

How to monitor people ‘smartly’ to help reducing energy consumption in buildings?

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There is a complex link between building fabric, habitant expectation and behavior, energy consumption and actual internal conditions. Home owners exert total control of their homes and how people actually use buildings is not as how we think they do. Therefore, mapping occupants’ behavior, and understanding how it relates to comfort and energy consumption is essential. To address this necessity, the paper reviews techniques and systems used to monitor occupants through time and location. Furthermore, it assesses the complexity, robustness, accuracy and performance of each method. To support this review, monitored data were collected using various methods to monitor people’s activities in their home. These could be supported by fix building sensors, or/and wearable sensors. Results from these studies established that systems, using ultra wide band technology and radio-frequency identification hold the highest precision and accuracy, being a non-intrusive method in everyday domestic settings. In conclusion, gathering occupancy data may lead to better and more energy-efficient control system of indoor environment.

Keywords: occupancy patterns; non-intrusive monitoring system; user location and tracking; energy demand reduction

1. Introduction

Across the world there are targets imposed by Governments to reduce the carbon emissions from existing buildings. Scientists showed that the energy use in homes as a result of human activities have contributed to the increase of carbon emissions. In the UK, in 2011, 26% of the total final energy consumption is attributed to dwellings (DECC, 2012). In addition, the UK’s Government aims to reduce greenhouse-gas emissions by 80% by 2050, with yearly reduction from current level of 574 MtCO₂e (carbon-dioxide equivalent) to 160 MtCO₂e (UK Fourth Carbon Budget 2011, House of Commons).

In order to achieve the carbon targets, various interventions programs have been introduced, such as Green Deal. Despite the fact that many initiatives have been rolled out over the past years, there has not been seen significant decrease in the energy consumed in dwellings. As recently published by DECC (2012), the electricity consumption from consumer electronics increased by 74% since 1990 and wet appliances by 23%. The only reductions since 1990 has been seen for lighting and cold appliance, respectively 21% and 19% (DECC, 2012).

If the electricity consumption will continue to increase, and people will not change their behavior and the way they use energy, it is likely that the targets imposed by the Government may not be

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reached. As highlighted by Spataru (2010), Spataru and Gillott (2011) and Ekins & Spataru (2012), behavioral changes can be more important in reducing electricity consumption than any energy efficiency intervention relating to household equipment. Therefore, it is important to understand individual behavior and to gather comprehensive evaluations of people's behavior and activities in order to see how this can be change at a national level in order to help reduce energy consumption and carbon emissions from existing buildings. Moreover, information on occupancy, may lead to very fine delivery of lighting and heating, ventilation and air conditioning (HVAC), and visualization of the use of space.

In the past few years, a number of field trials were undertaken, a number undergo and more are planning in the near future. The scope of these is to understand how different options could help to reduce energy consumption from existing buildings. The literature provides limited studies for complete monitoring of buildings and people. Such an example is Spataru, Gillott, & Hall (2010) and Spataru & Gillott (2011) which performed a complete monitoring program and an initial assessment has been undertaken, including occupants' behavior before and after various stages of refurbishment. Interesting results have been drawn from this study showing that a large part of the rooms in house are empty for most of the time (Spataru, 2010) and that the densest occupied spaces were when the house was heated with electrical heaters (Spataru et al., 2010). This understanding allows us to improve the interior design of a house and the service systems could be refined to give a more precise delivery in space and time. Moreover, information on occupancy, knowing where individual occupants are, may lead to very fine delivery of lighting and HVAC and visualize the use of space.

Vale and Vale (2010) revealed the complex linkages between building fabric, inhabitants' expectation and behavior, energy consumption and actual internal conditions. They have shown how people actually use buildings, rather than how we think they do. A Danish study investigating the heat consumption in 290 identical homes found that the highest heat consumption was up to 20 times higher than the lowest (Fabi, Korsholm Andersen, & Corgnati, 2012). Toftum, Andersen, and Jensen (2009) determined that the energy usage depends on the occupant behavior. In addition, significant savings can be achieved through consciously use of appliances, electronics and lights. Such studies are necessary in order to understand, for example, why housing occupants use more energy for heating as their neighbor, while living in exactly the same type of home. Also, information of occupants patterns are useful in determining the required building's heating and for thermal control. The building heating system can be adjusted relative to the body heat output of the occupants' number. Multiple electronics lead to an increased temperature of the room. When this happens, the heating system can be automatically lowered. The same principle can be applied to adjust building's ventilation needs and decrease CO₂ emissions. This is important because respiratory diseases can occur in an improper ventilated space, but also this may lead to better and more energy-efficient indoor environment control. In addition, if occupants are informed on their energy consumption, they could change their behavior and actions become more conscious (Darby, 2006). Powerful information could be sent to building systems; so that efficiency of lighting and heating be improved; concurrently safety and security.

In order to understand better how occupant behavior relates to energy consumption, options for monitoring people within dwellings needs to be researched. Therefore, the authors tested over the past few years various techniques and monitoring systems. This paper investigates the use of different methods to measure building occupant activities in order to develop metrics related to total building occupancy and assess the impact of occupancy on energy use in buildings. Occupancy data and metrics related to building occupancy and comfort can be valuable in forecast models of building power draw. Moreover, information on occupancy may lead to more energy-efficient indoor environment control.

The paper is organized as follows: Section 2 provides a review of various sensors and methods for monitoring people indoor, debating their accuracy, costs, performance and the challenges imposed. Section 3 provides a comparison between two established evidence-based protocol methods and lessons learnt, followed by Section 4 where two methods used for data analyzing were presented.

2. A review of methods for indoor location monitoring

The interest in indoor localization has rapidly expanded with the development of a variety of sensors for people tracking and activity recognition. For ubiquitous computing, people tracking represents a fundamental interest, for which has been considered a variety of sensors, including: wireless networks, radio-frequency identification (RFID) tags, cameras and laser range finders (Abowd et al., 2000; Adlesee, 2001; Bennewitz, Burgard, & Thrun, 2002; Clarkson, Sawhney, & Pentland, 1998; Fox, Hightower, Liao, Schulz, & Borriello, 2003). For people's activity assessment, there are sensors which can provide us information about motion and sensors which simultaneous provide information about location and activity. The latest tell us which rooms are occupied, the number of occupants, who are the occupants, if they move or not and record their movements. Nowadays, the most popular technique for in-home use is Wi-Fi (Vance, Prasad, Harkin, & Callaghan, 2007; Hightower & Borriello, 2002). Liu, Darabi, Banerjee, & Liu (2007) provide a comprehensive review of systems for indoor localization based on radio-based techniques; evaluating position precision, robustness, complexity and cost.

