approximately 4 dB higher.

Table 3.1: Comparison of the NLC method extracted performance parameters obtained by EMI noise suffering data and the respective using the three EMI noise reduction filters

Performance Parameter	EMI suffering	EMI Free (brick wall)	EMI Free (Gaussian)	EMI Free (interpolation)
Conversion gain (e^-/DN)	4.26 ± 0.10 (S)	4.49 ± 0.04 (S)	4.48 ± 0.04 (S)	4.47 ± 0.04 (S)
	4.53 ± 0.06 (N)	5.10 ± 0.02 (N)	5.09 ± 0.02 (N)	5.09 ± 0.02 (N)
Read Noise (e^-)	51.7 ± 0.6 (N)	36.4 ± 0.2 (N)	36.7 ± 0.2 (N)	36.4 ± 0.2 (N)
Full Well Capacity (e^-)	$(48.9 \pm 1.2) \times 10^3$ (S)	$(52.5 \pm 0.4) \times 10^3$ (S)	$(52.5 \pm 0.5) \times 10^3$ (S)	$(52.4 \pm 0.4) \times 10^3$ (S)
Dynamic Range (dB)	59.5 ± 0.6	63.2 ± 0.2	63.1 ± 0.2	63.2 ± 0.2

Table 3.1 shows that the filtered results have a greater precision, as expected, because the filtration removes the fluctuations on the gain curves caused by the EMI noise consequently smoothing the data. The noise gain $N(e^-/DN)$ has a higher precision compared to the signal gain $S(e^-/DN)$ because it is related to the square root of the signal, thus error propagation results in a smaller uncertainty.

After the demonstration of the EMI noise reduction algorithm functionality on a single ROI, the same algorithm (using Gaussian cross-shaped notch-reject filter) was applied on 50 ROIs (250×125) of LAS detector. This number arises from the fact that LAS consists of 1350×1350 pixels, using combination of 5×5 stitched arrays (5 chips column-wise and 5 chips row-wise) and 10 column analog-to-digital converters

(ADCs). Therefore, this combination leads to the formation of 50 different areas (270 x 135 pixels each). The overall performance evaluation of two LAS sensors is described in detail elsewhere (Zin *et al.*, 2010). Briefly, the effect of stitching on the performance parameters of LAS 1 and LAS 2 was studied. It was found that the stitching process adds non-uniformity variations as a function of the signal level (1.5-3.5 % at dark signal, rising to 3-8 % at high signal levels). However, this non-uniformity can be removed using standard calibration (gain correction) methods. Finally, Table 3.2 shows the overall performance parameters of LAS 1 by implementing the suggested EMI reduction algorithm (Gaussian notch-reject filter).

Table 3.2: Overall performance parameters of LAS using the EMI reduction algorithm

Performance Parameter	Conversion gain (e ⁻ /DN)	Read Noise (e ⁻)	Full Well Capacity (e ⁻)	Dynamic Range (dB)	Dark current (pA/cm ²)
Value of each parameter	4.9 ± 0.50 (S) 5.4 ± 0.50 (N)	39.8 ± 3.7 (N)	(59.1 ± 6.8) x10 ³ (S)	63.4 ± 0.5	7 ± 2 (K)

A comparison between these values and the nominal ones presented in Table 1.1 shows 3 dB difference on the dynamic range. This happens due to the overestimation of the read noise by around 35 %, which is affected by the presence of the EMI noise. The respective difference between the full well capacity levels is 3.5 %. Finally, LAS appears to have a relatively small dark current (7 pA/cm²). The constant conversion gain $K(e^-/DN)$ was used for the calculation of the dark current, because it was extracted mainly from lower signal levels where the effect of nonlinearity is small.

3.2.4 Dexela CMOS sensor – experimental setup

The experimental setup for the electro-optical evaluation of Dexela's CMOS sensor is similar to the one followed in the case of LAS. To obtain the images used for the PTC calculation the sensor was uniformly illuminated with a pulsed LED with a peak wavelength at 530 nm (green light) and full width at half maximum (FWHM) 20 nm. This set of measurements was made at Dexela. To achieve different illumination levels, the pulse times of the LED were varied (between 0.1-19.6 ms and 0.1-6.4 ms for the HFW and LFW modes, respectively). For each illumination level 30 frames operated at 1x1 binning mode were captured. Again, the data analysis for the electro-optical

performance evaluation of Dexela sensor was made using custom built software written in MATLAB version 7.6 (The MathWorks, Natick, MA, USA).

3.2.5 The Dexela CMOS sensor – results and discussion

Figure 3.11 shows the PTC curves for Dexela's sensor for HFW and LFW mode, respectively. It can be seen that the LFW mode results in higher shot noise at a given signal level, which according to Eq. (2.13) corresponds to lower conversion gain $K(e^-/DN)$. An analysis of the figures shows that the full well capacity of the photodiode (i.e. the point corresponding to the maximum shot noise) is found at about 13100 DN for the HFW and 12000 DN for the LFW.

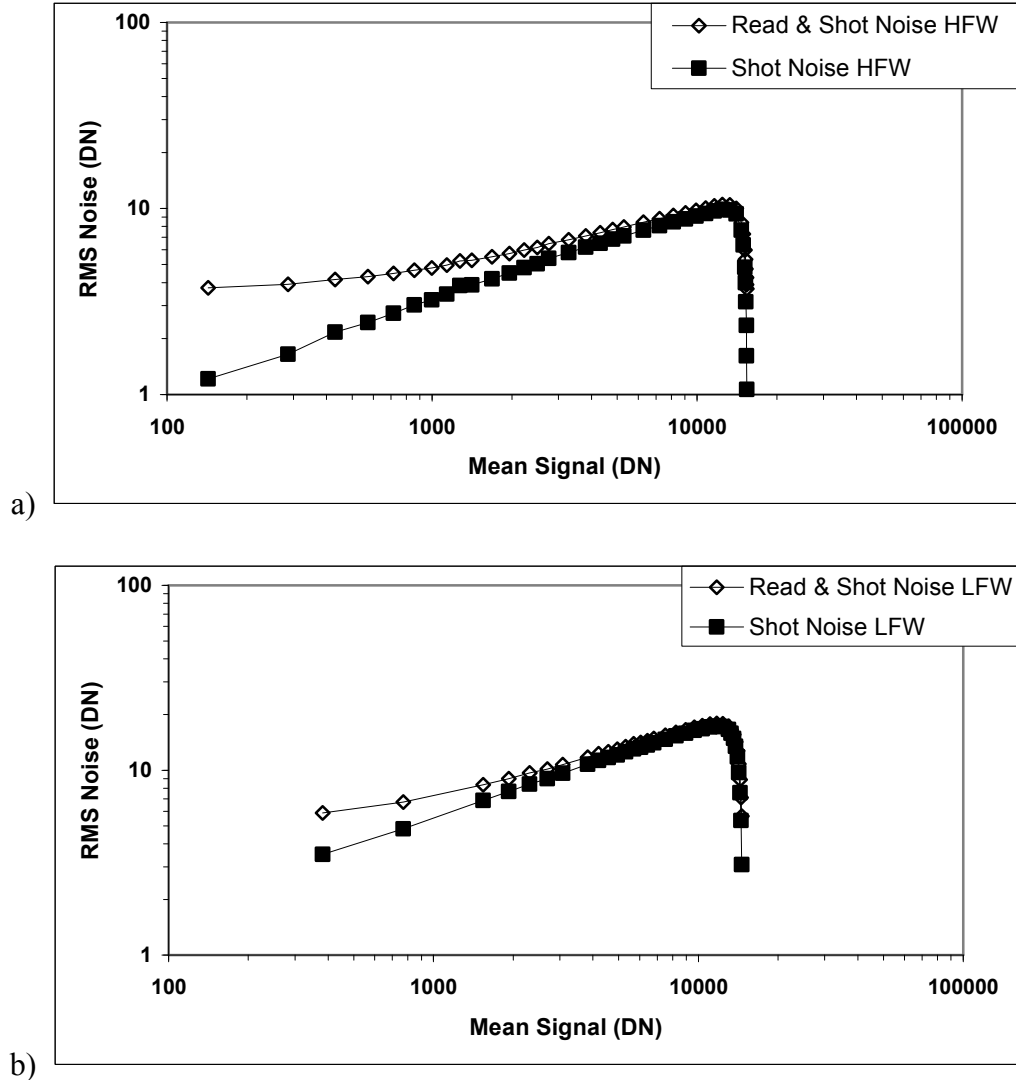


Figure 3.11: Representative PTC curves for a) HFW and b) LFW modes

Table 3.3 provides the main detector parameters in terms of the electro-optical characterization. The performance parameters were extracted from the PTC curves for

both HFW and LFW modes. The conversion gain can be changed at the pixel level by switching from one full well mode to another. In particular, switching from LFW to HFW mode corresponds to a 3-fold gain increase. This option enables a choice between low read noise at a lower dynamic range, or higher dynamic range with a reduced noise performance (Naday *et al.*, 2010a). In other words, LFW mode is suitable for low DAK levels, where the electronic noise dominates, while HFW is best for higher exposure levels.

Table 3.3: Summary of the performance parameters of the Dexela sensor using the PTC method

Parameter (1x1 mode)	HFW mode	LFW mode	Units
Conversion Gain	101.1 ± 14.4	33.7 ± 3.0	e^-/DN
Read Noise	354.7 ± 50.4	157.4 ± 14.0	e^-
Full Well capacity	$(1.3 \pm 0.2) \times 10^6$	$(4.2 \pm 0.4) \times 10^5$	e^-
Dynamic Range	71.4 ± 4.0	68.5 ± 2.5	dB
Dark current at around 30 °C	6 ± 1	3 ± 1	pA/cm^2

The following table shows the respective optical evaluation results using the mean-variance method. This method is similar to the PTC and it can be used to crosscheck the results (Bohndiek *et al.*, 2008a). Similar results are demonstrated compared to the previous ones but with higher accuracy due to the smaller uncertainty on the conversion gain. However, the PTC is necessary to extract the NLC method. Both methods were applied over a limited range of the sensor assuming linear behaviour. The linear range used was around 22 % of the dynamic range for the HFW mode and 33 % for the LFW mode respectively.

Table 3.4: Summary of the Dexela sensor's performance parameters using the mean-variance method

Parameter (1x1 mode)	HFW mode	LFW mode	Units
Conversion Gain	104.6 ± 1.6	34.8 ± 0.4	e^-/DN
Read Noise	361.8 ± 5.6	159.8 ± 2.0	e^-
Full Well capacity	$(1.42 \pm 0.02) \times 10^6$	$(4.31 \pm 0.05) \times 10^5$	e^-
Dynamic Range	71.5 ± 0.4	68.6 ± 0.4	dB

A nonlinear analysis was also applied to the Dexela sensor to take into account its inherent nonlinearity. The following figure shows the conversion $K(e^-/DN)$, signal $S(e^-/DN)$ and noise $N(e^-/DN)$ gains extracted from the NLC method for both full well modes. All three gains are shown for signal levels up to the full well capacity. All of them are equal at lower signal levels due to the absence of the V/e^- nonlinearity. However, at higher signal levels they diverge significantly due to the presence of nonlinearity. From these figures it is estimated that the V/e^- nonlinearity starts at around $500 \times 10^3 e^-$ which corresponds to around 42 % of the dynamic range for the HFW mode. For the LFW mode the nonlinearity begins at higher signal levels in respect to the dynamic range. In other words, the nonlinearity becomes obvious from around $200 \cdot 10^3 e^-$ which corresponds to 51 % of the dynamic range. This indicates that the Dexela sensor demonstrates linear behaviour in a wider range when operated in the LFW mode.

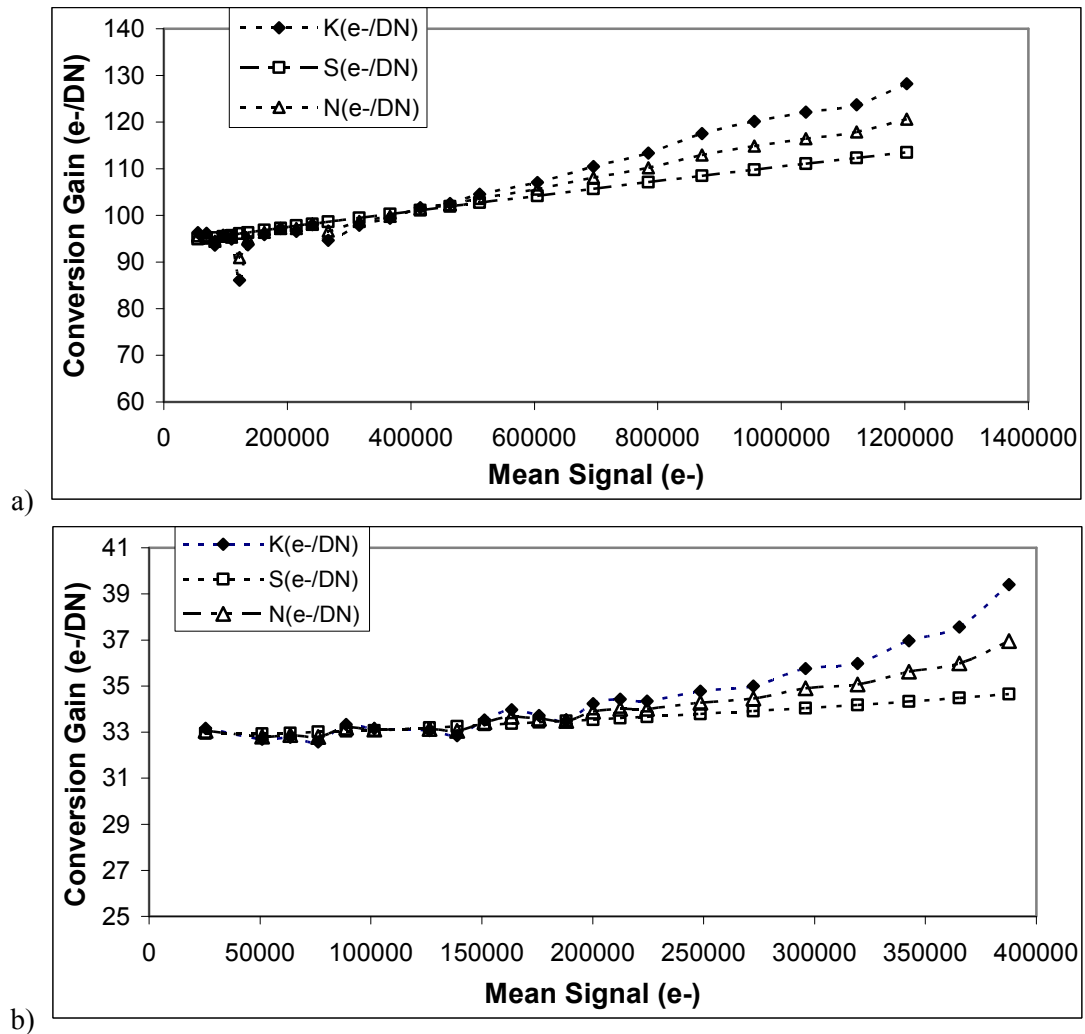


Figure 3.12: Representative gain curves from NLC method for a) HFW and b) LFW

The performance parameters extracted from the NLC method are shown in Table 3.5. The signal gain at full well level is higher than the constant conversion gain extracted from the linear (PTC and MV) methods. This leads to higher full well capacity and dynamic range. In particular, the PTC method underestimates the full well capacity by around 18.8 % and 4.5 % and the dynamic range by 1.4 dB and 0.4 dB for the HFW and LFW modes respectively. The respective underestimation of the MV method on the full well capacity is around 12.5 % and 2.3 % for the HFW and LFW modes respectively. These values lead to a subsequent underestimation of the dynamic range by 1.3 dB and 0.3 dB for the respective FW modes. A smaller difference between the linear and nonlinear methods is observed when the sensor is operated in the LFW mode. This happens due to the higher linearity demonstrated in this mode. Also, the MV method results in values closer to the NLC method ones. On the other hand, the noise gain is comparable to the constant conversion gain $K(e^-/DN)$ leading to similar read noise values, up to 1.1 % absolute difference. The underestimation of the full well capacity and the dynamic range from the linear methods is already mentioned in the literature (Janesick *et al.*, 2006, Janesick, 2007 and Bohndiek *et al.*, 2008a). On the other hand, the use of the conversion gain $K_{high}(e^-/DN)$ at full well level would lead to significant overestimation of the full well capacity and the dynamic range due to the presence of V/e^- nonlinearity.

Table 3.5: Summary of the performance parameters of the Dexela sensor using the NLC method

Parameter (1x1 mode)	HFW mode	LFW mode	Units
Signal Gain	120.6 ± 1.3	35.7 ± 0.2	e^-/DN
Noise Gain	102.0 ± 0.5	33.9 ± 0.1	e^-/DN
Read Noise	357.9 ± 1.9	158.4 ± 0.4	e^-
Full Well capacity	$(1.57 \pm 0.02) \times 10^6$	$(4.42 \pm 0.02) \times 10^5$	e^-
Dynamic Range	72.8 ± 0.2	68.9 ± 0.1	dB

A comparison between the performance parameters extracted from the NLC method and the nominal design specifications of the Dexela sensor (see Table 1.1) shows that the actual read noise is higher by 15.8 % and 25.7 % for the HFW and LFW modes respectively, compared to the expected values. Again, the nominal specifications underestimate the full well capacity by around 14.3 % and 10 % for the HFW and LFW modes respectively. The underestimation of the nominal read noise leads to

overestimation of the dynamic range by around 0.3 dB for the HFW mode and 1.2 dB for the LFW mode. In conclusion, the experimental results are in agreement with the nominal ones.

3.3 X-ray performance evaluation of the detectors

The x-ray performance evaluation of the five x-ray detectors was made at UCL using a W/Al (anode / filtration) combination. Three different beam qualities were used at 28, 52 and 74 kV to investigate the performance of the detectors in a range of different x-ray medical imaging applications. The Dexela CMOS x-ray detector was further investigated at Dexela using W/Rh combination at 25 kV. The following section (3.3.1) describes in detail the selection of the beam qualities.

3.3.1 Radiation beam qualities used in this thesis

The x-ray performance evaluation of the four digital x-ray detectors (LAS, Hamamatsu, Dexela and RadEye) was carried out using a Tungsten anode (W) x-ray tube at UCL (20° anode angle). The nominal focal spot size of this detector is from 0.4 x 0.4 mm up to 3.0 x 3.0 mm depending on the tube load, i.e. from 160 kV and 4 mA up to 160 kV and 19 mA. Three beam qualities were used to cover a range of different medical applications: 28 kV for mammography, 52 kV (RQA3) and 74 kV (RQA5) for general radiography according to the IEC standard (IEC 62220-1, 2003 and IEC 62220-1-2, 2007). The selection of the specific tube voltages was assessed using the nominal values of 28, 50 and 70 kV and adjusting the tube voltages to reach the required half value layers (HVL) within 3 % accuracy. The measurements of the HVLs were made using thin Al foils with 99% purity (Goodfellow Corp.) and a calibrated ion chamber (KEITHLEY 35050A Dosimeter). The inherent filtration of the x-ray tube was estimated to be 1.4 mm Al using the *Total Filtration Calculator* software (Reilly, 1999). Therefore, 1.1 mm Al (99.999 % pure (Goodfellow Corp.)), 10.6 mm and 20.2 mm dural were taped on the output of the x-ray tube to simulate the breast and parts of the human body respectively according to the specified beam qualities. Figure 3.13 is a diagram giving the geometry used for the detectors measurements under mammographic conditions. In this case the source to detector surface distance (SDD) was 65 ± 1 cm in all cases. This distance was set to meet the mammographic IEC standard requirements which set a range between 60 and 70 cm (IEC 62220-1-2, 2007). On the other hand, the

SDD for higher energies was 153 ± 1 cm in all cases to meet the limit of at least 150 cm according to the general radiography IEC standard (IEC 62220-1, 2003).

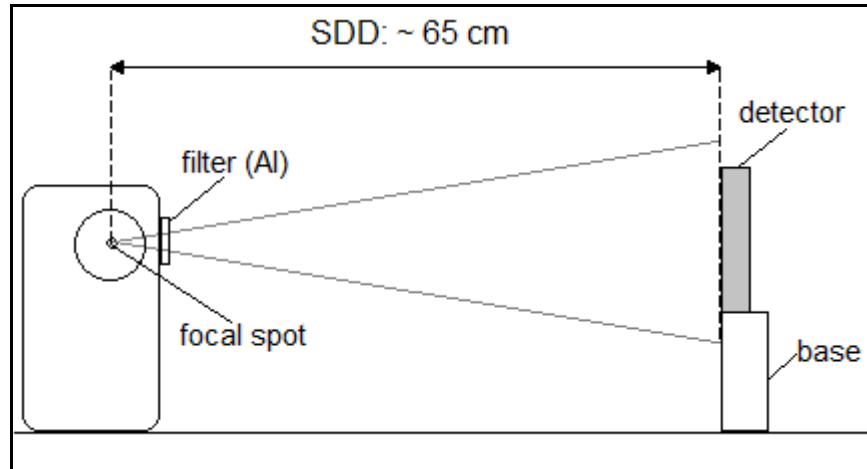


Figure 3.13: The geometry used for the DQE measurements under mammographic conditions

Figure 3.14 shows a photograph of the experimental set up using LAS detector to capture flat images for the NNPS calculation.

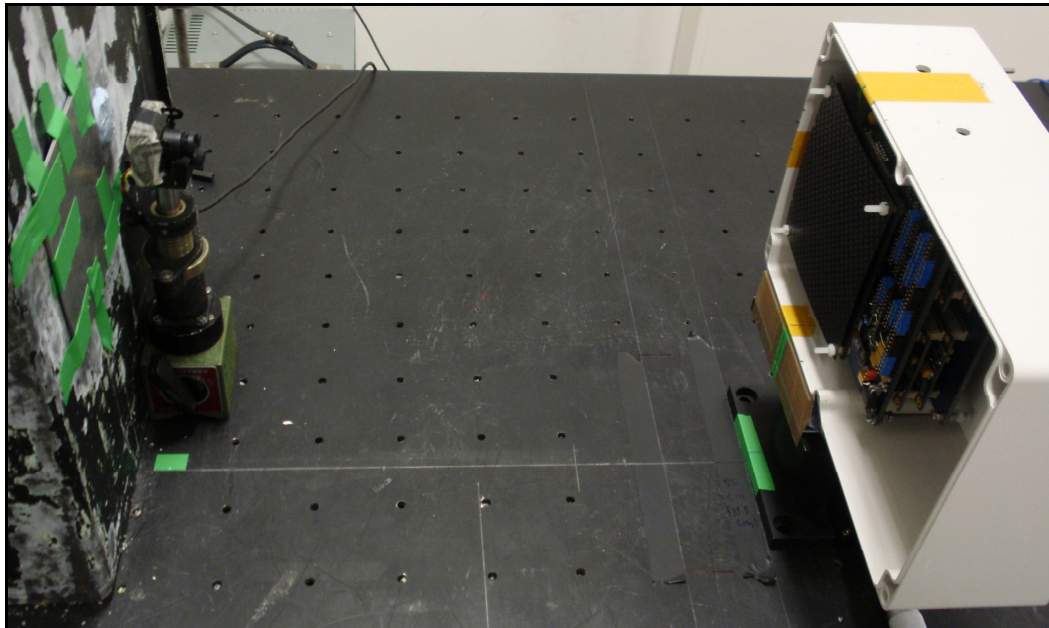


Figure 3.14: Photograph of the set up using LAS detector under mammographic conditions

According to Samei (2003a) RQA3 is suitable in neonatal and paediatric extremities imaging, while RQA5 is commonly used to image extremities, head and shoulder in adults. Inserting the kV/HVL combinations into a spectrum simulator software (*Spektr*) the fluence per exposure (Φ/K_a) ratio (or ideal SNR^2 input per K_a) was enabled (Johns

and Cunningham, 1983, Boone, 1998, Cunningham, 2000 and Samei and M. Flynn, 2002). This parameter is required for the DQE calculation. *Spektr* is a MATLAB based graphical user interface (GUI) (Siewerdsen et al., 2004) which adapts the *Tungsten Anode Spectral Model using Interpolating Polynomials (TASMIP)* algorithm of Boone and Seibert (1997). The Anrad SMAM detector was evaluated using a different W/Al combination at UCL (25° anode angle). The nominal focal spot size of this W anode tube is from 25 up to 50 μm depending on the tube voltage. Both the tube voltage and the additional filtration were adjusted to get an HVL value very close to the required one. Therefore, 27.5 kV and 1.1 mm Al (as external filtration) were used to get an HVL equal to 0.84. This beam quality corresponds to an estimated Φ/K_a value equal to 6951 x-rays per μGy per unit area. Finally, the Dexela CMOS x-ray detector was further investigated at Dexela using W/Rh combination (16° anode angle) at 25 kV. In this case 0.05 mm Rh added on the W anode and then the additional mm Al and the tube voltage were adjusted to reach an HVL very close to the IEC standard requirements (less than 1% difference). Table 3.6 shows the required, measured and estimated values of the beams used.

Table 3.6: Values related to the used beam qualities for the x-ray evaluation of the digital detectors

Parameter	Beam Qual. 1a (Mammo)	Beam Qual. 1b (Mammo)	Beam Qual. 2 (RQA3)	Beam Qual. 3 (RQA5)	Units
Anode/filtration combination	W/Rh	W/Al	W/Al	W/Al	
IEC nominal tube voltage	28	28	50	70	kV
Indicated Tube voltage	25	28	52	74	kV
IEC total filtration (inherent + added)	0.05 + 2.0 (Rh + Al)	0.5 + 2.0 (Al + Al)	2.5 + 10.0 (Al + Al)	2.5 + 21.0 (Al + Al)	mm
Total filtration (inherent + added)	0.05 + 1.7 (Rh + Al)	1.4 + 1.1 (Al + Al)	1.4 + 10.6 (Al + Dural)	1.4 + 20.2 (Al + Dural)	mm
IEC HVL	0.75	0.83	4.0	7.1	mm Al
Measured HVL	0.75	0.83	3.9	6.9	mm Al
IEC Φ/K_a	5975	6575	21759	30174	x-rays/ $\mu\text{Gy}/\text{mm}^2$
SPEKTR Φ/K_a	6138	7009	22469	30401	x-rays/ $\mu\text{Gy}/\text{mm}^2$

3.3.2 Signal detection

The type and thickness of the scintillator affect the absorption efficiency of the conversion layer. As mentioned in section 1.7, structured CsI:Tl was coupled to LAS, Hamamatsu and Dexela sensors at three different thicknesses (150, 160 and 600 μm respectively) and Gd₂O₂S:Tb 85 μm thick was coupled to RadEye sensor. On the other hand, Anrad SMAM detector used 200 μm a-Se to detect the x-rays. The absorption efficiency is quantified from the EAE and QDE parameters, i.e. the absorption efficiency of the x-ray photons and the absorption efficiency of their energy respectively. Since scintillators produce light photons as a function of the absorbed x-ray energy (energy integrating detectors), the EAE parameter is considered to describe more precisely the absorption efficiency. Both parameters are explained in section 1.7 based on the Eq. (1.4) and (1.5) respectively. Figure 3.15 shows the comparison between the monoenergetic QDE(E) of all detecting setups excluding the one of 160 μm CsI and the normalized incident amounts of x-ray photons (photon fluence) for the four beam qualities used. It can be seen that the effect of the K-absorption edges of Se (at 12.7 keV), Cs (at 36.0 keV), I (at 33.2 keV) and Gd (at 50.2 keV) elements on the absorption efficiency of the x-rays. Also, it is observed that the thickness of the scintillator has a very strong absorbing effect, especially at energies higher the K edge. The QDE(E) of CsI at 160 μm thickness was not included because it is almost identical to the one at 150 μm . The QDE(E) of Gd₂O₂S at 85 μm is slightly higher than that of CsI at 160 μm at low energies (less than 33.2 keV) and at energies higher the K edge of Gd (i.e. 50.2 keV). Therefore, it can be considered suitable either for low energies used in mammography or for energies higher than 50.2 keV. Finally, the QDE(E) of a-Se at 200 μm is high at low energies but lower than CsI and Gd₂O₂S at energies higher than the k-edges of their heavy elements. The required values for the total attenuation and the total energy absorption coefficients of the a-Se, CsI and Gd₂O₂S materials were calculated from tabulated data on energy absorption and attenuation coefficients of their respective elements (Hubbel and Seltzer, 1995).

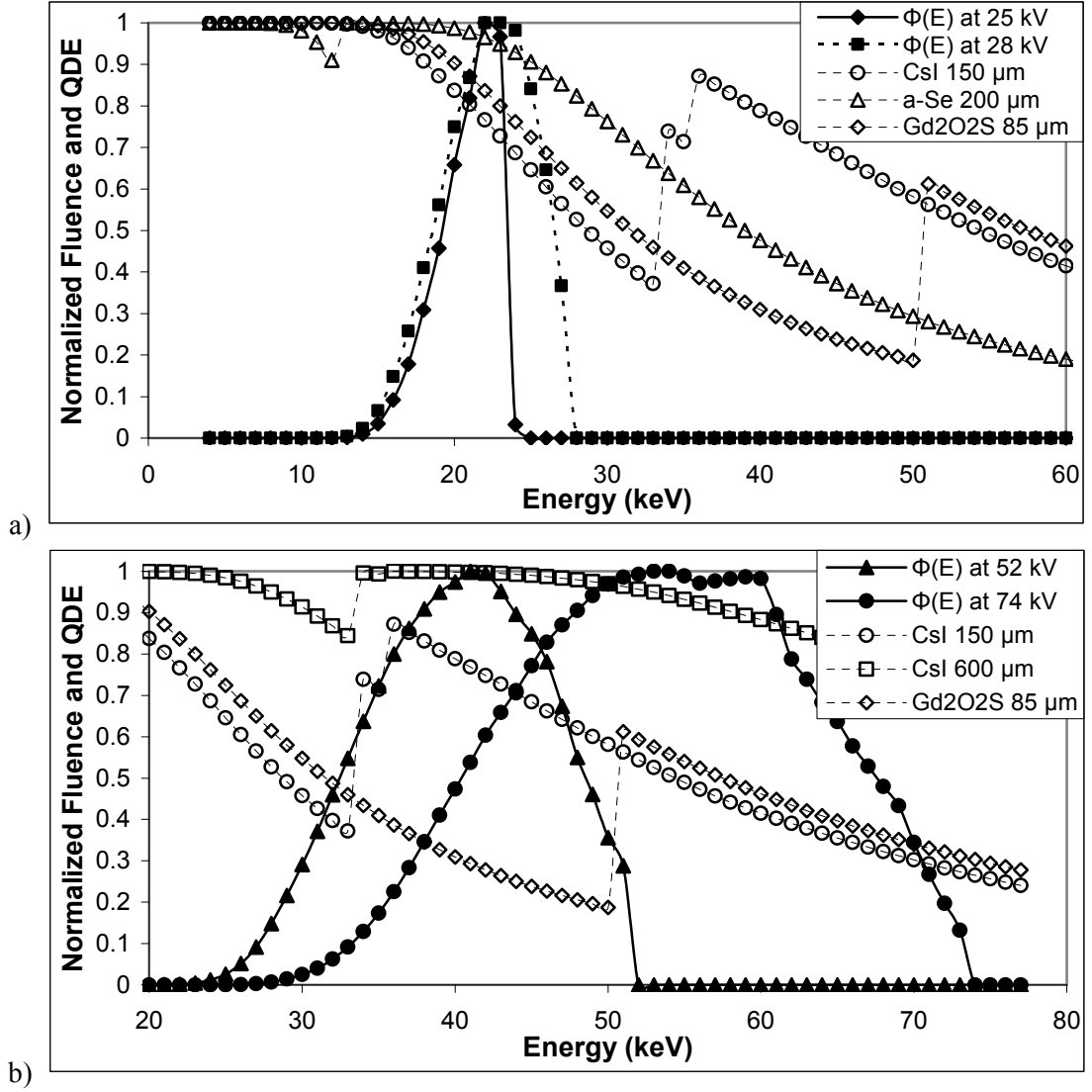


Figure 3.15: QDE(E) of the used detecting materials compared to the normalized photon fluencies (a) for 25 and 28 kV data and b) for 52 and 74 kV data)

Figure 3.16 compares the monoenergetic EAE(E) of the four scintillating setups to the normalized incident quantity of x-ray energies (energy fluence) for the four beam qualities used. However, the EAE shows a strange pattern, i.e. decrease at the K edge, slight increase at the subsequent energies and then decrease with the increase of energy) after the K edge. This pattern occurs because the EAE(E) by definition includes the ratio $\mu_{tot,en}(E)/\mu_{tot,t}(E)$ (Eq. (1.5)), which drops at the K-absorption edges, as mentioned in section 1.7.

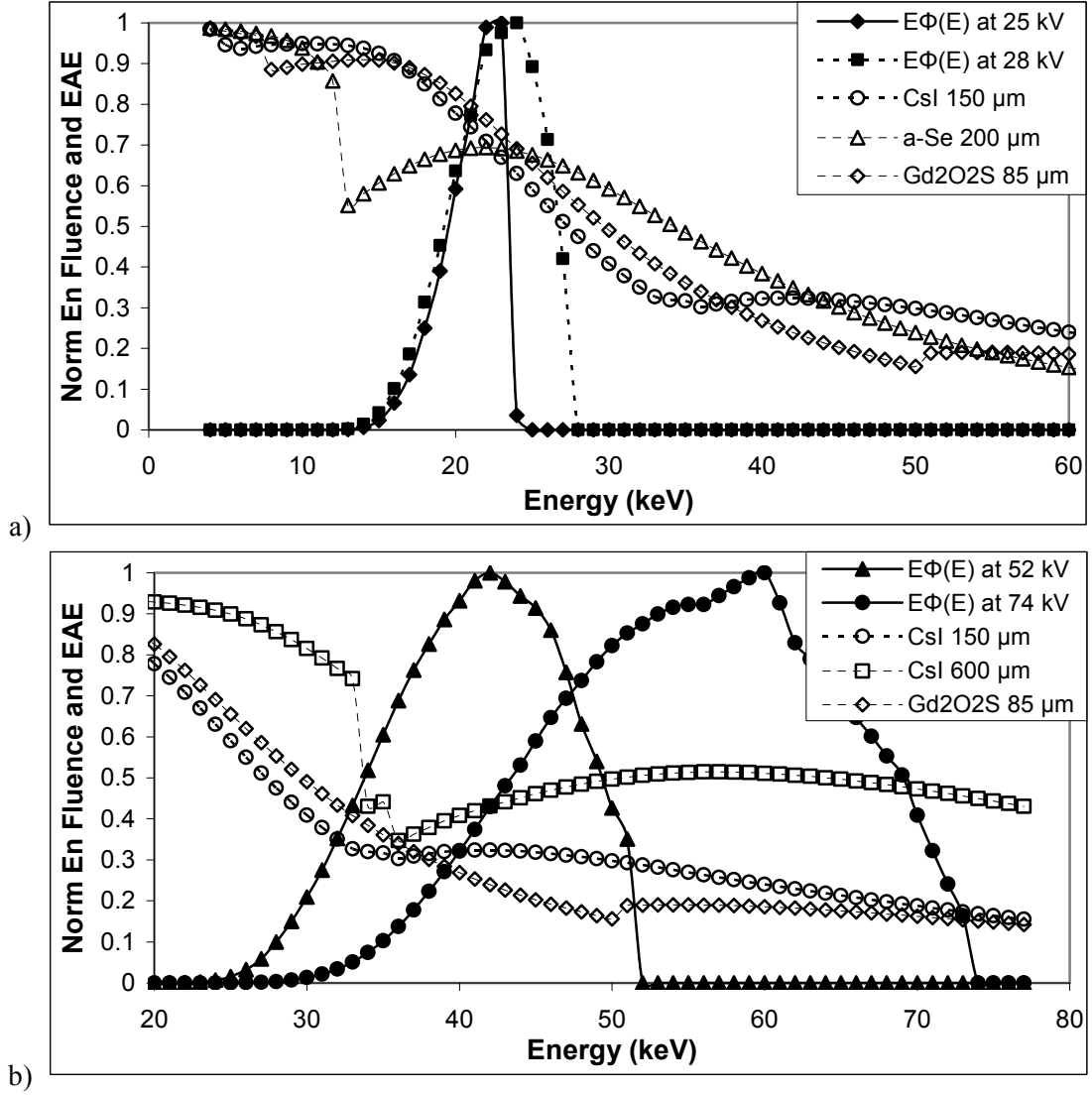


Figure 3.16: EAE(E) of the used detecting materials compared to the normalized energy fluencies (a) for 25 and 28 kV data and b) for 52 and 74 kV data)

Finally, Table 3.7 quantifies the above two figures by presenting the total QDE and EAE for the detecting material/thickness combination and beam quality combinations used. These parameters affect the DQE since the x-ray photons are information carriers and their increased absorption efficiency increases the SNR (Cunningham, 2000). It may be observed that thin CsI and Gd₂O₂S scintillators (150, 160 and 85 μm respectively) appear high EAE (> 0.68) at low energies (28 kV). On the other hand, the thick CsI scintillator (600 μm) appears to have acceptable EAE (> 0.47) at high energies. It is observed that the EAE at 74 kV is slightly higher than at 52 kV (0.49 in comparison to 0.47). This happens because the effective energy for the RQA3 beam quality was 43.2 keV, while the one for RQA5 was 52.2 keV. The EAE(E) of the scintillator is affected strongly at 43.2 keV by the K-edge, which explains the smaller detectability of

the x-ray signal at RQA3. This comparison predicts slightly higher DQE values for the 74 kV and 600 μm combination. Finally, the a-Se material appears to have high x-ray detection efficiency at low energy (28 kV) and relatively low efficiency at higher energies. This happens because Se is not a heavy element and its K-edge is at low energies.

Table 3.7: Total QDE and EAE values for various x-ray detecting materials at different beam qualities

X-ray detecting material, thickness	QDE at 25 kV	EAE at 25 kV	QDE at 28 kV	EAE at 28 kV	QDE at 52 kV	EAE at 52 kV	QDE at 74 kV	EAE at 74 kV
CsI, 150 μm	0.808	0.743	0.754	0.683	0.695	0.323	0.528	0.264
CsI, 160 μm	-	-	0.774	0.703	0.717	0.334	0.549	0.275
CsI, 600 μm	-	-	0.992	0.914	0.978	0.472	0.922	0.490
Gd ₂ O ₂ S, 85 μm	-	-	0.822	0.737	0.335	0.272	0.396	0.193
a-Se, 200 μm	-	-	0.949	0.679	0.491	0.378	0.277	0.208

3.3.3 Suggested gain and offset correction algorithm

As in the aforementioned theory in section 2.2.1 the main noise sources that affect the signal on the x-ray detectors are the quantum (or shot), the electronic (or read) and the structure (or fixed pattern) noise. The first two are uncorrelated noises because they consist of the stochastic variations of the signal in the spatial domain, which differ for individual images taken with the same detector. On the other hand, FPN is correlated noise because its pattern remains the same in repeated images taken with the same detector (Illers *et al.*, 2004). Therefore, the FPN is not a stochastic noise process and it needs to be removed to improve the SNR of the digital x-ray detector. This process, known as “flat field correction”, is applied either by normalizing with the flat-field image or by subtraction of the flat-field image (Evans *et al.*, 2002). As mentioned in section 2.3.3, in the electro-optical performance evaluation (based on the PTC algorithm) of a digital sensor the FPN is removed by subtracting two consecutive frames at the same illumination level (Janesick *et al.*, 1987, Janesick, 2002, EMVA Standard 1288, 2005 and Bohndiek *et al.*, 2008). On the other hand, in the x-ray performance evaluation of the detector the FPN is usually removed by normalizing with the flat-field image. The most common flat field correction method for a given linear detector is the gain and offset correction formula based on normalization (Moy and Bosset, 1999):

$$\overline{Flat}_{cor}(x, y) = \frac{Flat_{raw}(x, y) - \overline{Dark}(x, y)}{\overline{Flat}_{raw}(x, y) - \overline{Dark}(x, y)} \cdot K \quad (3.4)$$

where $Flat_{raw}(x, y)$ is the raw flat image, $\overline{Flat}_{raw}(x, y)$ is the average over n_f reference flat frames at the same irradiation conditions (i.e. beam quality (kV/filtration combination) and DAK) and integration time compared to $Flat_{raw}(x, y)$ and $\overline{Dark}(x, y)$ is the average over n_d reference dark frames at the same integration time. To eliminate offset variations due to the temperature effect all the images need to be captured after warming up sufficiently the detector. In the current thesis all the detectors were warmed up for at least half an hour before the measurements. Finally, K is a scaling factor equal to $\frac{\overline{Flat}_{raw}(x, y) - \overline{Dark}(x, y)}{\overline{Flat}_{raw}(x, y) - \overline{Dark}(x, y)}$ (Vedantham *et al.*, 1999, Samei, 2003d, Hunt *et al.*, 2004, Medic and Soltani, 2005, Greer, 2005, Arvanitis, 2007b and Tortajada *et al.*, 2008) or to $\overline{Flat}_{raw}(x, y)$ (Moy and Bosset, 1999, Kwan *et al.*, 2006, Schmidgunst *et al.*, 2007 and Tortajada *et al.*, 2008) or to $\max(\overline{Flat}_{raw}(x, y) - \overline{Dark}(x, y))$ (Elbakri *et al.*, 2007 and Elbakri *et al.*, 2009). Usually, the scaling factor K equals to the average value of the offset corrected average reference flat image (first case).

