Development of Surface Electromyographic Spectral Analysis Techniques for Assessing Paraspinal Muscle Function

A Dissertation Submitted by

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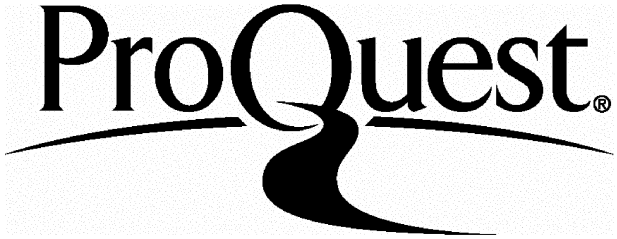

Abstract

In every industrialised society, back pain is the most common musculoskeletal ailment and is the most costly disease process in the working age population. Back pain is a difficult disease to classify and is even harder to objectively measure. In assessing back pain it may be easier to assess function rather than pain. If the deficient anatomical site can be tested, it will be more likely that reproducible information may emerge. It is thought that deconditioned and weakened muscles are associated with back pain. To test lumbar muscle dysfunction ideally the system should be isolated as much as possible, and the test system should have minimal artefacts.

To objectively measure function of the lumbar paraspinal muscles a regulated isometric stress testing was used with simultaneous recording of surface electromyograms. Signal analysis of the filtered and digitised signal was then processed by fast Fourier transformation. From the processed signal, power spectrum, median frequency and halfwidth were plotted. Sampling and smoothing software programs were used to produce three-dimensional images representing time on the *X* axis, frequency of motor unit firing on the *Y* axis and signal amplitude on the *Z* axis. The signal amplitude was a different colour on a two-dimensional spectrogram plot of time versus frequency, producing a colour 'contour map' of the data. These graphical representations demonstrated the dynamic changes of signal amplitude and frequency with time. Reliability and repeatability studies were performed at two isometric loads. To objectively measure the spectrogram data artificial intelligence neural networks were implemented.

Normal subjects and back pain sufferers in this study were shown to demonstrate statistically different power spectra and median frequencies. Spectral colour maps and neural networks showed apparent differences between chronic back pain and normal subjects. Artificial intelligence appeared to be good objective method of measuring paraspinal electromyogram power spectra. The spectral colour maps appeared to reflect altered motor unit firing rates and recruitment patterns

These new methods of objectively measuring lumbar function could have clinical application in assessing back pain patients.

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Acknowledgements

The work for this thesis was completed during the period when I was Spinal Research Fellow to the Back Care Project to the Acute Unit-South Tees Hospitals National Health Service Trust. The data collection was performed at South Cleveland Hospital and Middlesbrough General Hospitals, Cleveland. The further interpretation of the electromyogram power spectra by the use of an artificial intelligence neural network was performed at the Institute of Orthopaedics, Robert Jones and Agnes Hunt Orthopaedic Hospital, Oswestry. The thesis was supervised in Middlesbrough by Mr Charles G. Greenough MD FRCS, Consultant Orthopaedic Surgeon with a specialist interest in Spinal Surgery. Without his support, encouragement and guidance none of this work would have been possible.

Mr Robert Royall BSc, Principal Medical Physicist at South Cleveland Hospital gave technical advice on the set-up of the electronic recording, computer hardware and software. Dr Patrick Jones PhD, Medical Physicist at South Cleveland Hospital and Michael Heally, BSc Computer Sciences student at Teeside University also gave help writing the software programs under my guidance in Middlesbrough. Mr Willem Atsma, a Dutch BSc Biomedical Engineering student gave additional help with software development of the neural networks the Institute of Orthopaedics at Oswestry.

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Declaration

The study was the expansion of the role of The Research Fellow to the South Tees Acute Back Care Project. I was Research Fellow to the Back Care Project. The study was a direct suggestion by Mr Charles G. Greenough MD FRCS as a method of assessing the paraspinal muscles of the lumbar spine.

Three-dimensional and spectral colour mapping technique of frequency-time mapping was my own original idea. The application of an artificial intelligence neural network to the interpretation of the electromyogram data was also my own original idea. These new techniques may have a place in the objective measurement and classification of paraspinal muscle dysfunction electromyogram power spectra and in the classification of low back pain.

I was responsible for the design and implementation of the study with help and advice from Mr C.G. Greenough MD FRCS.

Development and experimental work were carried out in the South Cleveland Hospital and Middlesbrough General Hospitals. The Research Project was approved by the South Tees Hospitals National Health Service Trust Ethics Committee. The further development of the an artificial intelligence neural network was carried out whilst I was Senior Registrar in Orthopaedic and Trauma surgery at Robert Jones and Agnes Hunt Orthopaedic Hospital, Oswestry. All the subject interviews, examinations and electromyographic testing were all carried out by myself, each subject understood and consented to each testing session. I received support with software development from Michael Heally BSc, Patrick Jones PhD and Willem Atsma BSc

I was responsible for the analysis of the data with the assistance of Mr Malcolm Tillotson BSc CStat, Statistician at the Spinal Research Unit, University of Huddersfield who gave statistical advice and processed the reliability and repeatability data.

Published Abstracts

The following abstracts from scientific meeting have been published.

Reproducibility of surface lumbar paraspinal electromyograms
C.W. Oliver, R.A. Royall, C.G. Greenough
J Bone Joint Surg [Br] 1993;75-B:Supp III-229
Societe Internationale de Recherche en Orthopedie et Traumatologie, Seoul, Korea

3-D and surface spectral colour mapping of lumbar paraspinal muscle fibre and recruitment patterns
C.W. Oliver, C.G. Greenough
J Bone Joint Surg [Br] 1993;75-B:Supp III-273
Society for Back Pain Research, Manchester

Electromyogram colour spectral mapping correlates with chronic low back pain
C.W. Oliver, C.G. Greenough
J Bone Joint Surg [Br] 1994;76 - B:Supp II - 91
British Orthopaedic Research Society, Oxford

The role of paraspinal surface electromyography in low-back pain
C.W. Oliver, C.G. Greenough
J Bone Joint Surg [Br] 1994;76-B:Supp I-44
British Orthopaedic Association, Torquay

Scientific Presentations

The following scientific presentations have been given

How should cost effectiveness of a back care program be assessed ?
C.W. Oliver, C.G. Greenough
Society for Back Pain Research
Royal Society Medicine, London 1992

Surface electromyogram median frequency fatigue of lumbar paraspinal muscles: Reproducibility
C.W. Oliver, C.G. Greenough (poster)
British Orthopaedic Research Society
St. James' University Hospital, Leeds 1993

Spectral Colour Mapping of Lumbar Paraspinal fatigue and endurance
C.W. Oliver
Combined Leeds/Newcastle/Sheffield Orthopaedic Trainees Meeting
Freeman Hospital, Newcastle 1993

Surface electromyogram median frequency fatigue of lumbar paraspinal muscles: Relationship to Isometric Load
C.W. Oliver, R.A. Royall, C.G. Greenough
International Society for Study Lumbar Spine
Marseilles, France 1993

Spectral colour mapping of lumbar paraspinal surface electromyograms
C.W. Oliver, P. Jones, C.G. Greenough
European Spine Society
Bochum, Germany 1993

The role of paraspinal surface electromyography in low back pain
C.W. Oliver, C.G. Greenough
European Spine Society
Bochum, Germany 1993

Surface Electromyogram Power Spectra in Chronic Back Pain
C.W. Oliver, C.G. Greenough
Society for Back Pain Research
London 1993

Artificial intelligence in the detection of low back pain
C.W. Oliver
Royal Society of Medicine, Section of Orthopaedics
London 1994

Choice of neural network algorithm to differentiate electromyogram power spectra in low back pain
C.W. Oliver, P. Jones, C.G. Greenough (poster)
British Orthopaedic Research Society, Nottingham 1994

Spectral colour mapping correlates with chronic low back pain
C.W. Oliver, P. Jones, C.G. Greenough (Poster)
International Society for Study Lumbar Spine, Seattle, USA 1994

Computer Aided Neural Network Diagnosis of Low Back Pain
C.W. Oliver, P. Jones, C.G. Greenough
European Orthopaedic Research Society, London 1994

Artificial intelligence in the detection of low back pain
C.W. Oliver
Royal Society of Medicine, Section of Orthopaedics, London 1994

Artificial intelligence analysis of paraspinal power spectra
C.W. Oliver, WJ Atsma, J. Richardson
BOA Instructional Course, Stoke-on-Trent 1995

Chapter One - Introduction

Body movement is the prime functional sign of animal life. Without movement there can be no life and without life there can be no movement - *'Life is Movement, Movement is Life'* (Muller 1991). Skeletal muscle provides the motive forces for locomotion and throughout history human beings have shown a perpetual curiosity about the structure and function of this fascinating contractile organ.