In the building energy research area, the most common methods used in applications are CO₂ sensors and passive infrared (PIR) sensors. People's CO₂ measurements depend on their metabolic rate, which at its turn depends on people activity in the home, but also on other factors, such ventilation rate. Unfortunately the method does not provide us accurate information on the number of occupants and can lead to inaccurate or misinterpretation in the results in some cases, such as the delay in reaction time when the space is occupied for a short time, or the increase in the metabolic rate when one occupant is doing physical exercise.

Another common method is PIR sensors. These sensors can detect the presence of someone in a building. However, there are issues with this method. For example, when low motion, the PIR sensors sometimes do not record; when more than one person is in the same space, the PIR readings do not show greater peaks and do not differentiate between presences of different persons; when occupants perform physical activity, the PIR sensors record higher values. It has been already demonstrated (Akhlaghinia, Lotfi, Langensiepen, & Sherkat, 2009) that in a domestic environment, the PIR sensors cannot cover the required visual area, in addition they can record information about events from another neighbor's space. Therefore, PIR readings can provide information on the amount of movement which takes place in the area they are located.

The advantage of CO₂ and PIR sensors is that the cost of them is low, they are easy to deploy, and they can operate in real-time; while the disadvantage is they can provide limited accurate information and sometimes misinterpretation in the results. This is in part due to the fact that these two sensors are connected to the building, rather than the residents. To address these issues, wearable sensors may be used concurrently, or as a stand-alone method. Indoor localization may be determined through motion and direction, as the output of accelerometer and magnetometer; radio-based techniques. There are also systems which can detect and track people with a single camera, or using stereo vision and color, or video motion detectors which compare a stationary image stored in a memory with the current image, or video face recognition system. This is a well-explored topic, but this option is difficult to be implemented in homes due to privacy reasons.

There are many sensors or combinations of sensors used in other research areas such as health, which can be used to detect the presence of occupants and their motion. For example, it may be detected through any means associated with some kind of a human body weight, heat, sounds, dielectric constant and so forth. Some of these examples are: acoustic (detectors of sound produced by people); air pressure sensors (which detects changes in air pressure resulted from opening doors and windows); infrared motion detectors: devices sensitive to heat waves emanated from warm or cold moving objects; etc.

In a domestic environment, an unobstructed method should be considered. It is important because not many people are comfortable living with cameras and microphones, or wearing a badge or RFID tag. A RFID tag is a small device which needs to be worn by the person to identify her or him by radio frequency transmission using wireless identification technology that communicates data by means of radio waves.

However, in any method used, accuracy is important so as to avoid misinterpretation of data. In addition, some systems may not work in some environment and situations, but may work in other environment and situations. In the indoor environment, different challenges on location determination can occur due to the multipath effect and building material propagation effects on technologies (such as wireless local area networking (WLAN), ultra-wideband (UWB) and indoor global positioning system (GPS)) making them unsustainable in a dynamic environment (Khuory & Kamat, 2008). As seen in Table 1, some systems are costly, but provide high accuracy (such as UBISENSE system which is using UWB technology and has the highest precision and accuracy), others are low cost but provide lower accuracy. Spataru et al. (2010) have been used UBISENSE to detect the location and movements of people within a test house and indeed the system performed with high precision, but relied on occupants wearing tag. The communication

Table 1. Comparison on existing wireless-based indoor positioning systems (with space dimension 2D and 3D) (Source: Liu et al., 2007).

System	Wireless technologies	Accuracy	Precision	Complexity	Cost
Microsoft RADAR	WLAN RSS	3–5 m	50% within around 2.5 m and 90% within around 5.9 m	Moderate	Low
DIT	WLAN RSS	3 m	90% within 5.12 m for SVM; 90% within 5.4 m for MLP	Moderate	Low
Snap Track	Assisted GPS, TDOA	5–50 m	50% within 25 m	High	Medium
WhereNet	UHF TDOA	2–3 m	50% within 3 m	Moderate	Low
Ubisense	Unidirectional, UWB TDOA + AOA	15 cm	99% within 0.3 m	Real-time response (1 Hz–10 Hz)	Medium to High
Sapphire Dart	Unidirectional, UWB TDOA	<0.3 m	50% within 0.3 m	Response frequency (01 Hz–1 Hz)	Medium to High
MPS	QDMA	10 m	50% within 10 m	1 s	Medium
PinPoint 3D-ID	UHF (40 MHz) (RTOF)	1 m	50% within 1 m	5 s	Low
GSM fingerprinting	Weighted kNN	5 m	80% within 10 m	Medium	Medium

is taken place between the reader and the tag. When each tag moves into the proximity range of the sensors, the sensor detects the unique ID of the tag and in turn updates the tag's location and information recorded in a computer. Tags can be either active or passive (Krohn, 2005); the first being powered by a battery to send and receive data, while the second type are powered by the reader field. However, despite the fact that UWB can be a very effective method, with a lower power and a high speed technique compared to WLAN and Bluetooth, making it more reliable in indoor positioning, it requires a high cost to implement.

Moreover, the person needs to accept to wear the tag at all times, but when the occupants forget to wear the tag on a daily basis, the system will provide less efficient results. However, a friendly method can be used for tags, in the form of a bracelet or a necklace, so that people can use it as an accessory.

Recently a new technique for localization has been discussed, the device-free localization (DFL) which gives freedom to the user to do his activities without the requirement to wear a tag. As the human body crosses a transmission-receiver path, the received signal strength (RSS) of transmitted wireless signals is given. Various techniques have been proposed in the field of DFL (Patwari & Wilson, 2010). However, Kosba, Abdelkader, and Youssef (2009) showed that the communicating radios line-of-sight is sensitive to human presence. In addition, the number of people present in a space is still a challenge for the DFL technology. It can be used in combination with CO₂ sensors and PIR sensors. However, considering the problems encountered with these methods, wearable devices will provide more accuracy and precision about occupants' presence in an indoor space and in combination with energy consumption valuable information can be drawn.