However, it is known that the number of frames n_f used in the average reference flat image affects the SNR in the corrected image, due to the noise propagation. Consequently it affects the DQE, which expresses the ability of the detector to transfer the SNR from its input to the output (Cunningham, 2000). Moy and Bosset (1999) mentioned that it is desirable to average a high number of reference flat images to improve accuracy. They also mention that, if averaging is performed over n_f identical frames, the noise power is divided by n_f . The decrease in NPS when reference flat images are averaged follows the classic statistics: if n_f is 1 the noise on the corrected image will be 2x that of the uncorrected image, if n_f is 2 the respective increase of the noise will be 1.5x and in the case that n_f is 8 this increase will be 1.125x. The effect of the dark image noise can be neglected when compared to the NPS of a flat image, because the latter is generally larger due to the photon noise. However, their study just quantifies the effect of n_f frames on the NPS based on the statistics principle, which intrinsically implies that a relatively large number of reference frames is required to reduce it. More specifically, they suggest using 8-16 reference flat frames and 4-10 dark

frames. Other x-ray performance characterization studies combined 15 (Vedantham *et al.*, 2000), 24 (Cunningham *et al.*, 2007) or 48 flat frames (Hunt *et al.*, 2004) to obtain the average reference flat image. In this thesis the effect of n_f on the NPS and DQE values has been studied in detail, and an alternative method allowing the use of a minimum number of frames and simultaneously eliminating the effect of the propagated noise is suggested.

Figure 3.17 shows the effect of the number of frames n_f used for the average reference flat image on the DQE of the Hamamatsu C9732DK detector at 120.5 μGy and 28 kV with the W/AI combination recommended by the mammographic IEC standard (IEC 62220-1-2, 2007). It can be noted that the DQE is low when a single reference image is used and it increases as a function of the number of frames n_f . On first inspection, this figure does not give precise information about the number of frames required to completely eliminate the effect of the propagated noise on the DQE values.

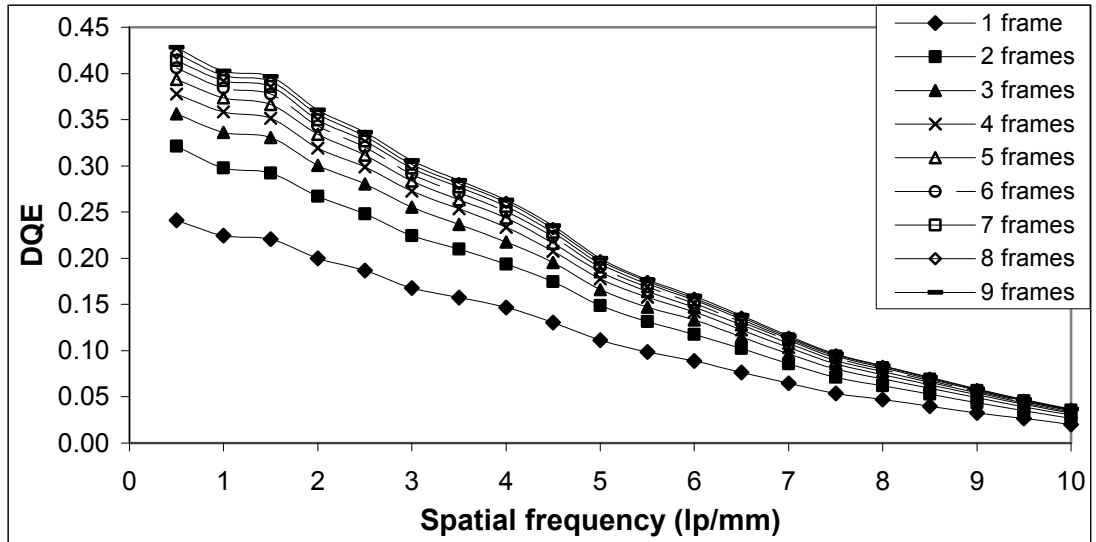


Figure 3.17: The effect of n_f frames on the DQE of the Hamamatsu detector at 28 kV and 120.5 μGy

However, useful information can be extracted from the combination of Eq. (2.29) and (2.30), i.e. the DQE is inversely proportional to the NPS which expresses the distribution of the variance over the spatial frequencies. Therefore, the $1/\text{DQE}$ parameter is proportional to the NPS. This parameter is calculated for three different spatial frequencies (2, 4 and 6 lp/mm) and normalized to 1. The normalization is achieved by dividing the $1/\text{DQE}$ values by the respective ones calculated using a single

reference flat image. Figure 3.18 shows that this normalized parameter follows a specific pattern as all three spatial frequencies. Also, this figure demonstrates that the normalized propagated noise in terms of variance follows exactly the same pattern. This parameter is simply calculated from the sum $1+1/n_f$ normalized to 1.

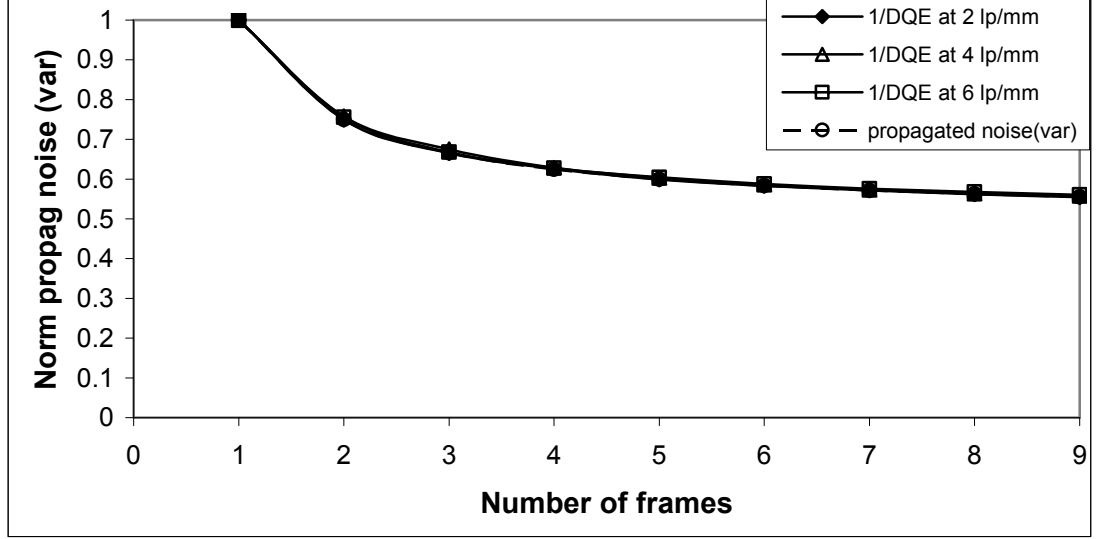


Figure 3.18: Normalized propagated noise (in terms of variance) and 1/DQE ratio at specific frequencies as a function of the number of frames n_f used for the average reference flat image

Our starting point is the simple error propagation formula for two independent (or uncorrelated) values A and B multiplied or divided. In this case the fractional uncertainty is propagated as follows (Taylor, 1997):

$$\left(\frac{\delta_C}{C}\right)^2 = \left(\frac{\delta_A}{A}\right)^2 + \left(\frac{\delta_B}{B}\right)^2 \quad (3.5).$$

where δ expresses the uncertainty of the values. In our case the signal is expressed from the average DN value and the noise from the r.m.s. standard deviation (in DN). Assuming that A corresponds to the raw flat image on the nominator of Eq. (3.4) and B corresponds to the reference flat image the above equation becomes:

$$\sigma_c^2 = \sigma_A^2 + \sigma_B^2 \quad (3.6).$$

The denominator of Eq. (3.5) is excluded because it is assumed that $A \cong B \cong C$. The standard error propagation analysis is followed because A and B are uncorrelated values due to the fact that the reference average flat image does not include the frame A itself. It may be observed that Eq. (3.6) is equivalent to the one which describes the

propagation of noise for two uncorrelated values which are added or subtracted. If n_f equals 1, the noise in the reference image is almost equal to the noise of the raw flat image, so the previous equation becomes:

$$\sigma_c^2 = 2\sigma_A^2 \quad (3.7).$$

In this case, the noise in the corrected flat image is twice as much that of the raw flat image, as mentioned by Moy and Bosset (1999). If n_f is higher than 1, the noise of the reference image is divided by this value. Following the same principle, for n_f frames we can write:

$$\sigma_B^2 \cong \frac{\sigma_A^2}{n_f} \quad (3.8).$$

Therefore, Eq. (3.6) can be written as:

$$\sigma_c^2 = \sigma_A^2 + \frac{\sigma_A^2}{n_f} = \sigma_A^2 \left(1 + \frac{1}{n_f}\right) \quad (3.9)$$

which expresses the total noise in the corrected image (in terms of variance) for n_f frames. If n_f is very high, the propagated noise is negligible and $\sigma_c^2 = \sigma_A^2$. Practically, this happens when the curves in Figure 3.18 reach the value 0.5, which corresponds to double DQE values compared to those calculated using a single reference flat image. Table 3.8 shows the effect of the number of frames n_f on the r.m.s. standard deviation and the variance. Both parameters are shown because the former is directly related to the noise of the output digital image, and the latter affects the DQE.

Table 3.8: The effect of n_f frames used in the reference image on the noise of the corrected image

Number of frames n_f	% prop. noise (Std)	% prop. noise (Var)
10	4.9	9.9
15	3.3	6.6
20	2.4	4.9
25	2.0	3.9
30	1.6	3.3
50	1.0	1.9
100	0.5	0.9

It can be seen that 10 reference frames affect the DQE by around 10 %, 15 reference frames by 6.6 % and 25 reference frames by around 4 %. The effect of the noise on the DQE of the corrected image is less than 1 % when 100 or more frames are used. To get a practically noise free image, e.g. <0.1 % noise in terms of variance, around 1000 frames are required. However, Eq. (3.9) can be used to compensate for the number of frames n_f used. This compensation can be applied using the following formula (Konstantinidis *et al.*, 2011b):

$$\text{Flat}_{\text{cor,free}}(x, y) = \frac{\text{Flat}_{\text{cor}}(x, y)}{\sqrt{1 + \frac{1}{n_f}}} + \left(\overline{\text{Flat}_{\text{cor}}(x, y)} - \left(\frac{\overline{\text{Flat}_{\text{cor}}(x, y)}}{\sqrt{1 + \frac{1}{n_f}}} \right) \right) \quad (3.10)$$

where $\text{Flat}_{\text{cor}}(x, y)$ is the gain and offset corrected flat image defined in Eq. (3.4), and the second term of the equation is a constant value used to rescale the suppressed average value of the image (in DN). The rescaling is required because the DQE depends on the average value of the digital image (which is the aforementioned “large area signal” parameter in the NNPS calculation). Eq. (3.9) is suggested to compensate for any number of frames n_f used for the average reference flat image.

Figure 3.19 demonstrates the validity of Eq. (3.10) in four cases where different number of frames n_f are used for the average reference flat image (1, 4, 6 and 9 frames respectively). They all result in identical DQE values, which are twice as high those obtained by using a single reference flat image (Figure 3.17). To quantify the above, the ratio between the DQE calculated using $n_f=1$ and the ones using compensation for the propagated uncorrelated noise was found to be 0.501 ± 0.007 over all four cases.

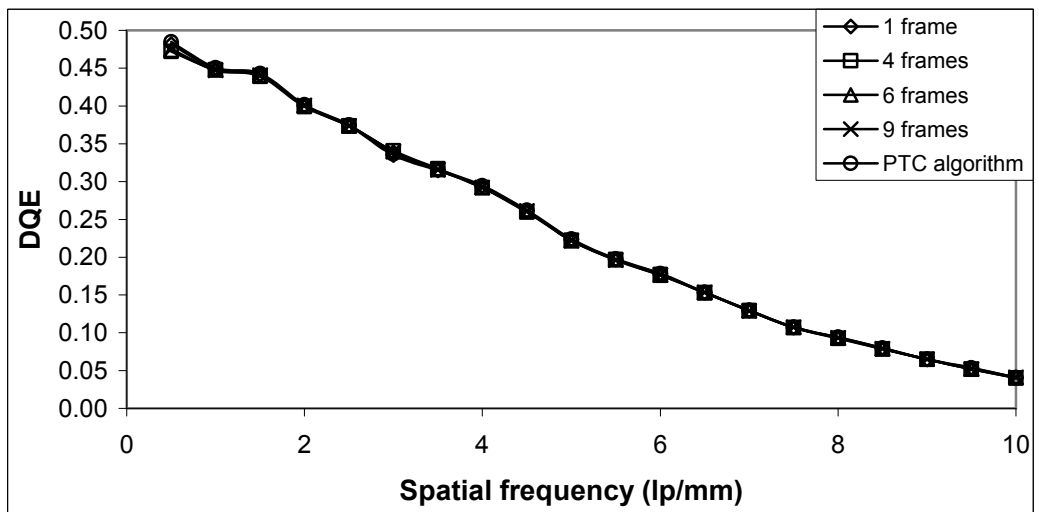


Figure 3.19: DQE of the Hamamatsu detector with reduced propagated noise

To further validate the suggested algorithm, the results of this method were compared to those obtained using the subtraction-based FPN reduction algorithm. The latter method is mainly used in the electro-optical evaluation, and can be found in a small number of x-ray performance characterization studies (Evans *et al.*, 2002, Yorker *et al.*, 2002, Suryanarayanan *et al.*, 2003, Burgess, 2004, Illers *et al.*, 2004, Li and Dobbins III, 2007 and Yun *et al.*, 2009). For clarity reasons, the latter method is referred to as “PTC algorithm” (see section 2.3.3). To implement the PTC algorithm in this study, two consecutive raw flat frames are subtracted to exclude the FPN. The difference flat image is divided by the square root of 2 to compensate for the propagated uncorrelated noise in terms of standard deviation (Eq. (3.7)). To rescale the difference image, the average DN over the 2 raw flat frames is calculated, and then the average DN of the average dark image is subtracted from this value (offset correction). This constant value is added to the modified (propagated noise corrected) difference image to get the signal (mean DN) and the noise (variance DN^2) required for the NPS and DQE calculation. Another study (Suryanarayanan *et al.* (2003)) subtracted a raw flat frame from an average over 16 frames reference flat image at the same acquisition conditions. They did this in order to eliminate the FPN and simultaneously reduce the introduced propagated noise. Figure 3.19 shows that both methods result in identical DQE results. Both of them require a minimum number of flat frames. The suggested algorithm requires at least 2 frames, 1 raw flat frame and 1 reference frame. The same happens using the PTC algorithm.

The validity of the suggested method was tested on the Dexela detector as well (Figure 3.20). In this specific case, the DQE was examined at 74 kV and 3.1 μGy . Again, 3 different numbers of frames n_f (1, 6 and 9 frames) were used for the reference flat image and compensated for the respective additive uncorrelated noise. The ratio between the DQE calculated using $n_f=1$ and the ones using compensation for the additive uncorrelated noise is 0.500 ± 0.005 in all 3 cases.

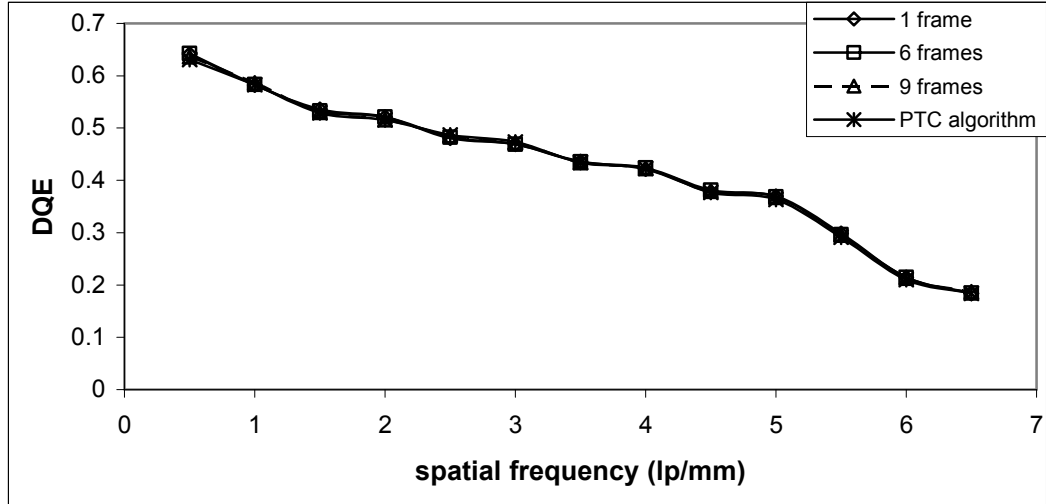


Figure 3.20: DQE of the Dexela detector using algorithms to reduce the prop. noise

The suggested gain and offset correction algorithm compensates for any number of n_f flat frames used. It requires a minimum number of reference frames, down to a single frame. In practical terms, this means smaller memory (capacity) size and reduced time to capture the reference frames. Also, the effect of reference frames on the NPS and DQE is precisely quantified in the case that the gold standard gain and offset correction algorithm (Eq. (3.4)) is employed. The validity of the suggested algorithm was further tested by comparison with the gain correction method mainly used in the electro-optical evaluation (PTC) of digital sensors. Both methods resulted in identical results. Hence, the suggested correction method can be employed in the x-ray performance evaluation of digital detectors, independently of the number of flat frames n_f .

3.3.4 Detection and removal of defective pixels (outliers)

Almost all digital detectors contain a certain proportion of pixels that are defective and are usually referred to as “bad” pixels. These pixels do not behave as expected due to defects in design of the semiconductor chip or manufacturing errors. Furthermore, they may appear when the operating conditions are harsh and the detectors are operated for long integration time. According to Ghosh *et al.* (2008) there are five common types of defective pixels: a) dead pixels, b) stuck pixels, c) hot pixels, d) abnormally sensitive pixels and e) column defects. Dead pixels are completely insensitive to the input signal and their value is always zero, i.e. they appear as black spots in the images. They exist due to defects in the hardware, i.e. the pixel’s photodiode may not integrate charge or the readout amplifier may have malfunctioned. Stuck pixels demonstrate constantly the

maximum value of the ADC and they appear as white spots in the image. They are caused by fabrication errors that result in odd pixels getting saturated or due to failure of the output transistor. Hot pixels are pixels with unusually large dark current due to higher leakage of charge. They appear at fixed spatial locations in a detector. The dark current increases as a function of the temperature. Therefore, shorter integration time and detector cooling can be used to eliminate the number of hot pixels. Abnormally sensitive pixels are the pixels that exhibit abnormally greater (hypersensitive) or lower (hyposensitive) sensitivity compared to the average intensity. They can also manifest due to the nonuniformity in the readout and digitization electronics of individual pixels. Finally, specific single or multiple columns of the detector can be bad due to fabrication faults during the manufacturing stage. Stitched detectors may contain one to three columns with limited (or zero) sensitivity in every stitched peripheral block because they contain a high number of readout electronics inside each pixel.

A number of defective pixels is removed through the gain and offset correction. However, some of them remain unaffected because they do not behave as expected. Therefore, their presence in the corrected flat images may decrease the calculated DQE due to the increase of the standard deviation (which expresses the noise). To eliminate their effect on the DQE calculation a custom built software was developed in MATLAB version 7.10 (The MathWorks, Natick, MA, USA). The developed algorithm detected the defective pixels based on a simple statistical analysis and then removed them using adaptive median filtering. Two ways to locate the defective pixels (outliers) were examined in this thesis. The first one used the interquartile range methodology to locate the outliers (NIST/SEMATECH, 2011). Briefly, the lower and upper quartiles (defined as the 25th and 75th percentiles) of the image histogram are defined as Q1 and Q2 respectively. Therefore, the difference (Q2 - Q1) is called the interquartile range (IQ). If the pixel value is lower than $Q1 - K \cdot IQ$ or higher than $Q2 + K \cdot IQ$ is considered an outlier. The parameter K is a constant number used to define the lower and upper limit (fence). In this thesis it was found that K equal to 5 sufficiently detected the outliers. The second detection method defined as outliers the pixels that their values were at least 4.5 times higher or lower compared to the standard deviation of the image. It resulted in similar output results compared to the first method. Both of them are based on arbitrary limits which sufficiently detect the defective pixels. For simplicity, the second detection method was applied on the gain and offset corrected flat images used for the NNPS

calculation. In order to remove the detected outliers a modified version of the adaptive median filter was used. The adaptive median filter is commonly used in image processing to selectively detect and remove the salt and pepper noise (i.e. extremely low or high pixel values) in the image (Gonzalez and Woods, 2008). Briefly, a median filter mask of small dimensions (i.e. 3x3 in the current thesis) scans the image by comparing the median pixel value with the minimum and maximum value of the mask. If the median pixel value is within the limits of the mask then the algorithm compares the central pixel of the mask with the current limits. If the central pixel is an outlier then the algorithm outputs the median pixel value of the mask. Otherwise, it retains the original value. If the median pixel value is an outlier the size of the filter mask increases until either the median value is not an outlier or a maximum window size (i.e. 15x15 in the current thesis) is reached. The advantages of the adaptive median filter compared to the “traditional” one (i.e. 3x3 median filter) are that it seeks to preserve detail while smoothing nonimpulse noise and reduces distortion, such as excessive thinning or thickening of object boundaries. A disadvantage of the specific filter is that it may not locate and remove sufficiently all the outliers in a uniform (flat) image. For instance, a hot pixel may exist in a uniform area. Therefore, the median value of this area is equal to the minimum one. In this case the algorithm increases the size of the filter as mentioned before. If it reaches the maximum allowed size and the median value is still equal to the minimum one the central value (which can be an outlier) of the mask remains the same. This is an extreme case but it may happen if the maximum allowed size of the mask is not selected properly. For the same reason, the adaptive median filter does not detect column defects with exactly the same number in all pixels.

To enhance the detection of the outliers in the flat images it was decided to use the statistical analysis method based on the standard deviation of the image to create a pixel correction map (i.e. zeros in the location of the outliers and ones elsewhere). Then, this map was multiplied to the original image and the adaptive median filtering was applied to substitute only the outliers. Another advantage of the pixel correction map is that it easily allows the calculation of the total number of defective pixels in the array and their proportion (%) compared to the whole array. It was found that the defective pixels were 0.1 % of the Anrad detector’s array, less than 0.1 % in Dexela, LAS and RadEye detectors and almost 0 % in the Hamamatsu detector.

Figure 3.21 shows an example of the automatic detection and removal of column defects present on the Dexela detector. It can be observed that the values of the defective pixels are more than ten times smaller compared to the others. However, for representation purpose the original image has got the same imaging scale as the corrected one. The corrected pixel values are within the limits of the normal pixels.

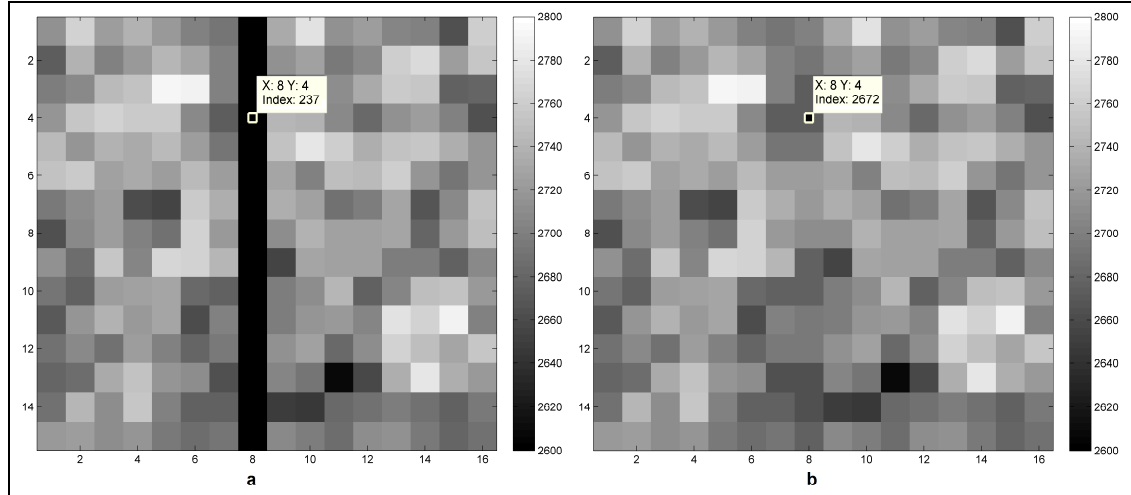


Figure 3.21: a) original image with column defects and b) the corrected one using an algorithm to automatically detect and correct the outliers.

In conclusion, the adaptive median filter is able to detect and remove individual (salt and pepper noise) or small clusters of defective pixels in an image. It does not work properly in flat images and column defects with the same pixel value. Also, it is time consuming because it scans the whole image pixel by pixel and once it finds a spike it increases the size of the mask and repeats the process. On the other hand, the suggested modification of the adaptive median filter is faster and can be used only in flat images or low contrast phantom images with homogeneous background because it detects the outliers based on the histogram of the whole image. It was able to sufficiently detect and remove the individual spikes and column defects in the flat images.

3.3.5 Validation of the x-ray performance evaluation algorithm

There are several commercial and scientific software packages available to calculate the MTF, NPS and DQE of digital x-ray detectors. A commercial available software package is *JDQE* (Elbakri, 2010) which is an ImageJ (Rasband, 1997-2011) plugin based on Elbakri's work on x-ray characterization of digital detectors (Elbakri *et al.*, 2006, Elbakri *et al.*, 2007 and Elbakri *et al.*, 2009). Two available software packages

distributed to researchers and members of the scientific community are *MIQuaELa* (Ayala *et al.*, 2009) which is a MATLAB-based GUI and *OBJ_JQ_reduced* (Marshall, 2009c) which is an IDL-based GUI based on Marshall's work (Marshall, 2006a, Marshall, 2006b, Marshall, 2007, Marshall, 2009a and Marshall, 2009b). The last two software packages were available throughout this study. However, it was decided to develop a customised piece of software written in MATLAB version 7.10 (The MathWorks, Natick, MA, USA) in order to have the flexibility in adjusting every step in the process of the x-ray performance evaluation according to the IEC standard (IEC 62220-1, 2003 and IEC 62220-1-2, 2007). *OBJ_JQ_reduced* is the most common x-ray performance evaluation software in the UK, supported by the Institute of Physics and Engineering in Medicine (IPEM, 2010). Therefore, a comparison between the custom built MATLAB software and the *OBJ_JQ_reduced* results was made in order to validate the developed software.

The comparison was made on the Dexela's x-ray detector at 74 kV and 3.1 μGy . The same set of gain and offset corrected edge and flat images was analysed from the two sets of code in order to compare the results. The standard parameters were selected in *OBJ_JQ_reduced* software without extra filtering on the LSF, according to the IEC standard. Figure 3.22 shows the average pMTF values calculated using the custom built MATLAB software in comparison to the respective values calculated using the *OBJ_JQ_reduced* software. Both curves are almost identical with average absolute difference equal to 1.7 %.

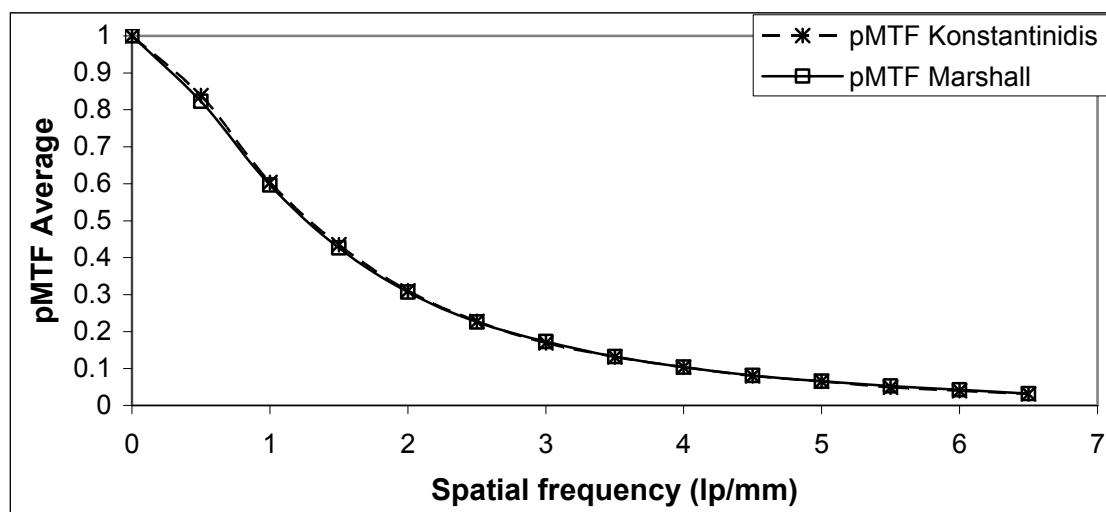


Figure 3.22: Average pMTF values calculated in this study in comparison to the respective values calculated using the *OBJ_JQ_reduced* software

Figure 3.23 compares the average NNPS values extracted from the two software packages. Again, both curves are almost identical (4.4 % average difference).

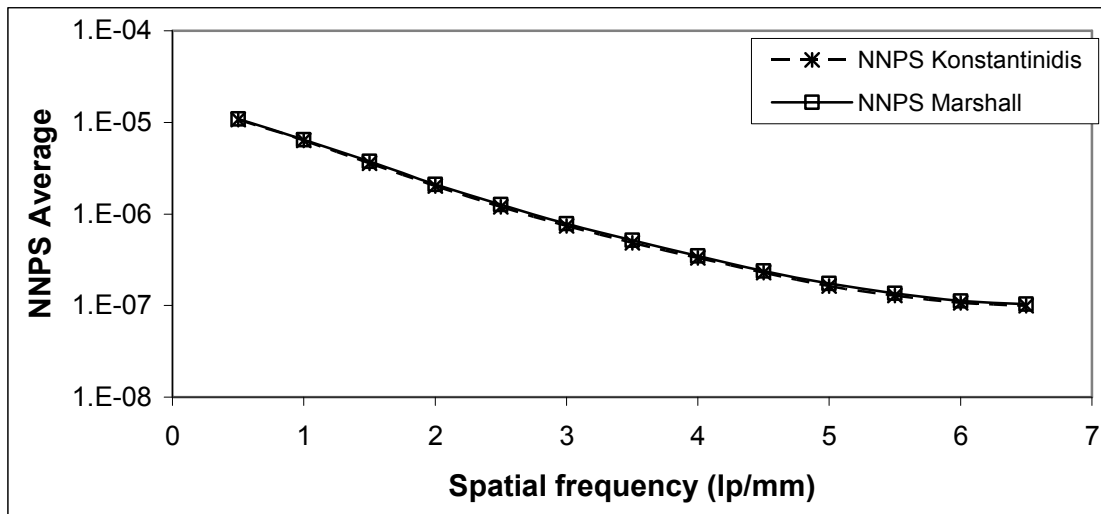


Figure 3.23: Average NNPS values calculated in this study in comparison to the respective values calculated using the *OBJ_JQ_reduced* software

Figure 3.24 shows the average DQE values calculated using the custom built MATLAB software in comparison to the respective values calculated using the *OBJ_JQ_reduced* software. Both DQE curves are similar with a slight difference. The absolute difference between the two curves is 4.6 %, probably due to different treatment of the statistical variations. However, according to the IEC standard an uncertainty of the MTF in the range of 1-5 % and a resultant uncertainty of the DQE in the range of 2-10 % is acceptable (IEC 62220-1, 2003, Samei *et al.*, 2005 and IEC 62220-1-2, 2007).

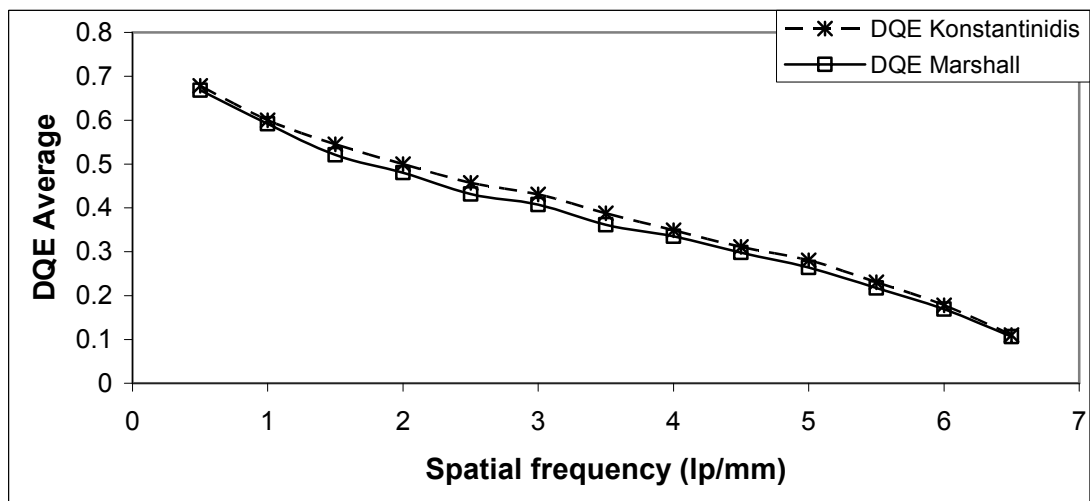


Figure 3.24: Average DQE values calculated in this study in comparison to the respective values calculated using the *OBJ_JQ_reduced* software

3.3.6 Evaluation using Beam Quality 1a (W/Rh at 25 kV; Mammography)

Figure 3.25 illustrates the signal transfer of the Dexela detector in both HFW and LFW modes at 25 kV using W/Rh combination. The signal transfer of the detector is linear with coefficients of determination (R^2) greater than 0.9996 in both cases. It can be seen that the sensitivity of the detector is very high in the LFW mode due to the higher conversion gain G (DN/e⁻; see section 3.2.5).

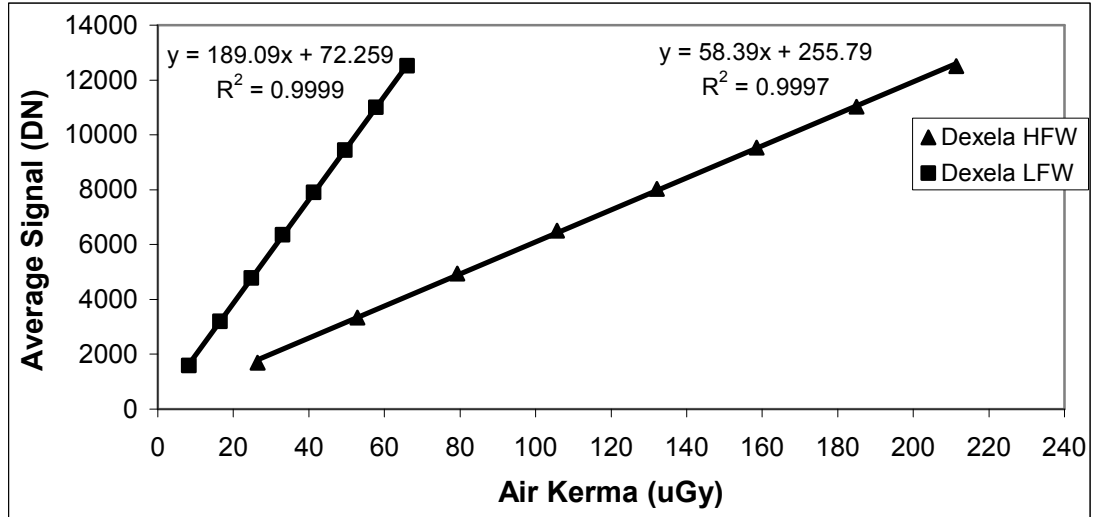


Figure 3.25: STP curves with fitting function equations displayed at 25 kV using 150 μm CsI:Tl

The mammographic DAK range used for the x-ray characterisation of the detector was from 26.4 to 211.3 μGy in the HFW mode. Average ranges normally found in the literature are of 100-120 μGy (Moy, 2000a, Rowlands and Yorkston, 2000b, Jee *et al.*, 2003 and Ghetti *et al.*, 2008). The IEC standard for mammography (IEC 62220-1-2, 2007) recommends that for a complete characterization of an x-ray digital detector the exposure range should be at least between half and double the “reference” level. The wide range used in this case was chosen to meet this condition. The respective exposure level for the LFW mode was from 8.3 to 66.0 μGy . The minimum DAK level was reached to study the performance of some detectors under breast tomosynthesis conditions, where around 15 views are combined and the average detector DAK per view is of the order of 7 μGy .

Figure 3.26 shows the horizontal, vertical and average pMTF of the Dexela CMOS x-ray detector at 25 kV. The thin CsI:Tl scintillator was used because it demonstrates high x-ray detection efficiency at low energy (QDE=0.808 and EAE=0.743; Table 3.7). The sinc function is also presented for comparison. A slight anisotropic behaviour is

observed on the pMTF curves. In particular, the vertical pMTF is around 14 % higher at F_{Nyq} . It should be noted that the vertical dimension corresponds to the column readout bus. The “chest wall” direction corresponds to the left side of the detector. There is a possibility that this happens due to different focal spot dimensions in different directions. Also, there is a suspicion that the thin polyurethane foam layer used at the time for compression between the scintillator and the graphite cover was slightly folded at one end. In this case a different pressure was applied on the scintillator at different areas leading to different spatial resolution between horizontal and vertical orientations. However, the Dexela detector showed higher isotropic behaviour when investigated at UCL (see Figure 3.31a). Therefore, the observed anisotropy is possibly due to external conditions. The average pMTF has a moderate residual value (around 0.15) at F_{Nyq} . Thus, an amount of high frequency signal beyond the Nyquist frequency may be aliased by the detector. The measured pMTF set of data was used for the calculation of the DQE in both HFW and LFW modes because the full well capacity switch does not modify the resolution of the detector. The spatial frequencies at 50 % and 10 % pMTF levels are sometimes mentioned in the literature to compare different x-ray imaging systems and define the resolution limit of the detector respectively. The Dexela detector at 25 kV appears horizontal and vertical pMTF values equal to 0.5 at 2.6 and 2.7 lp/mm. The horizontal, vertical and average pMTFs are 0.1 at 7.5, 7.9 and 7.7 lp/mm respectively.

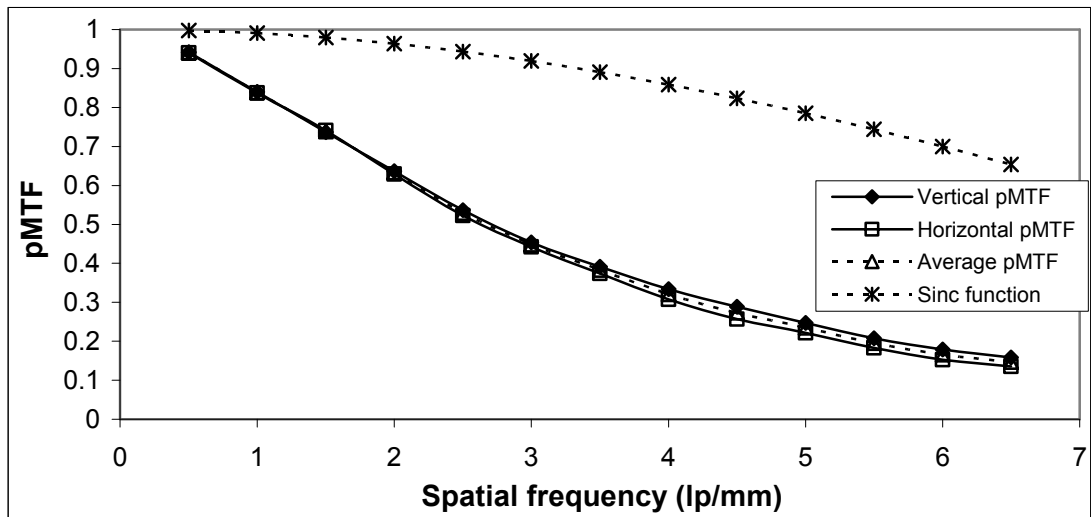


Figure 3.26: pMTF of the Dexela CMOS x-ray detector at 25 kV using 150 μm CsI:Tl

As in the calculation of the pMTF and NNPS, the DQE is presented in spatial frequencies from 0.5 to F_{Nyq} with an interval of 0.5 lp/mm according to the IEC

standard (IEC 62220-1, 2003 and IEC 62220-1-2, 2007). As mentioned in section 2.4.5, the DQE at zero frequency is excluded because low-frequency artifacts lead to underestimation of DQE. Marshall estimated the $DQE(0)$ values by applying either first-order linear extrapolation (Marshall, 2006a) or second-order polynomial extrapolation (Marshall, 2009a and Marshall, 2009b) to the measured $DQE(f)$ curves. However, in the current study there is not a particular need to estimate the $DQE(0)$. Therefore the minimum spatial frequency is 0.5 lp/mm according to the IEC standard.