Aspects of muscle function have been studied with the aid of electromyography which Basmajian (1985) describes as *'the enquiry of the electrical signals that the muscles emanate'*. Electromyography has made an important contribution to our knowledge of the physiology of muscle. In the context of physical impairment and therapeutic intervention electromyography has an important role clinically in classification and diagnosis of disease. One of the central considerations in chronic back pain and disability is the activity of the trunk muscles (Smidt 1983, Wolf 1991). Muscle function in terms of fatiguability and endurance is reduced in the deconditioned spine and sub-optimal paraspinal muscles are thought to contribute to long term disability. With the development of electromyography more insight has been gained into the complex relationship of metabolic and electrical factors within the paraspinal muscles. It must be noted that the paraspinal electromyogram recordings are confounded by many intrinsic and extrinsic factors that can be interpreted in many ways. Other factors such as trauma, psychology and malingering are known to be important in back pain (Jayson 1992).

A brief resume of the history of electromyography

To have an understanding of spectral analysis a brief resume of the history of electromyography will show how the development of the electrical study of muscle function. Some of the earliest scientific experiments known to us concerned the form of muscle. Anatomical study first began at the time of the Renaissance. Leonardo da Vinci devoted much time and thought to the analysis of muscles as witnessed by his beautiful

drawings. The 'father' of modern anatomy Andreas Versalius in *'Fabrica'* contributed much to the knowledge of the anatomy of muscles. However, the heritage of Leonardo da Vinci and Versalius although both artistically exquisite stressed the appearance and gross anatomy of dead muscles rather than their dynamic functions.

During the later Renaissance a series of scientists began to study the functions of muscles. The first logical deductions of muscle generated electricity was documented by the Italian Francesco Reudi in 1666 who suspected that the shock of an electric ray fish was muscular in origin. The relationship between electricity and muscle was first observed by Luiggi Galvani in 1791. In this famous series of experiments Galvani depolarised the muscles of frogs' legs by touching them with metal rods. This discovery is generally acknowledged as representing the birth of neurophysiology. Galvani wrote about his discoveries in *'De Viribus Electricitatis'*. Alessandro Volta produced a device, *'battery'* for stimulating muscles conveniently and used it to stimulate muscles and elicit muscular contractions.

It was not until 1849 when the Frenchman Du Bois-Reymond devised a practical galvanometer that it was possible to elicit electrical activity from human muscles. In Du Bois-Reymonds' experiment he devised a surface electrode that consisted of a wire attached to a blotting paper immersed in a jar of saline solution. He found that when his fingers were immersed in the saline solution, and his arms and hand were contracted the deflection of a galvanometer was minute, approximately two to three degrees. He realised that the impedance of the skin reduced the current that could drive the galvanometer. He circumvented this problem by inducing a blister on each forearm and measured a sizeable deflection; sixty-five degrees on his galvanometer. He repeated the experiment three times for each arm and always obtained the same result and to remove doubt repeated the whole experiment three weeks later when the skin had healed. He obtained the same results. This work was published in *'Uber Thiersche Electricat'* in 1849 (Basmajian 1985).

Techniques for detecting signals were much improved by the invention of the cathode-ray oscilloscope by Braun (1897) as this new tool allowed a dynamic visual display of events. The concentric needle electrode was introduced by Adrian and Bronk (1929) and enabled direct observation of the electrical activity associated with individual muscle fibres. With much improved amplification technique Gasser and Erlanger (1927)

could interpret action potentials and later won the Nobel Prize in 1944 for their research into single muscle action potentials.

The earliest clinical application of electromyography was made by Probster (1928) who obtained signals from muscles with peripheral nerve paralysis. Studies of muscle locomotion by kinesiologists began and the first study of movement of the shoulder region by Inman (1944) gained wide acceptance.

The earliest note of myoelectrical fatigue was made by Piper (1912) who noted that the frequency component of the surface myoelectric signal decreased when a muscle contraction was sustained. Cobb and Forbes (1923) not only noted this shift of frequency toward the lower end of the frequency spectrum but also described a consistent increase of the amplitude of the surface myoelectric amplitude with fatigue.

The first descriptive studies of function of the erector spinae in conjunction with movement and posture were made by Floyd and Silver (1951, 1955) and of the anterior abdominal wall by Floyd and Silver (1950). Floyd and Silver used a combination of electromyogram, photographic and radiographic techniques. Morris (1962) performed an admirable early study using embedded copper wire electrodes of the intrinsic muscles of the back and determined the individual actions in the erector spinae; multifidus, rotatores, iliocostalis lumborum, iliocostalis dorsi and longissimus dorsi in simple and combined movements.

Much pioneering research was performed on the electromyogram of the Lumbar spine by Andersson in the 1970's. Studies of sitting postures (Andersson 1974) compared surface and fine wire electrodes and found that surface electrodes gave smaller coefficients of variation as compared to fine wire electrodes. In conjunction with in vivo intradiscal pressure an early form of power spectrum analysis of the lumbar muscles was used by Andersson (1977a) It was found that the amplitude of the myoelectric signal correlated well the magnitude of the power spectrum at several levels of the lumbar spine. Andersson observed that the greatest shifts in power spectra occurred where the electromyogram signal amplitudes were greatest and hypothesised that localised muscular fatigue was occurring in those areas.

Development of power spectra analysis in the lumbar spine

It was not until the advent of powerful computers and the development of the fast Fourier transformation that power spectral analysis developed. Recently Kondraske (1987), Siedel (1987), Rosenburg (1989), Mayer (1989), Roy (1989), Sward (1990) Biedermann (1991) and Klein (1991) have used modifications of varying sophistication of power spectral analysis techniques in to analyse electromyogram activity in the lumbar spine. Cooper (1993), recently attempted to determine the proportion of paraspinal fatiguability that is contributable to 'central' or 'peripheral' processes. Although using surface electrodes the frequency analysis was as integrated electromyogram signal and no frequency analysis of components of the signal was made.

Surface electromyogram is attractive because it is non invasive and has direct and indirect relationships to physiological, biochemical, anatomical and pathological events within the muscle. Other currently used techniques and devices for evaluating the performance of back muscles measure mechanical variables associated with force, velocity, or displacement of the trunk. All approaches share a common flaw in that the measured kinematics and force variables may be voluntarily regulated in a manner that can meaningfully effect the values of the variables being measured. A highly motivated individual interested in knowing the upper limits of their strength would perform to the full extent of their capability. Whereas an individual with less motivation would perform at a lesser level, thus not revealing their full potential (DeLuca 1993, Mayer 1989). Electromyogram measurement techniques of paraspinal muscle are not routinely used within the United Kingdom although commercial machines capable of performing limited aspects of spectral analysis have recently become available. Some of the newer black-box type of machines have no real-time electromyogram display and could be misleading as artefacts unknowingly may be recorded.

Spinal muscular power is important as in a weakened state due to pain trunk muscles would have a reduced capacity to splint against excessive spinal segment motion, prevent ligamentous and capsular ligament sprains and withstand and control loads during functional activities (Andersson 1977a, Smidt 1983, Smidt 1988, Wolf 1991). Since trunk muscle action is an integral part of low-back function objective

measures of trunk muscle activity should be included in any estimation of a patient physical impairment assessment. Objective information is important in assessing low-back function, identifying changes in physical capability and the effect of a rehabilitation program.

The multiple spinal motion segments involved make it difficult however to standardise body position or body movement to a particular task. It is also very difficult to exactly mimic the exact task in the workplace. A recurrent problem occurring not only in animal testing but in human testing as well is that unnatural force, environment and testing apparatus are used to assess a subject that would not mimic the normal human daily activities. Little is known about the transferability of isolated muscle function to occupational and non occupational activities (Smidt 1988).