One method is SenseCam, which can include built-in sensors such as acceleration, PIR and temperature that may monitor motion, position, physiological and environmental variables. Another method is the use of a tracking system based on UWB technology that can be put together using available components at a low cost, and to monitor occupants' position and location in addition with sensors for electricity use and environmental conditions. To answer the limitations presented in this section, the next section is reviewing a practical assessment of two alternative systems: environment sensors – PIR and CO₂; and wearable sensors – a tracking system based on radio frequency (RF) and SenseCam. The devices holding these sensors may also store the data output, or be supported by radio-based signals. Off-the-shelf sensors were purchased to measure various parameters associated with the building, including indicators of occupant activity.

3. Practical assessment of different methods

The use of sensors enables a rich picture of people location, motion and activity in buildings. Knowing where the occupant is, and what the occupant does, can potentially help understand, conceptualize and influence some of the practices driving energy demand. In order to map an accurate picture of occupants' location and activity from wearable devices, by choosing an existing system or build a new one, a study-framework should be established, which should include the following five steps:

- (1) Specify which combination of hardware-based sensors to use.
- (2) Determine if this combination of sensors is already available on the market as a stand one device, or a combination of device. If this is not the case, the researcher may choose to build, its own device.
- (3) Establish each sensors specification, including its range, accuracy, power requirement, cost and manufacturer.
- (4) Confirm raw data processing and acquisition method.
- (5) Confirm the output analysis method.

In order to carry-out this study-framework, the following section will provide an overview of the different types of non-wearable and wearable sensors with examples for one day from the work the authors have done.

3.1 Non-wearable sensors/devices overview

Testing has been performed for slots of two weeks in different seasons in a flat in London, with two occupants. In addition to testing various systems for monitoring occupants, environmental factors, including air temperature and relative humidity in living area and bedroom has been monitored, using HOBO-U12 devices. Also the total electricity and water consumption has been monitored, as well as electricity use with different electronic devices. In this paper, examples of 24 h are provided only. [Figure 1](#) shows a print screen of the space use by the occupants during 24 h.

3.1.1 PIR Radiation motion sensor

PIR radiation motion sensors can be used to count the number of times people move through a space. PIR sensors have been used to analyze the expected trends, looking at weekly and weekend profiles as depicted in [Figure 2](#). Data have been collected for different weeks and it has been observed that profiles during the working days looked similar; with higher activity in weekdays than in the weekend as depicted in [Figure 2](#).

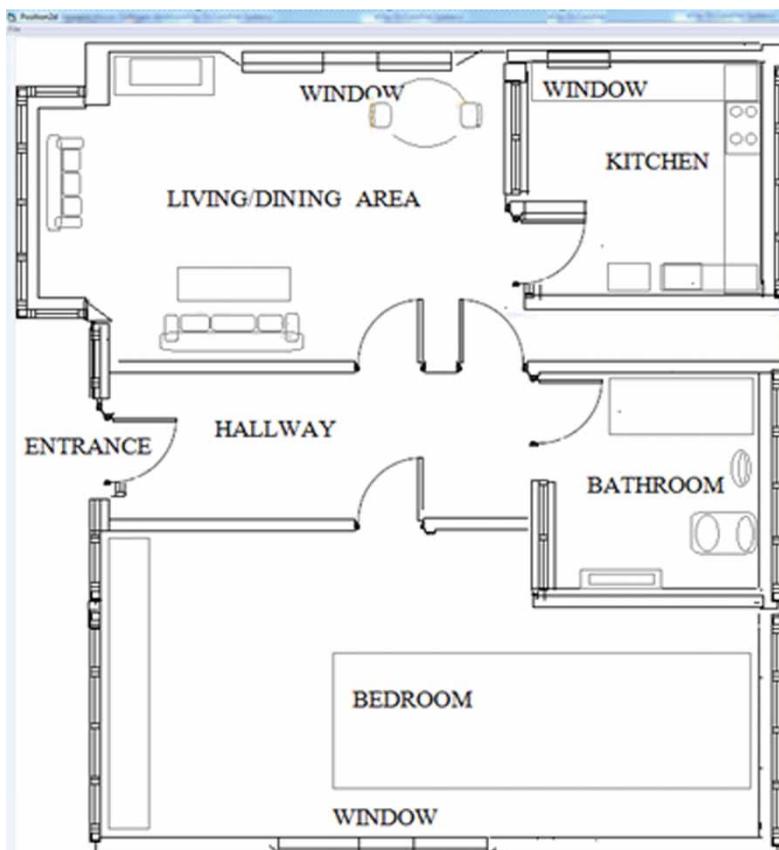


Figure 1. Printscreen of the space use.

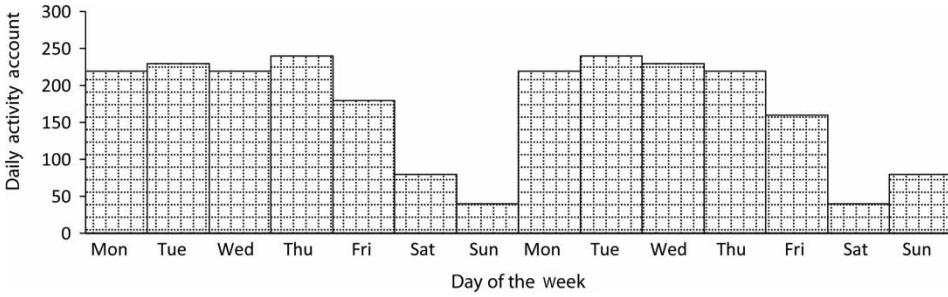


Figure 2. Total daily activity counts on the motion sensor for two-week period.