Figure 3.27 presents the average DQE curves of the Dexela detector in the HFW mode using W/Rh combination at 25 kV in the exposure range 26.4-211.3 μGy . As illustrated in this figure the DQE at 0.5 lp/mm ranges from 0.54 at 26.4 μGy to 0.63 at 211.3 μGy .

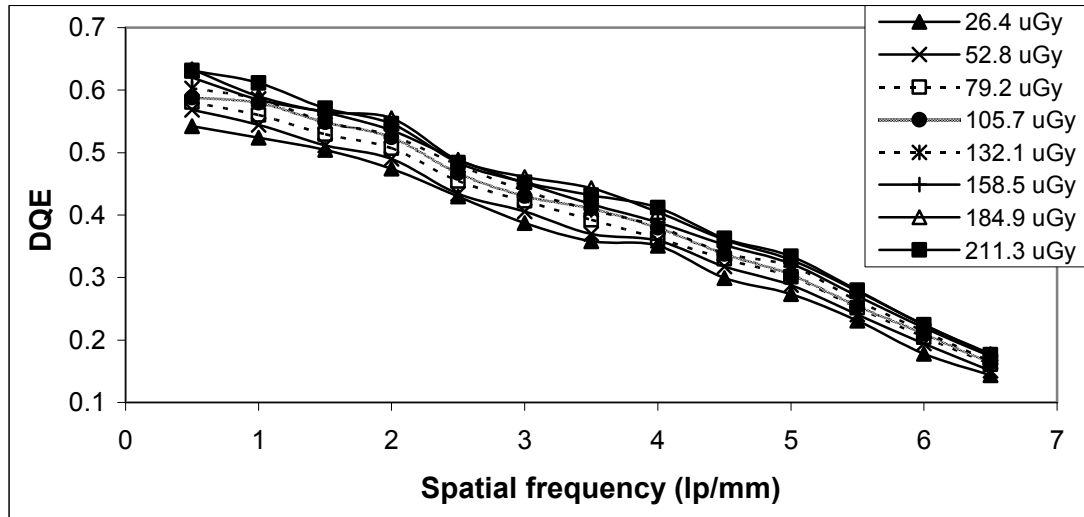


Figure 3.27: Average DQE of the Dexela detector in the HFW mode and 25 kV

Figure 3.28 illustrates the respective average DQE of the same detector in the LFW mode. The DAK range is smaller (8.3 to 66.0 μGy) due to the higher sensitivity of the detector which leads to quicker saturation. The $DQE(0.5)$ at 8.3 μGy is 0.57 which demonstrates the ability of the detector to be used in breast tomosynthesis conditions. Finally, the $DQE(0.5)$ at 66.0 μGy is 0.62, i.e. the SNR performance of the detector reaches the same levels at three times less exposure compared to the HFW mode. This occurs due to the increase on the conversion gain $G(\text{DN}/e^-)$ by a factor of three (see Table 3.3 in section 3.2.5). The deviation of the DQE curves is smaller due to the increased linearity when the detector is operated in the LFW mode (see sections 3.2.5 and 3.3.11).

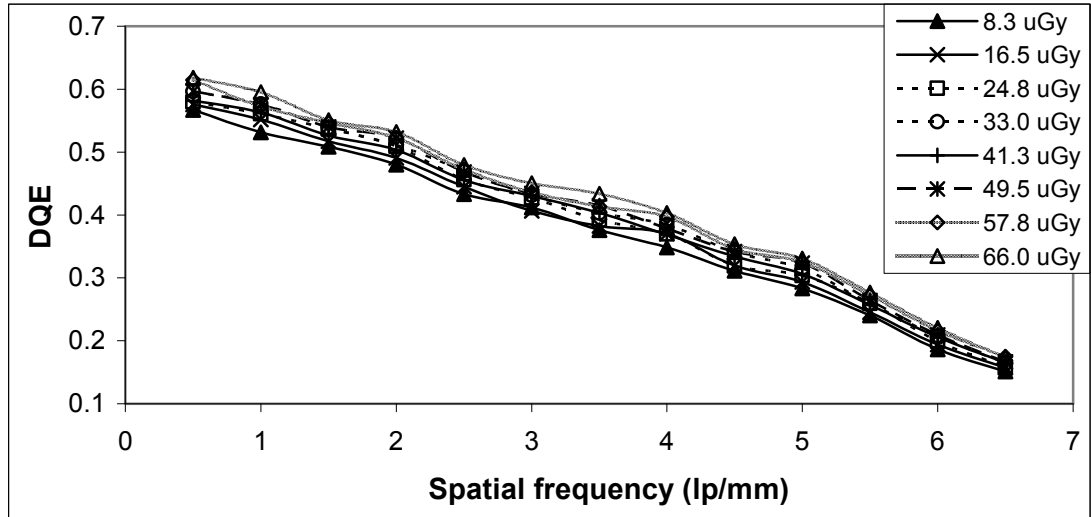


Figure 3.28: Average DQE of the Dexela detector in the LFW mode and 25 kV

3.3.7 Evaluation using Beam Quality 1b (W/Al at 28 kV; Mammography)

As mentioned in section 2.4.1, the STP curve gives information about the sensitivity and linearity of the signal transfer of x-ray detectors. Figure 3.29 shows the STP curves with linear fitting function equations for LAS, Dexela at both HFW and LFW modes and Hamamatsu detectors at 28 kV. These detectors show relatively high sensitivity to the incident x-ray photons. All of them show sufficient linearity in the signal transfer with R^2 greater than 0.999. It was found that the coefficient of variation (COV) did not exceed 4 % on the STP curves of all beam qualities. Hence, for clarity error bars on the data were not included on the STP curves.

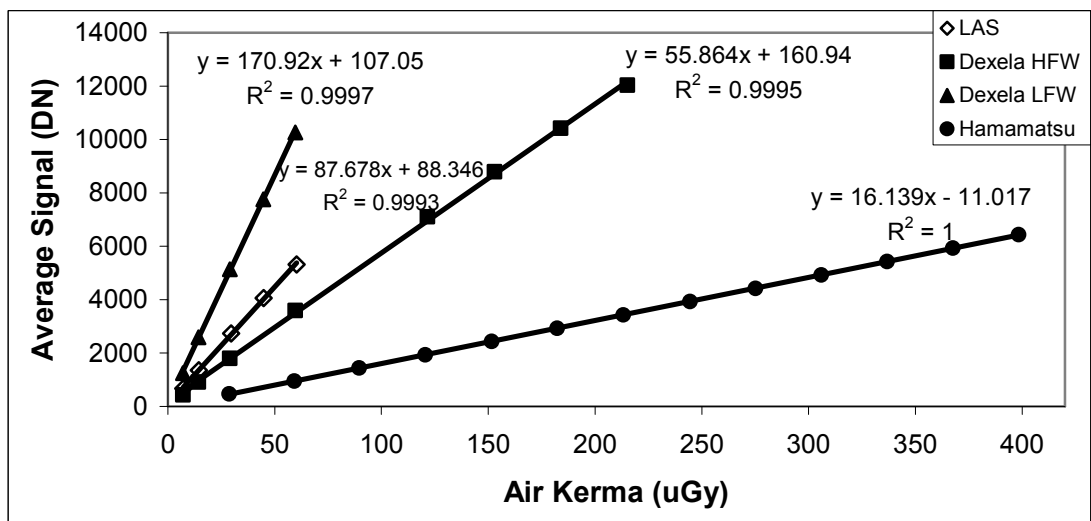


Figure 3.29: STP curves with fitting function equations for the high sensitivity detectors at 28 kV

Figure 3.30 demonstrates the respective STP curves for Anrad and RadEye detectors which present lower x-ray sensitivity. They are presented separately so that they can be shown in a clearer fashion. It is observed that they do not have as high a linearity as the previous detectors. The nonlinearity of RadEye detector is already mentioned in previous studies and some solutions are suggested in the literature (Rad-icon Imaging Corp., 2003 and Cao and Peter, 2008). Further details about this are given in section 3.3.11. However, both detectors meet one of the linearity criteria set by the IEC standard, i.e. $R^2 \geq 0.99$ (IEC 62220-1, 2003 and IEC 62220-1-2, 2007). The exposure range of all mentioned STP curves is from 7.1 to 398.3 μGy . The reason for this overall broad range is to reach exposures which are at least half and double the “reference” level ($\sim 100\text{--}120 \mu\text{Gy DAK}$) according to the mammographic IEC standard (IEC 62220-1-2, 2007). Furthermore, very high DAK levels were reached ($> 300 \mu\text{Gy}$) for the evaluation of Hamamatsu detector to study the observed quantum limited performance of the detector according to Saunders *et al.* (2005) over a wide exposure range.

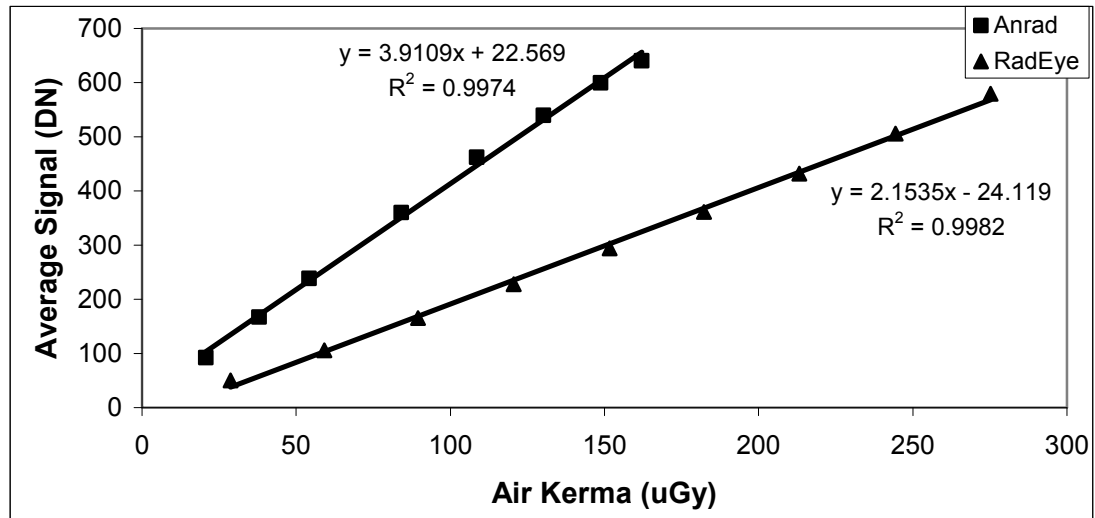


Figure 3.30: STP curves with fitting function equations for the low sensitivity detectors

Figure 3.31 shows the pMTF values of the investigated detectors. It is observed that the pMTF of LAS is quite low with its first zero before the F_{Nyq} (at around 9.5 lp/mm). This happens due to unoptimized usage of the optical coupling gel between the FOP and the detector surface (see section 1.7). This behaviour implies insignificant aliasing because the signal is already zero at F_{Nyq} . The vertical pMTF is slightly higher compared to the horizontal one (5.6 % average relative difference). A similar behaviour was observed for the other three digital detectors evaluated using the same x-ray source.

In particular, the vertical pMTF curve is higher by 2.2% for Hamamatsu, 3.9 % for Dexela and 0.9 % for RadEye detectors (average relative difference). All detectors were placed at the same orientation, i.e. the vertical direction corresponds to the column readout bus. Probably the reason for the small anisotropic behaviour is the asymmetry of the focal spot. Preliminary measurements showed that the focal spot is 12 % higher in the horizontal direction. The “chest wall” direction corresponds to the left side of Dexela and Hamamatsu detectors. Both LAS and RadEye detectors do not have a “chest wall” direction. The edge test object was put directly on the top of each detector’s shielding box to minimize the effect of the focal spot blurring (or geometric MTF) on the measurements. Nevertheless, from the observed behaviour possibly the focal spot introduces a blurring to a small extent. Therefore, the intrinsic behaviour of LAS, Hamamatsu, Dexela and RadEye detectors can be considered isotropic.

On the other hand, the Anrad SMAM detector demonstrates higher anisotropic behaviour, i.e. the horizontal pMTF is higher by 17 % compared to the vertical one at F_{Nyq} . However, both MTF curves reach the first zero value at around 12 lp/mm, which demonstrates that the pixel pitch is the same in both directions. As mentioned in section 3.3.1 a different W anode x-ray tube was used for the evaluation of this detector. The focal spot size of this anode for the particular tube load was not measured. However, an anisotropic behaviour was observed as well in Bissonnette *et al.* (2005) where they examine the x-ray performance evaluation of the Anrad LMAM detector. As stated in section 1.6.4 the Anrad LMAM detector has similar properties compared to the SMAM and the same pixel pitch. Therefore, identical pMTF curves are expected. In this study the pMTF of LMAM detector is 9 % higher in one direction at F_{Nyq} (the authors do not provide any explanation for this effect). A comparison between the average pMTF of LMAM detector and the current one resulted in an average difference equal to 0.9 %. A second comparison between the current results and the average pMTF of LMAM detector made by Tousignant *et al.* (2007) resulted in an average difference of 1.2 % between the curves. Both separate comparisons confirm the validity of the current pMTF measurements. The Hamamatsu detector demonstrates higher pMTF values than LAS. Its average pMTF value is around 0.09 at F_{Nyq} which corresponds to a small aliasing contribution. Concerning the Dexela detector, the thin CsI:TI scintillator was used because it demonstrates high x-ray detection efficiency at low energy (QDE=0.754 and EAE=0.683, see Table 3.7) and simultaneously retains the spatial resolution which

is an important task in mammography. The average pMTF at F_{Nyq} is higher than the respective ones for LAS and Hamamatsu detectors at this specific limit (i.e. it is around 0.21). The pMTF curves of the Dexela detector at 28 kV are higher compared to the respective at 25 kV (Figure 3.26). A similar behaviour is observed on the NNPS values. Probably the scintillator was not optimally coupled at the time. The pMTF of RadEye detector is zero before the F_{Nyq} (at around 17.5 lp/mm), despite the fact that a thin (85 μm thick) scintillator was used. The reason for this is the use of a $\text{Gd}_2\text{O}_2\text{S:Tb}$ granular scintillator instead of a columnar structure CsI:Tl.

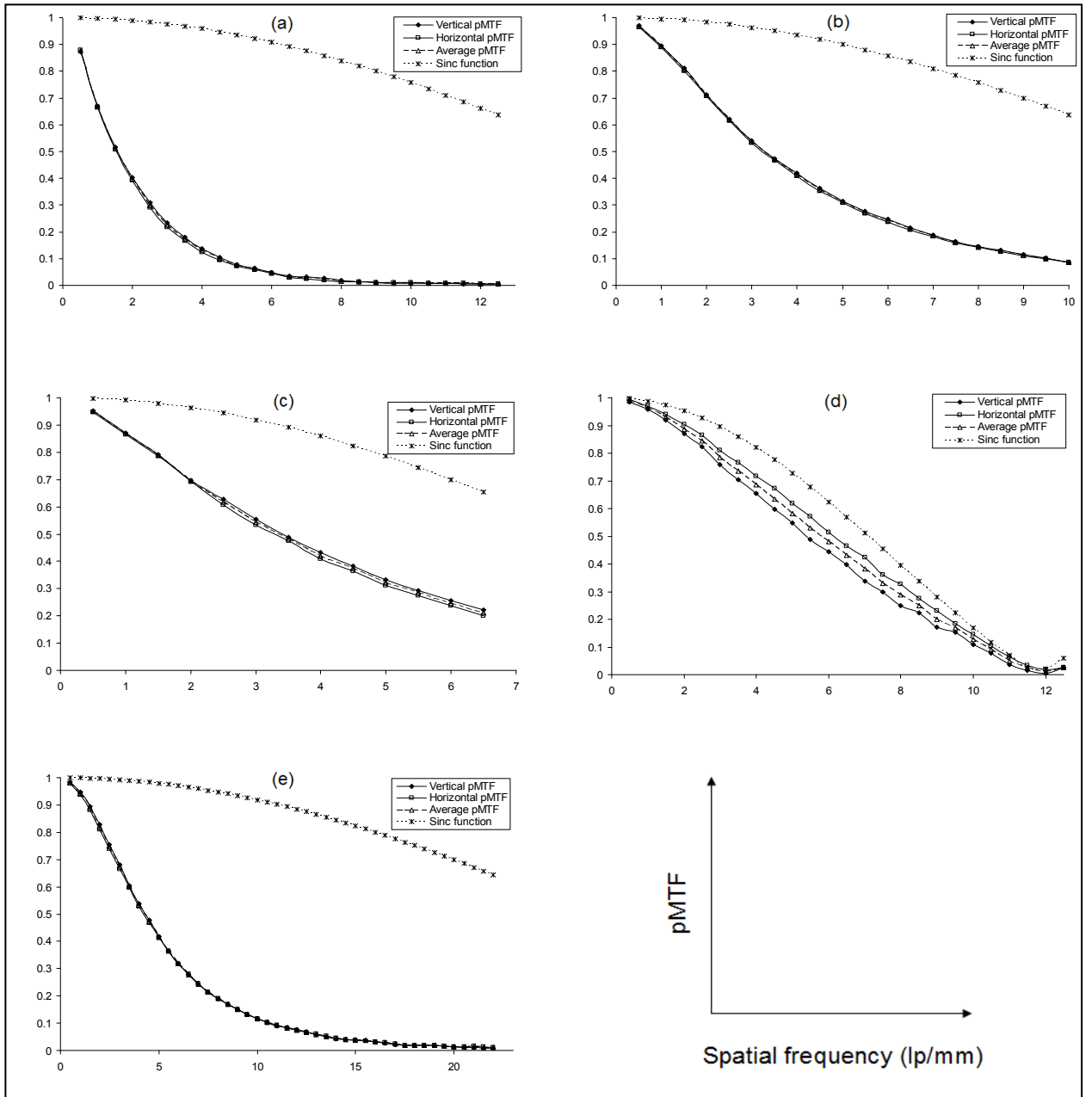


Figure 3.31: pMTF values of a) LAS, b) Hamamatsu, c) Dexela, d) Anrad and e) RadEye detectors.

Anrad SMAM detector does not suffer from scintillator blurring because it is a direct conversion detector. Hence, it demonstrates high pMTF values, which are close to the ideal ones (sinc function). More specifically, the ratio between the measured average pMTF and the sinc function drops from 1 to 0.78 in the frequency range from zero to F_{Nyq} . Probably this happens due to the focal spot blurring and the relatively low pixel fill factor (70 %). Also, according to Yorker *et al.* (2002) the secondary K-fluorescence x-ray photons created in the Se layer decrease the pMTF. The K-edge of Se is 12.7 keV, while the x-ray photon spectrum used in mammography contains higher energies. Therefore, a high number of secondary K-fluorescence x-ray photons can travel some distance in the layer and be absorbed away from the original incidence point. Furthermore, backscattering of x-rays from the glass substrate underneath the Se layer (see Figure 1.5) may decrease the pMTF to some extent. Also, two studies mention that the use of a specific glass substrate material is responsible for generation of additional secondary K-fluorescence x-ray photons (Yorkston *et al.*, 1998 and Samei and Flynn, 2003). The high average pMTF value (around 0.53) at F_{Nyq} suggests significant aliasing contribution from higher frequencies, which is a common effect on direct conversion detectors.

All the average pMTF curves are compared with one another in Figure 3.32 and Table 3.9. It is observed that Anrad SMAM detector demonstrates the highest average pMTF values and LAS the lowest ones. RadEye detector presents the second highest pMTF values due to the combination of thin scintillator (85 μm) and very small pixel pitch (22.5 μm). Hamamatsu and Dexela detectors show almost the same average pMTF values due to similar scintillator thickness and pixel pitch combinations (160 μm and 85 μm the former and 150 μm and 74.8 μm the later).

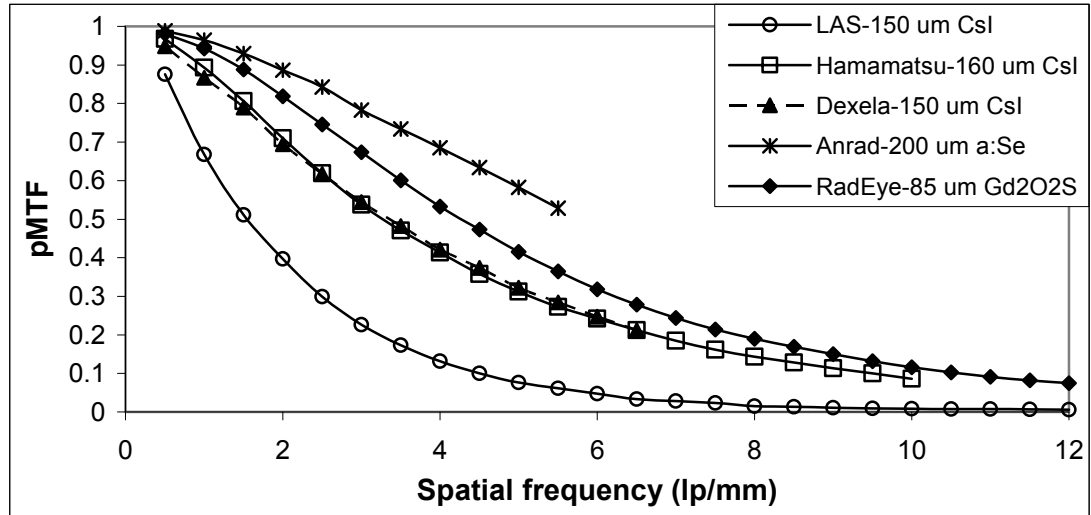


Figure 3.32: Average pMTF curves of the investigated digital x-ray detectors at 28 kV

Table 3.9: Spatial frequency values corresponding to two pMTF levels (10 and 50 %)

Detector	pMTF 10% (x;y-lp/mm)	pMTF 50% (x;y-lp/mm)
LAS	4.5	1.5
Hamamatsu	9.4	3.3
Dexela	8.8	3.3
Anrad	10.5; 10	6.1; 5.3
RadEye	10.6	4.3

Figure 3.33 shows a representative 2-D NNPS matrix which corresponds to LAS detector at 60.3 μGy DAK. A number of spikes is observed close to the vertical v axis, which indicate the presence of periodic noise despite the fact that a different set of read out electronics (namely the 3rd generation of stack board) is used in this case compared to the electro-optical evaluation. Nevertheless, it was found that using this specific set of electronics the magnitude of the periodic noise is smaller. Hence, it was decided not to apply the aforementioned EMI noise reduction algorithm on the x-ray performance evaluation of the detectors.

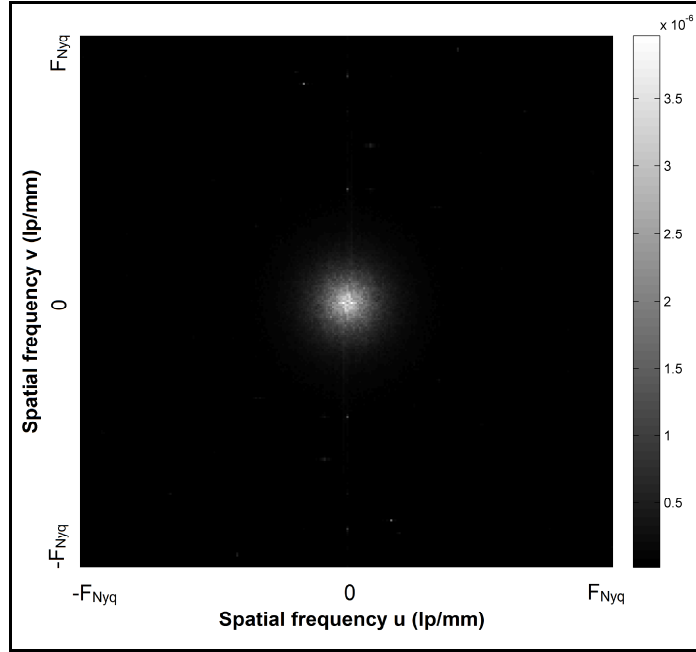


Figure 3.33: 2-D NNPS matrix of LAS detector at 60.3 μGy DAK level

Figure 3.34 shows a set of representative 1-D NNPS curves for all detectors at 28 kV (W/AI). The NNPS curves of LAS detector demonstrate a spike at 7.5 lp/mm due to the presence of the periodic noise. It is observed that the NNPS curves of Anrad detector are almost independent of the spatial frequency. This occurs because it is a direct conversion detector and the effect of aliasing is very strong. All detectors except the RadEye present NNPS curves independent of the DAK level. Finally, the NNPS of RadEye detector at specific DAK levels demonstrate slightly higher values at 0.5 lp/mm compared to the expected ones. Probably this happens due to unoptimized detrending.

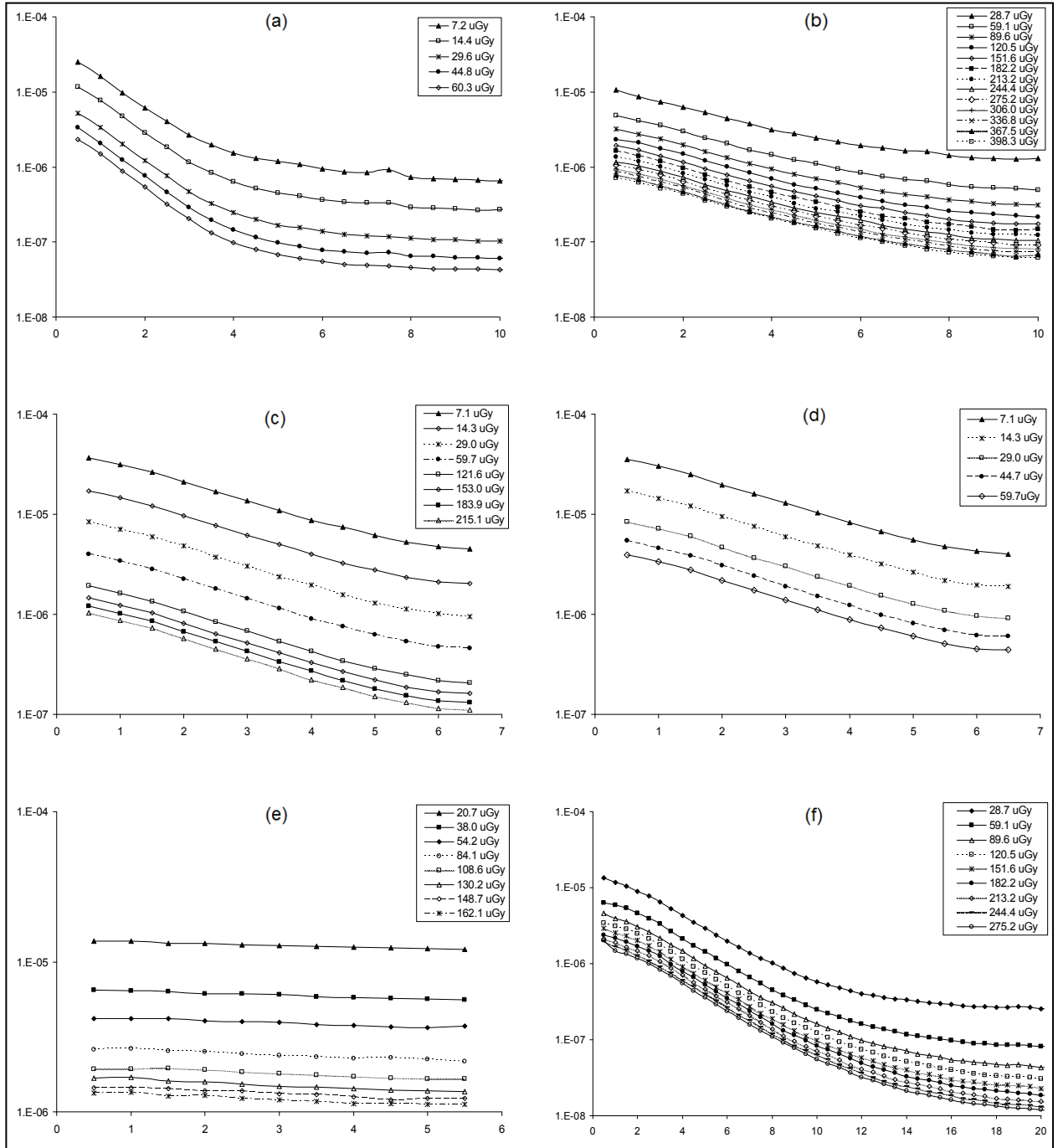


Figure 3.34: Average NNPS curves at 28 kV (W/Al) for a) LAS, b) Hamamatsu, c) Dexela HFW, d) Dexela LFW, e) Anrad SMAM and f) RadEye detectors. The x axis shows the spatial frequency (lp/mm) while the y axis represents the NNPS (mm^2).

It is observed from Figure 3.35a) that the DQE of LAS increases as a function of the DAK level (e.g. the DQE(0.5) is in the range 0.61-0.73). It demonstrates high DQE values at low spatial frequencies, and lower ones at medium frequencies (>4.5 lp/mm). Therefore, it is attractive for fine detail anatomic structures such as microcalcifications with diameter greater than $300 \mu\text{m}$. Furthermore, the performance of the detector at 7.2

μGy shows that it can be used for breast tomosynthesis. LAS DQE curves do not present quantum limited behaviour, i.e. they do not overlap at high DAK levels, probably due to the inherent V/e^- nonlinearity of CMOS APS sensors (see section 3.3.11). On the other hand, Hamamatsu detector presents a quantum limited performance according to Saunders *et al.* (2005) over a broad exposure range (e.g. the DQE(1) is in the range 0.45-0.47). This is related to the linear SNR transfer of Hamamatsu detector. A small drop of DQE curves is observed at 0.5 lp/mm, probably due to remnant low-frequency trends that affect the NNPS calculation. The DQE curve of the lowest DAK level (28.7 μGy) is slightly lower, probably due to the high read noise (1250 e^- r.m.s. nominal level) of the detector. The Dexela detector in the HFW mode presents higher DQE values compared to Hamamatsu detector. As in the case of LAS, the Dexela detector in the HFW mode does not present quantum limited behaviour (e.g. the DQE(0.5) is in the range 0.49-0.57). At the same exposure level, DQE values are higher in the LFW mode due to the decreased electronic noise (section 3.2.5). This is more evident at 7.1 μGy , where the average relative difference between the two modes is about 3 %. However, at high exposures the HFW DQE curves reach higher values than the LFW DQE curves, due to the lower effect of nonlinearity when the detector is operated in the LFW mode (see sections 3.2.5 and 3.3.11). The high DQE values at 7.1 μGy (in both full well modes) promise high detectability in breast tomosynthesis applications.

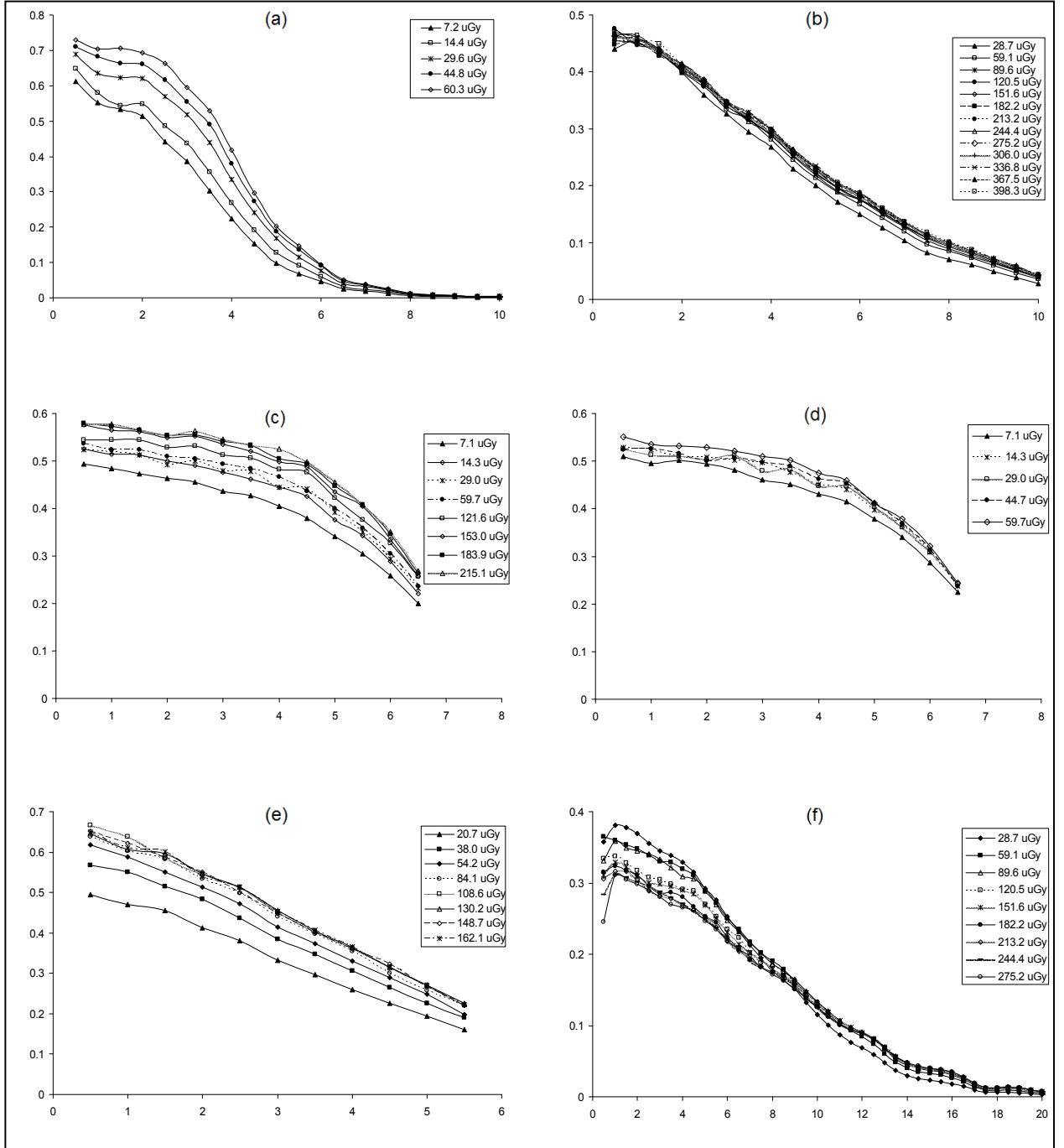


Figure 3.35: Average DQE curves at 28 kV (W/Al) for a) LAS, b) Hamamatsu, c) Dexela HFW, d) Dexela LFW, e) Anrad SMAM and f) RadEye detectors. The x axis corresponds to spatial frequency (lp/mm) while the y axis represents the DQE values.

Anrad SMAM detector demonstrates lower DQE values at low DAK levels (20.7 and 38.0 μGy), probably due to the strong effect of the read noise (5200 e^- r.m.s; Table 1.1). However, at high DAK levels (84.1-162.1 μGy) the DQE curves are overlapped, demonstrating a quantum limited behaviour. The DQE curves of RadEye HR detector demonstrate a strange behaviour. The DQE of the lowest DAK level (28.7 μGy) appears

the highest values at low frequencies and simultaneously the lowest ones at frequencies higher than 10 lp/mm. The DQE curves of the two subsequent DAK levels follow a similar pattern, while the DQE curves at higher DAK levels are almost overlapped. Probably this happens due to the observed nonlinearity of RadEye detectors at low signal levels (Rad-icon Imaging Corp., 2003 and Cao and Peter, 2008; see section 3.3.11). Also, most of the DQE curves show a drop at 0.5 lp/mm which indicates residual low-frequency trends (probably an unoptimized detrending matrix was applied in this case). The moderate DQE values (0.3-0.4 at low frequencies) of this detector indicate a medium SNR transfer.

A performance comparison between the five detectors at two DAK levels (around 60 and 120 μGy) is presented in Figure 3.36. The DQE curves of LAS and Dexela (in the LFW mode) detectors were calculated at around 60 μGy DAK level. This happens because both detectors demonstrate high x-ray sensitivity which leads to limited exposure range. On the other hand, Hamamatsu, Dexela in the HFW mode, Anrad and RadEye detectors appear to have lower sensitivity. Hence, their DQE curves at around 120 μGy are presented. LAS detector presents the highest DQE values at low frequencies (less than 4 lp/mm) and the lowest ones at higher frequencies (more than 5 lp/mm) due to its limited pMTF. Anrad SMAM detector appears the second highest detectability at low frequencies, less than 2.5 lp/mm. At this frequency range it appears moderate DQE values, i.e. more than 0.5. However, at higher frequencies the detector's detectability is limited, probably due to the aliasing noise. On the other hand, Dexela detector in the HFW mode presents DQE values between 0.5 and 0.55 in a broad frequency range (up to 4 lp/mm). This detector demonstrate the highest DQE values at higher frequencies, resulting to a reliable solution up to almost 6 lp/mm. This behaviour indicates that the noise does not degrade significantly the detector's detectability. It is observed that the DQE curve of the Dexela detector in the LFW mode (60 μGy) is almost the same to the respective one in the HFW mode (120 μGy), due to the lower read noise and higher sensitivity. Hence, the LFW mode can be used to achieve the same image quality in mammography at half dose. Hamamatsu detector appears moderate DQE values, less than 0.5 at low frequencies. Finally, RadEye detector presents limited and almost consistent DQE values in a broad frequency range, probably due to its high pMTF values.

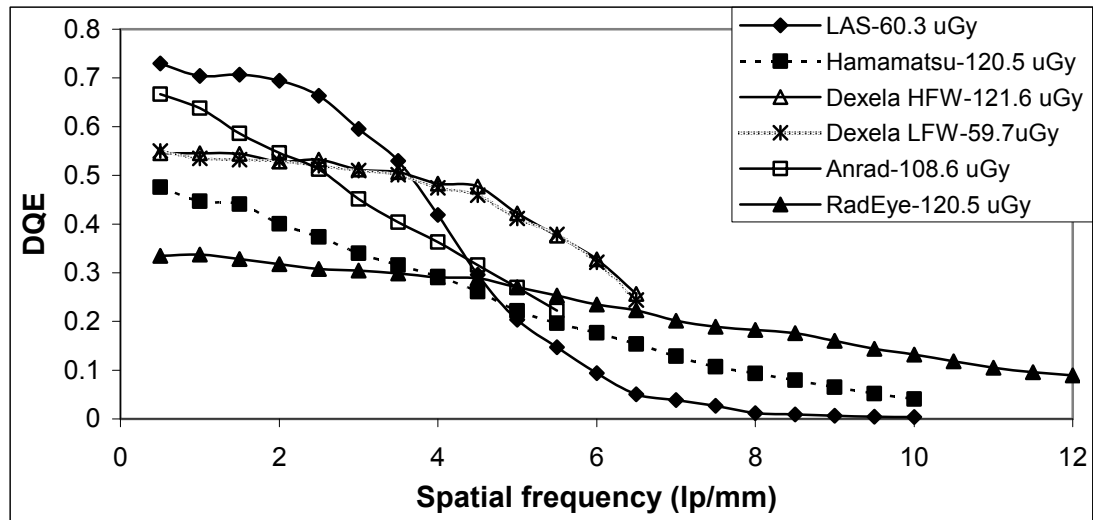


Figure 3.36: Average DQE curves of the investigated detectors at specific DAK levels and 28 kV

Table 3.10 compares the x-ray performance of the detectors in this study to others found in the literature. In particular, Fujifilm Amulet (Rivetti *et al.*, 2009), Sectra MicroDose (Honey *et al.*, 2006), Fischer Senoscan and General Electric Senographe 2000D (Lazzari *et al.*, 2007) and Hologic Lorad Selenia (Blake *et al.*, 2006) were evaluated using similar beam qualities according to the mammographic IEC standard (IEC 62220-1-2, 2007). However, there are some differences in the beam quality (anode/filtration combination and energy), experimental conditions, type and thickness of the x-ray detecting material (scintillator or semiconducting material) and data processing which may affect the results. In order to eliminate these differences, the x-ray performances of commercial detectors using W/Al or W/Rh combinations at 28 kV are presented in this thesis, with the exception of GE Senographe 200D and Hologic Lorad Selenia systems (Mo/Mo at 28 kV), which are broadly used in mammography. To the best of my knowledge, no one has characterized these detectors using W/Al or W/Rh combination for mammographic conditions. The comparison shows that the Anrad SMAM and Remote RadEye HR detectors have competitive pMTF values (at 50 % level) compared to other detectors. On the other hand, LAS, Dexela and Anrad detectors demonstrate high DQE peak values, due to the increased relationship between the pMTF and NNPS parameters.