Andersson (1977a), Kondraske (1987), Siedel (1987), Rosenburg (1989), Mayer (1989), Roy (1989), Roy (1990), Sward (1990), Simms (1989), Biedermann (1991) and Klein (1991) have all performed clinical studies of the lumbar spine employing the technique of spectral analysis. These studies are all of small series of subjects, the best studied group series is that of Roys (1989) comparing twelve normal subjects with twelve back pain subjects. All the workers performed fatigue studies of the lumbar extensor muscles and used some form of frequency analysis. Only Mayer (1989), Roy (1989), Roy (1990), Sward (1990) Biedermann (1991) and Klein (1991) used fast Fourier transforms to interpret their results. The subjects tested were placed in vertical or stooped postures and all the studies attempted to control posture and electrode placement to some degree. None of the researchers performed any reliability studies with freshly applied surface electrodes. Roy (1989) and Mayer (1989) both found significant differences between normal and back pain subjects. Roys' paper used the 'Back Analysis System' that was developed by their research team consisting of a six channel recording system that averages fatiguability from the multiple inputs. It is argued that this kind of multichannel system produces more reproducible results. Roy used the 'back analysis system' and was able to identify control subjects with an accuracy of 84% (10 of 12) and lower back subjects with an accuracy of 91% (11 of 12) purely on the basis of the electromyogram spectral variable test. In the two groups of Roy's series the maximum voluntary contraction was indistinguishable at the 95% confidence level.

Little work on spectral analysis in other disease conditions in the back has been performed but Simms (1989) compared subjects with fibromyalgia to normals and

subjects with low back pain. The information maps from the 'back analysis system' of five subjects with fibromyalgia syndrome who complained of pain in the back were compared to twelve subjects who had idiopathic low back pain and ten age-weight matched normal control subjects who never had experienced back pain. The fibromyalgia subjects were identified according to currently proposed diagnostic criteria. By orthogonal t-tests it was found that the information map from the 'back analysis system' for the low back subjects was statistically distinctive ($P < 0.05$) from that of both the control and fibromyalgia subjects. The fibromyalgia and control groups were statistically indistinguishable at the $P = 0.05$ level.

Spectral analysis has been described by Deluca (1985) as having possible future roles in pre-employment screening of a work force, however, before spectral analysis could be used for such a use the technique would need to be very carefully evaluated and multicentre tested for reproducibility and reliability amongst a broad spectrum of the population. Other uses of spectral analysis have been described for uses in athletic training (Sward 1990), ergonomics (Lacuna 1983), (Hosea 1986), diagnosis of neuromuscular disorders (Boruta 1981), (Linssen 1991) and rehabilitation (Smidt 1988). Many studies throughout the body using spectral analysis to quantify fatigue have been made and caution must be taken extrapolating upper arm (Moritani 1982), forearm (Daanen 1990), hand (Alfonsi 1991), thigh (Linssen 1991), leg and cervical spine (Philips 1983) to the lumbar spine. Extrapolation would have to take into account many factors including relative blood flow and fibre types to each muscle.

A discussion of muscular fatigue in the lumbar spine

The general concept of fatigue

The concept of fatigue is ambiguous and often misapplied. Fatigue may mean many different things to health specialists, scientists and patients. In man fatigue is a complex interaction of physiological and psychological phenomena. Testing fatigue is difficult and subjective for two reasons; firstly the subject being tested must co-operate with the

testing and secondly the observer may incorrectly set the expectation of fatigue limit. Fatigue does not always occur within a specific definable time. When an individual becomes fatigued they may not be able to perform a definite task and this should not simply be defined as the *'end point'* of failure. DeLuca (1984) gives the example of a steel girder in a bridge that stands for many years. Although the bridge remains in place for many years with no apparent signs of physical wear there may suddenly in one instant be a fracture in one of its girders. The bridge may then suddenly fail and collapse. If one observed from a distance the main structure of the bridge no outward sign of fatigue would be seen. All the while however the crystalline structure of the steel girder was undergoing an internal alteration caused by chemical and physical processes. To monitor fatigue, specimens of data from within the girder itself or externally observable modifications related to its internal structure need to be monitored. The girder in the bridge has a failure point that can only be seen to occur when it is no longer able to support a load and *the fatigue becomes visible.* Overt fatigue may be represented by a failure to perform a task previously satisfactorily performed. A similar parallel can be made to muscle which have internal changes before they manifest overt failure and can no longer sustain load. Physiological fatigue has been simply be defined *'as a reduction in muscle tension'* (Sandercock 1985) or *'failure to maintain desired or expected force'* (Edwards 1981). These simple definitions do not reflect the electrophysiological changes of fatigue seen with power spectral shifts during constant isometric loading. Access to physiological and biochemical data from within the muscle or nervous system can reveal time dependent change's indicative of a fatigue process, even though the externally observable mechanical performance would not be altered until the *'failure point'*. Table 1 presents some of the definitions of fatigue and its confounding factors.

Table 1. Possible meanings of fatigue

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Definition

1. Impaired intellectual performance
2. Impaired motor performance
3. Increased electromyogram activity for given performance
4. Shift of electromyogram power spectrum to lower frequencies
5. Impaired force generation

Confusion of perception associated with fatiguing muscular activity

1. Increased effort maintaining force
2. Discomfort or pain associated with muscular activity
3. Perceived impairment of force generation

After-Edwards (1981)

Bills (1943) suggested that fatigue be divided into three major categories. The first was subjective fatigue characterised by a decline in alertness, mental concentration and other numerous psychological factors. The second was objective fatigue characterised by a decline in work output. The third was physiological fatigue characterised by changes in physiological processes.

The mechanism underlying physiological muscle fatigue has been considered in terms of central nervous system fatigue versus peripheral fatigue by Bigland-Ritchie (1978, 1981). Table 2 presents a practical classification of fatigue. It was estimated by Bigland-Ritchie using surface electromyogram recordings that change occurring proximal to the neuromuscular junction *(central fatigue)* can consistently account for up to 30% of the total force loss even in apparently well motivated subjects (in the quadriceps muscle).

Table 2. Practical classification of fatigue

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Physiological mechanism	Clinical condition
Central fatigue	
Failure (voluntary or involuntary) of neural drive, resulting in: 1) reduction in number of functioning motor units	Neurasthenia, hysterical paralysis, and other conditions lacking motivation
2) reduction of motor unit firing frequency	
Peripheral fatigue	
Failure of force generation of whole muscle:	
high frequency fatigue a) impaired neuromuscular transmission	a) myasthenia gravis cooling, curare
b) failure of muscle action potentials	b) myotonia congenita glycolytic disorders
low frequency fatigue *impaired excitation-coupling*	*mitochondrial disorders* *dantolene sodium treatment* ? myotonia congenita ? hypokaelaemic periodic paralysis duchenne dystrophy
	After-Edwards (1981)

Myoelectric parameters of fatigue

The study of the surface myoelectric signal to demonstrate localised muscular fatigue has been very extensively employed. Many authors since Piper in 1912 have described the increase in myoelectrical signal with fatigue. The frequency shift towards lower frequencies has been observed in many muscles throughout the human body by: Andersson (1977a), Lindstrom (1977), Petrofsky and Lind (1980), Kranz (1983), Mills

(1984), Moritani (1986), Shochina (1986), Krondraske (1987), Siedel (1987), Mayer (1988), Roy (1989), Sward (1990), Biedermann (1991), Klein (1991). These two phenomena are interrelated as during a sustained contraction the low frequency components of the myoelectric signal increase and more myoelectric signal will be transmitted through the low-pass filtering effect of the body tissue. The magnitude of these two phenomena will be dependant on many physiological factors such as force level of contraction, duration of contraction, posture, the type of electrode used and the particular muscle being investigated (DeLuca 1984).

Four hypotheses to account for the increase in amplitude and frequency shifts of the myoelectric signal during sustained constant force isometric contractions have been proposed and summarised by DeLuca (1984). Deluca argues a case for motor unit recruitment, motor unit synchronisation, changes in conduction velocity of the muscle fibres and regularity (coefficient of variation) of the motor unit discharge.