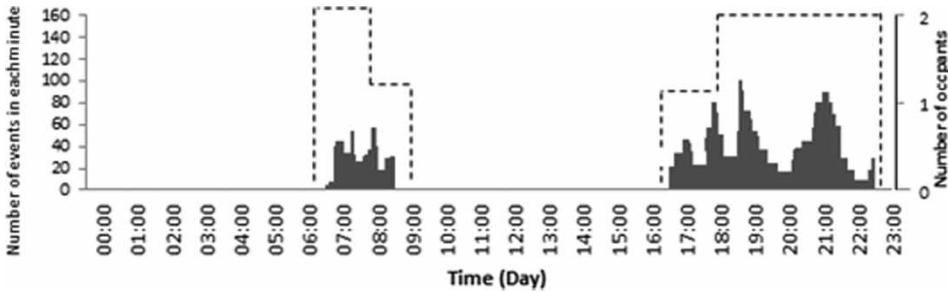


Figure 3. PIR measurements in all rooms versus overall human presence during a day.

Figure 3 shows the PIR measurements in all rooms versus overall presence of the occupants during a day. Using PIR it has been observed that when the room was occupied sometimes PIR shows no measurements. This is caused by a reduced amount of movement of the occupant.

Moreover, when more than one person is present in the same space, did not show greater PIR peaks. So, PIR can provide information on the amount of movement, but not the number of people.

3.1.2 Carbon-dioxide

A carbon-dioxide sensor was connected to a transmitter and included in the wireless network to record activity in the building. The CO₂ sensor (Vaisala GMW21) used was a commercially available sensor. The output of the sensor was capped at 4 V and then stepped this down to 2 V for transmission so that to ensure that the sensitivity of the device to the concentrations expected is maximized. Figure 4 shows the CO₂ content versus number of occupants.

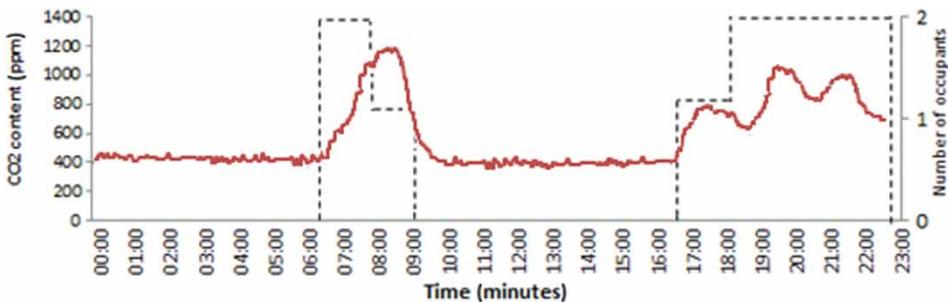


Figure 4. CO₂ content in all rooms versus overall occupants' presence during a day.

As it is shown in the figure above, when the flat is occupied there is an increase in the CO₂ content, with a fast increase when a door has been closed or with slightly decreased in unoccupied spaces or when door has been opened again due to air being mixed with the one from the unoccupied space. Unfortunately, this can conduct to misinterpretation of the results on actual change of location of an occupant. The sharp rise could be related to an increased in metabolic rate due to physical exercise, since the occupants own a static exercise bike. It was observed that CO₂ could provide wrong information on the number of occupants.

3.2 Wearable sensors/devices performance (Active RFID Tracking System and SenseCam)

Wearable device may have built-in sensors that monitor motion, position, physiological, and environmental variables. These sensors provide data, which may be used to monitor changes in location or activity.

3.2.1 Active RFID people tracking system

Companies like Ubisense (www.ubisense.net) or Time Domain (<http://www.timedomain.com>) have implemented the real-time location systems (RTLS) using UWB technology. Time Domain Company has developed an UWB location system with UWB tags based only on TDOA approach. Ubisense has developed a UWB hybrid location system, using TDOA with angle of arrival (AOA) techniques.

The Ubisense positioning system consists in an UWB tags, sensors and a software platform. UWB tags are usually active tags and transmit UWB pulse signals; which are received at the sensors and used to calculate the tag location from a combination the AOA and the TDOA between two sensors. Two sensors deliver a robust localization with an accuracy of up to 15 cm. When combining two particular location methods (like the hybrid location methods) and if UWB communications are used the results are more accurate than when just using only one location method (Gezici et al., 2005). A RFID tag is a small device which combines a chip and an antenna. UWB is a low-power and a high speed technique, which works in wireless space; it uses pulses sending pulses over the air.

UWB signals are received at the sensors and used to calculate the AOA and the TDOA between two sensors. Each sensor detecting a tag gives a 2D bearing (AOA) for Azimuth and Elevation. If sensors are connected to a timing cable network, they also report time-difference-of-arrival (TDOA) information. Ubisense has been used in the E.ON 2016 Test House by Spataru et al. (2010) as part of the CALEBRE Project. It provides information on the exact number of occupants in real-time in each space of the house and the exact 3D location of each occupants and when a person exits or enters a space. This information was coupled together with information from sensors for energy consumption and environmental conditions. Figure 5 shows an example for 24 h for electricity consumption versus number of occupants (Spataru, 2010).

In addition to the already available systems, there are also sensors from the shelf which can be put together that are cost-effective, creating your own monitoring system. This implies technical and software knowledge.

The localization method. A hybrid localization method using a combination of AOA and TDOA to determine the location has been used. Mathematical expressions have been generated as a combination of an exponential distribution (RSS location method) and Gaussian distribution (TDOA location method). First the RFID reader gets the metric, and then locates the RFID tag in the space. This can be done by using the metrics converting them to distances to estimate the

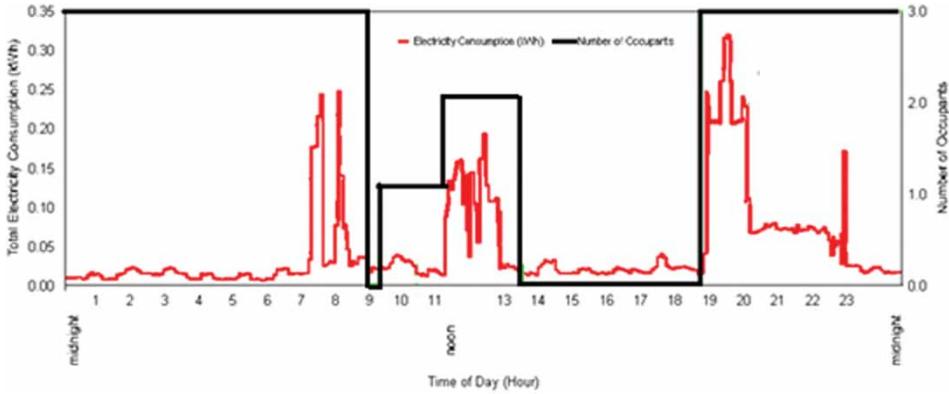


Figure 5. Total electricity consumption versus number of occupants during a day.

target position. The RFID readers are distributed in the space at fixed points strategically so as to cover all areas where occupants move.