Table 3.10: Comparison of the x-ray performance of different detectors used in mammography

Detector	Detector technology	X-ray absorber material	Radiation quality	pMTF 50% (x;y – lp/mm)	DQE peak (x;y) at specific DAK level
FUJIFILM AMULET	a-Se TFT	200 μm a-Se	W/Rh (28 kV)	4.4	0.75 at 103 μGy
Sectra MicroDose	Direct photon counting	Crystalline Si wafer	W/Al (28 kV)	6.2; 3.3	0.63; 0.61 at 113 μGy
Fischer Senoscan	CCD	180 μm CsI:Tl	W/Al (28 kV)	5.5	0.24 at 131 μGy
GE Senographe 2000D	a-Si:H TFT	100 μm CsI:Tl	Mo/Mo (28 kV) (RQA-M 2)	4	0.53 at 131 μGy
Hologic Lorad Selenia	a-Se TFT	200 μm a-Se	Mo/Mo (28 kV) (RQA-M 2)	5.8	0.59 at 92.5 μGy
LAS	CMOS APS	150 μm CsI:Tl	W/Al (28 kV)	1.5	0.73 at 60.3 μGy
Hamamatsu C9732DK	CMOS PPS	160 μm CsI:Tl	W/Al (28 kV)	3.3	0.48 at 120.5 μGy
Dexela 2932	CMOS APS	150 μm CsI:Tl	W/Rh (25 kV)	2.7	0.59 at 105.7 μGy (HFW mode)
Dexela 2932	CMOS APS	150 μm CsI:Tl	W/Rh (25 kV)	2.7	0.61 at 57.8 μGy (LFW mode)
Dexela 2932	CMOS APS	150 μm CsI:Tl	W/Al (28 kV)	3.3	0.55 at 121.6 μGy (HFW mode)
Dexela 2932	CMOS APS	150 μm CsI:Tl	W/Al (28 kV)	3.3	0.55 at 59.7 μGy (LFW mode)
Anrad SMAM	a-Se TFT	200 μm a-Se	W/Al (28 kV)	6.1; 5.3	0.67; 0.66 at 108.6 μGy
Remote RadEye HR	CMOS APS	85 μm Gd ₂ O ₂ S:Tb	W/Al (28 kV)	4.3	0.33 at 120.5 μGy

3.3.8 Evaluation using Beam Quality 2 (W/Al at 52 kV; RQA3)

Figure 3.37 shows the STP curves of the higher x-ray sensitivity detectors (LAS and Dexela sensor coupled to 150 and 600 μm CsI:Tl) at RQA3 beam quality (52 kV). Both detectors demonstrate high linearity for signal transfer with $R^2 \geq 0.9996$. The highest sensitivity corresponds to the Dexela detector when the thick scintillator is used and operated in the LFW mode. This combination leads to high x-ray detectability (high QDE and EAE) with simultaneous high conversion gain $G(\text{DN/e})$.

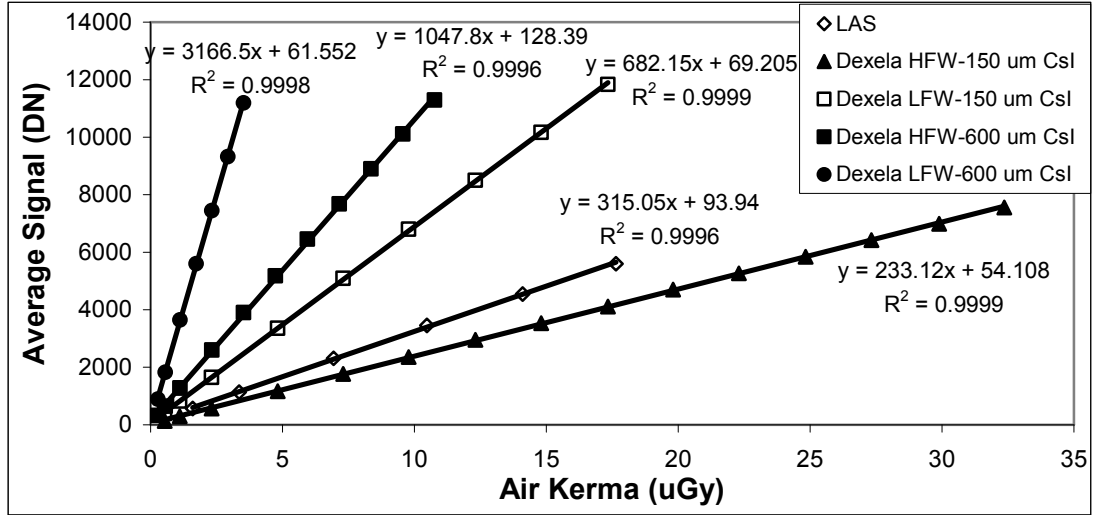


Figure 3.37: STP curves with fitting function equations for the higher sensitivity detectors at 52 kV

Figure 3.38 shows the STP curves for the lower sensitivity detectors (Hamamatsu and RadEye) at the same beam quality. A high linearity for signal transfer ($R^2 \geq 0.9997$) is also observed. However, the sensitivity of RadEye detector is very low due to the limited x-ray detectability of $Gd_2O_2S:Tb$ detector at the used energy (QDE=0.335 and EAE=0.272; Table 3.7).

The average detector DAK for general radiography is around 2.5 μGy (Moy, 2000a, Rowlands and Yorkston, 2000b, Jee *et al.*, 2003 and Ghetti *et al.*, 2008). The corresponding IEC standard (IEC 62220-1, 2003) recommends that the exposure range should be at least between 1/3.2 and 3.2 times the normal level (i.e. from 0.8 to 8 μGy). A wide exposure range was used in this thesis (0.3 to 32.7 μGy), which is close to the one used in neonatal and paediatric imaging (0.3 to 26.8 μGy ; Rowlands and Yorkston, 2000b).

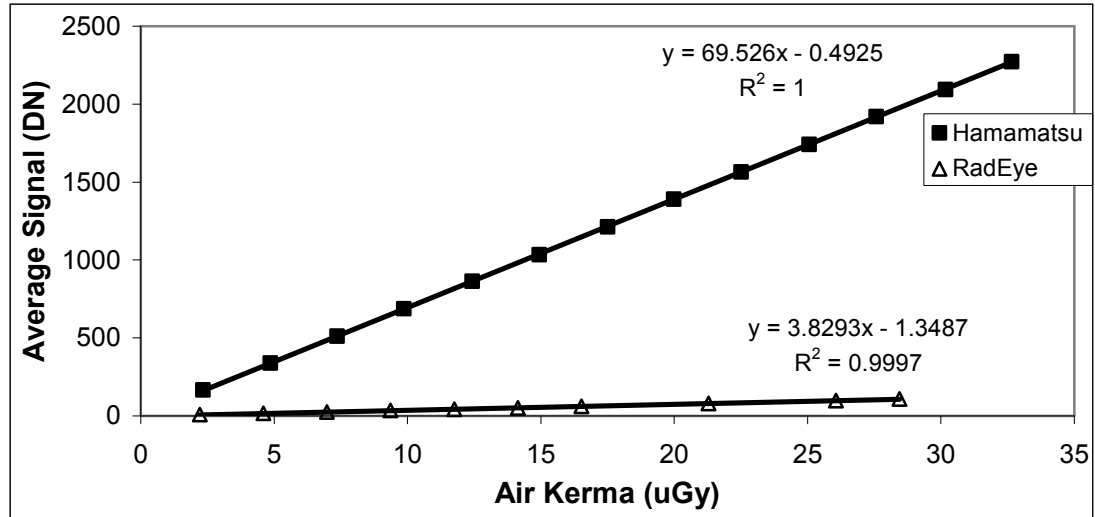


Figure 3.38: STP curves with fitting function equations for the lower sensitivity detectors at 52 kV

The average pMTF curves of the detectors at 52 kV are presented in Figure 3.39. As mentioned in section 3.3.7, Anrad SMAM detector is the only one that demonstrates significant inherent anisotropic behaviour. Since the Anrad is excluded from high energy evaluation (it should not be used for energies greater than 35 kV) there is no need to present both horizontal and vertical pMTF curves for each detector. RadEye HR detector presents the highest pMTF values due to the combination of the thin scintillator and very small pixel pitch. The detectors with the second pMTF highest values are Hamamatsu and Dexela coupled to 150 μm CsI:Tl. Both of them show similar pMTF values as observed in the mammographic study (Figure 3.32). Finally, the Dexela sensor coupled to the thick scintillator demonstrates similar pMTF values compared to LAS.

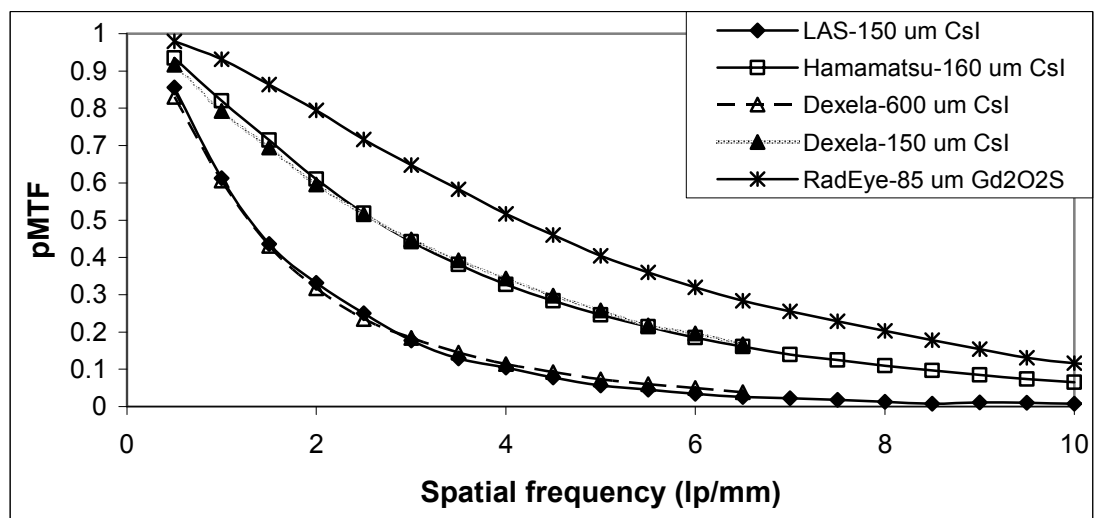


Figure 3.39: Average pMTF curves of the investigated digital x-ray detectors at 52 kV

A quantitative comparison of the above pMTF curves is presented in Table 3.11, using the 10 and 50 % pMTF levels.

Table 3.11: Spatial frequency values corresponding to 10 and 50 % pMTF levels

Detector	pMTF 10% (lp/mm)	pMTF 50% (lp/mm)
LAS	4.1	1.3
Hamamatsu	8.4	2.6
Dexela (coupled to 150 μm CsI)	7.7	2.6
Dexela (coupled to 600 μm CsI)	4.3	1.3
RadEye	11.4	4.2

Figure 3.40a) shows that LAS detector has moderate DQE values at low frequencies (e.g. the DQE(0.5) is in the range 0.44-0.54). This is due to the mediocre detectability of x-rays at the specific energy ($QDE=0.695$ and $EAE=0.323$; Table 3.7). A strange behaviour is observed at low frequencies (i.e. up to 4 lp/mm). This is due to spikes in the NNPS which indicate the presence of low magnitude periodic noise (the aforementioned EMI noise reduction algorithm was not applied on the x-ray performance evaluation of the detectors). The DQE of Hamamatsu detector is relatively low due to decreased x-ray detectability as well (e.g. the DQE(0.5) is in the range 0.37-0.40). The DQE curves of Hamamatsu detector are overlapped in the DAK range 9.9-32.7 μGy , which indicates quantum limited behaviour. The Dexela sensor coupled to 150 μm CsI scintillator demonstrates comparative DQE results to LAS and Hamamatsu detectors. For the reasons mentioned in section 3.3.7, the Dexela detector presents lower deviation from the quantum limited behaviour when is operated in the LFW mode. The Dexela detector demonstrates high performance when coupled to 600 μm CsI scintillator, due to the increased x-ray detectability ($QDE=0.978$ and $EAE=0.472$; Table 3.7). The exposure range is limited compared to the previous cases due to saturation constraints arising from the increased sensitivity. Its DQE values are high in a range of frequencies (up to 4.5 lp/mm). Hence, upon coupling with the appropriate scintillator, the Dexela detector maintains high performance levels at higher energies. The DQE curves of the Dexela detector using the thick scintillator show the trade-off between the x-ray sensitivity and resolution compared to the thin scintillator. The DQE curves of RadEye detector are very low (<0.16) even at low spatial frequencies. This happens due

to the aforementioned limited x-ray detectability of the used $\text{Gd}_2\text{O}_2\text{S}$ scintillator, which results in very low signal levels (see Figure 3.38).

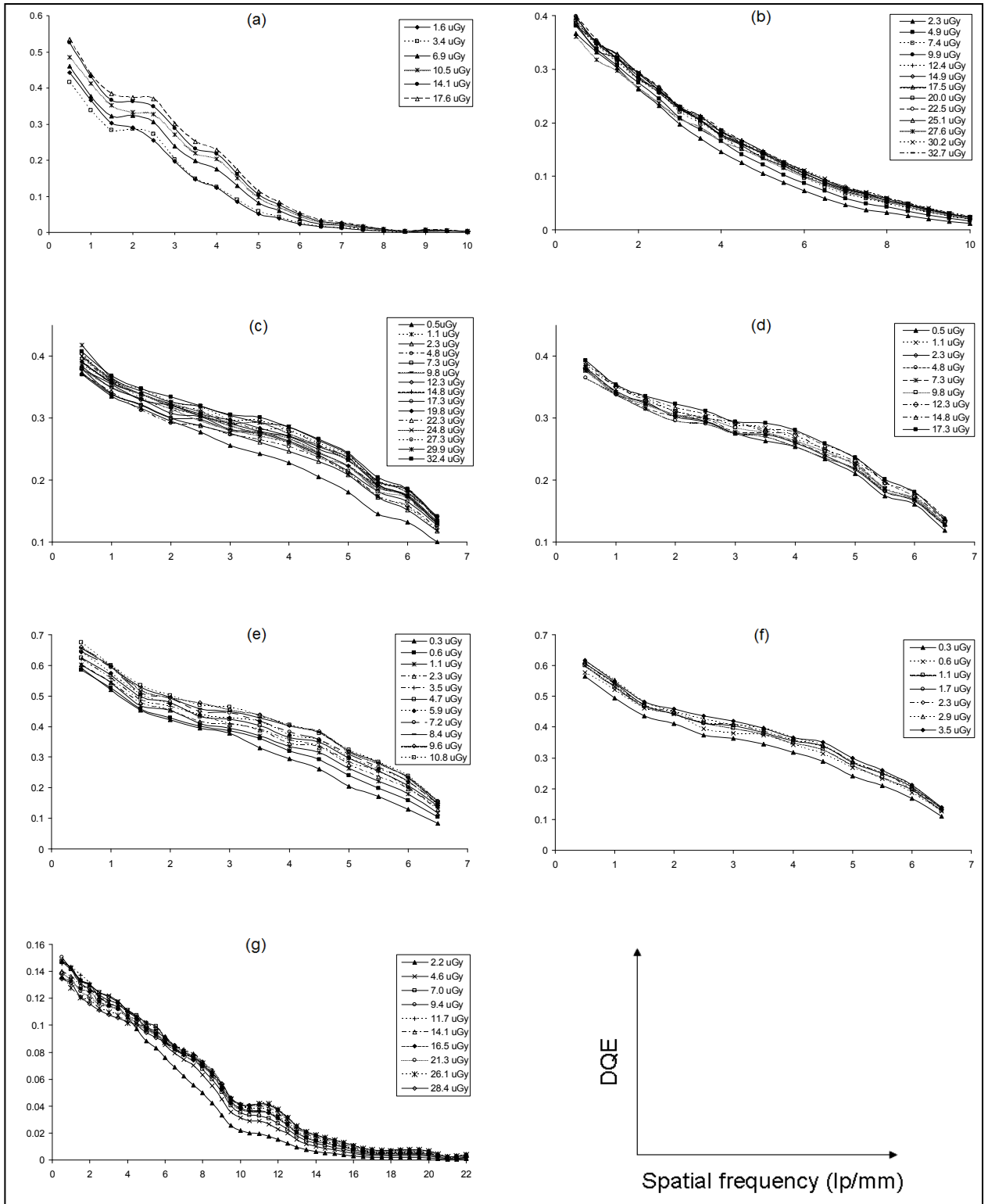


Figure 3.40: Average DQE curves at 52 kV for a) LAS, b) Hamamatsu, c) Dexela HFW, d) Dexela LFW (coupled to 150 μm CsI), e) Dexela HFW, f) Dexela LFW (coupled to 600 μm CsI) and g) RadEye detectors

Figure 3.41 compares the performance of the detectors at 52 kV and two DAK levels. The DQE curves of LAS and Dexela coupled to 600 μm CsI:Tl and operated in the LFW mode were calculated at 3.5 μGy . The DQE curves of the other imaging systems correspond to approximately 4.8 μGy . The Dexela sensor coupled to 600 μm CsI:Tl has the highest DQE values in both full well modes. It presents high x-ray performance (higher than 0.6) at low frequencies. LAS and Hamamatsu detectors illustrate moderate detectability at lower frequencies. The Dexela sensor coupled to 150 μm CsI:Tl presents similar DQE values compared to LAS and Hamamatsu detectors at low frequencies. However, at higher frequencies it shows higher detectability due to the lower effect of the noise at this frequency range. Finally, RadEye detector appears very low detectability compared to the other detectors.

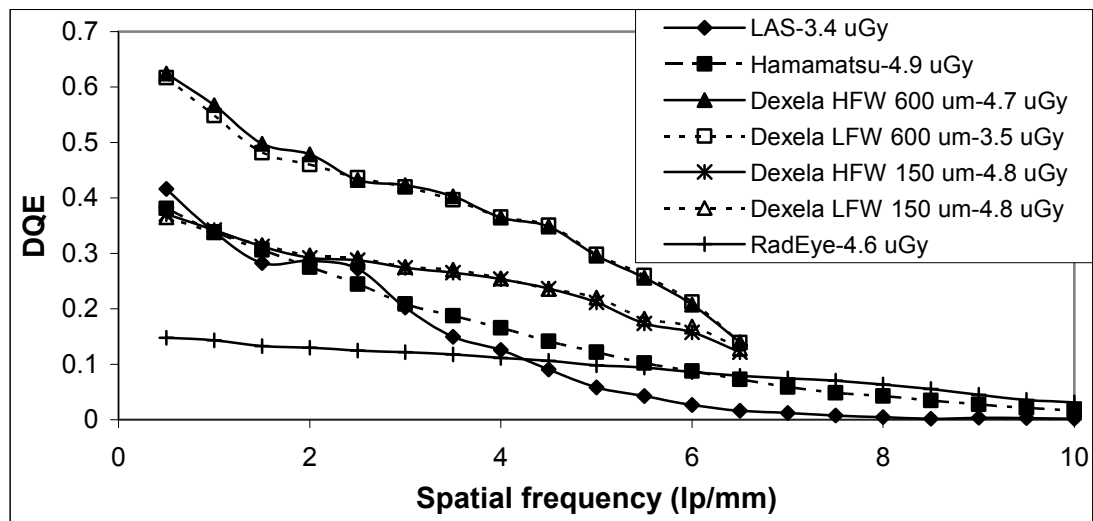


Figure 3.41: Average DQE curves of the investigated detectors at specific DAK levels and 52 kV

3.3.9 Evaluation using Beam Quality 3 (W/Al at 74 kV; RQA5)

The RQA5 is the commonly used beam quality for the x-ray performance evaluation in general radiography according to the respective IEC standard (IEC 62220-1, 2003). The STP curves are shown in two separate figures depending on the sensitivity. Figure 3.42 shows the STP curves for the higher sensitivity detectors, i.e. LAS and Dexela. Both detectors show high linearity on the signal transfer ($R^2 \geq 0.9994$).

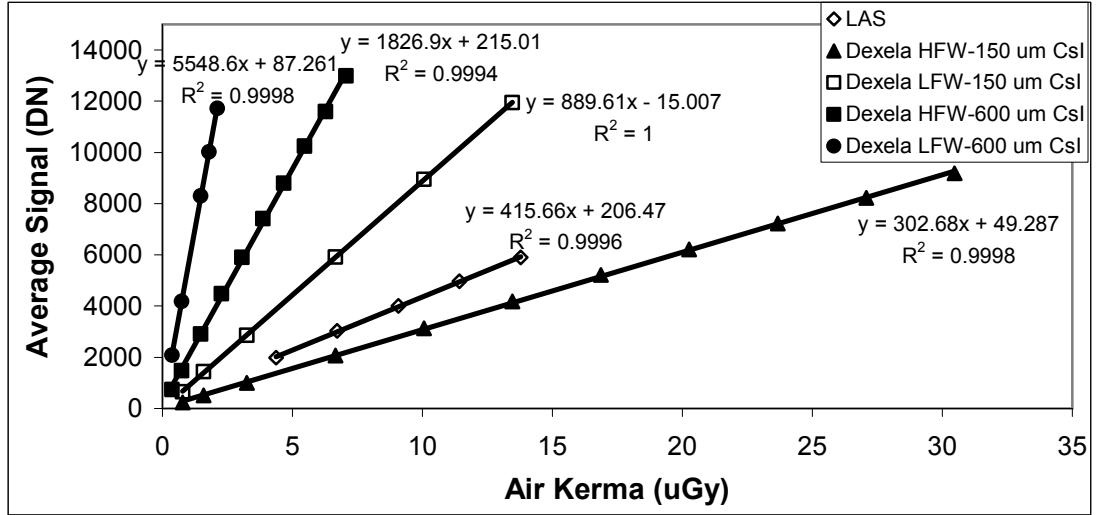


Figure 3.42: STP curves with fitting function equations for the higher sensitivity detectors at 74 kV

Figure 3.43 demonstrates the STP curves of the lower sensitivity detectors (Hamamatsu and RadEye). Both detectors demonstrate high linearity on the signal transfer ($R^2 \geq 0.9993$). For the highest sensitivity systems (i.e. LAS, Dexela in the HFW mode coupled to the thick scintillator and Dexela in the LFW mode coupled to both scintillators) the maximum DAK was 13.8 μGy . The maximum DAK level reached for the Dexela detector using the thin scintillator and operated in the HFW mode and RadEye detector was 30.5 μGy . Finally, a high exposure level (44.5 μGy) was reached for Hamamatsu detector to investigate its observed quantum limited performance over a broad exposure range.

A comparison between the STP curves of the detectors over the three energies (28, 52 and 74 kV) shows that the slope increases as a function of energy. This implies an increase of the output signal (in DN) per unit DAK as the mean x-ray energy increases. According to Marshall (2009b), this happens mainly due to three reasons. First, the number of x-rays per unit DAK per unit area (i.e. the Φ/K_a parameter) increases as the mean x-ray energy increases (see Eq. (2.31)). Therefore more x-rays which are signal carriers are impinging the scintillator per unit DAK. Secondly, more secondary quanta (light photons for scintillators and electronic charge for photoconductors) are generated assuming a fixed conversion efficiency (i.e. light yield for scintillator). Finally, there is a depth effect. As the mean energy increases the beam becomes more penetrating, so the interacting x-rays are absorbed at deeper points within the scintillator, closer to the

digital sensor. Hence, the created optical photons are reabsorbed less from the scintillator. This increases their collection efficiency from the digital sensor.

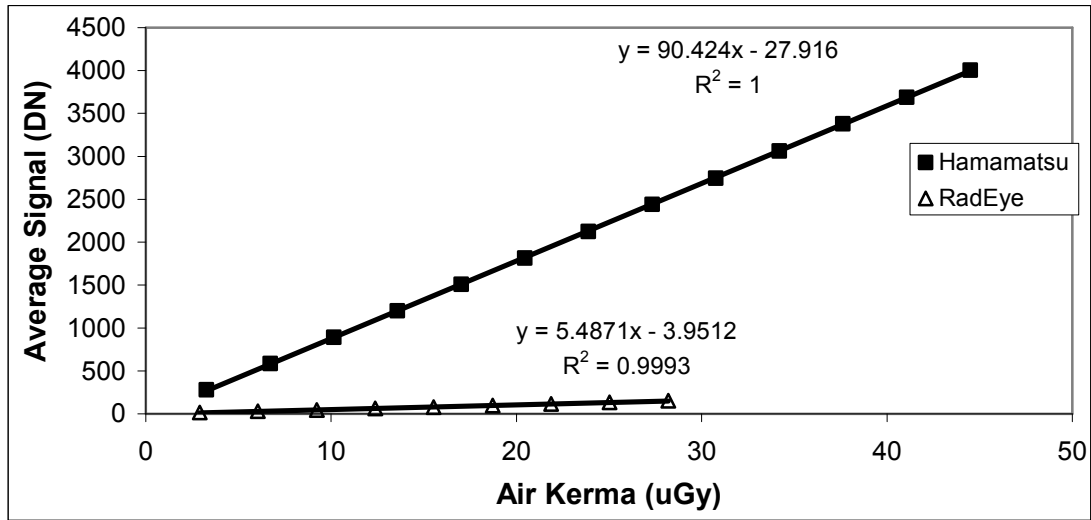


Figure 3.43: STP curves with fitting function equations for the lower sensitivity detectors at 74 kV

Figure 3.44 presents the average pMTF values of all digital detectors investigated under RQA5 beam quality. As in the RQA3 case, the RadEye detector presents the highest results. The Hamamatsu and Dexela sensor coupled to the thin scintillator demonstrate similar pMTF values. On the other hand, when the Dexela sensor is coupled to the thick scintillator it demonstrates similar pMTF values compared to LAS. The measured pMTF values at this energy are similar to the respective ones captured at 52 kV. For the CsI-based detectors (i.e. LAS, Hamamatsu and Dexela) the pMTF at 74 kV was slightly higher than the one at 52 kV due to higher absorption depth of the x-rays inside the scintillator. This results in limited spread of the secondary optical photons. In this case, the average absolute difference (%) between the pMTFs of the two energies was up to 7.7 % (for Hamamatsu detector). On the other hand, it is observed that the pMTF of RadEye detector is lower by 7.9 % on average for the high energy beam. This behaviour can not be explained from the depth effect.

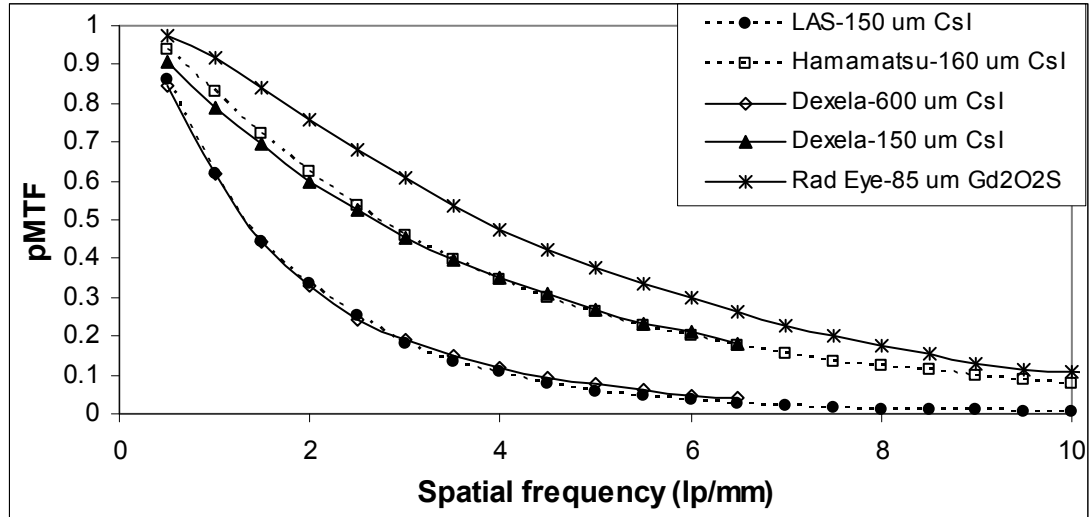


Figure 3.44: Average pMTF of the investigated digital x-ray detectors at 74 kV

A quantitative comparison of the above pMTF curves is presented in Table 3.12, by presenting the spatial frequencies of each detector that correspond to the 10 and 50 % pMTF levels.

Table 3.12: Spatial frequency values corresponding to 10 and 50 % pMTF levels

Detector	pMTF 10% (lp/mm)	pMTF 50% (lp/mm)
LAS	4.1	1.3
Hamamatsu	9	2.7
Dexela (coupled to 150 μm CsI)	7.7	2.7
Dexela (coupled to 600 μm CsI)	4.4	1.3
RadEye	10.9	3.8

Figure 3.45 shows the DQE results of the investigated detectors at 74 kV. It is observed that when thin scintillators are used (cases a, b, c, d and g) the DQE values at this energy are lower than those at 52 kV. The x-rays are more penetrating at this energy, leading to decreased detectability from the scintillator (Table 3.7). On the other hand, the thick scintillator results in higher DQE values (cases e and f) due to the increased x-ray detectability. This happens because the average EAE at 74 kV (0.491) is slightly higher compared to the respective one at 52 kV (0.480) for the reasons mentioned in section 3.3.2. At this energy, Hamamatsu, Dexela in the LFW mode and RadEye detectors demonstrate a quantum limited behaviour. However, the DQE values of the RadEye detector are very low (<0.12) due to the limited average EAE of $\text{Gd}_2\text{O}_2\text{S}$.

scintillator (0.193) at 74 kV. LAS detector demonstrates the higher x-ray performance among the detectors coupled to thin scintillators. The use of the thick scintillator results in high DQE values (e.g. the DQE(0.5) values are in the ranges 0.58-0.68 and 0.57-0.62 for HFW and LFW modes respectively) and limited exposure range due to the higher x-ray sensitivity.

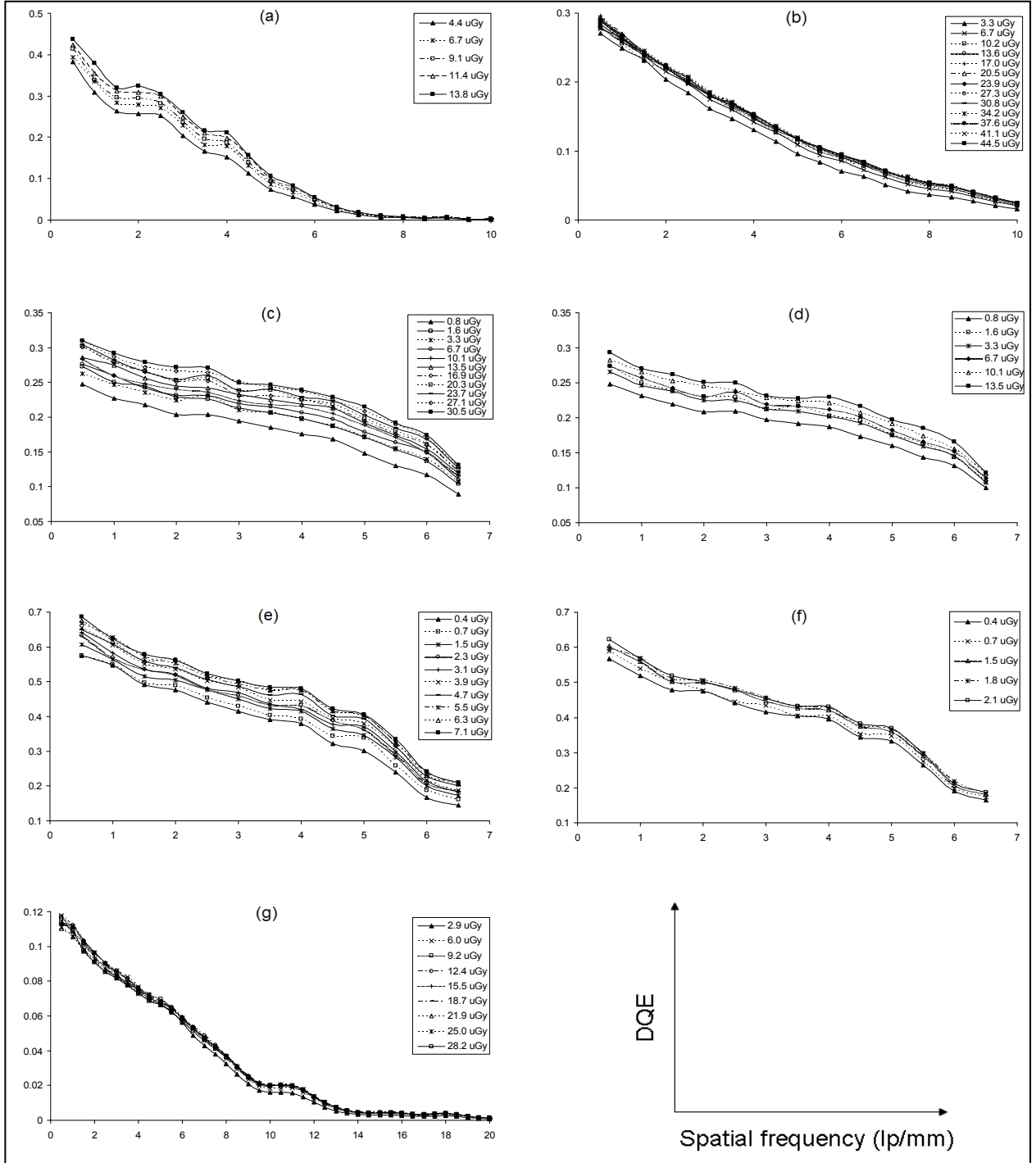


Figure 3.45: DQE curves at 74 kV for a) LAS, b) Hamamatsu, c) Dexela HFW and d) LFW (coupled to 150 μm CsI), e) Dexela HFW and f) LFW (coupled to 600 μm CsI) and g) RadEye detectors

Figure 3.46 presents the average DQE curves of the detectors using 74 kV. The Dexela detector using the thick scintillator appears the highest DQE values and the rest of the DQE curves are low (less than 0.4) due to the limited x-ray detectability of the thinner scintillators. LAS demonstrates moderate DQE values at low frequencies. At low spatial frequencies (less than 2.5 lp/mm), the DQE values of the Dexela detector using the thin scintillator are similar to the respective of Hamamatsu detector. RadEye detector shows very low DQE values, less than 0.12 at low frequencies.

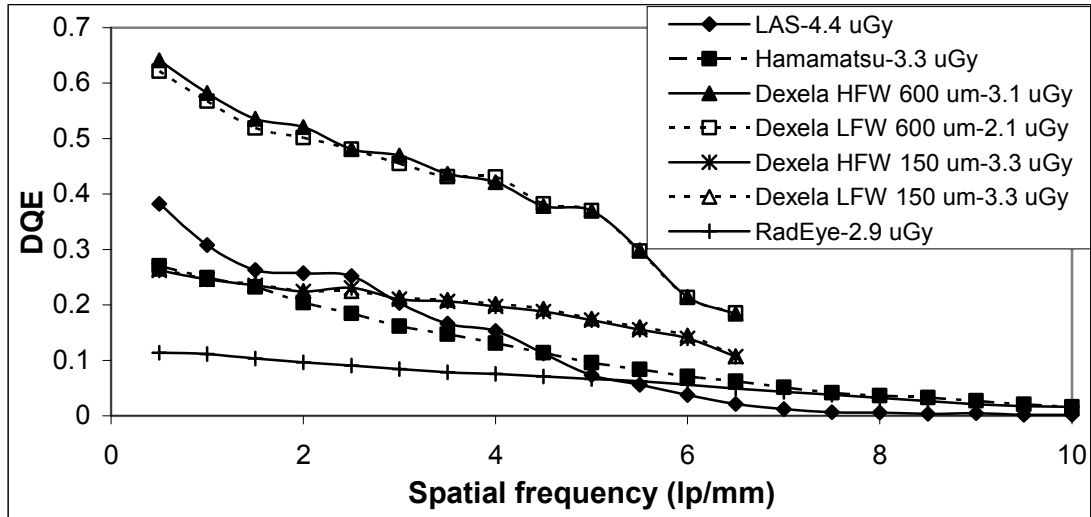


Figure 3.46: Average DQE curves of the investigated detectors at specific DAK levels and 74 kV

The x-ray performance of the Dexela detector using the thick scintillator is compared to five general radiography systems found in the literature (Lawinski *et al.*, 2005). The comparison is made under the same beam quality (RQA5) and presented in Table 3.13. Compared to other systems, the Dexela detector shows competitive spatial resolution and the highest DQE peak values. These results indicate high potential for use of this detector under general radiography conditions.

Table 3.13: Comparison of the x-ray performance of different detectors used in general radiography

System	Delft <i>ThoraScan</i>	GE <i>Revolution</i>	Hologic <i>DirectRay</i>	SwissRa <i>dOd</i>	Trixell <i>Pixium4600</i>	Dexela <i>2923</i>
Detector Technology	CCD	a-Si:H TFT	a-Se TFT	CCD	CCD	CMOS APS
X-ray absorber material	CsI:Tl	CsI:Tl	a-Se	CsI:Tl	CsI:Tl	CsI:Tl
Thickness of material (μm)	500	Undisclosed	500	600	550	600
Beam quality	RQA5 (70kV)	RQA5 (70kV)	RQA5 (70kV)	RQA5 (70kV)	RQA5 (70kV)	RQA5 (74kV)
MTF at 50% (lp/mm)	1.3	1.4	4.2	1.4	1.4	1.3
DQE peak at specific DAK level	0.43 at 4 μGy	0.61 at 4 μGy	0.39 at 4 μGy	0.39 at 4 μGy	0.63 at 4 μGy	0.66 (HFW) at 3.9 μGy

3.3.10 Additional study on dynamic imaging conditions (Dexela at RQA5 quality)

The capability of the Dexela detector to dynamically configure on-chip binning to be used in clinical applications requiring dynamic acquisitions, such as fluoroscopy or angiography, was investigated. Pixel binning leads to an increase in the acquisition speed from 26 fps to 86 fps for 4x4 binning mode. This comes at the price of reduced spatial resolution. To evaluate the performance of the detector at such low DAK levels, the tube current was kept constant in continuous operation mode (1mA) and the integration time was modified from 40 to 250 ms.

The following figure shows the STP curve for Dexela detector using 600 μm CsI and operated in the HFW mode for different binning modes. These data were acquired with beam type RQA5 for 1x1, 2x2 and 4x4 binning combinations. There was no significant difference in the detector gain: differences remained generally lower than 6% between full resolution (1x1) and 4x4 binning modes. The origin of the slight gain increase which is actually observed can be attributed to the increase of the dark current, which is linearly proportional to both pixel area and integration time. Pixel binning thus slightly affects the dark current mainly because the physical pixel size is increased (Miyata *et al.*, 2005). The R^2 in all three cases was equal to 1.

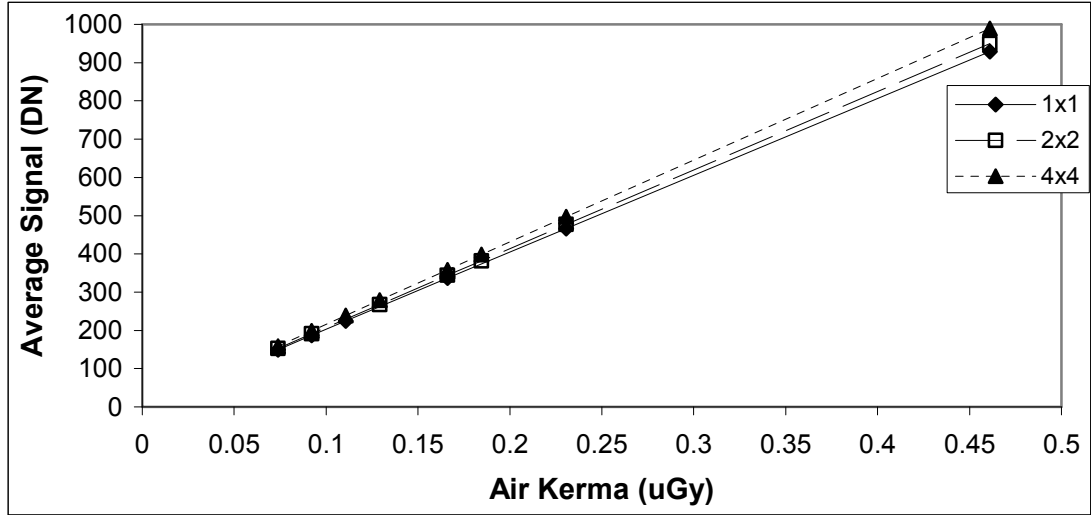


Figure 3.47: STP curves displayed at 74 kV for three binning modes in the HFW mode

Figure 3.48 presents the respective STP curve of Dexela detector operated in the LFW mode. In this case the sensitivity is almost 3 times higher due to the change of the conversion gain $G(\text{DN/e}^-)$. Again, a slight gain increase ($<6\%$) is observed due to the increase of the dark current. The R^2 of all STP curves was equal to 1 indicating perfect linearity on the signal transfer.