Moritani (1986) recorded elbow flexor surface electromyograms and intramuscular motor unit spikes simultaneously so that surface electromyogram spectral analysis and intramuscular spike amplitude frequency analysis could be performed under the same conditions, it was found that the mean power frequency fell more rapidly at maximum voluntary contraction than at 50% maximum voluntary contraction. During these fatiguing contractions intramuscular spike recording suggested equivocal new recruitment of motor units. Failure to record new recruitment was attributed to central fatigue. Synchronisation of the firing rate was thought to be the major factor, whereas Mills (1982) attributed the shift to changes in the motor unit action potential configuration. Sandercock (1985) stimulating cat gastronemius at high frequency to elicit '*high frequency fatigue*' observed changes in the amplitude and duration of motor unit action potentials that correlated highly with changes in tension development but that did not correlate with lower frequency stimulation and tension. Sandercock concluded that the electromyogram signal is dependant on a summation and cancellation of individual motor unit action potentials and that the electromyogram provides a reasonable estimate of high-frequency fatigue but an unreliable measure of low-frequency fatigue. In evaluating the spectral shift Bigland-Ritchie (1981) concluded that changes in muscle conduction velocity could not fully account for the frequency shift.

Mathematical models and the fast Fourier transformation

Mathematical models of the myoelectric signal have been used Blinowska (1987) to evaluate firing and synchronisation degree. These models only provide a limited insight as they are highly dependant on assumptions about the discharge statistics of motor units and the shapes of action potentials.

Time and frequency domain analysis, otherwise known as spectral analysis of the electromyogram since the common availability of the micro-computer has had considerable attention. The mathematics of the fast Fourier transforms are well known and its relationship to surface electromyogram has been reviewed by DeLuca (1984) and Basmajian (1985). Fast Fourier transforms in real time Basano (1986), and Castaldo (1991) has allowed almost instantaneous viewing of the power spectrum.

Shape of the myoelectric action potential waveform

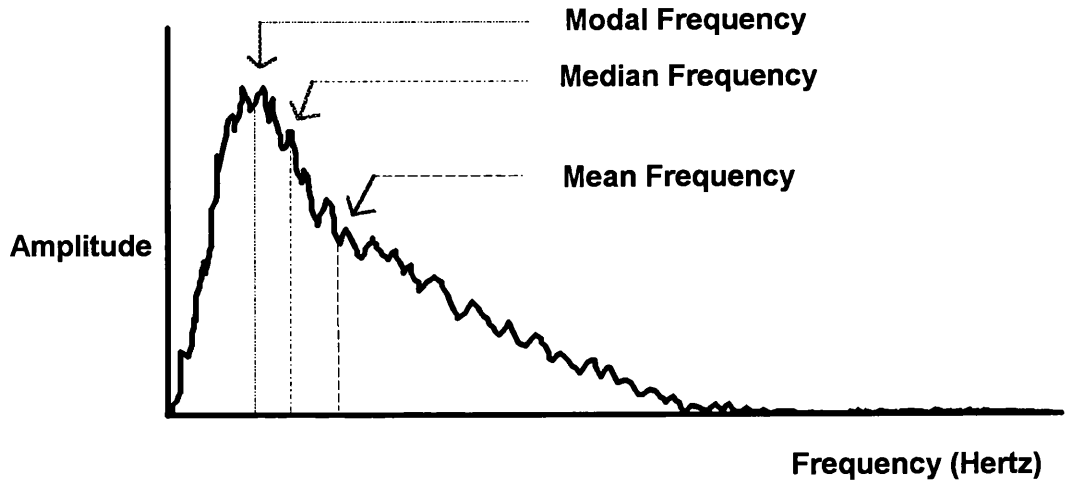
The shape of the wave form of the motor unit action potential contributes to the power density spectrum of the myoelectric signal. The waveform is affected by many known factors. The tissue filtering determines the actual motor unit action potential shape and the conduction velocity of the muscle fibres modifies the characteristics of the waveform. The amount of tissue filtering is determined by: the three-dimensional arrangements of the muscle fibres of an active motor unit, the distance between the surface electrodes and the active muscle fibres and the location of the electrode on the surface of the muscle as a function of the distance between the innervation zone and the tendon of the muscle (DeLuca 1984). It is therefore very important to control these confounding factors if any degree of reliability is to be achieved in experimental studies. The thickness of the fatty tissue between the electrode and the muscle affects the amount of spatial filtering on the signal. Surface recording may not work so well on obese individuals.

Measurement of electromyogram frequency shift

Measurement of the frequency shift can be performed in several ways. DeVries (1968b), Lloyd (1971), Petrofsky and Lind (1980) measured modifications of the root means square value of the myoelectric signal. As the myoelectric spectrum is modified by a concurrent increase in the low frequency components with a decrease in the high frequency components this measure of the total power density spectrum had a reduced sensitivity to any frequency shift of the spectrum. Therefore to look just at the amplitude or root means square value or integrated electromyogram (Moritani 1978) is not very accurate in defining a shift. Ratio parameters of the root mean squares were used by Bigland-Ritchie (1981) but have more recently been replaced by analysis of components of the power spectrum. The median-frequency, the mean frequency and the mode frequency are commonly used. The median frequency (sometimes called centre frequency) is the frequency at which the power density spectrum is divided into two equal regions of equal power. The mean frequency is the average frequency and the mode frequency is the frequency of the peak amplitude of the spectrum. All three are in a mathematical sense related to the conduction velocity of the muscle fibres (Stulen and DeLuca 1981).

The mean frequency has been usefully employed by: Moritani (1986), Barnes (1987), Siedel (1987), Mayer (1989), Rosenburg (1989), Daanen (1990), Alfonsi (1991) and Castaldo (1991). The mean frequency was said to be a more robust parameter and has a greater noise immunity on mathematical grounds (Castaldo 1991).The median frequency has been used by Petrofsky and Lind (1980a), Merletti (1983), Kranz (1983), Roy (1989), Merletti (1990), Biedermann (1991), DeAngelis (1990), Klein (1991) and Dolan (1992). The mode frequency is not very useful as it superficially may appear because even for a relatively minor change in the variance of the spectrum there would be a large change in the mode. Schweitzer (1979) estimated that the coefficient of variation for the estimate of mode frequency was five times greater than that of the mean frequencies obtained from the human diaphragm. It would be possible to produce instantaneous real time results if required. Parameters of the frequency shift are represented in figure 1.

Figure 1 Parameters of the Power Spectrum



Parameters of Power Spectrum

Correlation of electromyogram to force

Correlation of electromyogram with force has remained problematic. Lawrence (1983) found under careful and controlled conditions in the biceps, deltoid and first dorsal interossei that the myoelectric signal to force relationship exhibited considerable variability. Although the maximum voluntary contraction is a reliable reference level of force there was no consistent reference quantity for amplitude of the electromyogram signal. The signal to force relationship in the first dorsal interossei was linear but in the biceps and deltoid was non-linear; this may partially due to variation in fibre types within the muscles and different patterns of fibre recruitment.

Both the mean and median frequency have been shown to reduce as a function of time during sustained contractions and the rate of decrease has been found to be approximately quasi-linear (Petrofsky 1980a 1980b) or quasi exponential Lindstrom (1977), Hagberg (1981), Stulen and DeLuca (1982). The reduction in median frequency can be attributed to fatigue but some differences may be due to different muscles being studied or different processing schemes (Lawrence 1983). It is not known what the relationship to isometric loading is in the lumbar spine at varying loads.

Reliability, repeatability and reproducibility of the power spectrum

Reproducibility of a physiological experiment is crucial to the credibility of a technique. True reproducibility of results will be only be observed from several centres replicating a technique. Reliability will show the chance of a series of results repeating themselves on more than on occasion. Repeatability will give a measure of the reliability of these results (Fleiss 1986). There have only been scant reports of reproducibility, reliability and repeatability of median frequency recording techniques in the lumbar spine. The efficiency of electrical activity was used by Stokes (1987) to characterise the integrated electromyogram-extensor torque relationship. The efficiency index was found to be non-linear in each subject. The coefficient of variability (within subjects) was greater in day to day testing (24%) than with repeated pulls at the same testing session (14%). About 25% of the variability between subjects in Stokes series were found to be related to anthropometric differences. The efficiency of electrical activity is therefore not a useful parameter in assessing the torque of the lumbar muscles as assessed by the electromyogram. There have been no large reliability studies of spectral parameters on median frequency and power spectra published to date. Roy (1989) ascertained the error induced in the value of the electromyogram spectral variable by repeating a contraction within 15 minutes under similar conditions; the error was found to be 2% for the initial value and 6% for the slope of the median frequency. Performing similar evaluations on test/retest measurements, Biedermann (1990) found that the error in the repeatability of the median frequency slope measurement increased to approximately 10% when the electrode was replaced after a 5 day interval.