The main function of the RFID tag is to answer the interrogation of the RFID readers. When the RFID tag moves into the proximity range of the RFID readers, the RFID readers send RF signal to the RFID target tag questioning the position of the RFID tag in order to get the Time of Arrival metric. Then, each TOA metric proposed is converted into a Difference Time value. For the multilateration approach with TDOA metrics, it was assumed that RFID readers are located in one coordinates system and one RFID target tag comes into the area covered by the RFID Readers. When questioning the location of the RFID tag, each RFID reader gives one Time of Arrival measurement. It is considered that the distance between the points is proportional to the Time of Arrival. The position of RFID tag can be easily estimated by finding the intersection of at least two hyperbolas through Time Difference measurements, as shown in Figure 6.

The difficulty in using such a method consists of synchronized RFID readers in time. Literature provides us with different methods to achieve the solution. One method is Fan's

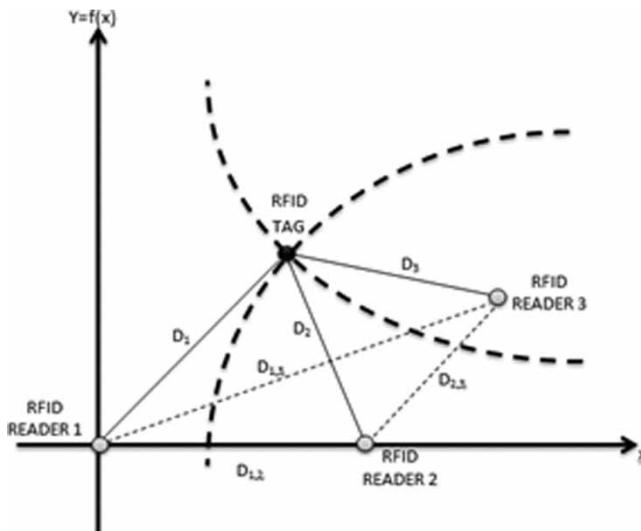


Figure 6. Location determination with time difference.

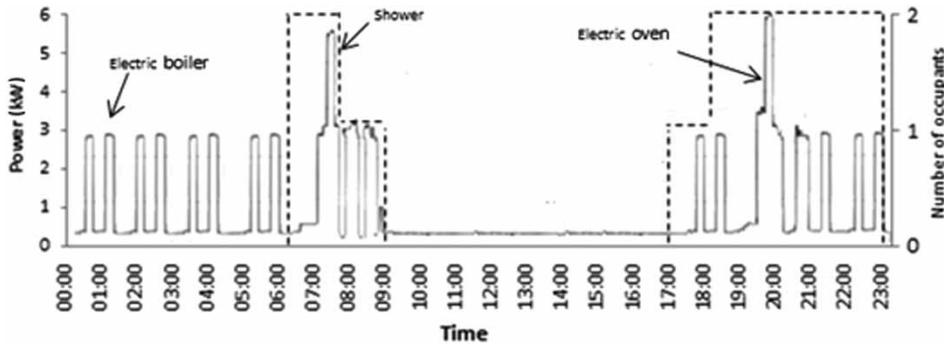


Figure 7. The occupancy patterns and power consumed during a day.

(Elkamchouchi, 2005; Stefanski, 2009). This method transforms the nonlinear expressions into a linear system of equations.

The distance was calculated by the time a signal travels from the sender to the receiver. Information about each tag (id, time and date, position) were stored by the software. This has been written in C#, because C# Express edition is available for free from Microsoft for viewing/editing the source code.

General trends can be drawn from combining information on occupants' position and on power used through the use of soft computing logic algorithms. As depicted in Figure 7 from the total power used and from occupancy time patterns, the power use for main activities during the 24 h was deducted. This includes the use of electric boiler, shower and electric oven.

Further applying logical algorithms attributed to the use of different electronics, the data could be translated into activities.

3.2.2 SenseCam

This section describes how SenseCam and heart-rate monitor outputs are analyzed, and combined to map people's activity and location in the home. The SenseCam was first developed by Microsoft Research labs in Cambridge to assist people with memory impairment (Hodges et al., 2006). Of similar size to a badge and wear around the neck of the participant, it provides two types of outputs: (1) a record of the measurements taken by the five sensors (2) a visual photographic diary. Table 2 summarizes the different types of hardware-based sensors most frequently used in wearable devices that monitor specific physical properties, such as acceleration, heart rate or temperature; data which may be used to monitor changes in location and activity.

Motion sensors include accelerometers, gyroscopes and gravity sensors. They measure the acceleration of the device along two or three axes. Acceleration is defined as the change in speed over time; it is influenced by the frequency, the duration and the intensity of the body movement.

The SenseCam device used in this study contains a three axes piezoresistive accelerometer, Kionix KXP84. Figure 8 shows an example of its output; during this one day sequence, we can observe that the occupant was very active during the lunch period (12–2 pm) and the early part of the evening. Also it is interesting to note the change in the y -axis around 7.20 pm, the visual diary confirmed that the occupant took the device off, and left-it facing downward. The occupant motion was analyzed using a two steps process (Kim, Cho, & Kim, 2012):

- (1) Analysis of the y -axis output, identifying a forward or backward movement, where three types of activity would be discerned, as motionless, walking or running.

Table 2. Overview of the most frequent sensors used in wearable devices.