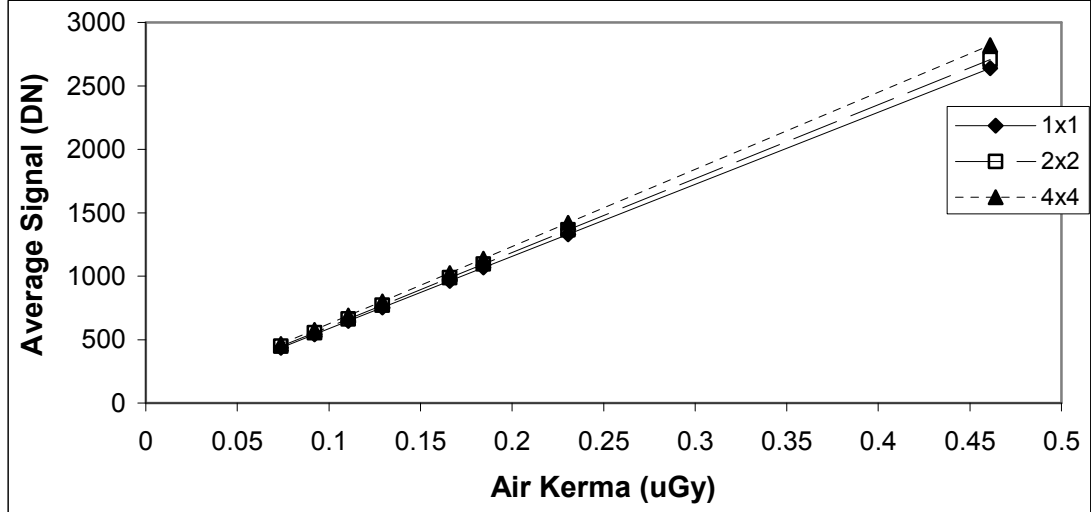


Figure 3.48: STP curves displayed at 74 kV for three binning modes in the LFW mode

Figure 3.49 demonstrates the average pMTF of Dexela detector for three binning modes, i.e. 1x1, 2x2 and 4x4. It is observed that the pMTF decreases as the pixel binning increases, i.e. the pMTF at a specific spatial frequency is higher at 1x1 binning mode. This decrease follows the sinc function. In other words, the ratio between the pMTF at 2x2 mode and the respective at 1x1 equals to the sinc function of the 2x2 binned pixel. The same effect is observed in the 4x4 binning mode case. Furthermore, a

study on the x-ray performance evaluation of an a-Si TFT detector for angiographic, radiographic and fluoroscopic imaging applications refers to this effect (Granfors *et al.*, 2003). This happens because the pixel binning averages the signal over a certain area of pixels, which corresponds to the convolution of the signal with the aperture function that represents the pixel. According the sampling theory this convolution in the spatial domain corresponds to multiplication with the sinc function in the frequency domain. Further details about this are given in section 4.3. On the other hand, the dependence of the NPS on the binning mode is more complicated due to the effect of aliasing. The presampling NPS is affected from the sinc function of the binned pixel. However, the measured digital NPS is the sum of the presampling NPS over aliases (Granfors *et al.*, 2003).

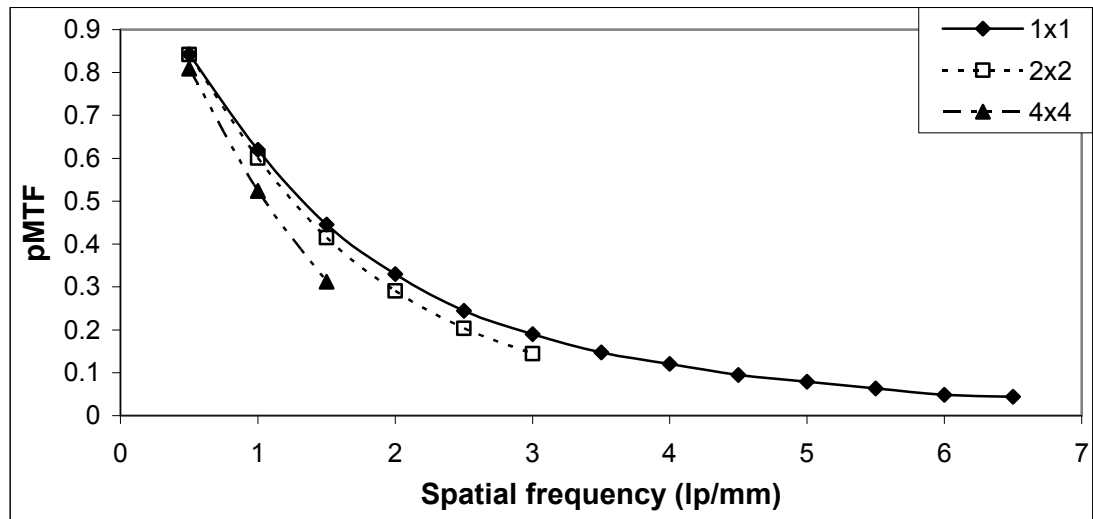


Figure 3.49: Average pMTF at 74 kV for three binning modes using 600 μm CsI:Tl

Figure 3.50 shows the DQE values of Dexela detector at low exposure levels (below 460 nGy) operated in both full well modes and two binning modes (1x1 and 2x2). The exposure range investigated in this case was between 70 to 460 nGy, which corresponds to the typical fluoroscopic range found in the literature (Rowlands and Yorkston, 2000b and Benítez *et al.*, 2009). When the detector is operated in the HFW mode and 1x1 binning mode (Figure 3.50a), the DQE at low frequencies is within a narrow range (e.g. the DQE(0.5) is in the range 0.56-0.59). However, it can be seen that at higher spatial frequencies the DQE increases as a function of the DAK level. This indicates that the shape of the DQE changes at higher frequencies as a function of the integration time used to get the required DAK levels. Probably this happens because the electronic noise (read noise and dark current) has a stronger effect at high frequencies in the HFW mode

operation. On the other hand, when the detector is operated in the LFW mode (Figure 3.50b) the DQE curves are different at low frequencies (e.g. the DQE(0.5) is in the range 0.59-0.64) and become almost identical above middle range frequencies (3 lp/mm). Probably in this case the electronic noise has a stronger effect at low frequencies. The same behaviour is observed when the detector is operated at 2x2 binning mode. In this case (Figure 3.50 c and d), the DQE values at 0.5 lp/mm are almost the same compared to the respective in 1x1 binning mode (Figure 3.50 a and b). This happens because the effect of the sinc function is insignificant at low frequencies. However, this effect is significant at higher frequencies. This is one of the reasons why the DQE values at 3 lp/mm are decreased when operated at 2x2 binning mode.

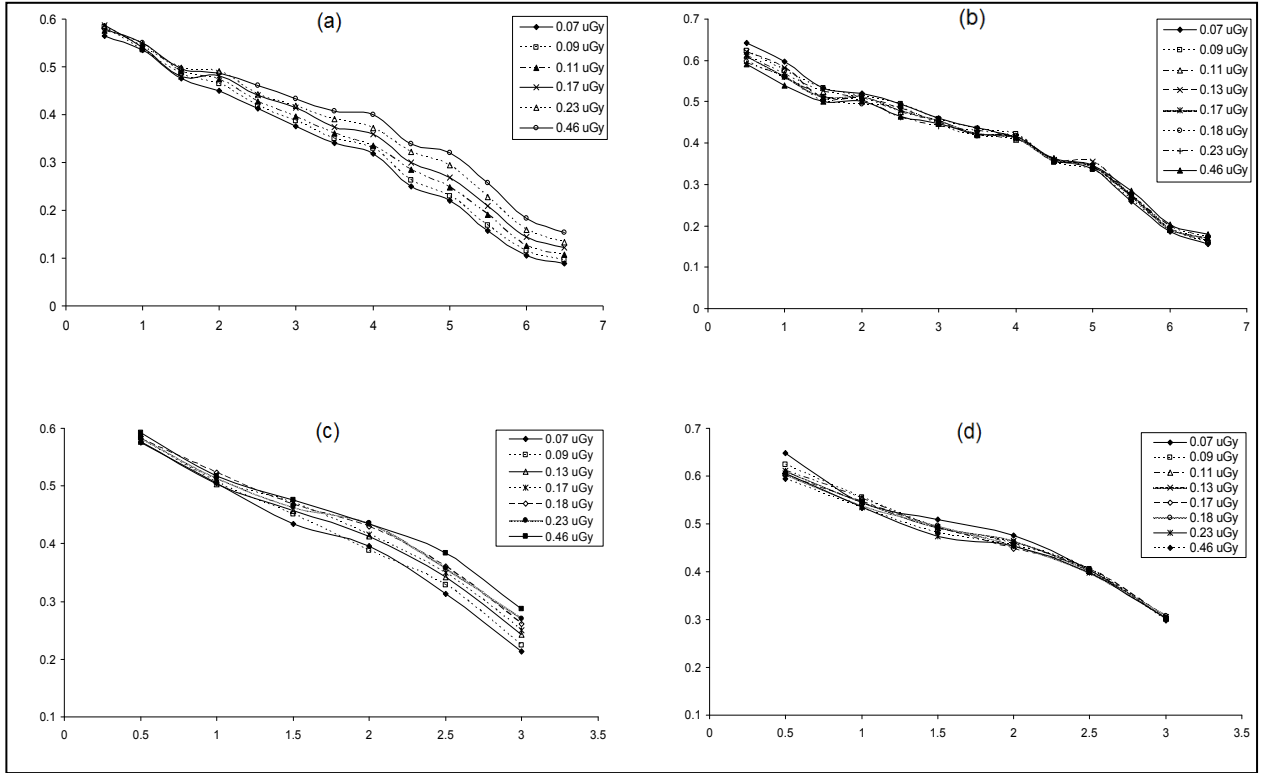


Figure 3.50: Average DQE values in the a) HFW mode and 1x1 binning mode b) LFW mode and 1x1 binning mode c) HFW mode and 2x2 binning mode and d) LFW mode and 2x2 binning mode

The DQE at 4x4 binning mode is not presented in this thesis as a function of the DAK level. Instead, the DQE response at this binning mode is compared to the other two binning modes at a specific DAK level (0.07 μGy). This level is the average exposure per frame in fluoroscopy and CB-CT. Figure 3.51 shows that the DQE curve

decreases as the binning of the pixels increases due to the decreased pMTF and the increased dark current.

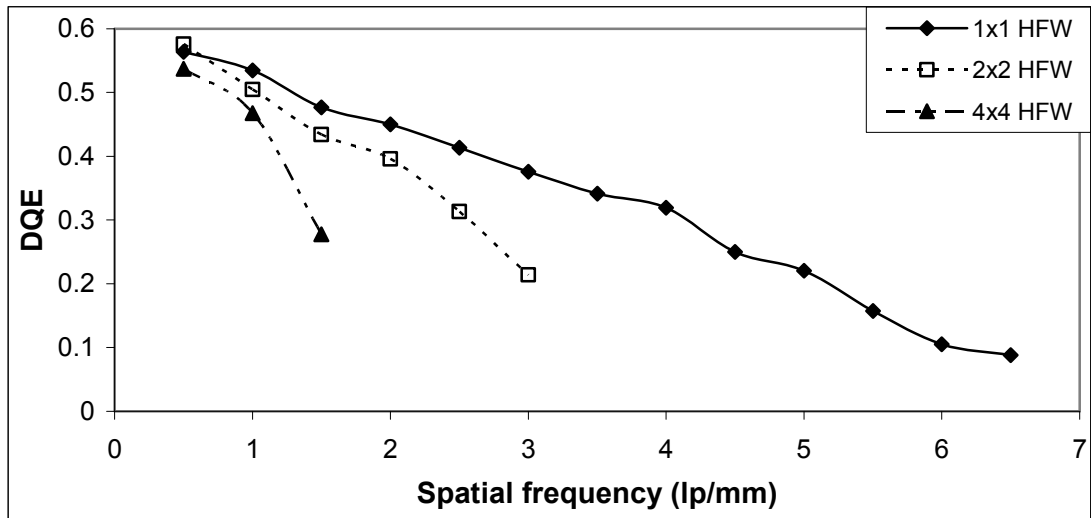


Figure 3.51: Average DQE in the HFW mode and 0.07 μGy (all binning modes)

Figure 3.52 presents the comparison between the three binning modes in the LFW operation mode and the same DAK level (0.07 μGy). It is observed that the DQE curves are slightly higher compared to the respective ones in the HFW mode due to the lower electronic noise that corresponds to the LFW mode.

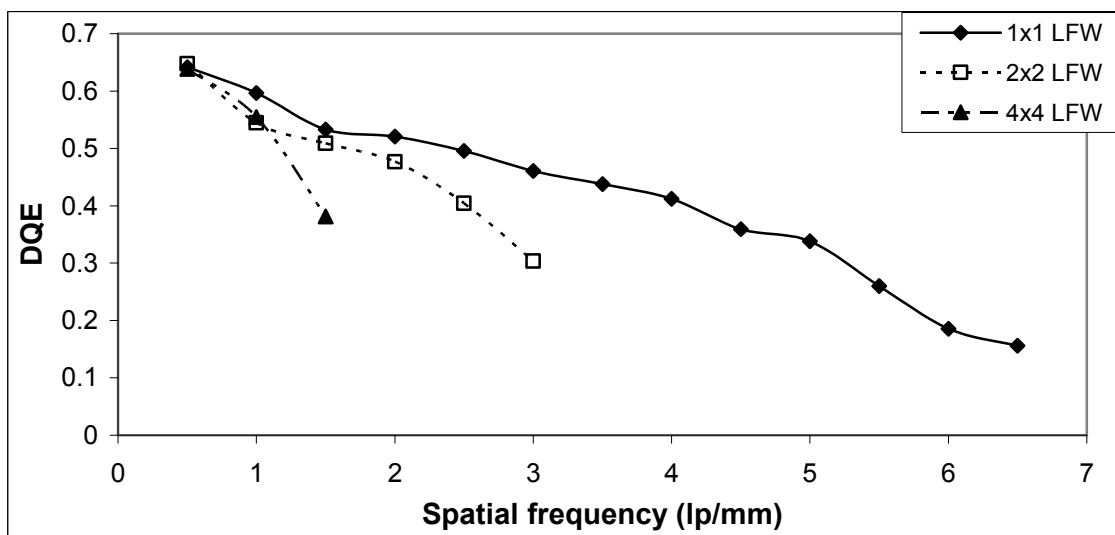


Figure 3.52: Average DQE in the LFW mode and 0.07 μGy (all binning modes)

Table 3.14 provides a comparison between the performance of the evaluated sensor and those of two commercial fluoroscopy and CB-CT systems available on the market (Benítez *et al.*, 2009). The 4x4 binning mode results in lower DQE values at specific frequencies compared to the other two binning modes. However high acquisition speed

(86 fps) and high DQE at low exposures (as well as possibly the lower data transfer rate) makes the 4x4 binning suitable for clinical application requiring high frame rate and high performance at low exposures while allowing some compromise in terms of resolution.

Table 3.14: Comparison of the x-ray performance of three detectors used in fluoroscopy

System	Varian <i>PaxScan</i> 2520	Varian <i>PaxScan</i> 4030CB	Dexela 2923
Detector technology	a-Si:H TFT	a-Si:H TFT	CMOS APS
X-ray absorber material	CsI:Tl	CsI:Tl	CsI:Tl
Pixel Size (2x2 binning)	254 μm	388 μm	300 μm
Beam quality	RQA5 (70 kV)	RQA5 (70 kV)	RQA5 (74 kV)
DQE peak at low exposure level	0.37 at 70 nGy	0.62 at 79 nGy	0.59; 0.65 (H; L) at 70 nGy

Detailed measurements on image lag (charge carry over into subsequent frames) were not performed due to the type of the current x-ray tube at UCL. Image lag would reduce the measured noise due to averaging of the uncorrelated noise between frames and hence increase the DQE. However, the analysis carried out on the flat images used for the DQE analysis allowed us to observe that the average DN fluctuated randomly over consecutive frames. This can be an indication of negligible additive image lag, as this would increase the average DN over consecutive frames (Granfors and Aufrichtig, 2000). Furthermore, the image lag of Dexela detector is expected to be small (less than 0.1 %) due to the crystalline Silicon of the used CMOS sensor. In conclusion, the Dexela detector is expected to show high performance in some advanced dynamic imaging techniques such as CB-CT, tomosynthesis and fluoroscopy, due to the high DQE results at low exposure levels under both full well modes.

3.3.11 The effect of nonlinearity on the DQE

According to the signal transfer theory (Cunningham, 2000), the x-ray detector needs to be linear and shift invariant in order to calculate the DQE (section 2.4.1). Based on this theory, the IEC standard (IEC 62220-1, 2003 and IEC 62220-1-2, 2007) recommends the linearization of gain and offset corrected images prior MTF and NPS calculation. This is mainly required for CR systems that have logarithmic response. In

particular, the IEC standard suggests the application of the inverse conversion function to the output data (in DN) on an individual pixel basis. The conversion function is the plot of the output signal (DN) of the x-ray detector versus the input exposure quanta per unit area Φ (x-rays/mm²) at the detector surface. The latter parameter is given by the product $(\Phi/K_a) \cdot K_a$ as mentioned in section 2.4.5. The IEC standard for linear detectors such as DR systems, recommends the application of a linear regression model to fit the data and determine the conversion function. According to the standard a detector may be considered linear if a) the final $R^2 \geq 0.99$ and b) the absolute difference (%) between the experimental data and the fitted ones is less than 2 % in all cases. Two x-ray performance characterization studies converted the original output images to input photons per unit area images, based on the IEC standard (Illers *et al.*, 2005 and Marshall, 2006b). However, since Φ is just the product of the fluence per exposure times exposure, a number of relative studies converted the output DN images to K_a images based on the STP curve which is the plot of the output DN versus the input DAK level. In particular, they used linear regression model to fit the experimental data for DR systems (Ranger *et al.*, 2007, Ghetti *et al.*, 2008, Samei *et al.*, 2008, Michail *et al.*, 2010 and Michail *et al.*, 2011) or both linear and logarithmic regression models for DR and CR systems respectively (Monnin *et al.*, 2005, Mackenzie and Honey, 2007, Marshall, 2007 and Monnin *et al.*, 2007). All these studies applied simple regression models without taking into account weighting factors or uncertainties on the measurements.

However, the DQE results may be affected by the presence of nonzero offset (i.e. interval) with significant magnitude on the linear regression model on the STP data. In particular, when the IEC linearization method was applied to the x-ray detectors in this study, we observed significant overestimation or underestimation of the DQE curves especially at low signal levels. Figure 3.53 shows the average DQE curves of RadEye detector at 28 kV after the IEC linearization of the original data. It can be seen that the DQE curve at the lowest DAK level (28.7 μ Gy) is very high (DQE(1)=0.95) and decreases as the DAK level increases. As mentioned in section 2.4.5, this behaviour is expected only in the presence of high magnitude FPN. However, this is not the case because gain correction was applied on the data prior linearization. Hence, since the x-ray photons are information carriers the increase of the DAK level is expected to lead to increased SNR and better image quality (Cunningham, 2000). A comparison between

the DQE curves at specific DAK levels that correspond to the linearized and the original data showed that the overestimation is independent of the spatial frequency and decreases as the signal level increases. In particular, the linearized DQE curves are overestimated by 158.6 % at 28.7 μGy and 9.2 % at 306.0 μGy . A similar behaviour is observed in Michail *et al.* (2010 and 2011) studies which examined the same chip under RQA-M2 (Mo/Mo at 28 kV) and RQA5 (W/Al at 70 kV) beam qualities. They applied the IEC linearization on the original data based on the linear regression model extracted from the STP data. They found DQE(1) values equal to around 0.90 at 20.29 μGy and 0.72 at 40.07 μGy using the RQA-M2 beam quality. For the RQA5 quality they found the respective DQE(1) values to be around 0.78 at 11.1 μGy , 0.65 at 34.3 μGy and 0.43 at 87.41 μGy . This behaviour verifies the suspicion that an unoptimized IEC linearization may overestimate or underestimate the noise compared to the signal.

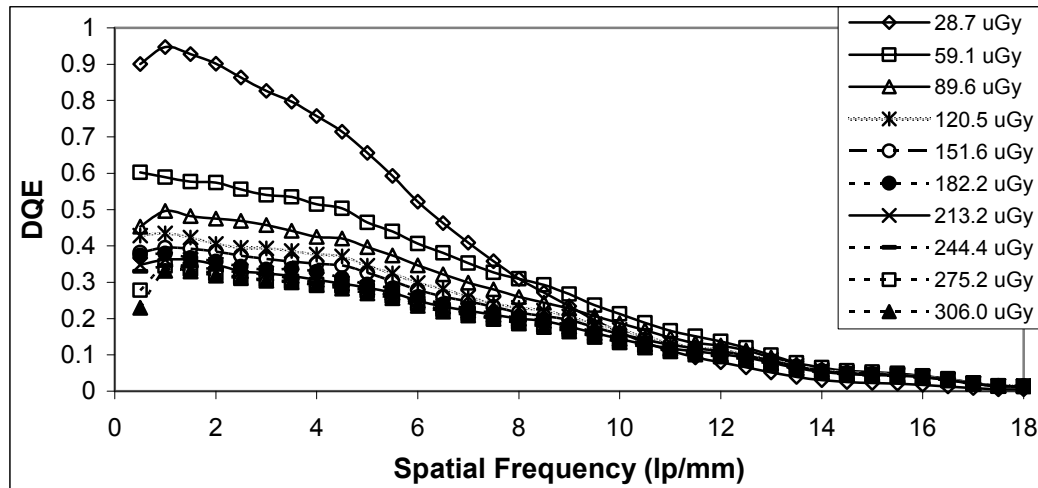


Figure 3.53: Average DQE of the RadEye detector at 28 kV using the IEC linearization method

In this case, probably the overestimation occurs due to the fact that the intercept of RadEye detector's STP curve is negative with significant magnitude compared to low signal levels (see Figure 3.30). During the linearization process, the intercept of the STP curve is subtracted from the original image and the result is divided by the slope of the STP curve. The division by a constant does not modify the ratio between the signal and the standard deviation compared to the original respective ratio. However, a high intercept compared to the slope adds (or subtracts if it is positive) a constant value on the already converted image with the same SNR ratio as before. This leads to higher signal compared to noise, i.e. higher SNR in spatial domain or DQE in frequency domain. This constant number is comparable to the low signal levels, leading to higher

overestimation of the SNR as the signal decreases. A high intercept may arise from unoptimized gain and offset correction method or from the presence of nonlinearity. A specific kind of nonlinearity with “sigmoid-like” shape is observed on RadEye detectors, which results in nonlinear behaviour at very low and very high signal levels. A couple of studies recommend a simple (Rad-icon Imaging Corp., 2003) or a piecewise (Cao and Peter, 2008) second order polynomial gain correction to linearize the signal transfer of RadEye detectors. The simple polynomial gain correction was tested during this study and it was found to improve the R^2 from 0.9982 to 0.9999. However, it resulted in unexpected DQE results as a function of the DAK levels because it modified the SNR at each signal level. Therefore, this method was not applied to the x-ray performance evaluation analysis.

Figure 3.54 shows that the IEC linearization method considerably underestimates the low signal DQE curves of the Dexela detector in the HFW mode and 28 kV. This happens due to the high magnitude of the positive intercept of the STP curve (see Figure 3.29) which leads to underestimation of the SNR for the reasons mentioned above. More specifically, the maximum underestimation (59.4 %) is observed at 7.1 μGy and the minimum (2.6 %) at 215.1 μGy . An attempt was made to linearize the signal transfer of the Dexela detector by applying a sectional linear approximation method (Naday, 2010b). As in the case of RadEye detector, this method linearized the signal transfer ($R^2=1$) at the expense of unexpected DQE results as a function of the DAK levels due to SNR modification.

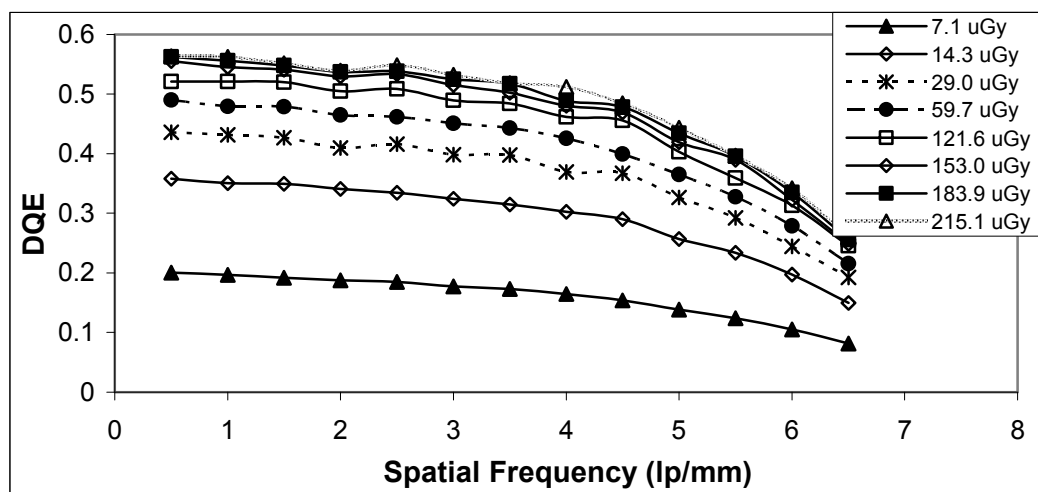


Figure 3.54: Average DQE of the Dexela in HFW and 28 kV using the IEC linearization method

On the other hand, the IEC linearization process does not significantly affect the DQE curves of the Hamamatsu detector at 28 kV (Figure 3.55). Figure 3.29 demonstrates the linear signal transfer behaviour ($R^2=1$) and relatively small intercept compared to the slope. However, it slightly overestimates the DQE curves due to the negative intercept, as in RadEye case. In particular, the maximum underestimation (4.8 %) is observed at 28.7 μGy and the minimum (0.3 %) at 398.3 μGy .

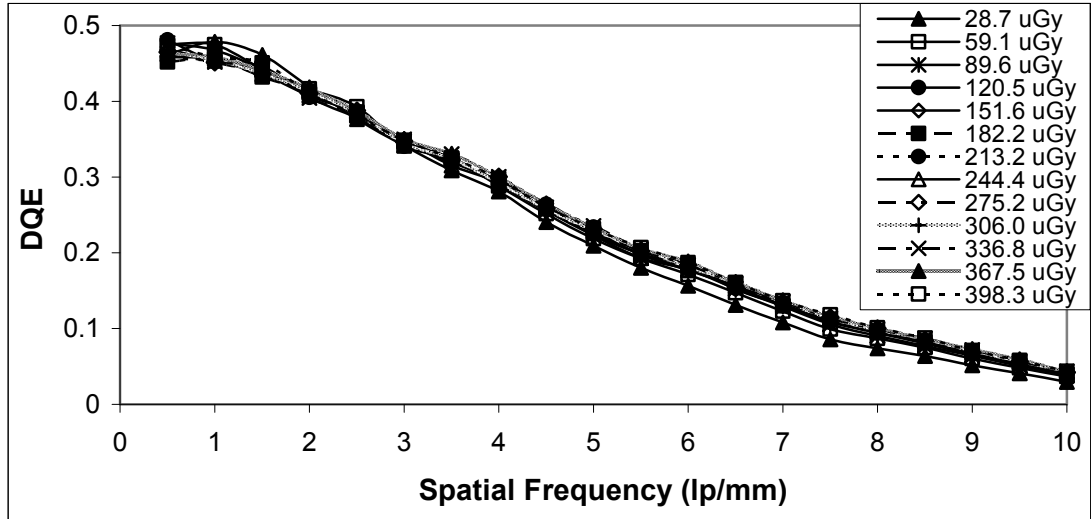


Figure 3.55: Average DQE of the Hamamatsu detector at 28 kV using the IEC linearization method

The above results demonstrate that any linearization method needs to be applied carefully on the raw data (especially at low signal levels) prior the DQE or SNR evaluation in order to minimize the linearization errors. For example, a polynomial or weighted fit could be used on the STP curve to convert the data instead of the simple linear regression one. Another solution is to ignore the data that present non linear behaviour. Finally, one can put a slope of one and intercept of zero on the linear fit to keep the original data. A non optimized method can easily modify the real SNR relationship leading to erroneous DQE results.

Additionally, it is observed that only the Hamamatsu and Anrad detectors show a quantum limited behaviour as a function of the input DAK level (Figure 3.35 b and e). More specifically, their DQE values increase as a function of DAK up to a particular level due to the effect of read noise. At higher signal levels they are independent of the DAK level, showing a quantum limited behaviour. On the other hand, LAS, Dexela and RadEye detectors show slightly different behaviour (Figure 3.35 a, c, d and f respectively). The former detector presents unusual DQE curves as a function of DAK

(decreasing at low frequencies and increasing up to a point at higher ones) probably due to the “sigmoid-like” nonlinearity. The DQE curves of the other two detectors continue to increase as a function of DAK level even at very high signal levels. LAS does not present a quantum limited behaviour, while the Dexela detector shows an almost quantum limited behaviour at signals higher than 75 % of dynamic range. Figure 3.56 shows the mean-variance relationship extracted from the flat images used for the DQE calculation of the Dexela detector at 28 kV and in the HFW mode. It can be seen that the relationship between variance and mean signal decreases as the signal level increases. The dashed curve corresponds to extrapolated variance values based on the linear regression fit of the first three experimental points. A comparison between the extrapolated and the actual points results in a difference of up to 19.1 %. Since the variance is directly related to the NPS (Eq. (2.29)), the DQE is expected to increase as the signal level increases. On the other hand, the relative difference between the extrapolated and the actual mean-variance points for the Hamamatsu detector is less than 1.9 %.

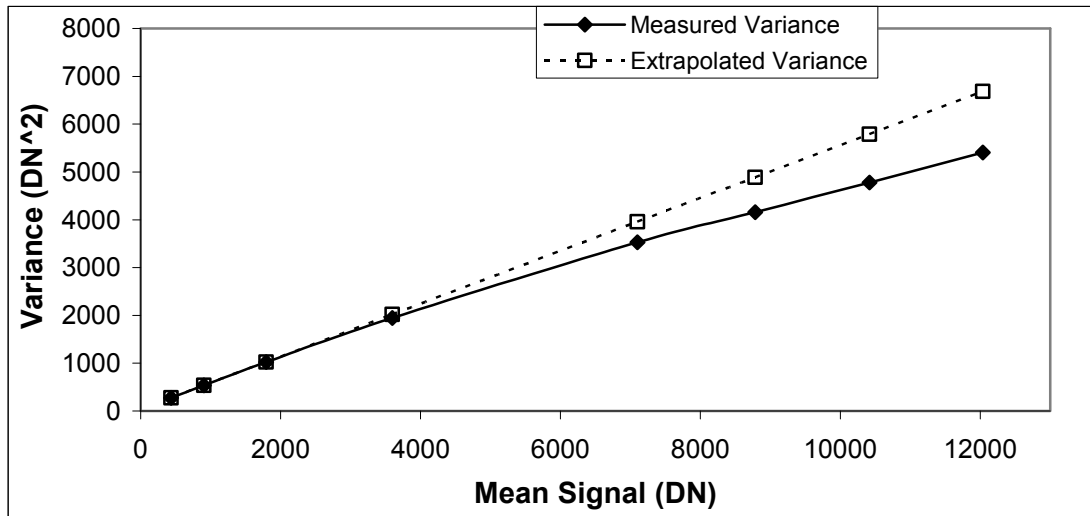


Figure 3.56: Mean-Variance relationship of the Dexela detector in HFW and 28 kV

This performance is expected to extend in some CMOS APS sensors. Tian *et al.* (2001) mention that the V/e^- nonlinearity decreases both signal and noise in CMOS APS as the illumination (signal) level increases. However, it improves the SNR at higher signal levels because it has a stronger effect on the noise. They described mathematically how the varying capacitance of the photodiode affects both the signal and noise and they proved it experimentally. This behaviour is also mentioned in studies related to the optical evaluation of CMOS APS sensors, where they observed that the

slopes of the PTC curves were less than 0.5 at higher signals (Janesick *et al.*, 2006, Janesick, 2007, Arvanitis, 2007 and Bohndiek *et al.*, 2008a; see section 2.3.4). To confirm the above, the slope of the standard deviation versus the mean signal plot (which is practically equal to the PTC) on logarithmic scale was compared for Hamamatsu, Dexela and LAS detectors. This slope for the Hamamatsu detector was 0.483 ± 0.001 , indicating a slight deviation from linearity. The slope for LAS was 0.370 ± 0.009 , indicating strong deviation from linearity. Finally, this slope for the Dexela detector was 0.451 ± 0.004 in the HFW mode and 0.476 ± 0.004 in the LFW mode respectively. This indicates that the effect of nonlinearity is lower when the detector is operated in the LFW mode and justifies the lower discrepancy of the DQE curves as a function the DAK observed at this mode. The same behaviour was extracted from the electro-optical evaluation of the Dexela sensor (section 3.2.5).

Finally, image simulation was performed to further demonstrate the effect of nonlinearity on the DQE curves of the Dexela detector at 74 kV using the thick scintillator and operated in 1x1 binning mode. To implement this simulation, synthetic flat images were constructed with perfect SNR transfer based on the methodology described in the following chapter. Briefly, for both HFW and LFW modes the NNPS was calculated at the lowest DAK level (0.4 μGy in both cases) assuming that the effects of V/e^- nonlinearity and read noise are negligible. The mean and the standard deviation of the experimentally captured flat images at this level were calculated and assuming zero intercept the mean was extrapolated at higher DAK levels based on the mean-DAK relationship at 0.4 μGy . To get a slope of 0.5 between standard deviation and mean (on logarithmic scale) the measured standard deviation (std) was extracted with a ratio equal to the square root of the ratio of the means, i.e. $\text{std}(\text{DAK}_2) = \sqrt{\text{mean}(\text{DAK}_2)/\text{mean}(\text{DAK}_1)} \cdot \text{std}(\text{DAK}_1)$ where the numbers 1 and 2 correspond to two different signal and DAK levels. Next, the standard deviation-to-mean ratio at different DAK levels was calculated and used to create simulated flat images at different DAK levels. This was based on Saunders and Samei (2003) methodology, assuming that the spectral distribution of the NNPS is independent of the DAK level. The following figure shows the DQE curves of the Dexela detector extracted from the synthetic flat images at a) HFW and b) LFW respectively. Perfect overlapping of the curves can be seen. Also, there is a small deviation of the spectral shapes between the two full well modes.

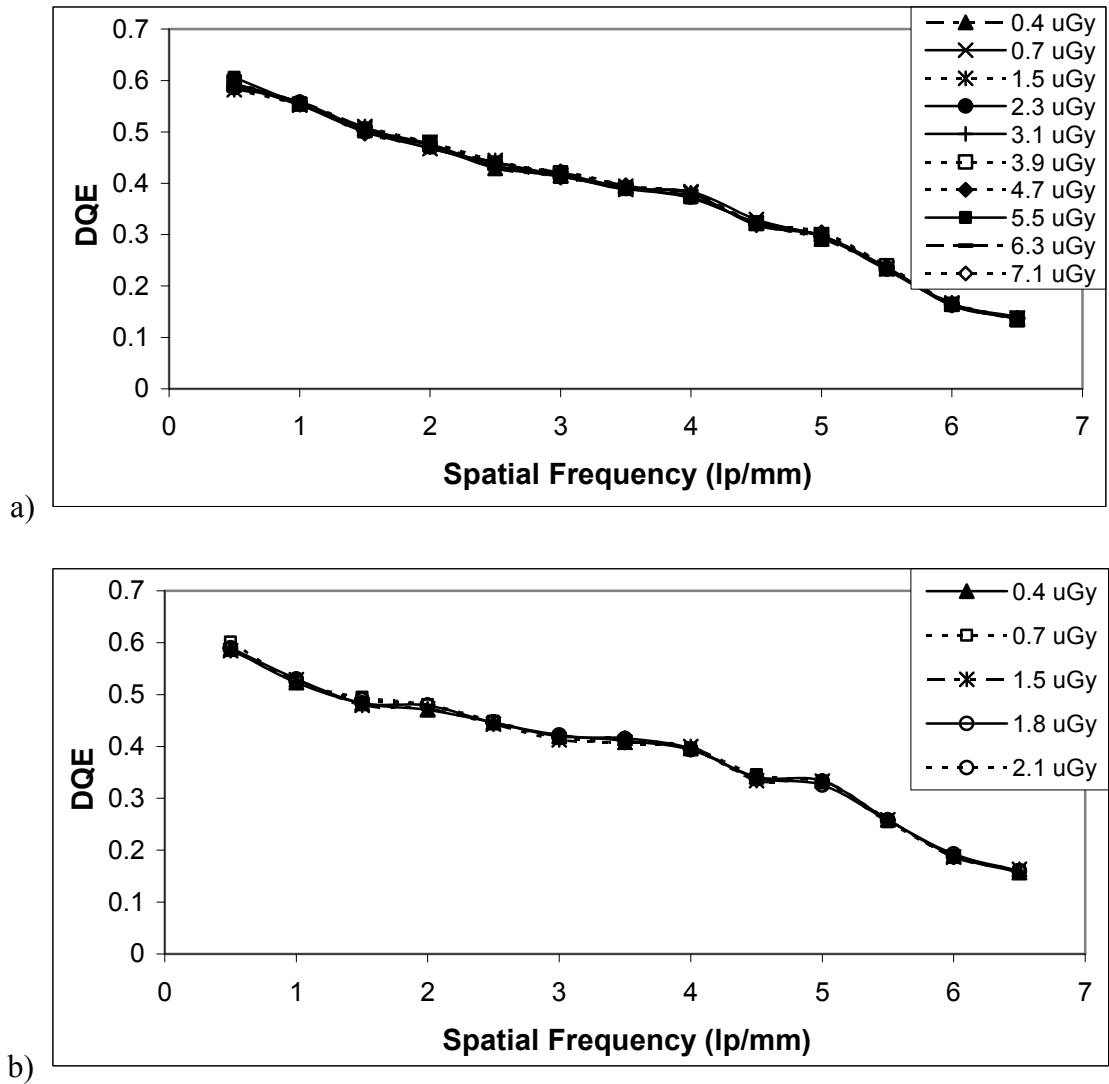


Figure 3.57: DQE curves of synthetic flat images with linear SNR transfer for a) HFW and b) LFW

Next, the experimentally measured SNR relationship as a function of DAK was combined with the measured NNPS at 0.4 uGy (lowest DAK level) in order to check if the nonlinearity is the only origin of the DQE curves' spread. Figure 3.58 shows the respective DQE curves at a) HFW and b) LFW modes. These curves are slightly different compared to the original ones (Figure 3.45 c and d) probably due to the fact that the spectral distribution actually depends on the DAK level. However, the same amount of spread is observed compared to the experimentally measured curves.