Bazzy (1986) noted in the biceps that the change in the length and geometry as muscle contracts isometrically can alter or induce indirectly an increase in the power of the low frequency content of the electromyogram. Muscle length would be very important to control in isometric studies. Isometric dynamometers that have a spring that will easily stretch will therefore not truly record muscle length. Daanen (1990) has shown in the forearm flexors that with the mean power frequency, the inter individual differences in mean power spectrum were large but individual differences were small.

Some difference in individual differences may be due to electrode placement and would be important for longitudinal studies.

Komi (1970) in the elbow and Wolf (1991) in the lumbar spine compared surface and fine wire electrodes in the same subjects. Surface electrodes record a larger portion of erector spinae muscle than needle electrodes. Komi (1970) at a test-retest interval of 55 days obtained relatively high reliability coefficients of repetition with surface electrodes as compared to needle electrodes. Using surface electrode recording techniques the multifidus muscle at L5 was shown by to give more consistent results than at L1 or L2 during fatiguing intermittent isometric extension by Van Dieen (1993). Surface electrodes have the advantage of being non invasive.

Strength and the lumbar spine

Males as a group are stronger than females, but when strength is normalised to body weight, females may be equivalent to males (Nachemson 1969, Smidt 1983). The spinal extensors are stronger than the flexors with an average extension to flexion ratio of 1.3 male and 1.7 female (Gomez 1991), 1.3 all (Sward 1990). Any value given to the extensor to flexion ratio is dependent on the type of muscle contraction, trunk angular velocity, fixity of the upper and lower limits of motion and spatial orientation of the trunk (McIntyre 1990, Smith 1985, Thorstensson 1982). Females have been shown to have a superior trunk muscle endurance to that of males (Smidt 1983). Savage (1991) using magnetic resonance imaging showed that lumbar muscularity declines with age in males and was surprisingly not significantly affected by occupation or by a history of low-back pain

Normalisation of maximum voluntary contraction has been used by Kondraske (1987) by expressing maximal voluntary contraction as a percentage of body weight in quantifying trunk muscle fatigue. This would normalise muscle performance concerning an anthropometric measure that is assumed to be related to muscle strength. However body weight has been shown to be a poor predictor of trunk muscle strength (Nicolaissen 1985).

The contribution to isometric trunk muscle strength in low back pain by either a muscle spasm model or a muscle deficiency model has been investigated by Cassissi (1993). Their electromyogram findings of lower peak torque and lower maximum

surface integrated electromyograms in more flexed positions supported a muscle deficiency model of back pain.

Effect of exercise and training on the lumbar spine

In an early study, Chapman and Troup (1969) attempted to evaluate mechanical and electrical changes in the back extensor muscles as a result of resistive exercise. In this study the isometric exercise produced similar gains in peak isometric strength and integrated electromyogram. In a six-week training session Smidt (1988) showed that in normal males and females who underwent high-intensity resistive exercise that trunk muscle strength gains occurred and were superior in eccentric (lengthening) exercise and that trunk muscle strength endurance was maintained when gains had occurred at six weeks. Resistive eccentric exercises require a well-motivated person to co-operate with the testing program and these exercises are known to be painful. Relatively rapid gains in strength should be expected early in an exercise training program and more gradual gains thereafter (Komi 1986). Morphological changes in muscle do not occur for several weeks into an exercise program, so early gains in strength can logically be attributed to an increased neural drive to the muscle (Komi 1986, Moritani 1979). The proportion of contribution from increased neural drive versus biological changes of structure, hypertrophy and biochemistry within muscles is unanswered.

Endurance testing by Mayer (1989) involved holding the trunk unsupported on a 'Roman chair' while mean power frequency was measured. Comparing normal and unfit deconditioned subjects there were significant differences between groups throughout early rehabilitation and at seven weeks. The test sensitivity was poor at identifying subjects with low endurance. There was no significant correlation between electromyogram initial mean power frequency measures and isokinetic extensor trunk exercises even though all subjects showed a isokinetic improvement. Although the group statistics reflected a change this could not be extrapolated to a normative database. There was also found a 5% non responder rate to treatment.

In elite athletes, wrestlers were found to be stronger than tennis players by Sward (1990). Wrestling demands more isometric and explosive strength than tennis that is more of an endurance sport. The tennis players were less susceptible to fatigue and in

addition were noted to have asymmetrical strength and endurance development, suggesting that asymmetrical endurance may be developed by training.

Screening the lumbar spine

Isometric lifting strength has been shown by Batti'e (1989) to be an ineffective measure of the predictability of a back pain report and that greater strength was associated with a higher risk of industrial back injury claims. Stronger subjects were found to be at a greater risk of claims. If isometric lifting strength had been used for screening it would not have reduced the number of back injury claims in this population. With sophisticated lumbar dynamometry such as the Isostation B-200, Hirsh (1991) has shown that there was a positive relationship between excessive illness behaviour and almost all biomechanical variables tested. Poor performance of this kind of population may be a form of abnormal illness behaviour and may not accurately reflect organic alterations of neuromusculoskeletal function. Therefore none of these more modern methods of testing have had any great impact on medico-legal cases in the settlement of malingering and compensation (Jayson 1992).

Early in the development of electromyogram screening for low-back pain, Hoyt (1981) suggested that surface electromyogram assessment may be a useful tool. Using a non-stressful measurement procedure in eighty subjects with band-passing between 100-200Hz only, he found it possible to differentiate between normals and low back pain subjects. Testing in Hoyts paper was performed in a sound attenuated box with a one way mirror to attempt to eliminate extraneous stimulus during testing. Large left-right differences in paraspinal activity were demonstrated in this study that did not use sophisticated frequency analysis.

A study by Roy (1990) was performed on varsity rowers and the cohort was tested without a prior knowledge of which, if any, of the subjects suffered from low back pain. There were thirteen port rowers and ten starboard rowers. After the tests, six of the rowers had supporting evidence that they had low back pain. Four had acute pain but were not experiencing pain during the tests; two had chronic pain, and were in pain during the tests. In this study the information map from the 'back analysis system' consisted of the initial value, the slope, and the value of the median frequency after one

minute recovery. The test identified 100% (six) of the subjects with low back pain and 93% (fourteen of fifteen) without low back pain, 100% of the starboard rowers, and 100% of the port rowers. Klein (1991) compared conventional clinical measures with electromyogram spectral variables in twenty sweep rowers to identify individuals with low back pain. A discriminant analysis for range of motion and maximum extensor voluntary contraction identified 57% of the rowers with low back pain and 63% of the rowers without low back pain. A similar discriminant analysis procedure for electromyogram spectral parameters identified 88% of the rowers with low-back pain and 100% of the rowers without low-back pain at one minute recovery time and 100% of the rowers without low-back pain and 88% of the rowers with low back pain at two minutes recovery time.

Application of artificial intelligence to the analysis of electromyogram power spectra

Background to artificial intelligence

Artificial intelligence systems such as neural networks have been used for a variety of medical data classification and image processing tasks (Wasserman 1989, Nishikawa 1990, Simpson 1990). Neural networks are computational techniques for recognising patterns that have undergone a renaissance of interest over the last decade. Networks employing various architectures and learning algorithms have found uses in both academic medical and industrial applications. Research into neural networks was active in the 1940s but has undergone recent increased interest because of the advent of powerful desk-top computers. A comprehensive revue of the medical applications of neural networks is given by Miller (1992). Wasserman (1989) gives an insight into the design and neural modelling of various networks.