Type	Sensor	Type	Data output	Units of measure	Common use
Motion sensors	Accelerometer	Hardware	Measures the acceleration that is applied to the device on two or three physical axes, including the force of gravity	m/s ²	Monitoring motion or acceleration along a single axis
	Gyroscope	Hardware	Measures the rate of rotation applied to the device around each of the three physical axes	rad/s	Monitoring rotation
Position sensors	Magnetometer	Hardware	Measures the ambient geomagnetic field around the device for the three physical axes	μT	Determining compass coordinate
Physiological sensors	Heart-rate monitor	Hardware	Measures the number of beat per minute of a person’s heart	Bpm	Determining activity, intensity and type
Environmental sensors	Thermometer	Hardware	Air temperature	°C	Monitoring air temperatures
	Barometer	Hardware	Relative humidity	%	Monitoring dewpoint, absolute and relative humidity
	Photometer	Hardware	Illuminance	Lx	Monitoring ‘brightness’, which could be related to the change of location
	PIR sensor	Hardware	Determine the presence of infrared light radiating from objects in its field of view. i.e. a person, a warm drink, or a radiator	Binary [0,1]	Monitoring motion and activity

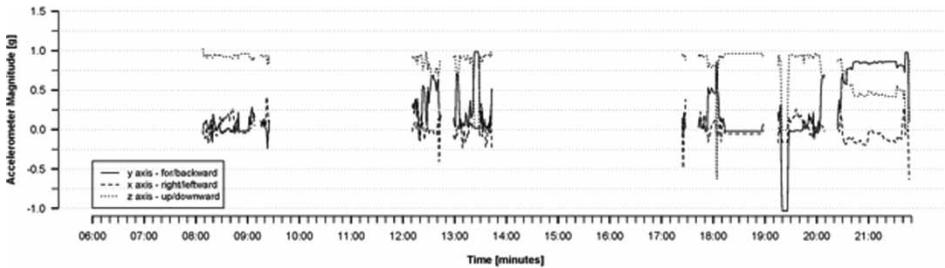


Figure 8. Example of motion sensor output from SenseCam accelerometer during a day.

- (2) Analysis of the z-axis, identifying an upward or downward movement, which could be recognized as walking, going upstairs or going downstairs.

The most important source of measurement error of an accelerometer is the offset of its output signal from the true value (Woodman, 2007). The main limitation of the accelerometer lies with its underestimation of the metabolic rate due to the confounding effect of several factors, including temperature (Jeukendrup & Gleeson, 2004). For example, if an occupant was to stay seated in a cold room, the accelerometer will indicate a low level of energy expenditure, which might be misleading.

Position sensors measure the physical position of the device. This includes magnetometers, which measures the components of earth's magnetic field – geomagnetic field along three axes in μT . Figure 9 shows an output as the normalized magnitude of the vector, where $\sqrt{(x^2 + y^2 + z^2)}$ of the SenseCam using a magnetometer. To determine the location of an occupant, the magnetometer and accelerometer output are analyzed together through an 'indoor-mapping' analysis process (Shala & Rodriguez, 2011; Xuan, Sengupta, & Fallah, 2010; Zhu & Zhou, 2004).

The main sources of measurement errors of a magnetometer are offsets of the frequency and magnetic 'contamination' by ferrous material on and around the participant or the device. Also if the sensor is rotated as the measurement is made, an additional error is generated (Shala & Rodriguez, 2011).

Physiological sensors measure occupants' physiological characteristics, such as heart rate. The monitoring study included two devices manufactured by Kalenji to monitor HR: the sensor and transmitter (Kalenji 300 coded) fitted into a chest-strap belt and the receiver and data logger (Kalenji Cardio Connect) fitted into an independent device, which can be attached to the belt or kept in the occupants's pocket. The sensor is recording heart electric activity, using electrocardiography as shown in Figure 10.

It was observed that records exceeding 95 bmp are matched with most of the peaks of the normalized magnitude of the accelerometer vector. By combining the output of the heart-rate monitor and accelerometer, an occupant's activity patterns can be determined with relatively a high level of accuracy (Gauthier & Shipworth, 2013). The output from the heart-rate monitor can be analyzed with the ISO 8996, level-3 approach and associated set of equations, to estimate metabolic rate. This method uses an indirect determination, based on the relationship between oxygen uptake and heart rate under defined conditions. This method holds some limitations, for example emotions or small movements while resting can increase the occupant's heart rate, while the energy expenditure remains almost the same (Jeukendrup & Gleeson, 2004).

Environmental sensors measure various environmental variables, such as air temperature, relative humidity and illuminance. This includes barometers, photometers and thermometers. Also temperature and relative humidity in the living area and bedroom have been monitored. The four HOBO-U12 devices were attached to a wooden pole and positioned at 0.1, 0.6, 1.1

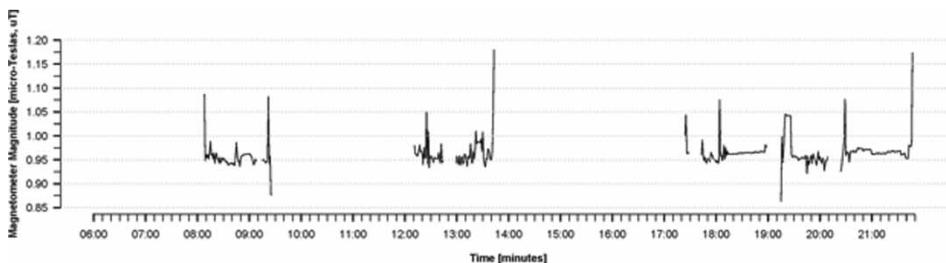


Figure 9. Example of position sensor output from SenseCam magnetometer during a day.

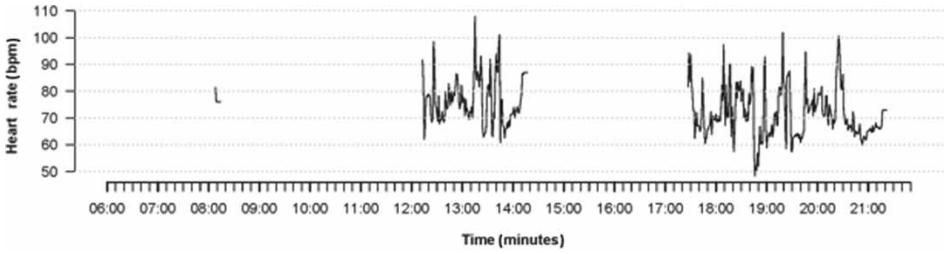


Figure 10. Example of physiological sensor output from Kalenji heart-rate monitor during a day.

and 1.7 m from the ground to comply with the requirements set by EN ISO 7726. The poles were positioned according to the room layout (cold/warm places) and the most likely occupied places.