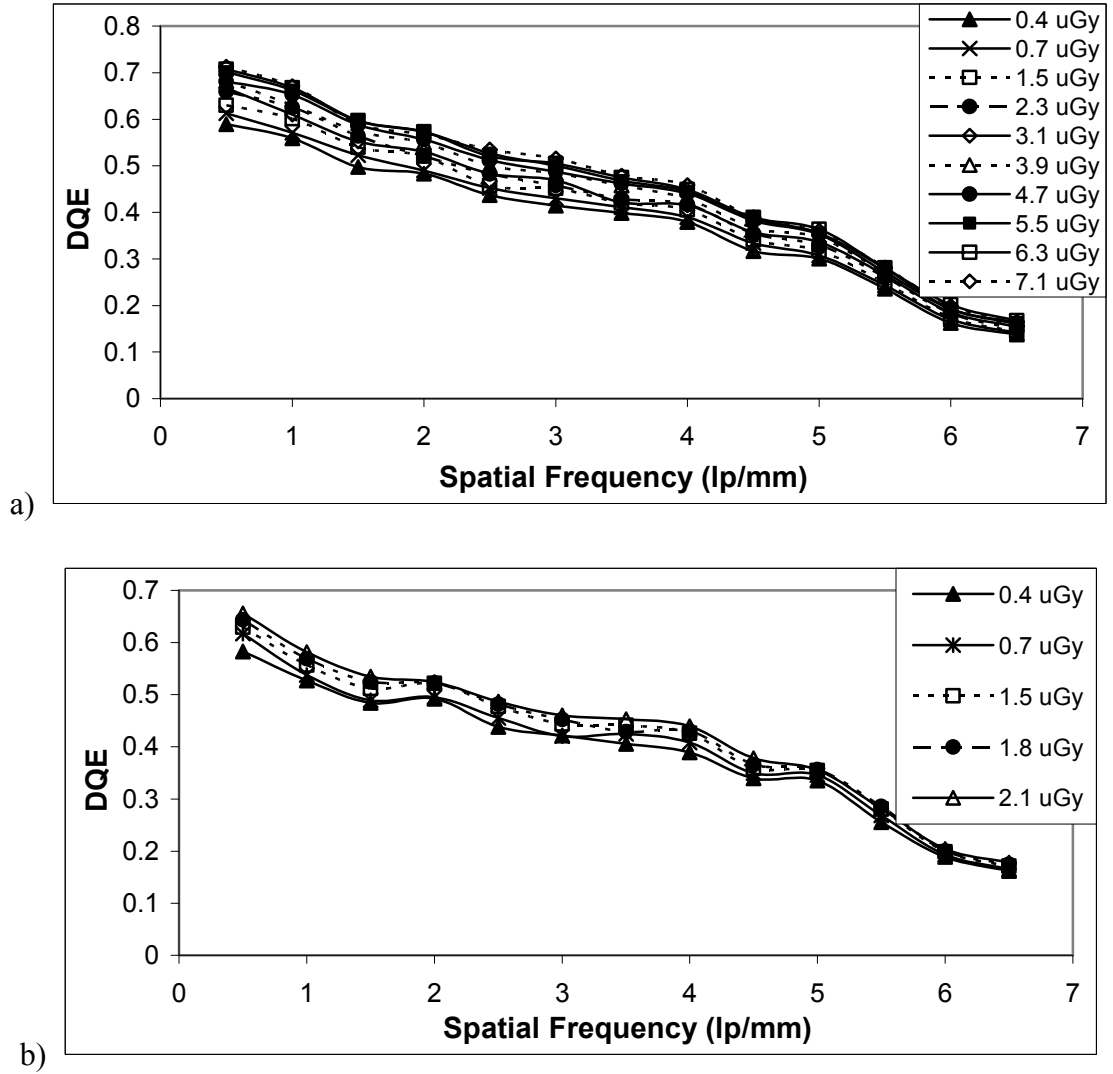


Figure 3.58: DQE curves of synthetic flat images with measured SNR transfer for a) HFW and b) LFW modes

3.4 Summary

This chapter presents the experimentally measured results from the electro-optical and x-ray performance evaluation of the investigated detectors. In particular, the PTC, MV and NLC methods have been used for the electro-optical evaluation of LAS and Dexela sensors. Both of them demonstrate low read noise. It is found that the EMI noise overestimated the calculated read noise by 42 %. The dynamic range of LAS is relatively low (around 63 dB), whilst that of the Dexela in the HFW mode is comparative to other detectors (almost 73 dB). The x-ray performance of all investigated x-ray detectors has been made in 28, 52 and 74 kV using W/Al combination. Both LAS and Dexela detectors demonstrate high DQE results at low

DAK levels, which is an important requirement for adequate image quality. The Dexela CMOS x-ray detector has been further evaluated for W/Rh at 25 kV and under fluoroscopic conditions at 74 kV. In both cases it demonstrates high DQE values. A novel gain and offset correction method that requires a minimum number of reference flat frames has been used. A single reference flat frame can be used for the x-ray performance evaluation. Finally, the effect of the CMOS APS detectors inherent nonlinearity on the DQE values has been investigated. In particular, Hamamatsu detector demonstrates quantum limited behaviour due to its marginal nonlinearity. The inherent nonlinearity of LAS, Dexela and RadEye CMOS APS affect their DQE values as a function of the DAK level.

Chapter 4

4 Image simulation based on the empirical x-ray performance evaluation

4.1 Overview of chapter

Image simulation based on the measured x-ray performance parameters was performed in order to investigate the effect of the signal and noise transfer (pMTF and NNPS respectively) on the associated radiographs. This chapter presents the image simulation methodology and validates the simulated signal and noise transfer. Finally, the software phantoms used as input data in the simulation algorithm are presented.

4.2 Motivation and implementation of the image simulation method

The objective x-ray performance evaluation of an x-ray detector (pMTF, NNPS and DQE) allows a quantitative comparison between different radiographic systems. However, this method does not involve the radiologists, the technicians or the patients. There is a significant debate on whether a decreased spatial resolution (pMTF) presents a lower effect on extracted diagnostic information than increased noise (NNPS) and vice versa (Tingberg *et al.* 2002, Saunders *et al.* 2004 and Saunders *et al.* 2007). A detector may be superior in one metric while being inferior in another. In this case it is unclear which metric has got a higher impact on specific clinical tasks, because the diagnostic information depends on the x-ray (beam quality and DAK level), object (size of the investigated object, the effect of the background, etc.) and conditions (Saunders and Samei, 2003 and Saunders *et al.* 2007). Furthermore, even when a system has superior signal and noise transfer compared to another, the quantitative difference in terms of image quality is unknown (Saunders and Samei, 2003).

An image simulation study based on the empirical x-ray performance evaluation quantifies the impact of the x-ray performance parameters on the appearance of the

radiographic images. Also, it gives the ability to predict the image quality of the digital x-ray detectors at different x-ray conditions and various combinations of spatial resolution and noise characteristics (Tingberg *et al.*, 2002). This prediction gives the ability to optimize the conditions in order to get high image quality parameters and at simultaneously reduce the required time and cost. More specifically, simulation of the x-ray detector's signal and noise transfer (pMTF and NNPS) at specific x-ray conditions is used to produce synthetic radiographic images. Image quality parameters, such as contrast-to-noise ratio (CNR), signal-difference-to-noise-ratio (SDNR), SNR and contrast-detail (CD), can be extracted from these synthetic images. In this case objective x-ray measurements are used to predict the subsequent subjective image quality measurements.

A first attempt to create synthetic radiographic images based on the empirical x-ray performance parameters of a digital x-ray detector was made in 1999 (Bochud *et al.*, 1999a). In this study they inserted the measured power spectrum from mammograms and angiograms captured from digital x-ray units. Then they modified the power and phase spectra to investigate the role of stationarity on the detection performance in patient structured images. The response of a stationary (or shift invariant) system to an input signal is the same at all locations relative to the pixel array (see section 2.4.1). Another study was made in the next year to investigate the influence of the various system noise components on the image quality (Bruijns *et al.*, 2000). In this study they inserted the empirically measured MTF of a digital system (a-Si:H TFT) and they simulated the main noise components (read, shot, FPN and quantization noise) based on the nominal design specifications of the digital detector. Furthermore, Moy (2000b) combined the experimentally measured MTF with a white noise image consisted of quantum noise with Gaussian fluctuation and electronic noise. This study was made to demonstrate that the spatial resolution of a digital detector can be reliably described by the DQE parameter instead of the MTF, in the presence of noise, parallax and blurring. However, this study did not take into account the NNPS noise correlation. The first study that creates synthetic radiographic images based solely on the measured signal and noise transfer was made by Tingberg *et al.* (2002). In this study they created for each patient synthetic radiographic images with different combinations of MTF and NPS to simulate various screen-film systems which were not necessarily available on the market. The main object of the study was to investigate the relative importance of

the spatial resolution and noise on the image quality from the observer point of view. However, they do not give any kind of detail about the simulation algorithm. Saunders and Samei (2003) wrote a paper based on the previous studies (Bochud *et al.*, 1999a and Tingberg *et al.*, 2002) where they describe in detail the simulation algorithm to create synthetic radiographic images based on the measured pMTF and NPS of digital detectors. The aim of this study was to present a methodology that allows independent modification of the spatial resolution and noise characteristics for a given image based on the MTF and NPS. These modifications allow someone to quickly model the effect of various configurations of these parameters on the appearance of a radiographic image.

Many studies were based on the Saunders and Samei (2003) work to create synthetic radiographic images. In particular, Chawla *et al.* (2006, 2007, 2008a, 2008b and 2009) applied a noise modification routine to add synthetic radiographic noise to clinically acquired mammograms and breast tomosynthesis images in order to predict the noise appearance on radiographic images that correspond to reduced dose levels. Zhou *et al.* (2007) created synthetic tomosynthesis images to predict the imaging performance of a breast tomosynthesis system (Anrad LMAM a-Se TFT detector) with different detector properties and imaging geometry (such as focal spot blur (FSB) which depends on the x-ray tube motion, source-detector movement speed, view angle, exposure time, pixel binning, etc.) to optimize these parameters before building the system. Also, they investigated the effect of two image reconstruction algorithms (namely expectation maximization (EM) and filtered back projection (FBM)) on the synthetic tomosynthesis images. In this study they used empirically measured pMTF and NPS values described in Zhao *et al.* (2003). Then they modified the pMTF with an optional FSB function and they used the resultant values to blur super-sampled “analog” synthetic images. After that they modified three detector properties (i.e. the x-ray conversion of a-Se, the thickness of the blocking layers and the electronic noise) using a cascaded linear system model (Cunningham, 1998, Cunningham and Shaw, 1999, Cunningham, 2000 and Zhao *et al.* (2003)) until the calculated and measured DQE at different exposure levels agree. After the determination of the above three detector properties they used the cascaded linear system model for the detector to produce NPS for a given x-ray dose. Then they used the predicted NPS at various DAK levels to introduce the noise on the synthetically blurred tomosynthesis images. They did not use the experimentally

measured SNR relationship (given from the average signal intensity and the noise variance) to rescale the NPS at different DAK levels as Saunders and Samei (2003) suggest. They do not explain the reasons for this. On the other hand, Yip *et al.* (2007, 2008, 2009 and 2010a) combined the Saunders and Samei (2003) methodology with experimentally measured pMTF and NPS in order to assess the effect of the x-ray performance parameters on the clinical outcomes. To implement this they created a super-sampled synthetic CDMAM phantom image and they applied to this different signal and noise transfer of various digital detectors in a range of DAK levels. CDMAM phantoms are used to assess the contrast-detail performance of mammography systems utilizing small size and low contrast disc details (see section 1.9.2).

Alternative image simulation studies based on the signal and noise transfer characteristics were made by Carton *et al.* (2005), Workman (2005), Båth *et al.* (2005) and Li and Dobbins III (2007). In particular, Carton *et al.* (2005) inserted noise, scatter and flat-field nonuniformities on ideal synthetic edge images with a known MTF. The aim of this study was to quantify the effect of the nonuniformities on the accuracy of the MTF. They inserted experimentally measured NNPS on the ideal synthetic edge images and they rescaled the noise level based on the experimentally determined SNR relationship at different DAK levels. They refer to the work of Bochud *et al.* (1999b) and therefore used a similar NNPS simulation methodology compared to the one described in Saunders and Samei (2003) study. Their novel work in terms of the noise simulation was the NNPS rescaling methodology which again is similar to the one presented in Saunders and Samei (2003). Workman (2005) presents a simulation methodology similar to the ones presented in Saunders and Samei (2003) and Carton *et al.* (2005). However, this study does not refer to any of the aforementioned studies probably because it was made almost simultaneously to the Saunders and Samei (2003) and Carton *et al.* (2005) studies. A disadvantage of this study is that it does not describe in detail the simulation algorithm. Båth *et al.* (2005) presented a novel simulation algorithm. They mention that Saunders and Samei (2003) method requires ideal original images that are noise free and that it assumes to have radially symmetric (isotropic) imaging properties. Their method can be applied to images already containing noise, making it suitable for clinically collected images. Also, it takes into account the full 2-D imaging properties of the system, based on 2-D pMTF (Båth *et al.*, 2001 and Fetterly *et al.*, 2002) and DQE (Båth *et al.*, 2003b) characterization studies. The suggested method

by Båth *et al.* (2005) was suitably modified for breast tomosynthesis conditions to simulate dose reduction in noisy clinical tomosynthesis projection images collected at different angles (Svalkvist and Båth, 2010). Finally, Li and Dobbins III (2007) present another method to rescale the noise of clinically acquired images at different dose levels. Their aim was the simulation of the dose reduction in chest tomosynthesis. Nevertheless, they assume isotropic imaging properties.

Recent studies have been based on the aforementioned image simulation algorithms. For instance, the Saunders *et al.* (2007) study is based on Saunders and Samei (2003) method to thoroughly examine the effects of spatial resolution and noise on the detectability of microcalcifications and discrimination of benign and malignant masses. Richard and Samei (2010a and 2010b) studies are based on Saunders and Samei (2003) method to provide a methodology for predicting the performance of quantitative imaging systems from the basic x-ray performance parameters (MTF and NPS). Smans *et al.* (2010) combined their Monte Carlo simulated CDRAD images to the signal and noise transfer of digital x-ray detectors based on both Saunders and Samei (2003) and Carton *et al.* (2005) methods. Their aim was the development of a computer model to simulate the image acquisition for two CR detectors used for neonatal chest imaging. Finally, Mackenzie *et al.* (2010) study is based on Båth *et al.* (2005) method to introduce a methodology to convert an image acquired from an a-Se TFT detector (DR) to appear as a generic CR image. Their ultimate aim is to apply their suggested methodology to a set of clinical images captured using DR technology to compare the performance of DR and CR systems for the detection of cancers at several dose levels.

In this thesis a modified version of Saunders and Samei (2003) method was used in order to compare the performance of the investigated detectors in digital mammography using ideal software phantoms (see section 4.6). Once the feasibility of the combined methodology is demonstrated, the simulation algorithm can be used for different x-ray imaging applications. Figure 4.1 shows the flowchart of the implementation of the signal and noise transfer on ideal images to get the synthetic radiographic images. Briefly, the 2-D pMTF matrix of a digital x-ray detector is multiplied with an ideal input image in the frequency domain in order to insert blurring. Then an inverse Fourier transform is applied on the product and the blurred image is sampled to form the pixels of the digital image. The measured NNPS distribution is used to create a flat image with noise. This noise image is rescaled at specific DAK level and added to the blurred and

sampled object image. In this study three modifications were made on the signal transfer simulation (or modification routine; Konstantinidis *et al.*, 2011a). Further details about the signal and noise modification routines are given in sections 4.3 and 4.4. All image simulation algorithms were developed using custom built software written in MATLAB version 7.10 (The MathWorks, Natick, MA, USA).

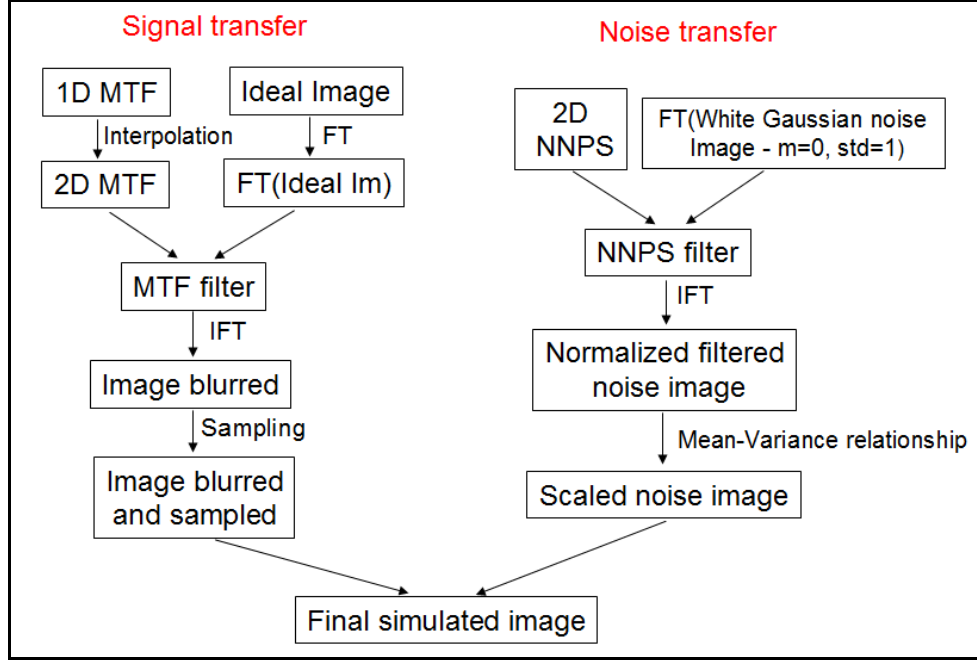


Figure 4.1: Flowchart of the image simulation algorithm

4.3 Simulation of the signal transfer (pMTF)

To apply the spatial resolution of a digital x-ray detector to an ideal input image, the pMTF of the detector is required. Figure 4.2 shows the horizontal, vertical and average pMTF of the Dexela CMOS x-ray detector (using 150 μm CsI:Tl at 28 kV) up to 70.7 lp/mm frequency. This frequency value is calculated from the pitch of the ideal “analog” image, prior to the detector’s digital sampling. In this thesis the “analog” pitch of the ideal input image equals to 10 μm , which corresponds to F_{Nyq} equal to 50 lp/mm. This particular input pitch was used in all image simulations in this study to avoid aliasing effects. Furthermore, it results in a sufficient number of pixels to avoid system crashes from excessive RAM memory use during the simulation process. All the simulations were carried out using a desktop pc with 16 GB RAM memory. According to the trigonometric theory the maximum frequency in a diagonal orientation (i.e. 45°) equals to $\sqrt{2} \cdot F_{Nyq}$, i.e. 70.7 lp/mm in this case.

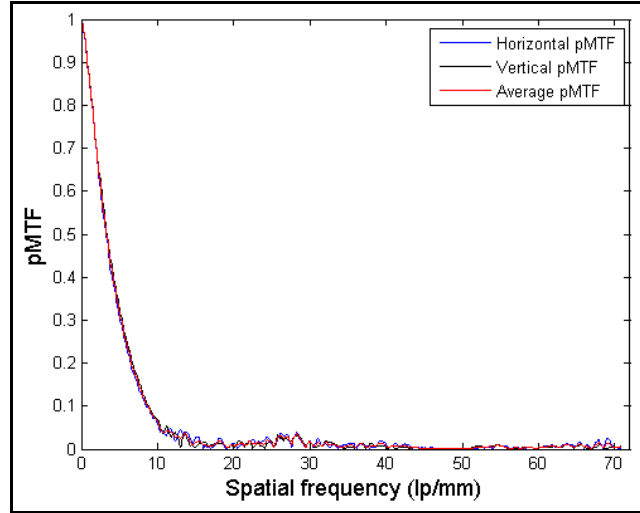


Figure 4.2: pMTF of the Dexela CMOS x-ray detector used in the simulation algorithm

Next, a high (at least 9th) order polynomial fit is applied on the original average pMTF values in order to expand the 1-D pMTF to a 2-D matrix. In this thesis a 22nd order polynomial fit was used to preserve the high frequency pMTF values. However, someone could probably use a lower order polynomial fit and force the pMTF values to be zero above 20 lp/mm because at higher frequencies there is not deterministic signal but only noise. Figure 4.3 compares the two pMTF curves up to 70.7 lp/mm frequency. A slight discrepancy between the two curves is observed at higher frequencies, i.e. higher than 10 lp/mm in the Dexela detector's case. However, a comparison between the original pMTF and the respective calculated from synthetic edge images shows that it does not introduce a significant error in any case (see section 4.5). Afterwards, the coefficients of this polynomial fit were evaluated at the 2-D frequency matrix in order to reconstruct a 2-D pMTF matrix.

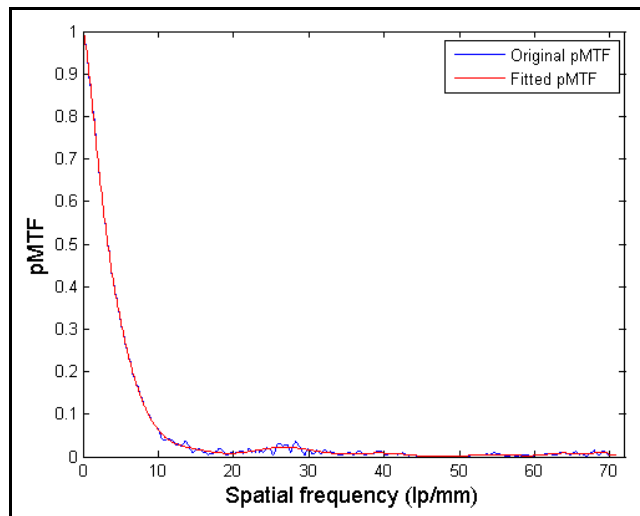


Figure 4.3: Fitted pMTF in comparison to the respective original average pMTF

Figure 4.4 shows the resultant 2-D pMTF matrix of the Dexela detector assuming isotropic symmetry. This matrix is multiplied with the Fourier transform of the ideal input image in order to apply the blurring which corresponds to the pMTF of the detector. The centre of the matrix corresponds to zero spatial frequency, while the maximum frequency in the horizontal and vertical orientations corresponds to the F_{Nyq} , i.e. 50 lp/mm in the case of 10 μm “analog” pitch.

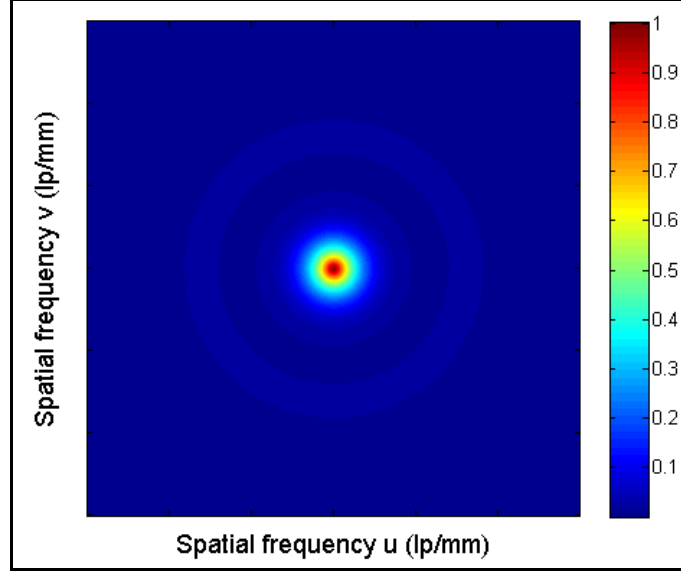


Figure 4.4: 2-D pMTF matrix of the Dexela CMOS x-ray detector assuming isotropic symmetry

However, the Anrad SMAM detector demonstrates anisotropic behaviour (see section 3.3.7). In this case a method to introduce the anisotropic symmetry on the 2-D pMTF matrix was developed. This method is based on the use of two 2-D matrices with circular symmetry to weight differently the vertical and horizontal pMTFs (see Figure 4.5). It can be seen that in the vertical case the 2-D weighting matrix is one in the vertical orientation and zero in the horizontal one. On the other hand, the horizontal 2-D weighting matrix is one in the horizontal orientation and zero in the vertical one. Both matrices are 0.5 in diagonal orientations (i.e. 45°). The vertical 2-D weighting matrix was constructed by the cosine square of the phase angle. The respective horizontal matrix corresponds to the sine square of the phase angle. Therefore, according to the Pythagorean theorem their summation at a specific point equals to one. Each weighting matrix was multiplied by the respective 2-D pMTF matrix and the summation of the two products results in the anisotropic 2-D pMTF matrix (Konstantinidis *et al.*, 2011a).

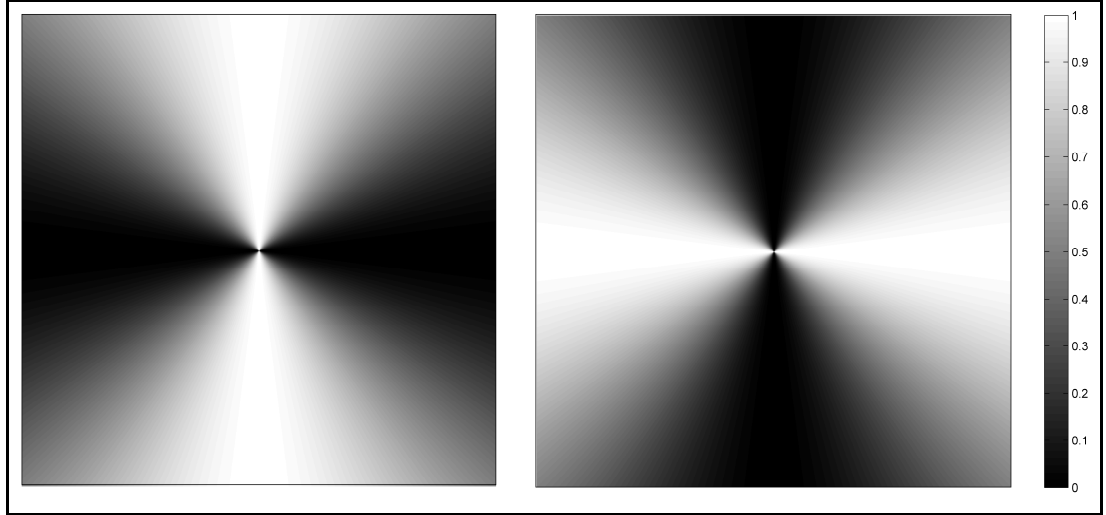


Figure 4.5: Suggested 2-D weighting matrices to take into account the measured a) vertical and b) horizontal pMTF

Figure 4.6a shows the resultant 2-D pMTF of Anrad SMAM detector. Figure 4.6b demonstrates good agreement between the original pMTFs and the extracted ones in the two directions.

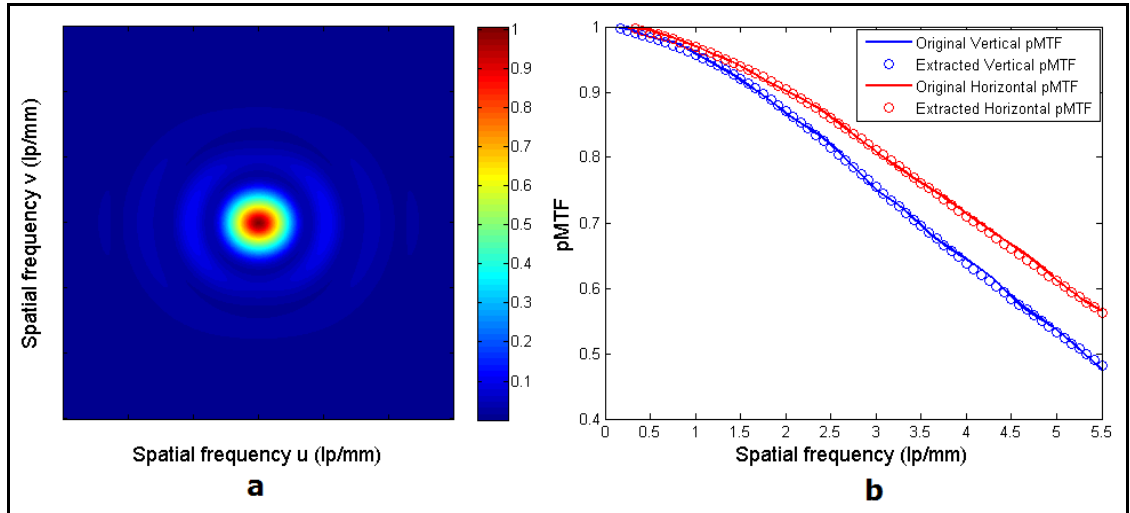


Figure 4.6 a) 2-D pMTF of Anrad SMAM detector assuming anisotropic behaviour and b) the extracted 1-D vertical and horizontal cuts in comparison to the respective original pMTFs

Finally, the blurred image is reduced to the desired pixel size by applying sampling methods. Saunders and Samei (2003) suggest the use of a moving ROI that locally averages the pixel values to form the pixels of the final image. However, this method requires the input pMTF to be divided by the sinc function of the final sampling aperture. The explanation for this is based on the applied linear-systems theory

(Cunningham, 2000). According to this theory, an input sample distribution of x-ray quanta $q(x)$ on a linear and shift invariant system $S\{\}$ is the convolution of the $q(x)$ with the impulse-response function (IRF) which is the response of the system to a delta (or impulse) function (see section 2.4.2). The IRF is equal to the PSF when used to describe a 2-D imaging system. The Fourier transform of the PSF is the 2-D pMTF. Therefore in the previous blurring step the PSF of the detector has been convolved with the input signal because convolution in one domain corresponds to multiplication in the other domain (as mentioned in section 2.4.1). According to the same theory when the pixel sampling is applied on the blurred signal $S\{g(x)\}$, the digital signal d_n from the n^{th} element centred at $x=xn_0$ is given as:

$$d_n = k \int_{-\infty}^{\infty} S\{g(x)\} \prod \left(\frac{x - xn_0}{a_x} \right) dx \quad (4.1)$$

where k is a constant relating the number of interacting quanta to the detector output as a DN and $\prod \left(\frac{x}{a_x} \right)$ is the rectangular function which is 1 for x within the pixel pitch a_x or 0 otherwise. The above equation denotes convolution in order to simulate the way that the pixel works, i.e. it averages the analog signal with pitch x over the pixel pitch a_x . However, the blurred signal $S\{g(x)\}$ already contains convolution between the input signal and the IRF. The extra convolution with the rectangular function corresponds to multiplication with the sinc function in the frequency domain. This multiplication affects the product of the 2-D pMTF times the Fourier transform of the input image, so the input pMTF needs to be divided by the sinc function to compensate for this.

In this thesis a different sampling method was used. This method was implemented in 2-D matrices in the Giger *et al.* (1984b) and Dobbins III (1995) studies based on the theory described in Bracewell (1978) for 1-D signals. It uses the comb function $\Delta x \text{III}(x; \Delta x)$ which is a string of delta functions separated by the pixel pitch Δx . According to the theory, multiplication of a signal with the comb function equals to the convolution of the signal with the delta function at any position:

$$d(x) \Delta x \text{III}(x; \Delta x) = d(x) \sum_{n=-\infty}^{\infty} \delta(x - nx_0) = \sum_{n=-\infty}^{\infty} d_n \delta(x - nx_0) \quad (4.2)$$

Also, the Fourier transform of $III(x; \Delta x)$ is $\Delta x^{-1} III(f; \Delta x^{-1})$. Therefore, this method samples the data using the following equation:

$$d(x) = kS\{g(x)\}\Delta x III(x; \Delta x) \quad (4.3)$$

which, according to the above, does not affect the corresponding spectra in the frequency domain. In order to sample 2-D arrays in practice, instead of calculating the local average signal over the area corresponding to the pixel pitch and applying the sinc correction, the “analog” pixels were extracted based on the ratio $\Delta x/x$. For instance, in the case that $x=10 \mu\text{m}$ and $\Delta x=80 \mu\text{m}$ the 1st, 9th, 17th, 25th, etc. pixels were selected.

However, the pixel pitches of the Dexela and Anrad detectors are $74.8 \mu\text{m}$ ($\sim 75 \mu\text{m}$) and $85 \mu\text{m}$ respectively. Therefore, the above ratio is not an integer number in the case that $x=10 \mu\text{m}$. As mentioned above, this specific “analog” pitch offers a reliable compromise between the sampling criterion and pc memory constraints. A suggested sampling method was employed in the case of the above two detectors (Konstantinidis *et al.*, 2011a). This method is based on the combination of two sampling series (inner and outer) with different steps. Figure 4.7 shows the sampling method for the Dexela detector. The inner sampling series is represented by the red pixels, while the outer sampling series by the light blue ones. For each sampling increment the average of the two sampling series is calculated to get a step of 7.5. To achieve this both sampling series have got variable increments. The inner sampling series have got a sampling increment of 7, 8, 7, 8, etc. “analog” pixels, while the outer ones have a respective increment of 8, 7, 8, 7, etc. The feasibility of this sampling method is evaluated in the section 4.5. Furthermore, to compare the difference between the sampling method suggested by Saunders and Samei (2000) and the one used in the current thesis, the method was applied to the local averaging method for both the Dexela and Anrad detectors. In this case, the inner sampling series averaged the blurred image over an ROI of 7×7 pixels, while the outer ones were the average of 8×8 pixels. However, to get a step of 7.5×7.5 pixels the sampling increment of both sampling series was variable as well. To explain the above, the inner sampling series in both dimensions averaged the 1-7, 9-15, 16-22, 24-30, etc. pixels, while the outer sampling series averaged the 1-8, 8-15, 16-23, 23-30, etc. pixels respectively. Again, the two sampling series were combined by averaging.

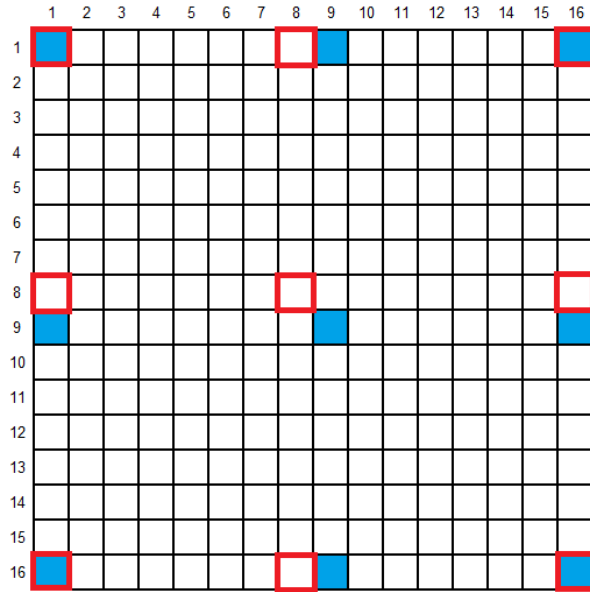


Figure 4.7: Suggested sampling method for the Dexela CMOS x-ray detector

Figure 4.8 shows an example of the effect of a) blurring and b) sampling processes on an ideal circle of 1 mm diameter and 30 % attenuation using the Dexela detector. Both images show the effect of signal transfer only, so they do not contain any kind of noise. The noise observed in the radiographic images is added to the blurred and sampled images after the simulation of the noise transfer (see the following section).

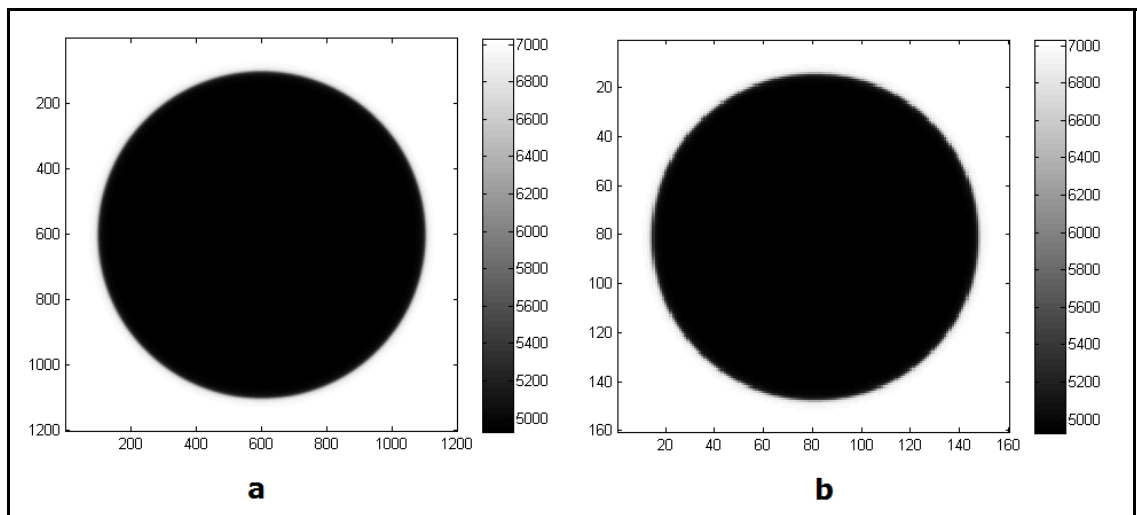


Figure 4.8 a) blurred and b) blurred and sampled synthetic circle of 1 mm diameter using the Dexela CMOS x-ray detector

4.4 Simulation of the noise transfer (NNPS)

To simulate the noise transfer the experimentally measured 2-D NNPS at different DAK levels were used. First, an uncorrelated (white) Gaussian noise array with zero mean and unit variance was created. The dimensions of this array are given from the blurred and sampled input image. This array corresponds to constant magnitude and random phase in the frequency domain, which randomizes the appearance of the noise. Then, the FFT of this array is multiplied by the square root of the input NNPS in order to introduce the noise correlation described by the NNPS. This is made because the NNPS is calculated from the squared modulus of the FFT of ROIs sampled from the flat images (see Eq. (2.28)). To apply the multiplication to any arbitrary point, a cubic spline interpolation is applied to the NNPS. Figure 4.9 shows that this interpolation method is sufficient to retain the input information. It is observed that the original 2-D NNPS matrix of 256x256 pixels is sufficiently applied to an 160x160 matrix.

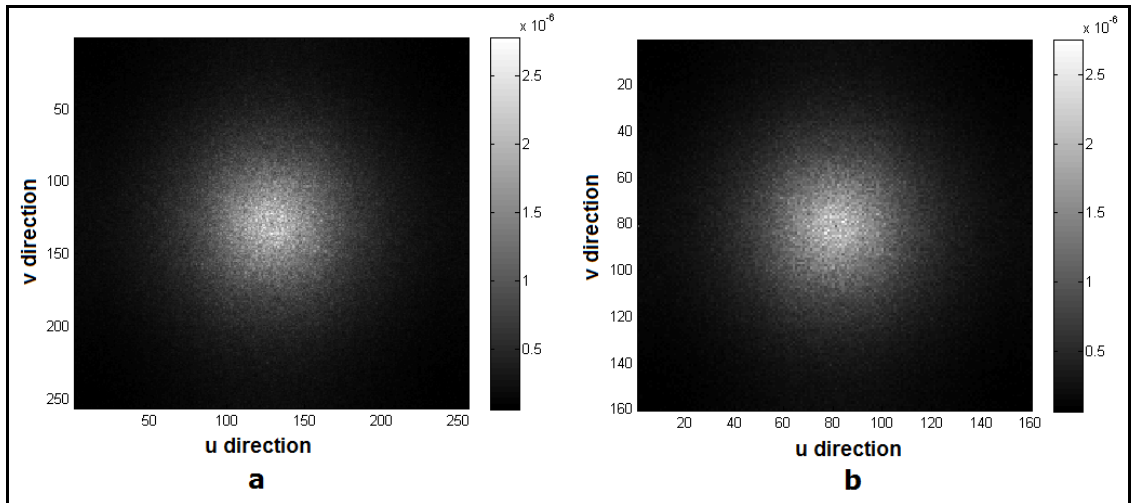


Figure 4.9 a) Experimentally measured NNPS compared to b) the interpolated NNPS used to insert noise on the synthetic images at 120 μ Gy using the Dexela CMOS x-ray detector in the HFW mode

Afterwards, an inverse FFT is used to transform the results into the spatial domain. The real part of the restored image is used because the Fourier spectrum is Hermitian and consequently its conjugate image is real. Then, the restored image is normalized to reach zero mean and unity variance. Therefore, the only difference between the restored image and the input white Gaussian noise one is the noise correlation inserted by the NNPS. Next, the noise is scaled following the empirically measured mean-variance relationship over the DAK level range. Saunders and Samei (2003) assumed that the

spectral distribution of the NNPS is independent of the DAK level so only the scale of the NNPS is affected by the DAK level changes. However, it was found that this is not true in some cases and the spectral shape is slightly modified as a function of the DAK level. To achieve a realistic simulation at any arbitrary DAK level the closest DAK level was found that corresponded to experimentally measured NNPS. Then, the magnitude of the experimentally measured NNPS was re-scaled based on the ratio between the two DAK levels. Figure 4.10a shows a flat synthetic image with zero mean at a specific DAK level (120 μ Gy) using the Dexela detector in the HFW mode.

Finally, the scaled noise array is added to the blurred and sampled input image in spatial domain. To properly scale the noise array a two-tier moving ROI method is incorporated. In this method, a 3x3 ROI scans the image to calculate local averages. Then the noise is scaled accordingly based on the empirically measured mean-variance relationship and applied at the central pixel of the 3x3 ROI. This method is used to simulate the different magnitude of the noise in a radiographic image based on the intensity level within the image. Figure 4.10b demonstrates the local scaling of the noise in a synthetic image of a 1mm diameter circle using the Dexela detector in the HFW mode (see Figure 4.8b). In particular, it shows a difference noise image (flat noise minus scaled noise synthetic image). The noise in the background remains the same resulting in zero difference. However, the scale of the noise inside the circle is different compared to the background noise so the rescaled noise has a circular shape.

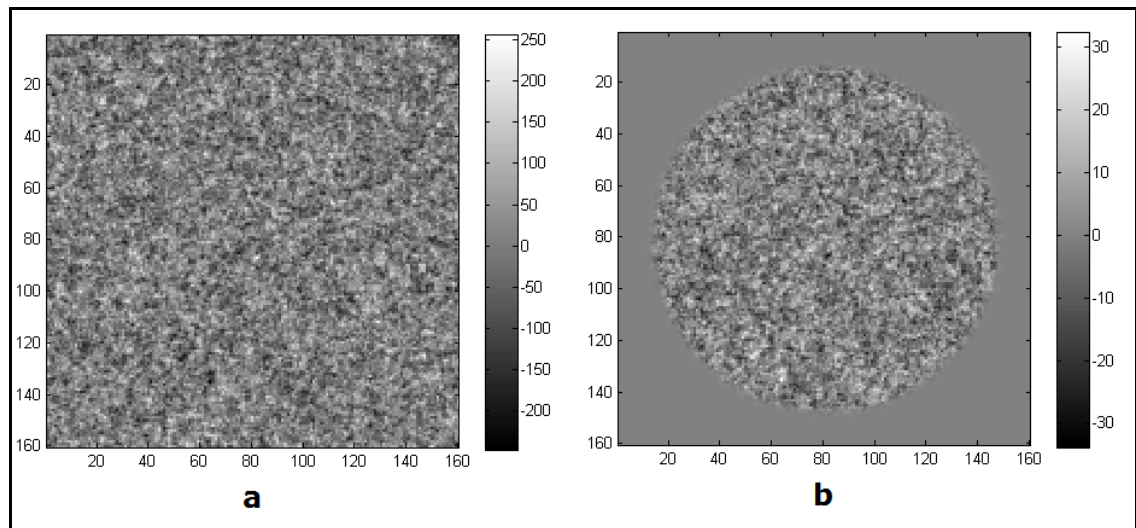


Figure 4.10 a) Flat synthetic image with zero mean at 120 μ Gy using the Dexela detector in the HFW mode, b) difference noise image (flat noise minus scaled noise synthetic image) to demonstrate the effect of the local scaling of the noise

Figure 4.11 shows an example of radiographic images of an ideal input circle of 1 mm diameter and 30% attenuation obtained using different detectors at two DAK levels and demonstrates the effect of the signal and noise transfer on the radiographic images. A detailed comparison is made in chapter 5, in terms of image quality metrics. The Remote RadEye HR detector was completely excluded from the simulation process because the suggested sampling method could not be used for the particular “analog” (10 μm) and pixel (22.5 μm) pitch combination.