A neural network consists of simple processing units called 'neurons' or 'nodes' which have a passing resemblance to actual biological neurons. Each neuron is connected to other neurons in the network by unidirectional neurons of different strength or weights. Early designs were based on the 'perceptron', a processing element that summed their weighted inputs and applied a linear transfer function to produce an

output. Currently networks exist which use both linear and non-linear functions and have either binary or continuous activation's.

The neurons are usually arranged in a series of layers bounded by input and output layers encompassing a variable number of hidden layers connected in a structure that depends on the complexity of the problem to be solved. Connections usually feed from the input to the output layers, a feedforward network, although feedback connections from hidden layer to input layer is possible. Information from the input layer is thus propagated down through the network to the output layer. A layer is fully connected if each node in the layer is connected to all the nodes in the adjacent layer. The input layer only serves as a means of acquiring an input and distributing it to the other network neurons.

The most important feature of neural networks is their ability to learn from examples. Because the learnt information is stored across the network weights can be used to generalise input information. This means appropriate classifications will be made even for input patterns not actually in the training set, provided the training set covered a representative group of patterns. The ability for to learn and generalise means that neural networks have the potential for solving image and signal processing problems that are not possible with rule based problem solving. Previous networks training times have been very long but since the advent of the desk-top personal computer these have been dramatically shortened.

Neural networks can be divided into two main classes, those employing supervised learning and those with unsupervised learning. Hybrid systems using both stategies have been developed.

There are several interpretations for the way neural nets work. A neural net is an abstract concept. It is a set of algorithms that could be implemented in hardware, but more often are simulated with a digital computer. When the neural net is regarded as a black box, then all there is to see is a number of inputs and a number of outputs. A neural network can be trained to associate sets of inputs with a set of output values.. Various neural networks have been described by Lippman (1987) as being constructed by "dense interconnection of simple computational elements". These are similar to structures found in the human nervous system. The computational elements are called nodes or neurons. A schematic diagram of a node is given in figure 2. The node was described by Rosenblatt in 1958. He called this simple neural "network" the perceptron.

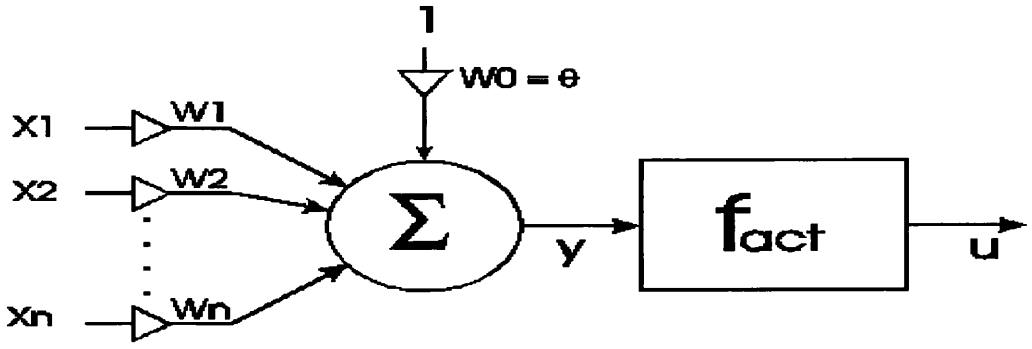


Figure 2 Diagram of a node; after Lippmann (1987)

The perceptron has an n-dimensional input vector; a bias value θ is added, which is the same as subtracting a threshold value $-\theta$. The value of y is the weighted sum of all the inputs; this value is then the input of a non-linearity, the activation function (f_{act}), which produces output u of the node. The relation between y and the input vector x is given by a linear equation: $y = \overline{w}^T \cdot \overline{x}$ where w is the vector containing all the weights, including w_0; x_0 is set to 1. The original perceptron had a hard-limiter as activation function, with $u=-1$ for $y<0$ and $u=1$ for $y \geq 0$, which mapped the output to the interval [-1..1]. The non-linearity used in this project is the logistic or sigmoid function, given by:

$$f_{act}(y) = \frac{1}{1+e^{-y}}$$

Figure 3 is a plot of the logistic function. The function maps input value y to the interval [0..1]. The disadvantage of the hard-limiter as activation function is that it is not differentiable. The sigmoid is, which allows gradient search learning algorithms for multiple layer networks.

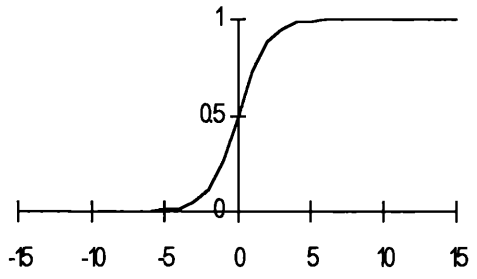


Figure 3: Logistic activation function; input y at the horizontal, output f(y) at the vertical axis.

The perceptron creates a hyperplane in the inputspace. This hyperplane is the decision boundary of the node and is given by: $\overline{w}^T \cdot \overline{x} = 0$

For a perceptron with two inputs the hyperplane this would be:

$$w_0 x_0 + w_1 x_1 + w_2 x_2 = 0 \quad \Leftrightarrow$$
$$x_2 = -\frac{w_1}{w_2} x_1 - \frac{w_0 \cdot x_0}{w_2}$$

where $w_0=\theta$ and $x_0=1$, so can be rewritten as:

$$x_2 = -\frac{w_1}{w_2} x_1 - \frac{\theta}{w_2}$$

which is a straight line in a two-dimensional space.

When nodes are combined to form a network, the number of functions that can be implemented increases dramatically. A simple network consists of two or three layers; all the outputs of nodes in one layer serve as inputs to the next. This kind of neural network is sometimes referred to as a multilayer perceptron. An example of a three layer perceptron can be seen in figure 4. The second, or hidden layer combines the decision boundaries of the nodes in the input layer. The hidden layer can be regarded as a feature detector. During training the neurons specialise in recognising a specific characteristic of the data at the input. A node in the hidden layer will produce a high output if the feature it has specialised in is present in the input pattern. The output layer finally forms weighted sums of the outputs from the hidden layer and "decides" what the result is going to be.

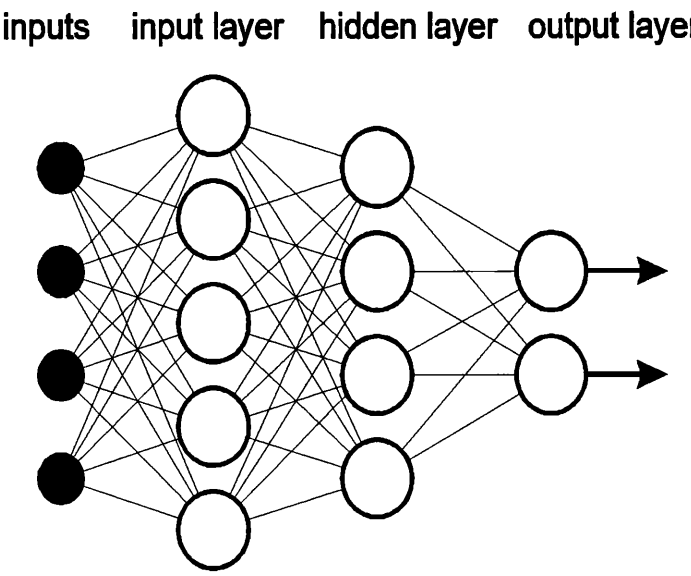


Figure 4: Typical structure of a three layer network.

Theoretically, a two layer network can form an arbitrarily close approximation to any continuous non-linear mapping. However, this does not imply that there is no reason for having no more than two layers. For some problems a small three layer network can be used where a two layer network would require an infinite number of nodes. It has also been shown by Hush (1993) that there are problems that require an exponential number of nodes in a two layer network that can be implemented with a polynomial number of nodes in a three layer network.

Neural networks have been rapidly finding new applications within medical science. The applications fall into three broad classes; interpretation, enhancement and data compression. It was intended in this thesis to use a neural network for interpretation of spectral analysis data. Electromyogram data after collection would be presented to the network. The neural network would then produce an output that would be directly interpreted in terms of variables that describe the state of the system.

Chapter Two - Aims and Scope of Enquiry

The aims and scope of this thesis were to:

- To develop a reliable method of surface electromyogram recording from the paraspinal muscles.

- To investigate the relationships between electromyogram measurements and spinal muscle.