It has been noted as shown in Figure 11 that the peaks in the internal living room temperature occur when the flat is occupied. Future studies might explore the relationship between the activity level and the variation in the indoor temperature through time and location.

Figure 12 shows an example from SenseCam PIR sensor. It was used to record particular types of activities, such as the intake of warm food or liquid, the proximity to a heat such as a radiator or contact with other occupants.

As shown in Figure 12, and after validation from the visual diary, it was confirmed that when count of [PIR = 1] per minute > 20, the occupant had warm food or liquid intake or close contact with another occupant. This result is particularly useful to enable activity recognition.

3.3 Lessons learnt from the use of the methods presented above and potential savings

It was concluded that the ideal sensors when used in an indoor environment should be: ‘discreet’ to not influence occupant’s activities; private – not revealing sensitive information; invasive; for researchers should be: inexpensive, easy to install, well documented, easy to replace

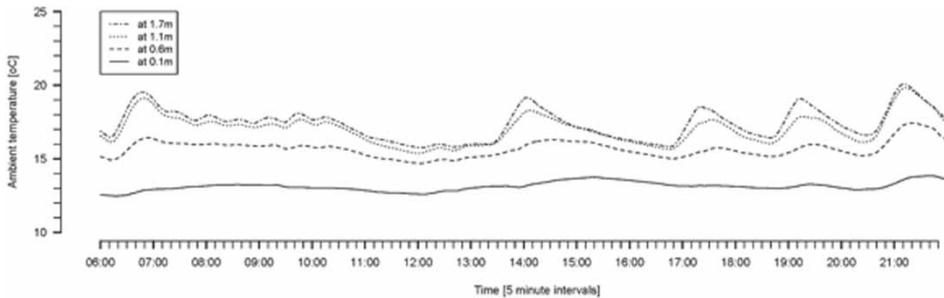


Figure 11. Example of environmental sensor output from living room thermometer during a day.

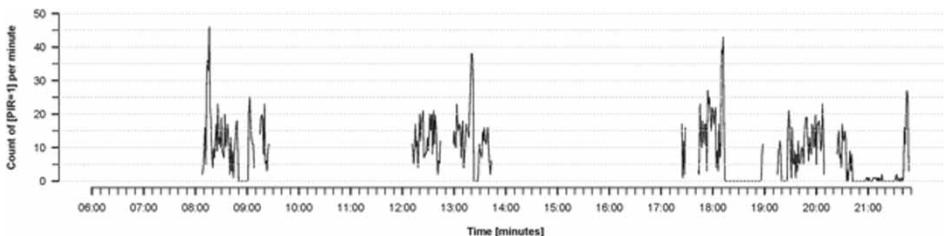


Figure 12. Example of environmental sensor output from SenseCam PIR during a day.

and maintain, robust to damage, wireless connected to avoid use of cables, should require minimal computational resources, low-power, requiring no external power or able to run as long as possible on batteries. Appendix 1 provides a table with a list of commercialized wearable devices and sensors.

Collected data were manipulated and translated to a descriptive series of activities performed regularly in the house by occupants. Energy savings due to different measures can be calculated following occupants' activities. The following measures were considered and assessed for this case study: change in internal temperatures (thermostat) for heating, switching off unnecessary lighting, use of heating only on occupied spaces, switching off electronics appliances and lights when not in use; reduce energy use for cooking, setting the washing machine to 30°C, filling the kettle with the required water needed, watching less TV. This resulted in identifying occupants' energy use behavior and potential energy savings.

The fridge/freezer in the kitchen is class A+. Each space has halogen bulbs. It was observed that the TV is left on standby all time and two laptops are in used most of the time or stay on, while the occupants performed other activities (such as cooking or watching TV). A potential energy savings of 4.8 kWh for the monitoring week was calculated. If we consider that as an average per week, that will mean a total of 249.6 kWh annually. If we consider 26.35 pence/kWh of electricity than the occupants can save around £65 per year.

A recent report (Zimmermann et al., 2012) with a survey of 251 households in England for which the electrical power demand and energy consumption was monitored for the period May 2010 and July 2011 was published by the Department for Environment, Food and Rural Affairs, the Department of Energy and Climate Change and the Energy Saving Trust. This study is the largest one until now in Europe which assessed the energy saving potential of domestic appliances. It was determined that in England the potential annual electricity saving per household ranges from 491 to 677 kWh depending on the type of household. In our case, we obtained a potential annual saving of 249.6 kWh, which is less than the one indicated by the study.

4. Data analysis methods used

Recording data include the concurrent use of sensor(s) to capture information, and the data logger (s) to store this information. Once the information has been recorded, it may be downloaded manually with proprietary software, or automatically with the use of a transmitter, receiver and proprietary software. Various methods can be used for data recording and data processing.

To process the downloaded information, existing platforms may be employed, such as R (<http://cran.r-project.org>); which can be used as the main computational tool, but also can be used as an odd-on to an existing set of statistical tool. In the case of the SenseCam, R was used to synchronize time series data; carrying out descriptive and inferential statistics, implementing query to data set; processing signal output; and running algorithm. The most important future for the analysis was the capacity to 'slice' or/and to 'extract' data from a large data set. In particular, when validating an event or activity, the following steps were executed:

- (1) Extracting a subset of data – for example, 'looking for PIR output only';
- (2) Find a particular variable – for example, 'call for the corresponding set of photo, when [PIR = 1] per minute > 20'.

In addition, R might also be used to run query commands to retrieve data from database management systems, such as PostgreSQL (Li & Baron, 2012).

Also, for data recording and processing, the own software may be employed, such as the one developed by Spataru and used in Spataru and Gillott (2011), which has developed a soft-

computing application written in Visual Basic to correlate various information, such as occupancy information and electricity consumption to detect the events. The method consisted in pre-designing a series of event procedures which can perform a series of actions about energy consumption and occupants' activities. Soft-computing applications are important to correlate different databases sets and provide the necessary statistics. Data were collected as txt. files and then were read through Visual Basic in a Microsoft Access Database. All data records have an associated error code and validity check so any non-valid data can be removed. Data can be presented in 5 min, hourly and daily forms.