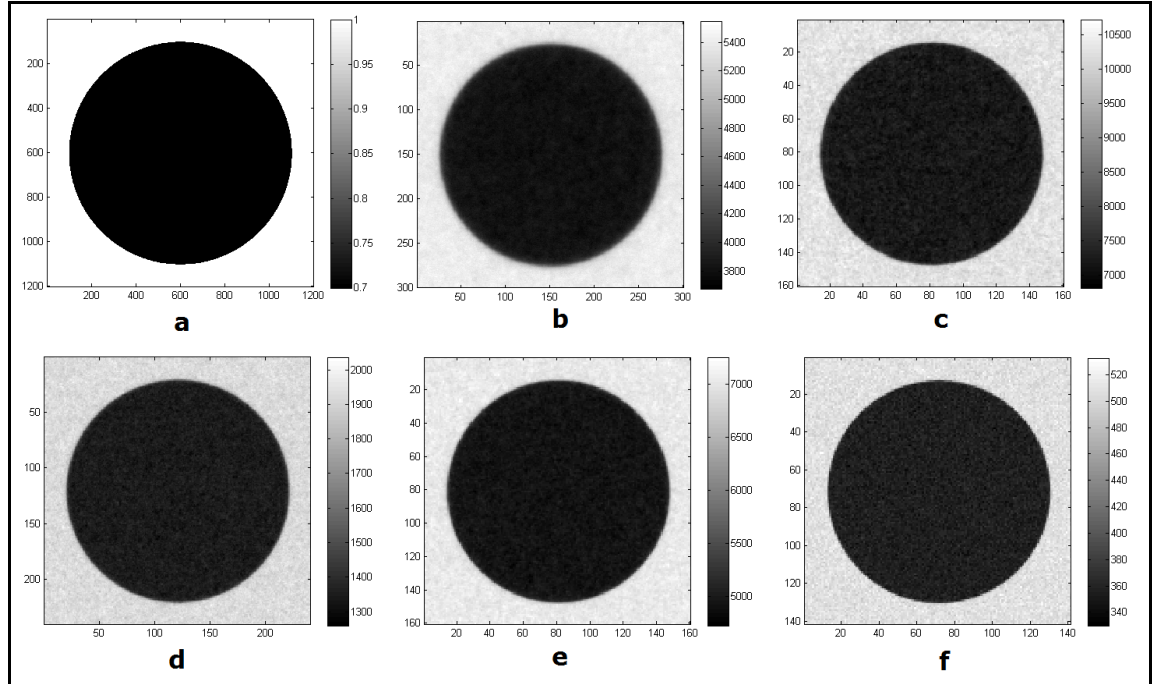


Figure 4.11: a) Ideal input circle of 1 mm diameter and synthetic radiographic images using b) LAS and c) Dexela LFW at 59.7 μGy and d) Hamamatsu, e) Dexela HFW and f) Anrad at 120 μGy

4.5 Validation of the simulation method

To validate the signal transfer simulation algorithm a vertical synthetic edge of 100 % attenuation was developed. Then this edge was rotated by 2° to extract the oversampled ESF which leads to the calculation of the pMTF according to the IEC standard (IEC 62220-1, 2003 and IEC 62220-1-2, 2007). A bicubic interpolation was used to implement the rotation. Since the synthetic edge image is noise free, a single oversampled ESF was used for the pMTF calculation. Figure 4.12 compares the original vertical pMTF of Anrad detector to pMTFs of synthetic edge images applying both the comb and rectangular functions. This figure validates the applied modifications

on both the blurring and sampling steps. It can be observed that without a sinc correction the used sampling method (i.e. comb function) leads to a pMTF almost identical to the original one. The average absolute difference (%) between the two curves is 0.9 %. On the other hand, the average absolute difference (%) between the pMTF curve extracted using the rectangular function and the original one is 13.1%. When a sinc correction is applied to the latter synthetic pMTF curve the average absolute difference (%) between the two curves is 0.9 %. The average absolute difference (%) between the original horizontal pMTF and the simulated one using the comb function is 0.7 %. This comparison demonstrates the validity of using the comb function without a sinc correction. The respective average absolute difference (%) between the synthetic and the original pMTF curves for the other detectors is 4.4 % for LAS, 0.9 % for Hamamatsu and 0.7 % for Dexela detectors. The origin of these small differences is probably due to the application of the 22nd polynomial fit (see Figure 4.3) and the interpolation method (bicubic) used to rotate the synthetic edge. It was found that a 2° rotation based on bilinear interpolation method resulted in respective average absolute relative differences (%) of 0.5% for Dexela, 3.0 % for LAS, 1.0 % for Hamamatsu and 0.8 % for Anrad detectors. However, both rotation methods result in insignificant differences.

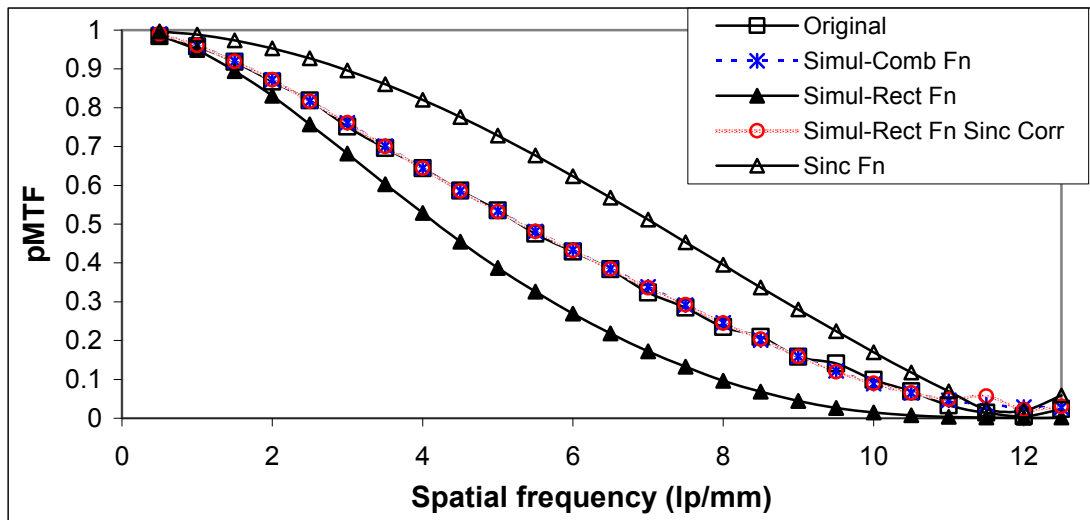


Figure 4.12: pMTF curve of synthetic edge images applying the comb and rectangular functions in comparison to the original vertical pMTF curve of Anrad detector

Figure 4.13 compares the average NNPS of the synthetic flat images to the experimentally measured average NNPS of the Dexela detector in the LFW mode and specific DAK level (29.0 μ Gy). The average absolute difference (%) between the two

curves is 0.8 %. Therefore, the simulation algorithm results in signal and noise transfer very close (less than 5% average difference) to the original ones.

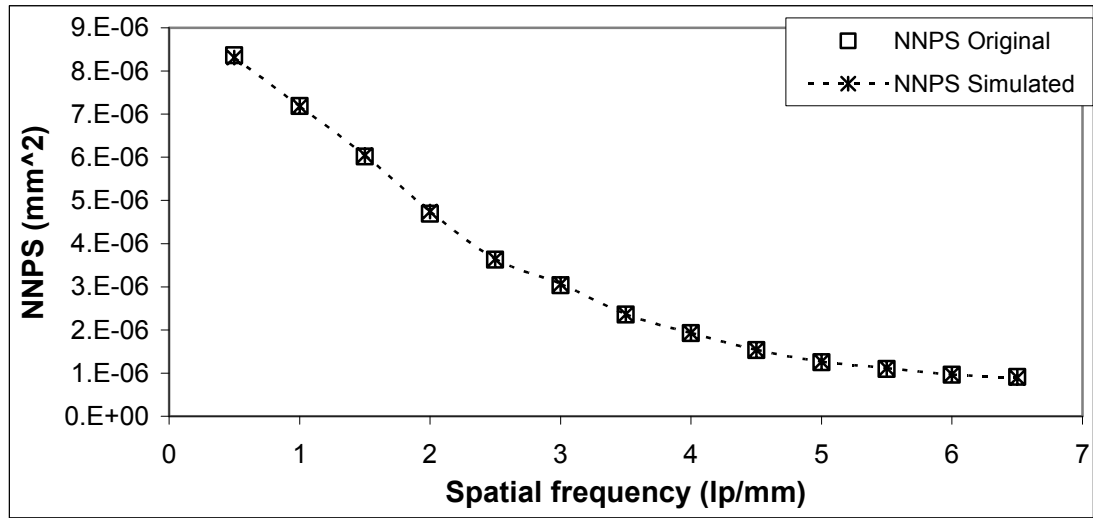


Figure 4.13: Average NNPS curve of the synthetic flat images in comparison to the original average NNPS curve of the Dexela detector (LFW mode and 29.0 μGy)

4.6 Software phantoms

Two software phantoms were used. One simulates the true anatomy of the breast and the other a mammographic test tool.

4.6.1 Breast software phantom

Breast software phantoms were used as ideal input images based on Bliznakova *et al.* (2003 and 2010) studies. In particular, the Bliznakova *et al.* (2003) study presented a 3-D non-compressed breast modelling that takes into account the full composition of the breast, i.e. the breast external shape, mammary duct system, breast abnormalities, mammographic texture, Cooper's ligaments and pectoralis muscle. They introduced a methodology for the generation of breast models of different size, shape and composition. Then, simulation of the x-ray beam transport through the models can generate 2-D x-ray projection images (Bliznakova *et al.*, 2006) or can be used in 3-D mammography, such as breast tomosynthesis (Ma *et al.*, 2009) or breast CT (Glick, 2007). The methodology was improved in a second study (Bliznakova *et al.*, 2010), by introducing a new algorithm for the generation of the 3-D breast models. Also, this study introduced new features such as lymphs, blood vessels and skin. Bliznakova and

Pallikarakis developed a user friendly GUI (Breast Simulator) that allows the composition and visualization of software breast models and the respective mammographic simulations using a monoenergetic (19 keV) x-ray beam. The following figure shows an example of a simple uncompressed breast software model, consisting of the breast shape and the duct system only.

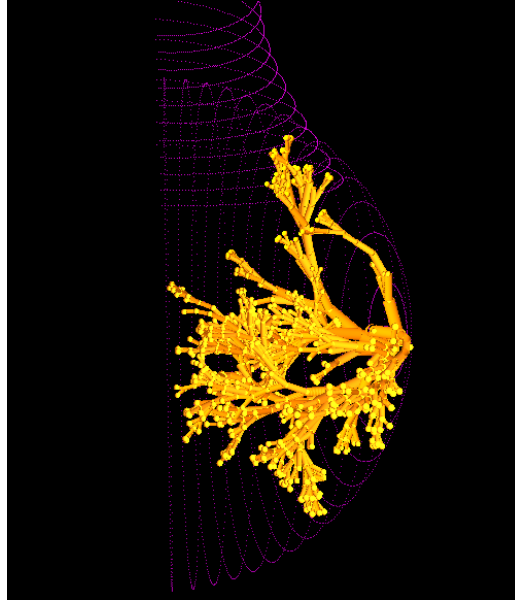


Figure 4.14: Representation of a simple 3-D breast software phantom using the Breast Simulator

In this thesis, four breast software phantoms were used at different composition and thickness. In particular, the glandularity percentage was 20, 45, 47 and 73 %. Simulation of breast compression was applied to the breast models for the purposes of mammography simulation, resulting in 5 and 6 cm thickness. The advantages of breast compression are a) the reduced superposition of adjacent tissues which allows an increased visualization of the boundaries of lesions, b) reduced scattered radiation, c) higher contrast, d) less absorbed dose and e) reduced effect of geometric magnification of tissues within the breast, since all anatomical parts are closer to the detector (Yaffe *et al.*, 2008). The simulation algorithm for soft tissue compression (SASTC) was introduced by Zyganitidis *et al.* (2007). Briefly, this algorithm uses the concept of a simple spring, i.e. during compression the volume remains constant due to the concept of spring variable equilibrium lengths. The mechanical properties of the tissues are assumed to be linear and isotropic and the attenuation coefficients corresponding to each tissue in the uncompressed breast phantom are mapped to their corresponding modulus of elasticity (Wellman *et al.*, 1999). All the breast models contained CaCO_3

spheres with different diameter (from 0.6 mm to 1.35 mm) to simulate microcalcifications (μ Cs). The 3-D breast models were reconstructed as 2-D projection images at a given angle θ to generate a set of line integrals with 10 μ m “analog” pitch. Each line integral represents the total attenuation of the x-ray beam as it travels in a straight line through the 3-D breast object. It expresses the integral of the products of the linear attenuation coefficient of each breast component and the respective thickness of the breast along the specific line.

Then, the input spectral shape was estimated by applying the Beer–Lambert law on the output spectrum used in the x-ray performance evaluation of the digital detectors at 28 kV. Therefore, 2 mm of Al were used as breast-equivalent filtration. A specific number of input x-rays was used at each energy interval to get certain ESAK (entrance surface Air Kerma) level used in mammography. The ESAK levels resulted in DAK levels within the dynamic ranges of the digital detectors. The simulation of the x-ray beam transport through the line integrals was made using the simple Beer–Lambert law. Hence, the effect of the scattering is ignored. Finally, the measured conversion function (i.e. signal transfer as a function of the input x-rays per unit area) of each detector was used to rescale the experimentally measured SNR relationship at a given DAK level. All the synthetic ideal breast images are compressed at craniocaudal (CC) orientation and the projections correspond to CC view. Figure 4.15 shows an example of a compressed ideal software breast phantom at 10 μ m pitch. A cluster of 6 microcalcifications is included inside the breast.

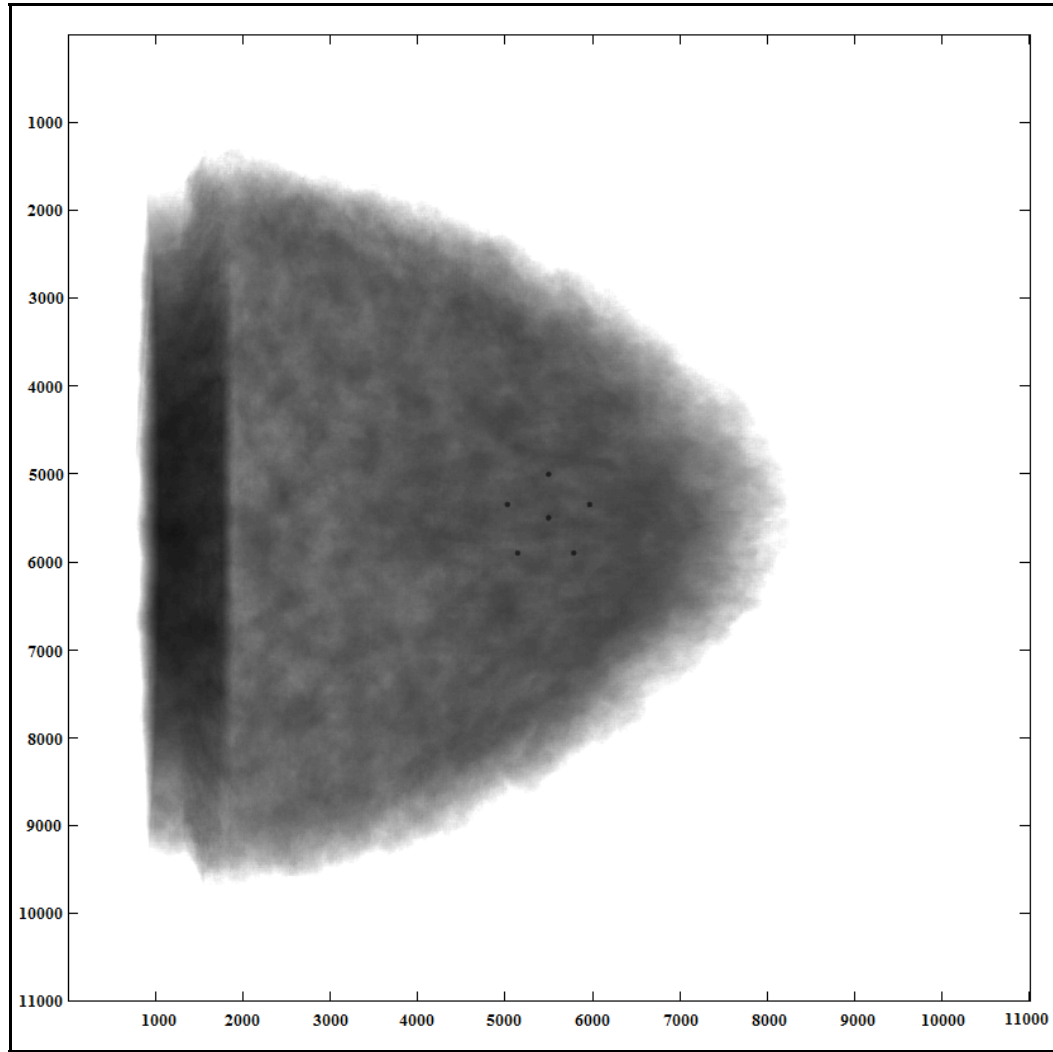


Figure 4.15: A compressed ideal software breast phantom at CC view

4.6.2 CDMAM software phantom

In this study a software CDMAM 3.4 phantom, provided by Yip (2010b), was used for the comparison of the digital detectors in terms of contrast-detail evaluation. The Al thickness of the software phantom was 0.3 mm instead of 0.5 mm, in order to simulate 50 mm PMMA in total (i.e. when combined with the additional 45 mm PMMA) at the current beam quality used for the x-ray performance characterization of the detectors (W/Al at 28 kV). Figure 4.16 shows the normalized ideal software CDMAM 3.4 phantom at 10 μm pitch. The term ideal implies that the phantom is not degraded by the digital detector's transfer. Therefore, it corresponds to the x-ray distribution at the detector's surface. Furthermore, the effects of geometric magnification and scattered radiation are added on the input phantom (see section 5.3.1).

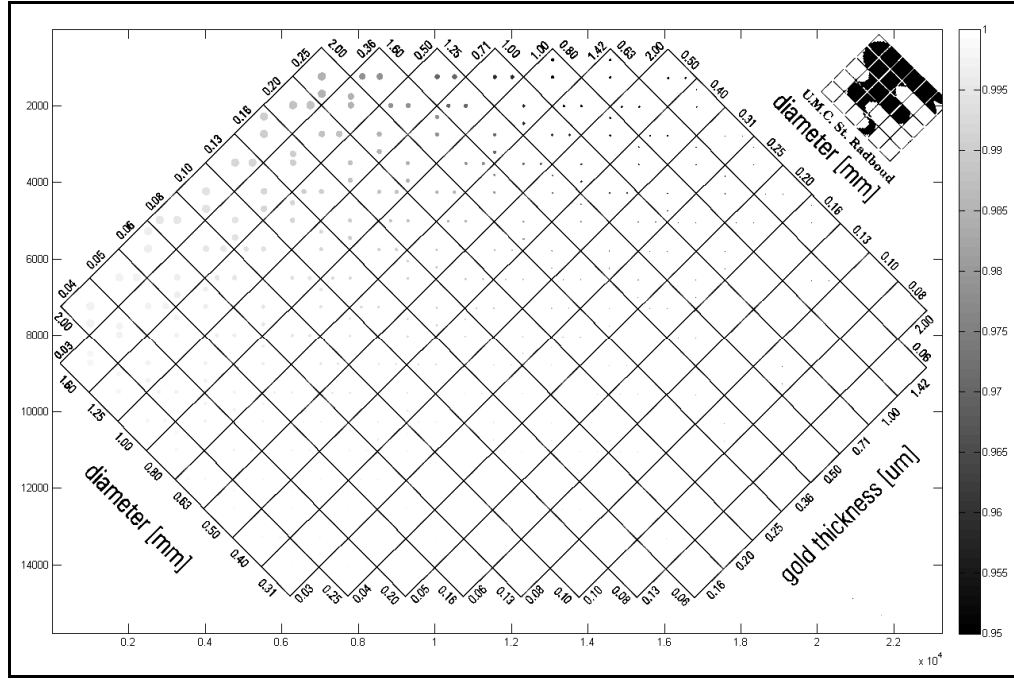


Figure 4.16: An ideal software CDMAM 3.4 phantom normalized to unity

As mentioned in section 1.9.2 at least eight CDMAM images are required for the contrast-detail analysis of a detector using the *CDCOM* software. Hence, eight noise images were generated and adapted with the NNPS of each detector at specific DAK. This was made to get the same input noise for a given CDMAM image using a specific detector.

4.7 Summary

In this chapter the simulation algorithm and its modifications have been described. In particular, it has been shown that the sinc correction can be avoided when comb sampling is applied. Also, the simulation of anisotropic signal transfer and sampling using weighting adjacent pixels were presented. The simulation method was validated by measuring the pMTF and NNPS parameters on the simulated images. The average difference between the results extracted from the simulated images and the original ones was less than 5 %. Finally, the synthetic breast phantoms and the CDMAM 3.4 test tool, which represent the ideal input data, were described.

Chapter 5

5 Image quality analysis of the simulated images

5.1 Overview of chapter

In this chapter the simulated images are evaluated in order to compare the performance of the different detectors. In particular, CNR analysis is applied on the synthetic mammograms and contrast-detail evaluation on the synthetic CDMAM 3.4 test tool. The latter is made using the software tool CDCOM to automatically score the images, followed by a human observer performance model. Finally, two combinations of spatial resolution and noise characteristics were examined in terms of contrast-detail analysis.

5.2 Analysis using the synthetic mammograms

5.2.1 Simulation conditions

As mentioned in section 4.6.1 the Beer–Lambert exponential law was applied to simulate the x-ray beam transport along line integrals through the breast. Hence, the effect of scatter was not included in the simulation. Figure 5.1 shows the normalized photon fluencies after the phantoms, compared to the transmitted fluence after 0.2 cm Al. The Al filtration was used for the x-ray performance evaluation of the detectors at 28 kV. It can be seen that all the breasts result in harder x-ray beams compared to that used for the evaluation of detectors. This happens because the thickness of Al used corresponds to around 4 cm breast thickness with a composition of 50% adipose and 50% glandular tissues by weight (i.e. 50% glandularity). The selection of this thickness was made based on the mammographic IEC standard (IEC 62220-1-2, 2007) to simulate the effect of a typical compressed breast, which is approximately 4.2 cm in the United

States (Boone, 1999). In this particular case, Breasts 1 and 4 are 6 cm thick, while Breasts 2 and 3 are 5 cm thick respectively. Table 5.1 provides further details about the composition, thickness and the effect of each software breast phantom on the beam quality. The relative values that are used to compare beam qualities are the average energy (E_{mean}) expressed in keV, the HVL (in mm Al) and the fluence per exposure ratio (Φ/K_a) expressed in x-rays per unit area per unit exposure (x-rays/mm²/μGy). The latter was calculated from Eq. (2.31) and was also used for the calculation of the HVL and the DAK. Concerning the HVL calculation, once the photon fluence is converted to exposure it is straightforward to calculate the required thickness of Al to reduce the exposure by half. The DAK is given by the ratio of the Φ/K_a to the total number of x-rays per unit area, Φ .

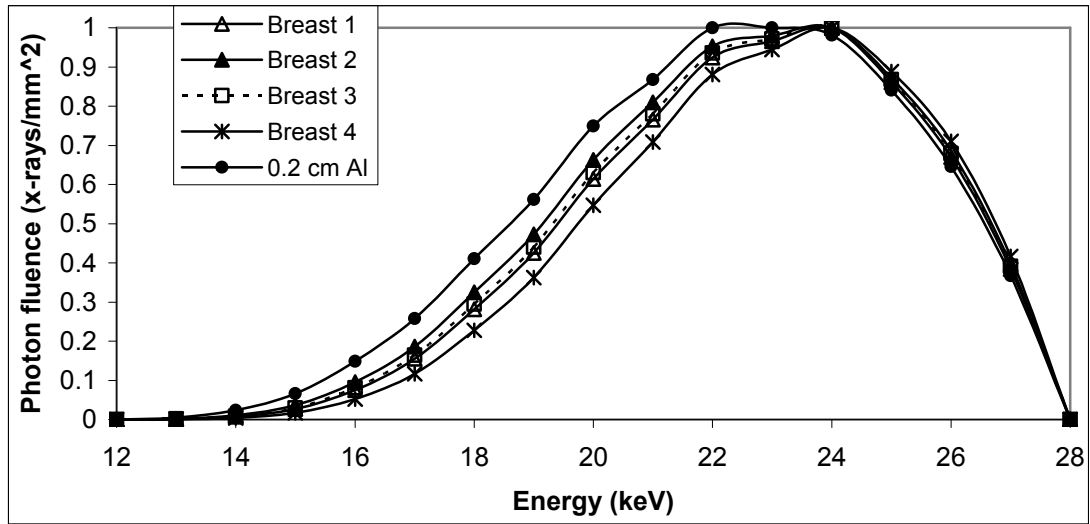


Figure 5.1: Normalized photon fluencies on the output of the phantoms

Table 5.1 also presents the absolute values of mean glandular dose (MGD) and the resultant DAK for each software breast phantom when 2 mGy ESAK was used. When an anti-scatter grid is employed in digital mammography, the ESAK is usually in the range 6-9 mGy (Chevalier *et al.*, 2004 and Gennaro and di Maggio, 2006). In the case where no anti-scatter grid is used, the ESAK is usually about half. In this study 2 mGy ESAK was selected to reach a DAK within the dynamic range of the high sensitivity detectors (i.e. LAS and Dexela in the LFW mode). The selected ESAK results in less than 60 μGy DAK. The MGD was calculated to estimate the absorbed dose in the “at-risk” glandular component of the breast, because it is the most sensitive organ within the breast to radiation induced carcinogenesis. The concept of MGD was first introduced by Hammerstein *et al.* (1979) and its calculation is made based on the fact

that it expresses the absorbed energy per unit mass of the glandular tissue. Many investigators estimate the MGD for various breasts based on conversion factors extracted from the Monte Carlo studies made by Dance *et al.* (Dance, 1990, Dance *et al.*, 2000, Dance *et al.*, 2009 and Dance *et al.*, 2011) or Boone (2002). In this study the MGD was calculated using the following formula extracted from the studies of Johns and Yaffe (1985), Boone (1999) and Thacker and Glick (2004):

$$MGD(Gy) = \frac{1.602 \cdot 10^{-13}}{f_g V_B \rho_B} \int_0^{E_{max}} EN_0 (1 - e^{-\int \mu_B(E,t) T_B dt}) \cdot \left(\frac{\mu_{en,B}(E)}{\mu_B(E)} + x(E) \right) \cdot G(E) dE \quad (5.1)$$

where f_g is the glandular fraction of the breast tissue, V_B is the volume of the breast (in cm^3) and ρ_B is the density of the breast (in g/cm^3). The product of these quantities results in the mass of the glandular tissue (in kg). The constant $1.602 \cdot 10^{-13}$ is used to convert the MeV to J in order to present the MGD values in Gy (1 Gy = 1 J/kg). E is the energy of the incident photons (in MeV) and N_0 corresponds to the incident x-ray photons per unit area (mm^2), $\mu_B(E)$ is the total linear attenuation coefficient of the breast, T_B is the breast thickness and $\mu_{en,B}(E)$ is the total linear energy absorption coefficient of the breast. The integral $\int \mu_B(E,t) T_B dt$ corresponds to the line integral. The ratio $\mu_{en,B}(E) / \mu_B(E)$ is the fraction of the energy removed from the primary beam which is deposited in the initial interaction. In other words, it takes into account the energy lost due to the K-fluorescence radiation. Finally, the quantity $x(E)$ is the fraction of the energy removed from the primary beam which is scattered initially but then absorbed on a subsequent interaction. In this study $x(E)$ was considered equal to 0.23 based on values extracted from the Monte Carlo study of Dance (1980). Finally, the factor $G(E)$ rescales the normalized dose calculation to the glandular component of the breast tissue in a heterogeneous tissue matrix. It is calculated from the following formula:

$$G(E) = \frac{f_g \left(\frac{\mu_{en}(E)}{\rho} \right)_g}{f_g \left(\frac{\mu_{en}(E)}{\rho} \right)_g + (1 - f_g) \left(\frac{\mu_{en}(E)}{\rho} \right)_a} \quad (5.2)$$

where $(\mu_{en}(E)/\rho)$ is the mass energy absorption coefficient and “a” and “g” are the subscripts for adipose and glandular tissue respectively.

Table 5.1: Parameters related to the effect of the synthetic breast phantoms on the beam quality

Parameter	Breast 1	Breast 2	Breast 3	Breast 4	Al
Thickness (cm)	6	5	5	6	0.2
Glandularity (%)	20	47	73	45	-
μ Cs diameter (mm)	0.6	1.35	0.6	0.6	
Equivalent PMMA thickness (cm)	5.1	4.5	4.8	5.4	
E_{mean} (keV)	22.6	22.5	22.6	22.8	22.2
HVL (mm Al)	0.93	0.90	0.94	0.96	0.83
Φ/K_a (x-rays/mm ² /μGy)	7334	7241	7302	7463	7009
MGD (mGy) using 2 mGy ESAK	0.81	0.9	0.83	0.74	-
DAK (μGy) using 2 mGy ESAK	41.8	56.5	46.7	32.5	194.9

From the data in Table 5.1 it can be seen that 0.2 cm Al results in DAK levels which are 4-5 times higher than those corresponding to the breasts. This happens because the specific thickness of Al was suggested by the mammographic IEC standard (IEC 62220-1-2, 2007) in order to simulate the beam quality in relative values (i.e. E_{mean} , HVL and Φ/K_a) instead of the absolute ones (i.e. total number of output x-rays and the resulted DAK).

Concerning the response of the x-ray detectors, Marshall (2009b) demonstrated experimentally that the DQE of a linear and quantum limited detector changes as a function of the QDE which depends on the beam quality. He also showed that the slope of the STP depends on the Φ/K_a ratio and the NNPS, which corresponds to the SNR ratio, is inversely proportional to the product $(\Phi/K_a) \cdot QDE$ at specific DAK levels. In the current study the inherent nonlinearity of CMOS APS detectors does not allow the precise estimation of the signal and noise transfer change. To avoid erroneous SNR transfers it was decided to use the experimentally measured ratio for the simulations. It was calculated that the beam qualities used modified the (Φ/K_a) and QDE parameters by less than 3 and 4 % respectively.

Finally, in these specific simulations it was assumed that all detectors (including Anrad SMAM) present isotropic behaviour. This is based on the fact that the relative difference between horizontal and vertical pMTF at 1.7 lp/mm is less than 3 % in all cases.

5.2.2 Analysis results

The following five figures show a specific region of synthetic mammograms of Breast 4 using four of the investigated detectors (LAS, Hamamatsu, Dexela in both full well modes and Anrad detectors). All of them correspond to 32.5 μGy DAK. The effects of the spatial resolution, noise and sensitivity of each detector on the same array of input data can be observed. The extracted information from the synthetic mammograms is quantitatively described by the CNR and SDNR by calculating the mean and standard deviation from the CaCO_3 spheres (microcalcifications) and the background. To implement this analysis, circular ROIs were extracted from the centre of each 2-D CaCO_3 disk image. The size of the ROI was taken in order to be in the central area of the disk (i.e. the diameters of the ROIs were in the range 0.4 to 0.5 μm). Then, four circular ROIs were selected from adjacent background areas with diameter three times larger than that of the disk ROI (i.e. in the range 1.2 to 1.5 μm). Both the number and size of the background ROIs was made to take into account the variations of the background. The whole process was made in ImageJ (Rasband, 1997-2011 and Abràmoff *et al.*, 2004). Figure 5.2 shows the simulated mammograms of the investigated x-ray detectors at a specific DAK level. Visually the simulated mammogram of LAS is blurred compared to the one using Hamamatsu detector. This is due to the decreased resolution of LAS compared to other detectors (Figure 3.32). However, LAS demonstrates higher SNR transfer as a function of the exposure and higher sensitivity. As mentioned in section 3.3.7 the Dexela detector in the LFW mode has higher sensitivity compared to the HFW mode. Hence, the pixel values in the simulated images are higher. The DQE of this detector in the LFW mode is slightly higher at a given DAK (Figure 3.36) and this translates into a higher SNR value. The same spatial resolution was used for both modes. Finally, the pixel values that correspond to Anrad detector's mammogram are very low due to the decreased sensitivity of the detector (Figure 3.30). For representation the position of the central and background ROIs around a disk is shown for Hamamatsu detector (Figure 5.2b).

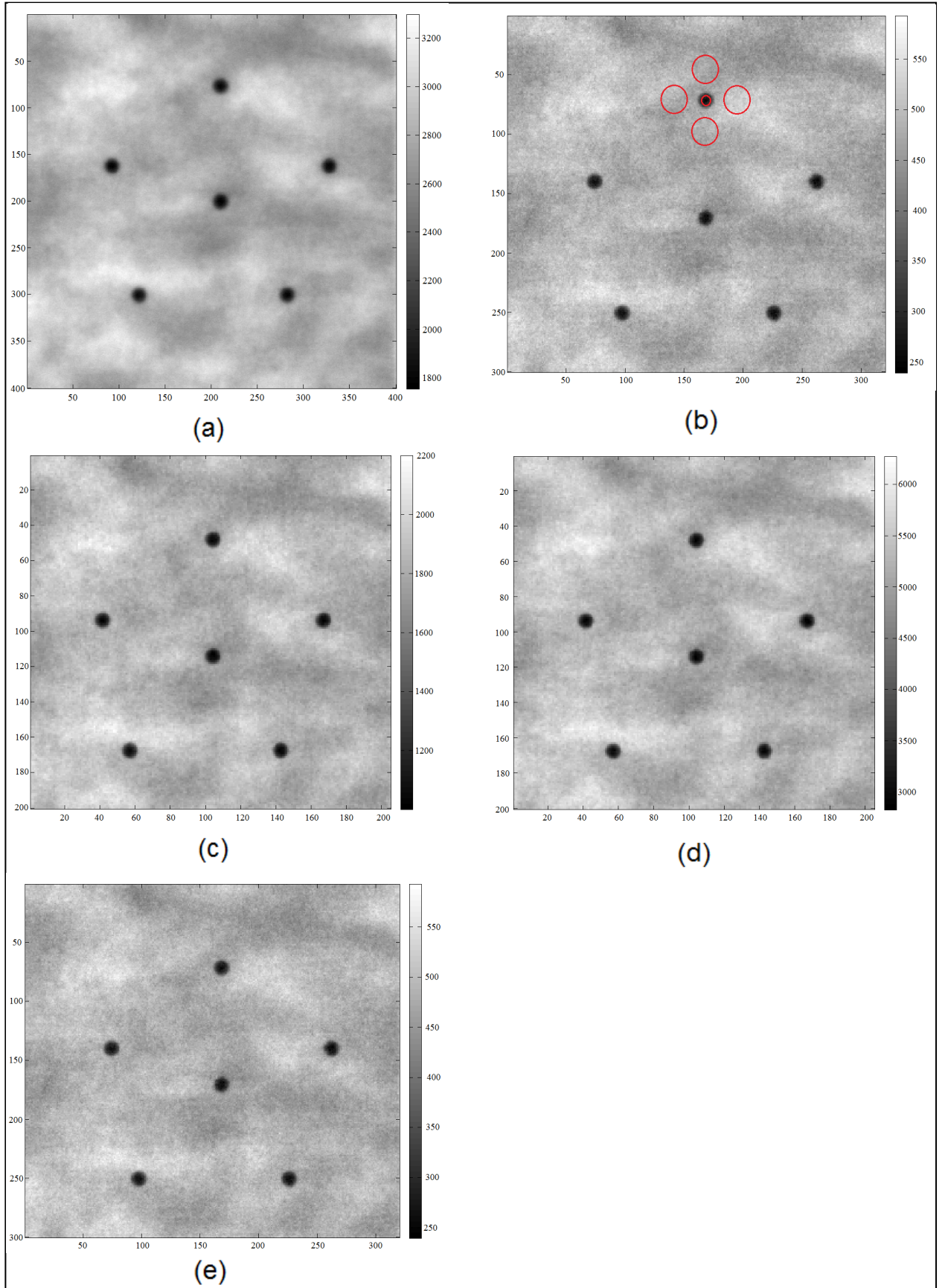


Figure 5.2: Region of synthetic mammogram at 32.5 μGy DAK using a) LAS, b) Hamamatsu, c) Dexela (HFW), d) Dexela (LFW) and e) Anrad detectors

Both the CNR and SDNR parameters are presented for the simulated mammograms of the four breasts in Figure 5.3. The precision (expressed as error bars) of the results was calculated by applying error propagation. It can be seen that in most cases the CNR is slightly higher than SDNR. This happens because by definition the CNR combines the noise of the area inside and outside the disk (Eq. (1.8)), while the SDNR considers only the noise of the background area (Eq. (1.9)). For thick and fatty breasts such as Breast 1, both LAS and Dexela detectors present higher visibility of microcalcifications with 600 μm diameter. On the other hand, both Hamamatsu and Anrad detectors demonstrate relatively low visibility. For Breast 2 (glandular composition equal to 47 %) LAS presents higher visibility of microcalcifications. Both CNR and SDNR parameters are almost equal for the rest of the detectors. For high glandularity (73 %) breast (Breast 3) the SDNR is high for both LAS and Dexela detectors. The comparison of the detectors in terms of CNR shows that LAS appears the highest visibility. Hamamatsu detector demonstrates similar CNR values compared to Dexela's ones. Finally, for Breast 4 both LAS and Dexela detectors demonstrate higher CNR and SDNR values compared to the other two investigated detectors.