- To develop simple and effective methods for analysing and displaying complex electromyogram data.

- To investigate the use of electromyogram spectral analysis in distinguishing subject groups.

Chapter Three - Materials and Methods

Materials

Subjects

One hundred and three subjects were tested. All were volunteers and signed written consent. The ethics committee of South Tees Hospital National Health Service Trust had given prior approval to electromyogram testing subjects paraspinal muscles.

At the time of testing all subjects were weighed and height measured with a stadiometer. Percentage body fat was estimated by the four point method with a skin fold calliper (Creative Health Products® Michigan 48170 USA). Lean body mass was calculated by subtracting the body fat weight from the total body weight. Body mass index was calculated by the formula: Body mass index = (Weight (Kg)/Height ^{2} (m)). Anthropometric details of the subjects tested are given in the result's section.

Clinical examination of the subjects was not performed. Subjects were classified from their clinical history into groups of: 1) 'normal' subjects who had never had back pain at any time of their life and 2) 'chronic back pain' subjects with a recurring history of back pain (> six months) that had lost time from their employment, at time of testing. Finger floor distance, Schober's test, back extension, straight leg raising was not recorded. No radiological investigations were performed on any of the subjects.

All subjects completed the 'low back outcome score' (Greenough 1992) to give a functional outcome score for low back pain. Two psychological questionnaires; the modified somatic perception questionnaire (Main 1983, Main 1984) and modified Zung (Main 1992) was completed. Simple job satisfaction scores and exercise histories designed by the author were recorded (see appendix).

All subjects performed two tests at 2/3 maximum voluntary contraction. Surface electrode recordings were collected from these subjects from the left and right side of the lumbar paraspinal muscles at the level of L4/L5.

A small reliability and repeatability study was performed in normal subjects at 2/3 maximum voluntary contraction on the left side of the back. The reliability test was

performed on three separate occasions, under the same experimental conditions with fresh surface electrodes.

Small studies looking at the relationship to very low at 10Kg and 20Kg loads in normal subjects were performed and to see if the same bandwidths of muscle fibres were recruited at low loads as compared to high loads. One increasing isometric load test was performed to determine the relationship of increasing isometric load with time. The isometric load level was increased from 0Kg to 140Kg in 20Kg divisions in three second intervals. A small study looked at the effect of breath-holding on the electromyogram signal.

Times of day, temperature and sound were not controlled or recorded during the reliability studies or routine studies.

METHODS

Lumbar extensor muscle test frame

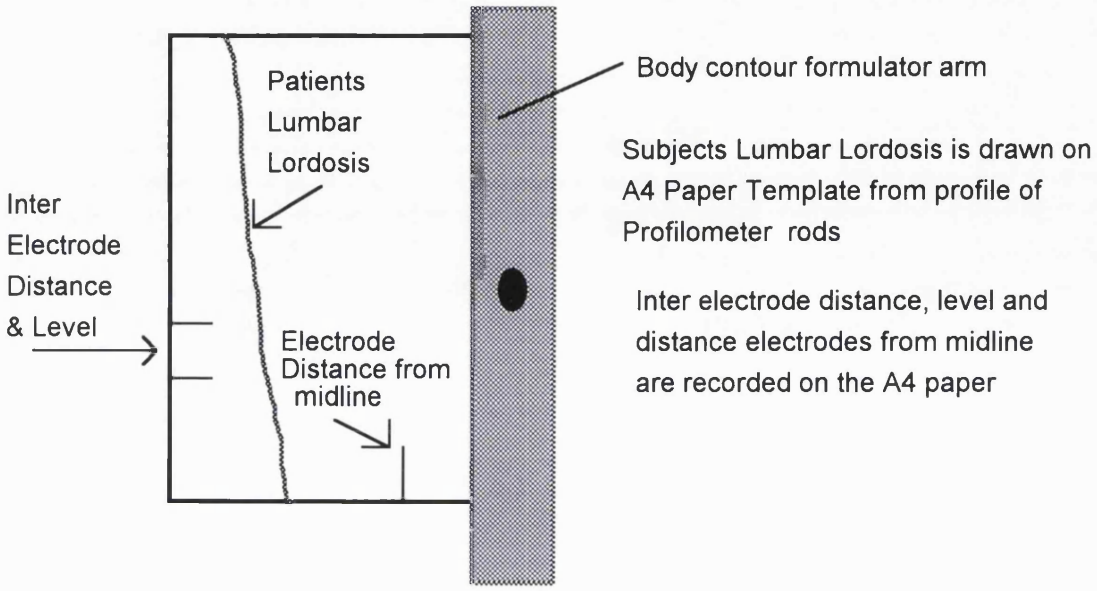
An isometric stress test frame was constructed and is shown in figure 5. To a metal baseboard with a non-slip rubber under surface was bolted a 10cm by 10cms 'U' section beam in a longitudinal axis to increase its rigidity. Two vertical frame works, one on either side of the 'U' section supported a pelvic rest. Height of the pelvic rest was adjustable. 40cm in front of the centre point of the pelvic rest, a pulley was mounted in the 'U' section and forward to this point a loadcell was fitted (TWL Force Systems®-Appendix). The subject applied a load to the loadcell by pulling vertically on a chain that was taken around the pulley and entered the loadcell horizontally. At the end of the chain a handle bar fitting was attached and this was moveable along the chain to allow for different heights of subjects. The frame itself was collapsible to allow testing to occur in different locations. The loadcell was calibrated to 200Kg with a safety tolerance of 1000Kg. The loadcell had been satisfactorily calibrated by the manufacturer. Continuous liquid crystal digital display and computer monitor display from the loadcell were visible during subject testing.

Subject positioning during testing

During testing the subject was required to stand with his/her legs straight, 20cm apart and to lean forward until the lumbar spine made an angle of 30 degrees with the vertical. This angle was controlled by the use of a body contour formulator that was fixed to a rigid arm at 30 degrees to the vertical (Appendix). This arm could be swung across when positioning the subject and then moved away during the period of the tests. The body contour formulator was also used to measure and record the lordosis or kyphosis of the lumbar spine. The body contour formulator arm was positioned on the midline of the lumbar spine by eye and the body contour formulator rods could be pressed down onto the skin and secured with a wing nut. The profile of the body contour formulator was transferred to A4 paper by tracing along the tips of the rods to allow a permanent record to be kept and allow the subject to be positioned in exactly the same manner during subsequent tests. On the same sheet the distances the surface electrodes were positioned from the midline and the exact level at which the electrodes had been positioned were recorded. A typical template is shown in figure 6.

The pelvic rest and chain length through which the subject pulled were adjustable so that the differing heights of subjects could be accommodated. Pelvic rest was adjustable in the vertical axis and was positioned 6cm below the anterior superior iliac crests. Both pelvic rest and chain length were marked with permanent markers so that subject position could be reproduced. When positioning the subject on the test frame care was taken to position the subject symmetrically to prevent twisting of the pelvis during testing.

Figure 6 Paper template used for reliability study



Determination of maximum voluntary contraction

Once the subject was positioned satisfactorily on the reference frame a maximum voluntary contraction was established. The subject was not permitted to observe any kind of visual display during the setting of the maximum voluntary contraction. A 100% maximum voluntary contraction was maintained for three seconds and registered three times with at least four minutes rest between tests. The subject was asked to *'pull as hard as he/she comfortably could'*, subjects were instructed not to pull with their arms or leg muscles. No verbal encouragement was given through out any of the testing. A maximum voluntary contraction was set for each subject by averaging the three recordings if the three trials fell within 10% of each other. From the three trials the average was taken to be the subjects maximum voluntary contraction.