Automated standard graphs to analyze data and spot problems in monitoring from an early stage were designed so that any problem occur in monitoring can be detected. Automated information can be provided; such as a breakdown of domestic energy consumption for any specific period: day/month/year; statistical analysis of the performance of the technologies and occupants. This approach is valuable in ensuring that solutions and problems encountered are quickly shared.

Depending on the type of data, it is recommended to have a synthetic view of the consumption figures. Electric appliances can be grouped and a few summary statistics can be calculated to give an idea of what is important in terms of consumption. Information can be extracted from load curves to detect distribution of starting time, frequency of run per day, week. The method is easily set up and feasible to any users and enables to analyze data for any dwellings without having any knowledge of coding programming. Moreover, pre-designed automated standard graphs will help to analyze data efficiently and spot problems in monitoring from an early stage.

5. Discussions and conclusions

The aim of this paper was to compare the performance of various sensors for monitoring people within buildings, systems which can help us to assess potential energy savings due to activity and building occupancy and energy use. Two methods for analyzing data have been discussed also. Occupant location was tracked during slots of two weeks, but due to the focus of this paper on different methods, only examples of output for 24 h are presented.

In this study, various challenges were faced. Each technology as shown in the review has intrinsic restrictions. CO₂ sensors are highly depending on air circulation patterns and PIR sensors are prone to negative false outputs. DFL, a relatively new method looks like a promising technology with future potential as mention in literature to detect position and number of occupants without the need for complimentary information. Both methods the SenseCam and the method based on RFID tags can be improved significantly by adding more sensors and make it more comfortable to the users through the use of bracelets instead of necklace tags or through the integration of the tags within a security system. Therefore, the aspect of replacing the tag with a more handy method will be further assessed. With the recent emergence and advancement of more accurate and affordable technologies, components, etc. this may be overcome. For example, in the future, people localization may be determined through TV remote control. The authors will continue to further develop the method and search for new challenges and combinations.

It has been shown the combination of UWB with RFID provides accurate results. The combination is working because in UWB, TDOA is based on time approaches, while in UWB the time resolution is higher due to ultra wideband range of operation than the one used in RFID systems. In addition, using RFID systems with UWB errors are minimized and the accuracy is improved.

Gathering information on occupants' behavior and their energy consumption will help to understand better how to reduce energy consumption in buildings. Compared to the survey method, actual monitoring shows exactly how people behave. Occupancy data are often an

assumed variable in energy models. Therefore, more data should be collected to validate existing models.

Moreover, such studies help in understanding various relationships between occupants and buildings, for example, by looking at energy use variations when identical homes and different occupants are considered. In the future, within smart homes and smart grids, these methods could potentially be used to forecast energy demand for heating and to manage power distribution peaks automatically, as well as to address conservations alongside energy management and providing for rising expectation toward thermal comfort.

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Appendix 1. Examples of commercialized wearable devices

Type	Device	Sensors	Description	Data storage	Cost	Manufacturer	Common use
Motion, position and environmental	Revue 3MP (SenseCam)	Camera, and five sensors: Accelerometer, Magnetometer, Thermometer, Photometer, PIR sensor	Monitor activity through the output of five sensors, and a visual diary of photos (low resolution photo). The five sensors records changes in color, motion, direction, and temperature	Data logger	£299	Vicon Motion Systems, Microsoft, UK. www.viconrevue.com	Life logging. Developed as medical assistance device for patient with memory impairment
Motion, position and environmental	Autographer	GPS, camera, and five sensors: Accelerometer, Magnetometer, Thermometer, Photometer, PIR sensor	Monitor activity through the output of five sensors, GPS, and a visual diary of photos (high resolution photo). The five sensors records changes in color, motion, direction, and temperature	Data logger, and Bluetooth (to pair with smartphone via an app.)	£399	Oxford Metrics Group, UK. www.autographer.com	Life logging, photography
Motion, position and environmental	Smartphone	GPS, Accelerometer, Magnetometer, Photometer, and Microphone	Monitor motion, position, light level and sound pressure level. www.programmingiphonesensors.com	Data logger, Bluetooth, Wi-Fi, and mobile telecommunication network	Variable	Variable	Phone communication, media player, navigation system, audio player and recording, digital photo and video camera

(Continued)

Appendix 1. Continued.

Type	Device	Sensors	Description	Data storage	Cost	Manufacturer	Common use
Motion	Fuelband	Accelerometer	Wristband measuring arm acceleration.	Data logger, and Wi-Fi_33 (sync with iOSapp)	£129	www.nikeplus.nike.com	Tracking activity, training tools in endurance sports, will not register any activity where the arms are not moving (i.e. cycling)
Motion	Fitbit Tracker	Accelerometer	Wear on a wristband or clip to waistband or carry in a pocket; measuring the number of steps taken and sleep quality	Data logger, and Bluetooth	£60–110	www.fitbit.com	Tracking activity
Motion and position	Intersense NavShoe	GPS and Magnetometer	Sensor located within the shoe, monitoring a person indoor and outdoor location. The inertial-magnetometer is wirelessly coupled to a PDA	GPS and wireless	–	www.inition.co.uk	Real-time tracking of people working in hazardous environments
Physiological	Kalenji-Geonaute (1) cardio 300 coded and (2) geonaute cardio connect	Heart-rate monitor	Heart-rate monitor formed of two parts: (1) chest belt with sensor and transmitted, (2) button with receiver and data logger	Data logger, analog encoded transmission	(1) chest belt (£22) (2) data logger (£15)	www.kalenji-running.com	Monitoring heart rate, training tools in endurance sports
Physiological	NuMetrex	Heart-rate monitor	Smart fabric technology. Sensors are knit into the fabric, relaying the data to a transmitter attached into a pocket at the front of the garment, then the data is transmitted to a logger encompassed in a watch	Data logger, analog encoded transmission	Bra or T-shirt + transmitter + watch (Polar) £75	www.numetrex.com www.textronicsinc.com	Monitoring heart-rate, activity intensity and type