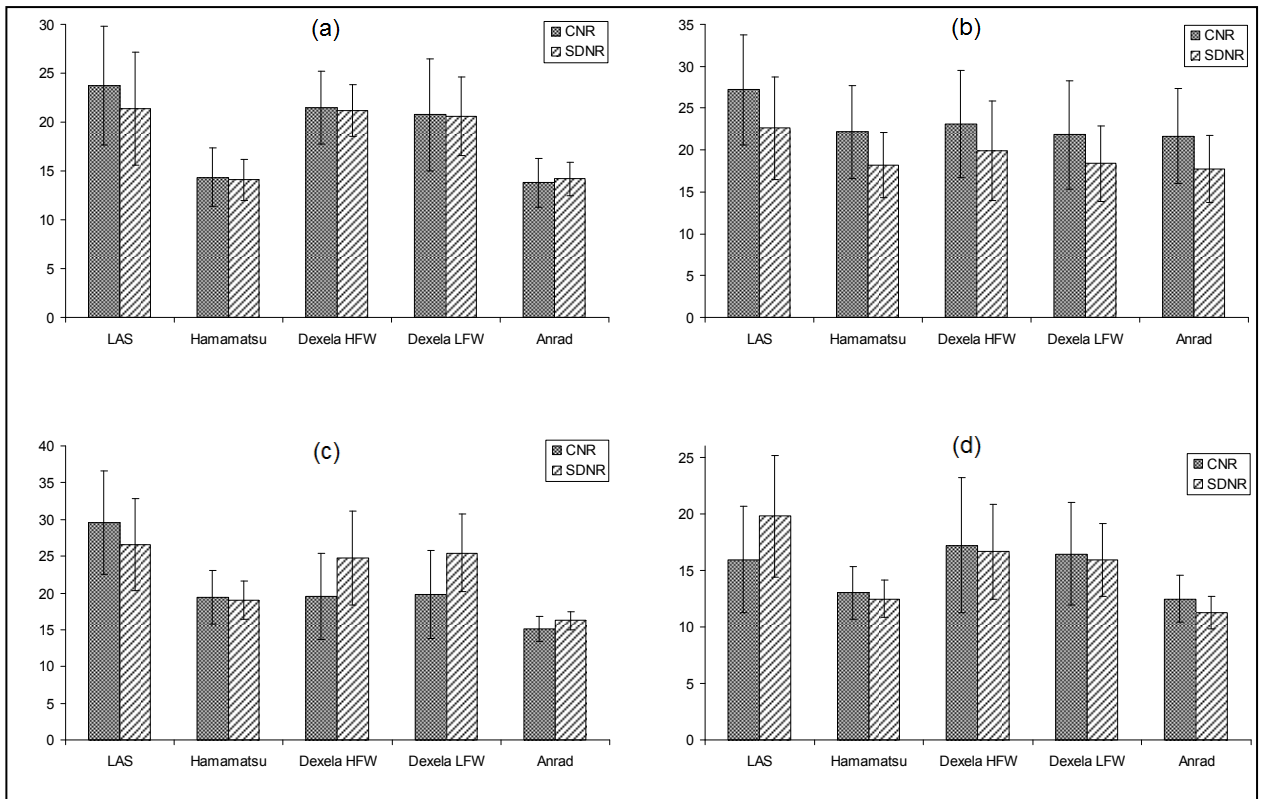


Figure 5.3: CNR and SDNR at 32.5 μGy for a) Breast 1, b) Breast 2, c) Breast 3 and d) Breast 4

Overall, both LAS and Dexela detectors present higher CNR and SDNR values compared to the other two detectors. All detectors demonstrate higher visibility of the details inside thinner breasts (Breasts 2 and 3), indicating that in our case the breast thickness has a higher impact on the visibility of the microcalcifications than the glandularity. On the other hand, the combination of fatty and average glandularity breast (Breast 4) results in the lowest CNR and SDNR values for all detectors. This happens because this combination corresponds to higher absorption of x-rays from the background tissue, which limits the contrast. This behaviour is in agreement with the values presented in Table 5.1 where it is observed that Breast 4 results in the hardest beam quality. The CNR and SDNR values are relatively high due to the absence of the scattered radiation. According to Marshall (2009a) the effect of contrast and noise on the CNR (or SDNR) can be further investigated. In particular, Eq. (1.6) shows that the CNR is the product of contrast times the relative noise (i.e. average signal of the background divided by the noise). Figure 5.4 shows the individual contrast results used to extract the CNR and SDNR data at a given DAK level (32.5 μGy). It may be observed that LAS demonstrates slightly lower contrast compared to the other detectors. On the other hand, Hamamatsu, Dexela and Anrad detectors present similar contrast.

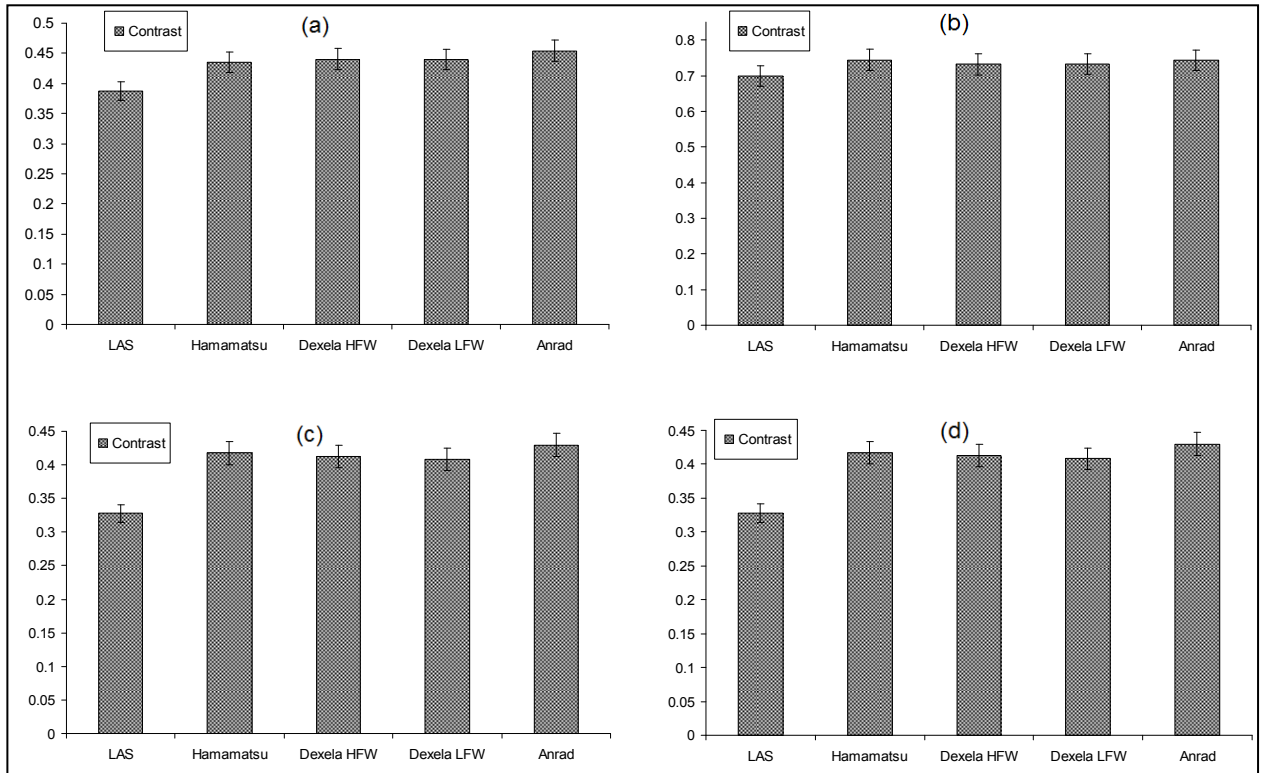


Figure 5.4: Contrast results at 32.5 μGy for a) Breast 1, b) Breast 2, c) Breast 3 and d) Breast 4

Figure 5.5 shows the relative noise results used to extract the CNR and SDNR data at the same DAK level (32.5 μGy). It can be observed that the noise is different between the different detectors. The LAS detector demonstrates the highest relative noise which explains why its CNR and SDNR values are high. Probably this happens due to the combination of the low quantum noise with the relatively poor spatial resolution. The Dexela detector presents higher relative noise values compared to Hamamatsu and Anrad detectors.

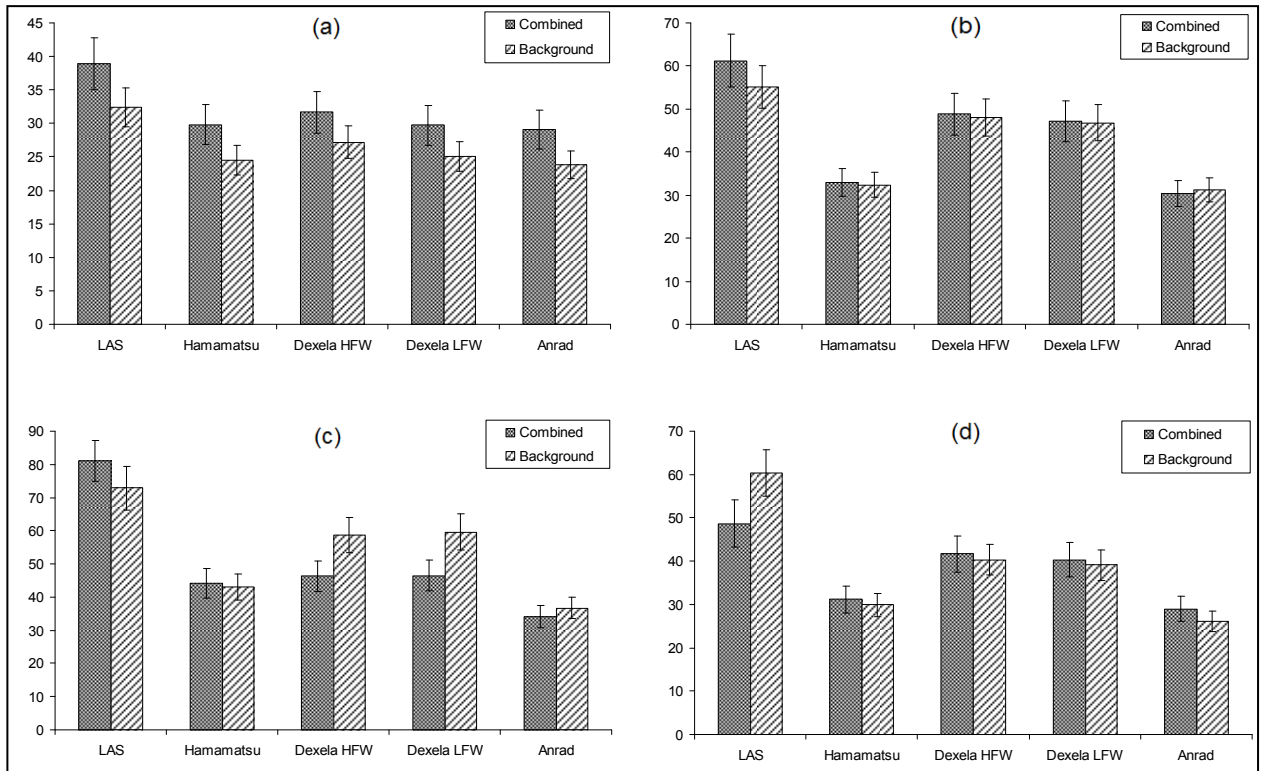


Figure 5.5: Relative noise (both combined and background) results at 32.5 μGy for a) Breast 1, b) Breast 2, c) Breast 3 and d) Breast 4

It should be noted that direct comparison of different systems using CNR or SDNR may be problematic. Comparing two systems (e.g. A and B), it is possible for system A to have higher CNR or SDNR than B but for B to have a better (i.e. lower) low contrast detectability result. Therefore, there is no universal target CNR or SDNR used as a minimum image quality standard for all systems. As mentioned in section 1.9.2, the European Guidelines for quality control in digital mammography compare the image quality of mammographic systems in terms of threshold contrast visibility using the CDMAM test tool (van Engen *et al.*, 2006). Furthermore, this comparison depends mainly on the SNR transfer of each detector due to the relatively large dimensions of

the simulated microcalcifications. It does not fully examine the effect of the detector's signal transfer at different frequencies. For the above reasons the performance of the detectors was also compared using the CDMAM 3.4 test tool (see the following section).

5.3 Analysis using the synthetic CDMAM 3.4 test tool

5.3.1 Simulation conditions

As mentioned before (section 4.6.2) the effect of scattered radiation was added using the ideal software CDMAM phantom by applying the following formula (Dobbins III, 2000, Bushberg *et al.*, 2002 and Marshall, 2006a):

$$C = \frac{C_P}{(1 + S/P)} \quad (5.3)$$

where C_P is the generated radiation contrast, C is the degraded radiation contrast and S/P is the ratio of the scattered to primary radiation. The S/P ratio for 6 cm breast thickness was calculated to be equal to 0.62 (Dance and Day, 1984) for the beam quality used (W/Al at 28 kV).

Furthermore, it was found that the geometric unsharpness due to the finite size of the focal spot (i.e. the geometric MTF) affects the scoring of the CDMAM (Yip *et al.*, 2008). To simulate this, the size of the ideal software phantom was magnified by a magnification factor (m) equal to 1.08, which represents the ratio of the source to detector (SDD) to the source to object (SOD) distance (SDD/SOD), since the CDMAM phantom is not usually placed directly on the detector. Assuming that the focal spot emission profile follows a Gaussian distribution, the width of the focal spot, f_0 , corresponds to the full width at half maximum (FWHM) of the distribution. In this study f_0 was equal to 300 μm which represents a typical screening mammographic x-ray source. The FWHM and the standard deviation of the distribution, σ , are related by $FWHM = 2.35\sigma$. In the Gaussian distribution case, the geometric MTF is given by (Prasad *et al.*, 1976, Sandborg *et al.*, 1999 and Sandborg *et al.*, 2003):

$$MTF_{geo} = \exp(-2\pi^2 \cdot \sigma^2 \cdot f^2 \cdot (m-1)^2) \quad (5.4)$$

where f is the spatial frequency. The geometric MTF was expanded into a 2-D array and multiplied by the 2-D pMTF of each detector. Then, the combined MTF was used to simulate the blurring of the system.

The *CDCOM v1.5.2* reads images in DICOM (Digital Imaging and Communications in Medicine) format. A single DICOM image contains both the header (which stores information about the patient's name, the type of scan, image dimensions, pixel spacing, etc.) and the image data (which can contains the pixel values in two or three dimensions). *CDCOM v1.5.2* extracts information from the DICOM header related to the pixel spacing (pitch), image dimensions, bits allocated, bits stored and pixel intensity relationship sign which is related to the location of the significant bit. In this study the synthetic CDMAM images were converted in DICOM format and then the pixel spacing information was modified for each digital detector. All the processing was made using a custom built software written in MATLAB version 7.10 (The MathWorks, Natick, MA, USA).

5.3.2 Analysis results

Figure 5.6 presents an example of a simulated image of CDMAM 3.4 test tool using the Dexela detector in the LFW mode and 59 μGy DAK. The window width of the image was adjusted for display purposes. Both the central and eccentric disks on each cell can be easily observed at the upper part of the image. However, the visibility is lower as the diameter and the thickness of the gold disks decrease.

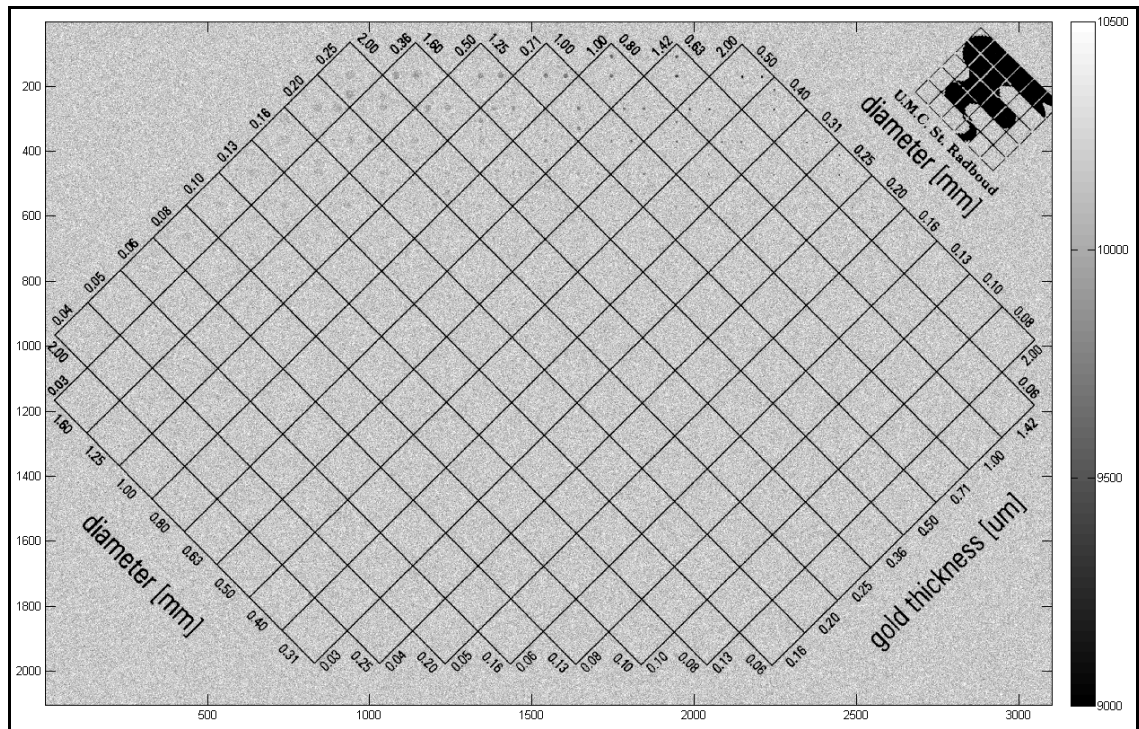


Figure 5.6: A simulated image of CDMAM 3.4 using the Dexela detector at 28 kV and 59 μGy

Figure 5.7 presents the threshold contrast curves for four detectors as a function of disk diameter for low (59 μGy) DAK level. All of them were extracted using *CDCOM v1.5.2* software tool by combination of 8 CDMAM 3.4 images. For clarity a 10 % error bar is presented only on the Hamamatsu data points to indicate typical uncertainty for the results. The uncertainty is expressed by the 95 % confidence level on the nonlinear least mean squares fit using custom built software written in MATLAB version 7.10 (The MathWorks, Natick, MA, USA) to define the threshold thickness (see section 1.9.2). It was found that it did not exceed 10 % in all cases. As the study covered the performance of the detectors in the range 0.1-1.0 mm, the anisotropic behaviour of Anrad SMAM detector was simulated. It is observed that Hamamatsu detector has the highest threshold contrast values at almost all disc diameters, which corresponds to a lower performance compared to the other three detectors. On the other hand, LAS, Anrad and Dexela detector in the LFW mode demonstrate similar performance at almost all disk diameters except 0.1 mm. The lower performance of LAS at high frequency objects is due to its limited pMTF.

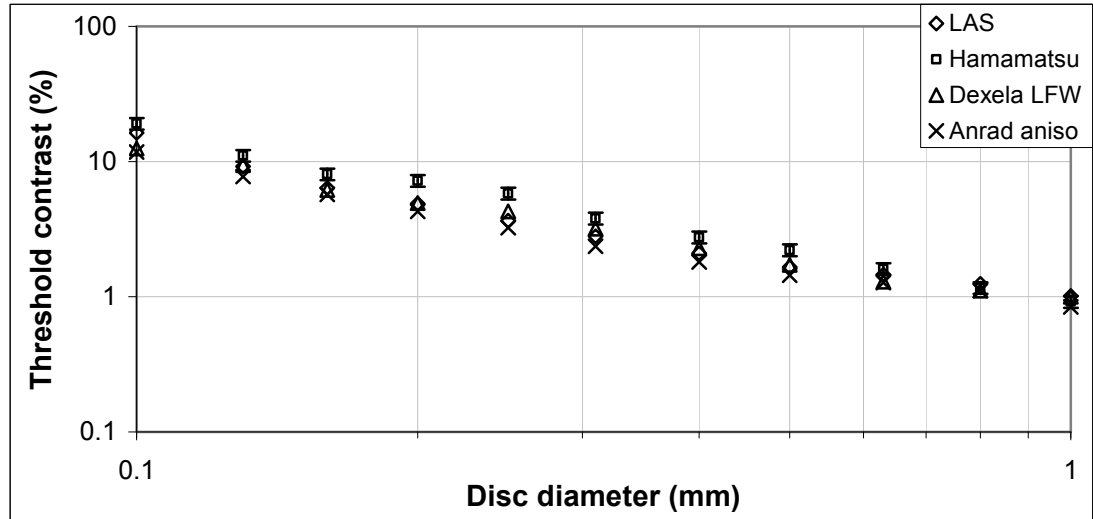


Figure 5.7: Threshold contrast versus the disk diameter for three detectors at low DAK

Figure 5.8 shows the threshold contrast curves of the lower sensitivity detectors (Hamamatsu, Dexela in the HFW mode and Anrad) at higher DAK level (120 μGy). The threshold contrast values in this case are lower compared to the respective ones at low DAK because the SNR increases as a function of exposure. It is observed that Hamamatsu detector demonstrates lower performance in the diameter range 0.1-0.4 mm. On the other hand, Dexela detector in the HFW mode presents a similar performance compared to Anrad SMAM detector in almost the whole range of disk diameter. Hence, the increased noise transfer of the Dexela detector in the HFW mode has got the same effect as the increased pMTF of Anrad detector (see section 3.3.7) on the detectability of low contrast-details.

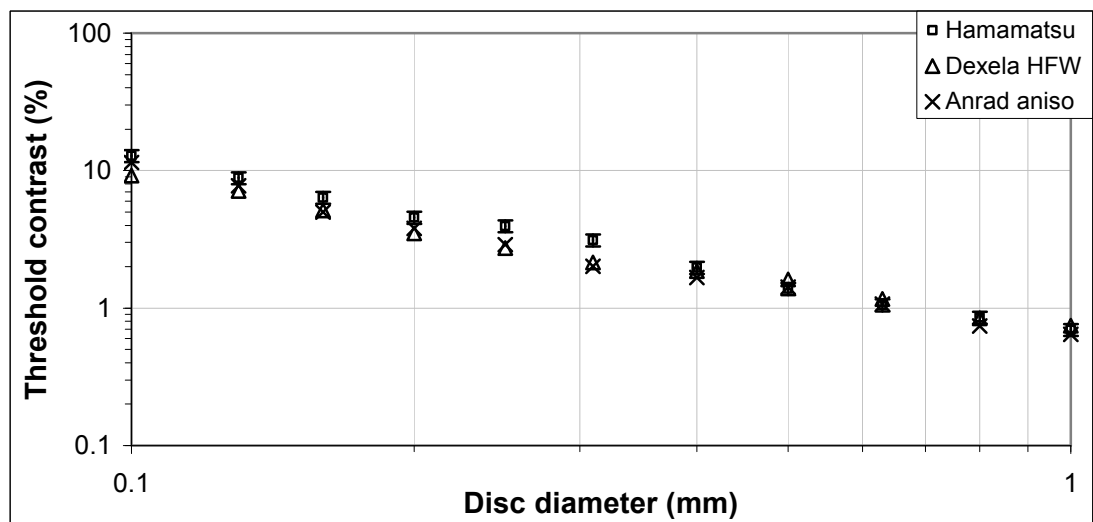


Figure 5.8: Threshold contrast versus the disk diameter for three detectors at high DAK

Figure 5.9 and 5.8 demonstrate the predicted threshold contrast curves of the four detectors at both DAK levels. The original threshold contrast data points were converted to predicted human readings using Eq. (1.14) and the converted values were fitted from the curve described using Eq. (1.12) (van Engen *et al.*, 2010). It can be seen that the Hamamatsu detector demonstrates the lowest detectability in almost the whole diameter range, while LAS presents the highest ones in the diameter range 0.16-0.40 mm.

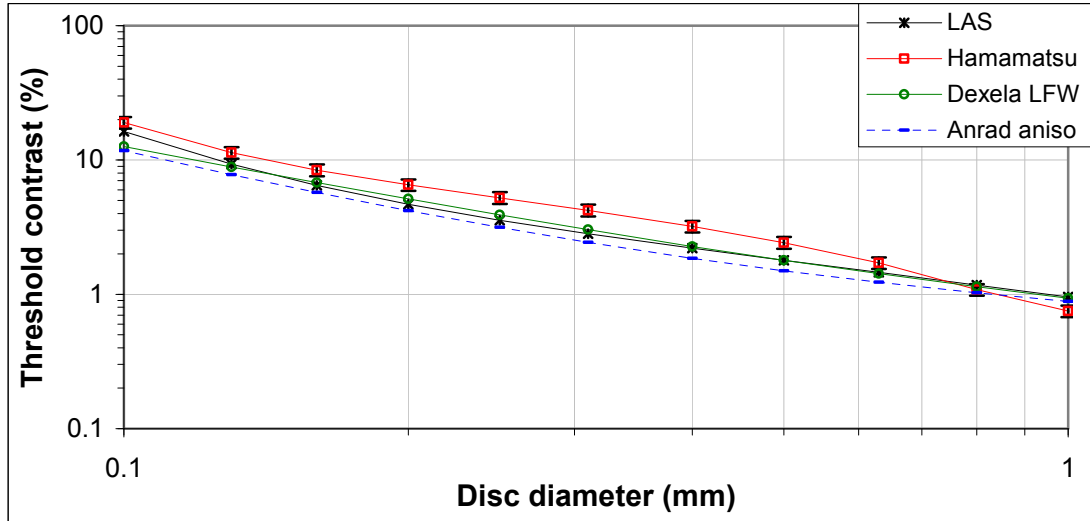


Figure 5.9: Predicted threshold contrast for four detectors at 59 μGy DAK

Figure 5.10 shows the predicted threshold contrast values at higher DAK level (120 μGy). Again it is observed that Hamamatsu detector demonstrates the lower performance in almost the whole diameter range. On the other hand, the Dexela detector in the HFW mode presents a similar performance compared to Anrad detector in medium disk diameter range (0.16-0.5 mm). Finally, it is observed that Anrad has lower performance than Dexela at low disk diameters (i.e. 0.1 and 0.13 mm) despite its high pMTF values. This happens due to the aliasing effect that increases the NNPS and consequently decreases the DQE at high spatial frequencies (see Figure 3.35e).

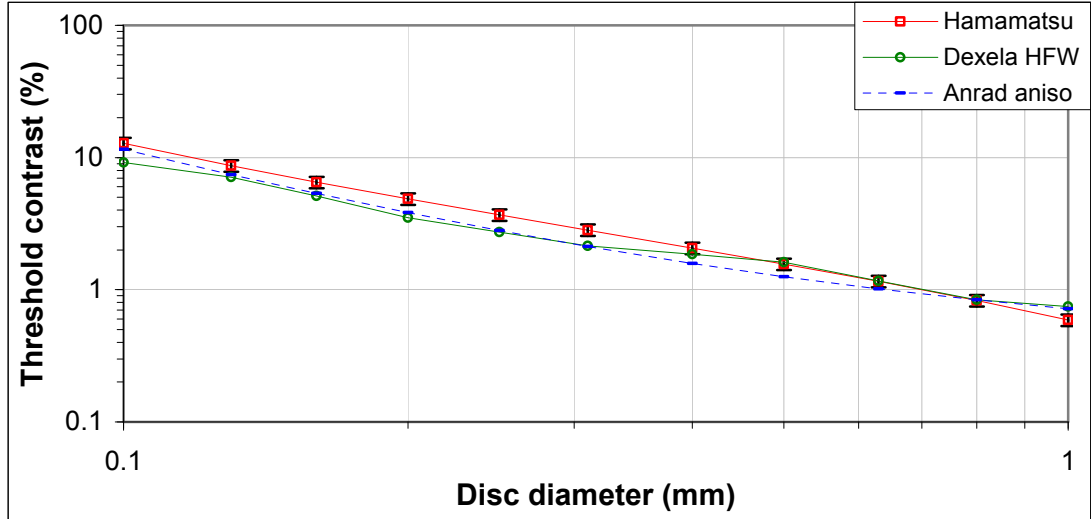


Figure 5.10: Predicted threshold contrast for three detectors at 120 μGy DAK

The overall performance of the detectors is described by the inverse IQF parameter. The following table compares the IQF_{inv} results of all detectors at both DAK levels. At 59 μGy LAS, Dexela at both FW modes and Anrad detectors demonstrate similar values. The IQF_{inv} values increase as a function of the DAK level due to the increased SNR transfer ratio. The performance of the Dexela detector in the HFW mode is similar to the Anrad SMAM detector.

Table 5.2: IQF_{inv} of the investigated detectors at two DAK levels

DAK (μGy)	LAS	Hamamatsu	Dexela LFW	Dexela HFW	Anrad
59	126 ± 14	98 ± 10	130 ± 9	129 ± 11	128 ± 14
120	-	145 ± 12	-	178 ± 17	176 ± 17

Since the followed methodology allows an independent modification of the spatial resolution and noise characteristics for a given image (see section 4.2) two hypothetical cases were simulated by combining the signal and noise transfer of different detectors (Tingberg *et al.*, 2002). In particular, the performance of a detector was simulated by combining the spatial resolution of Hamamatsu with the noise characteristics of LAS. This was made in order to evaluate the effect of a better scintillator coupling on the LAS detector which could result in Hamamatsu's pMTF. Also, the spatial resolution of Hamamatsu was combined with the noise transfer of the Dexela detector in the LFW mode. Both detectors demonstrate similar pMTF values up to 6.5 lp/mm frequency

which corresponds to the Nyquist limit of the Dexela detector (see Figure 3.32). However, the Hamamatsu detector, due to its smaller pixel spacing, can detect objects up to 10 lp/mm without aliasing. Hence, this combination allows us to examine the case where the pixel spacing of the Dexela detector is 50 μm and simultaneously maintain the same SNR performance. Figure 5.11 shows that both combinations would result in better performance in terms of threshold detectability. In particular, the Hamamatsu-LAS combination would result in high performance mainly at low disk diameters, while the Hamamatsu-Dexela in the LFW mode combination at higher disk diameters. At 59 μGy DAK the IQF_{inv} value for Hamamatsu-LAS combination would be equal to 168 ± 13 , while the respective one for Hamamatsu-Dexela (LFW) combination would be 150 ± 11 .

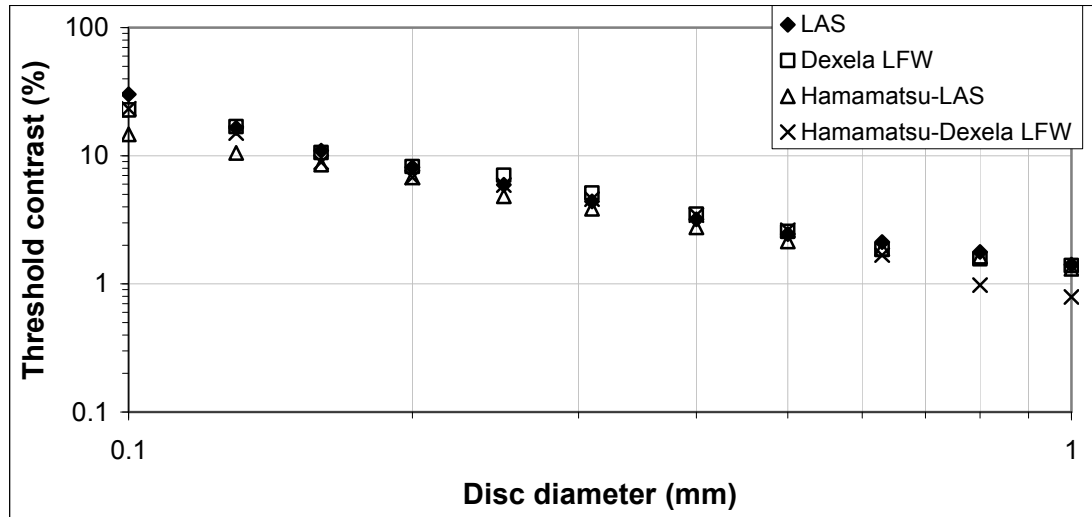


Figure 5.11: Threshold contrast for combined detectors at 59 μGy DAK

It should be noted that the above combinations are somewhat idealized because the pMTF, pixel pitch (noise aliasing) and NNPS are interlinked (see Eq. (2.25)). Hence, it is doubtful that pMTF, pixel pitch and NNPS can be selected independently. This discussion is made to estimate the performance of the detectors under optimized signal and noise transfer conditions.

5.4 Summary

In this chapter the synthetic mammographic images have been evaluated to compare the performance of the detectors in terms of image analysis. Both LAS and Dexela detectors demonstrate high CNR values compared to Hamamatsu and Anrad SMAM

detectors at the same conditions. Therefore, the increased SNR transfer of LAS plays the most crucial role on the detectability of microcalcifications with diameter down to 600 μm . The contrast-detail evaluation is made at a range of contrasts and diameters. Both LAS and Dexela detectors demonstrate high performance at mammographic conditions. Finally, the spatial resolution of Hamamatsu has been combined with the noise characteristics of LAS and Dexela detectors. Both combinations resulted in higher image quality.

Chapter 6

6 Concluding remarks and future potential

6.1 Potential x-ray applications for LAS and Dexela detectors

In this chapter suitable x-ray imaging applications for LAS and Dexela detectors are suggested, based on the experimental and simulation findings. LAS detector presents low read noise (40 e^-) and relatively low dynamic range (63 dB). However, it demonstrates high DQE values at low DAK levels due to its increased SNR transfer. The CNR analysis presents that LAS detector has high visibility of object details larger than $600\text{ }\mu\text{m}$. From the contrast-detail evaluation it is observed that LAS demonstrates similar high performance compared to Dexela and Anrad detectors. Hence, it can be used in mammography to detect low contrast tumours in soft tissue and relatively large ($> 600\text{ }\mu\text{m}$) clusters of microcalcifications (Moy, 2000a). The hypothetical combination of LAS noise with Hamamatsu spatial resolution resulted in 33 % improved performance. This finding allows an estimation of the improvement in low contrast and small size details visibility in the case of an optimum scintillator coupling which would result in MTF values similar to Hamamatsu detector. At 52 kV LAS presents average DQE values at low frequency (less than 2 lp/mm). Hence, the current LAS detector (i.e. coupled with $150\text{ }\mu\text{m}$ thick CsI:Tl scintillator) can be used in general radiography to detect and identify cracks or fractures in extremities (Moy, 2000a). The combination of LAS high sensitivity, high DQE values at low DAK level ($\text{DQE}(0.5) > 0.6$ at $7.2\text{ }\mu\text{Gy}$) and the achievable maximum frame rate (20 fps) means it could find applications in advanced imaging techniques, such as breast tomosynthesis and contrast enhanced (dual energy or digital subtraction mammography) digital mammography (Rafferty, 2007). In particular, dual energy or temporal subtraction applications in mammography aim to depict vessels down to 3 mm diameter (Skarpathiotakis, 2002 and Diekmann and Diekmann, 2008), and LAS is expected to reach high performance in this case. Unfortunately, LAS was not coupled with a thicker scintillator to investigate its performance at higher energies ($> 80\text{ kV}$).

The Dexela CMOS x-ray detector presents low read noise (158 e^-) and average dynamic range (69 dB) when it is operated in the LFW mode. On the other hand, the same detector in the HFW mode demonstrates higher read noise (358 e^-) and dynamic range (73 dB). From both CNR and contrast-detail analyses the performance of the Dexela detector is high compared to the other detectors. This performance was predicted from both the signal and noise transfer characteristics. Hence, the Dexela detector using the thin scintillator can be used in mammography. The combination of LFW mode performance (i.e. high sensitivity, low read noise and high DQE at low DAK levels) with the achievable maximum frame rate in 1x1 binning mode (26 fps) allows the detector's use in breast tomosynthesis. Furthermore, the pixel binning (such as 2x2 or 4x4) results in higher achievable frame rate (up to 86 fps) and improved SNR performance. Therefore, the detector could find applications in breast CT (Wu et al., 2003 and Glick, 2007) and contrast enhanced digital mammography, where the spatial resolution is not the most important task. The combination of the Dexela sensor and $150\text{ }\mu\text{m}$ CsI:Tl scintillator demonstrates high DQE values at higher energies (52 and 74 kV) compared to the other detectors. Additionally, the coupling of the Dexela sensor with a $600\text{ }\mu\text{m}$ thick CsI:Tl scintillator results in excellent DQE performance compared to commercially available detectors for general radiography. Hence, the Dexela detector can be used in general radiography in a range of energies. Due to its high dynamic range in the HFW mode it can be used in chest radiography to check for lung abnormalities, diseases, thorax bones and heart failure (Schaefer-Prokop *et al.*, 2008). Furthermore, the Dexela detector demonstrates high DQE performance under fluoroscopic conditions, compared to other commercially available detectors. A possible suitable application is CB-CT for dental imaging, where 80-120 kV are commonly used and the main requirements are 20-30 fps and 200-300 μm pixel pitch (Hashimoto *et al.*, 2003, Baba *et al.*, 2004 and Vannier, 2009). The Dexela detector can meet the requirements when is operated in the binning mode and further measurements need to be done to evaluate its suitability for dental imaging. Means to evaluate the effect of the image ghost and lag on the measurements were not available. However, lag on consecutive frames was not observed. According to the manufacturers (Dexela, 2011) the image lag is expected to be small (less than 0.1 %) due to the crystalline Silicon of the CMOS sensor used in the Dexela detectors. In other words, the structure of the Silicon allows the electrons to pass through easily and eliminates the electrons traps, which is typical of amorphous Silicon

TFT technologies (Cowen *et al.*, 2008 and Kim *et al.*, 2008). Finally, the hypothetical combination of the noise of the Dexela detector in the LFW mode with the spatial resolution of Hamamatsu detector resulted in 16 % improved performance. The selection of the particular MTF was made based on the fact that the MTF values of Dexela and Hamamatsu detectors are similar up to the Nyquist limit of the former. Hence, this combination investigates the case where the pixel pitch is 33 % smaller and the detector retains its high SNR transfer.

6.2 Future work

This thesis compares the digital detectors in terms of primary physical characteristics (MTF, NPS and SNR) and overall system performance (DQE, CNR and contrast-detail resolution). According to Lança and Silva (2009) the latter investigation offers higher level of ambition compared to the former. The highest level of ambition is extracted from analysis related to the images of patients (i.e. receiver operated characteristics (ROC), ROC related methods, visual grading analysis (VGA) and image criteria (IC)). Therefore, the suitability of the detectors for various imaging applications needs to be further validated through clinical trials.

The performance comparison of the x-ray detectors in terms of image quality evaluation can be made for advanced mammographic applications such as breast tomosynthesis using synthetic 3-D phantoms (Ma *et al.*, 2009 and Bliznakova *et al.*, 2010). Furthermore, it can be applied at higher energies using either anthropomorphic software phantoms (Sandborg *et al.*, 2001, McVey *et al.*, 2003 and Demarco *et al.*, 2007) or software CDRAD test tool (Smans *et al.*, 2010). The performance of the investigated detectors can be compared to commercially available ones using clinical radiographs. In particular, the known signal and noise transfers of a commercial detector at specific DAK level can be used to remove the spatial resolution (deblurring) and the noise (denoise) from a captured radiograph. The resultant ideal image can be inserted in the input of the presented simulation algorithm to evaluate the performance of the investigated detectors in real radiographs. Detailed image lag measurements can be made by synchronizing the x-ray source and the digital detectors (Mail *et al.*, 2007 and Zhao and Zhao, 2008). A detailed x-ray performance evaluation of the detectors can be made for breast tomosynthesis and CT applications by calculating the coronal and axial

MTF and NPS as a function of the acquisition angle (Zhao, 2007, Richard and Samei, 2010a and Richard and Samei, 2010b).

As aforementioned, advanced x-ray imaging techniques can be used (dual energy, breast tomosynthesis etc.) in the case of dense and thick breasts. Furthermore, combination of the temporal and spatial resolution of x-ray imaging with data from other imaging modalities could allow more precise characterization of breast lesions and result in enhanced diagnostic accuracy (Rafferty, 2007). In other words, the development of a hybrid imaging system can improve the sensitivity and specificity of the diagnostic process. According to Fass (2008) the development of a positron emission tomography (PET)/CT hybrid system promises high diagnostic quality due to the combination of the metabolic sensitivity of PET and the temporal and spatial resolution of CT. This combination is commonly used to guide biopsy by highlighting the metabolically active region. Another alternative hybrid system is the x-ray/ultrasound (US) combination (Fass, 2008 and Karellas and Vedantham, 2008). The screening US increases the detection of small cancers and depicts more cancers at a smaller size and lower stage compared to a physical examination. The US imaging technology demonstrates higher sensitivity than x-ray imaging, due to the investigation of the perfusion. Furthermore, magnetic resonance imaging (MRI) appears to be superior to x-ray imaging and US for assessing pathological response and a low rate of re-operation for positive margins (Fass, 2008). Therefore, a combined x-ray/MRI system could allow more precise characterization of breast lesions and result in enhanced diagnostic accuracy (Rafferty, 2007). Both US and MRI techniques are non-ionizing which is an important advantage in the case of high radiation-risk patients. However, the high cost and the limited access to MRI machines are important limitations for its widespread availability. In addition, a compromise between spatial and temporal resolution is inevitable in MRI technique, potentially increasing the number of repeated examinations (Diekmann and Diekmann, 2008). The Dexela detector demonstrates large area, low noise and wide dynamic range, which probably enables simultaneous collection of the transmitted beam and scattered radiation. Therefore, the suitability of this detector for x-ray diffraction imaging needs to be examined. X-ray diffraction is used to obtain biologically relevant scatter signatures from breast cancer (Bohndiek, 2008b and Fass, 2008). Both detectors can be examined for phase contrast imaging methods, which are based on observing variations of the

transmitted intensity behind the object, due to interference or change in propagation direction. This technique results in enhanced contrast which allows improvement of spatial resolution with reduced radiation dose (Keyriläinen *et al.*, 2010).

Recently, combinations of the advanced techniques are suggested in the literature. Graser *et al.* (2009) studied dual energy CT in the abdomen. They defined that using this technique a temporal resolution of 83 ms is possible. This limit is reached from the Dexela detector, because its minimum integration time at 1x1 binning mode is 38 ms. The other important requirement is high SNR at low signal levels. The Dexela detector is expected to meet this limit as well when is operated in the LFW mode. Another study (MacMahon *et al.*, 2008) focused on the combination of dual energy subtraction and temporal subtraction chest radiography to reduce misregistration artifacts and improve the computed-aided detection (CAD) of lung nodules and pulmonary lesions. The main requirements of this combination are high frame rate and high SNR at low DAK levels, which are met by the Dexela detector. Another combined application with similar requirements (i.e. high frame rate and SNR) is the dual energy contrast enhanced digital breast tomosynthesis (Carton *et al.*, 2010), which is an alternative to the contrast enhanced MRI. Further experimental analysis needs to be performed to evaluate the suitability of the detector on the above combined applications.

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