Isometric loading conditions

During initial development of the test frame the subject controlled isometric load by observing a digital liquid crystal display on the loadcell. Some subjects found it difficult to control load by observing a digital display. To simplify and improve the consistency of

isometric loading by the subject a computer program was written which displayed, time on the X axis and load on the Y axis transmitted from the loadcell. On a computer monitor a red line displayed the subjects target load and once the subject pulled on the loadcell a green line would indicate the actual load (loadcell program-Appendix). One low load 1/3 maximum voluntary contraction rehearsal was allowed and nearly all subjects learnt control of the loadcell within 10 seconds. Tests were rejected if the isometric load level drifted more than 5% from the target level. Duration of tests was recorded by the loadcell software program. Recording of electromyogram signals was not commenced until the subjects target load level had been achieved. Synchronisation of commencement of recording electromyogram signal and constant target isometric load was manual. Once maximum voluntary contraction had been established there was at least four minutes rest before testing was commenced. Two tests were undertaken one at 1/3 and one at 2/3 maximum voluntary contraction. Each was held for 30 seconds whilst surface electromyograms were recorded. If subjects failed to maintain a load during a test the results were tagged and not used in analyses. At least four minute's rest was maintained between the 1/3 and 2/3 tests.

Electrode positioning

Surface electrodes were positioned at the level of the transverse line between the highest point of the ilaic crests. This level lies at the level of the L4/L5 interspace, Last (1984). The electrodes were placed over the greatest convexity of the erector spinae. At this point the surface electrodes would be lying over the multifidus muscle (Bogduk 1980, Last 1986). The electrodes were placed with an inter electrode distance of 4cm (between the centre snaps) in a longitudinal axis to the muscle Typical placement of surface electrodes is shown in figure 7. The earth electrode was placed in the midline of the back. All placement sites were bilateral at the level of L4/L5, no other levels or inter electrode distances were studied in this series.

Electrode application

The skin was vigorously prepared with alcohol wipes to remove the surface grease from the epidermis. The epidermis was then gently abraded with fine commercial surgical abrasive skin preps (Cardio Preps®-MSB Ltd). When abrading the skin linear transverse abrasions were made in one direction only, the sandpaper was not rubbed back and forth.

Electrode type

Commercially available (Biotrace®-MSB Ltd.) Ag/AgCl surface electrodes were used (See Appendix). The electrodes were supplied with a male metallic centre snap which attached to a female electrode lead. The base plate of the electrode was a fabric material. The base plate of the electrode was coated with an adhesive gel containing Ag/AgCl. Contact resistance was checked with an impedance tester that is an integral part of the electromyogram preamplifier. Contact resistance was maintained below 8 KΩ or the electrodes were reapplied.

Two different fabric surface electrodes were tested, 1) Medicotest®-Blue Sensor (Ag/AgCl) was compared to 2) Biotrace® Neonatal (Ag/AgCl) (See Appendix). One set of Medicotest® and Biotrace® electrodes were applied to the right and left side of the lumbar spine respectively. The subject tested was a normal subject who was known to have identical initial median frequency and median frequency regression lines on each side of the back. No difference in initial median frequency or median frequency regression lines was observed comparing the two different electrode sets. The Biotrace® surface electrodes had superior skin adhesive properties and were chosen for all tests.

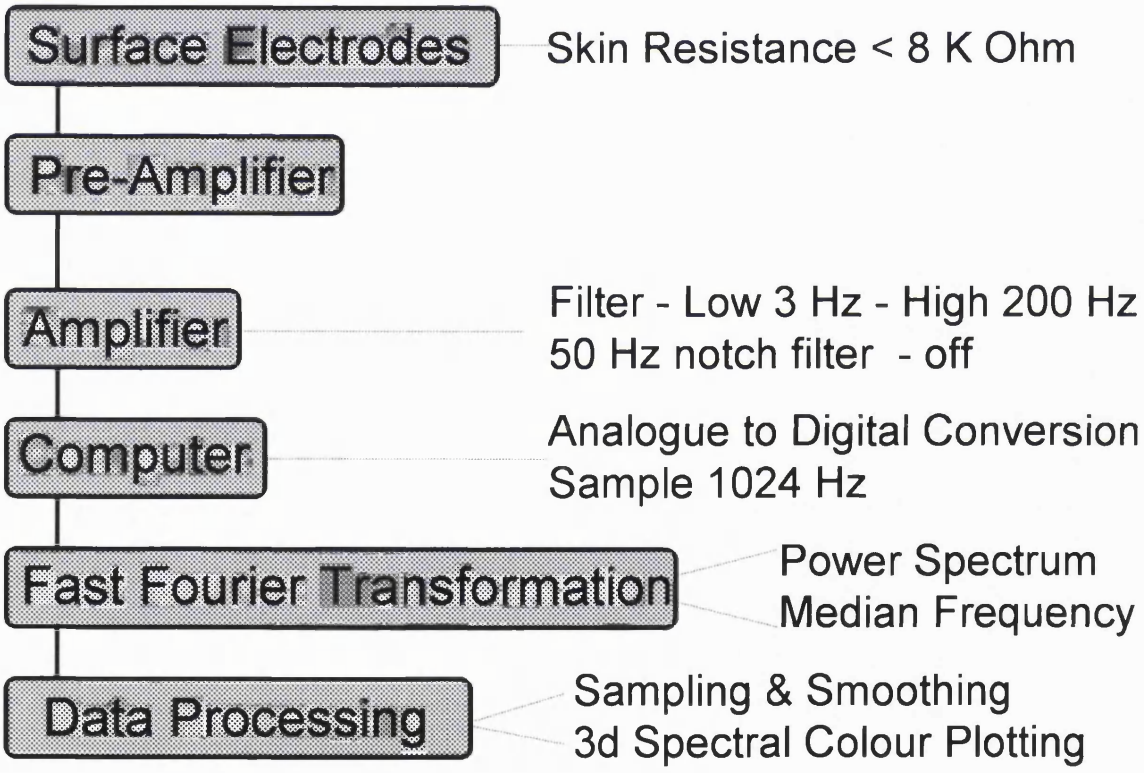
Acquisition of signal and filter settings

The filter settings on the Medelec® electromyogram machine were set to pass signals between 3Hz and 200Hz. Following the observation that above 200Hz there was only 2.2% of the total signal amplitude in normal subjects and unnecessary data was being recorded and displayed the upper filter level of 200Hz was established. At a sampling rate of 1024Hz there should be no ailiasing of the signal when processed through a fast

Fourier transform according to the Nyquist Criteria. For technical specification of electromyogram recording equipment see Appendix. The 50Hz main's electricity filter was off. The low filter was set at 3Hz to eliminate electrocardiogram interference.

Both channels of the Medelec® were used, channel one for the left side of the back and channel two for the right side of the back. Thirty seconds of raw electromyogram signal was acquired each as a one second cascade and digitised by analogue to digital conversion, stored in a temporary memory on the Medelec® and then stored on floppy discs. Figure 8 shows a schematic diagram of the electromyogram recording equipment.

Figure 8. Schematic Diagram of electromyogram Recording Equipment for Spectral Analysis



During early development of signal acquisition there were problems with the amplitude of signals unexpectedly falling once they had been processed by the electromyogram to personal computer transfer program. When recording in cascade mode the Medelec® can only store 50 seconds of two channel cascades. If the memory of the Medelec® was not erased between tests the current test would summate with

previous tests disrupting the test results at the point of wrap-around. All previous traces were erased before starting new tests. The manufacturer was advised to improve the instruction manual.

Sources of signal artefact

Mains interference

The Medelec® electromyogram machine was equipped with an integral 50Hz notch filter to dampen main's voltage interference. Two subjects were tested with the filter on and off and the electromyogram signals processed by fast Fourier transform. There was no observed difference in the median frequencies or spectrum shape whether the filter was on or off. There were no problems with main's electricity interference during any of the tests in this series. The oscilloscope screen was routinely continuously observed whilst the electromyogram signal was recorded to safe guard against main's electricity signal or movement artefacts being accidentally recorded.

Electrocardiogram interference

Interference from electrocardiogram signals can be a problem in electromyogram recording. When subjects were asked to stand on the reference frame in full extension there would be no loading on the paraspinal muscles and no muscle activity. In this position the electrocardiogram signal was visible. One subject was tested for a full thirty seconds in extension under no paraspinal loading and the signal processed through a fast Fourier transform. The signal was found to be less than 5% of the amplitude a normal person's signal and 50% of this signal were found to be below 5Hz. Setting the low filter at 3Hz for all subjects would remove virtually all of the electrocardiogram interference.

Movement artefact

Low frequency movement artefacts are a problem in electromyogram recording. Anders (1991) recommended that to avoid movement artefacts the filter setting should be set at 10 Hz. To reduce movement artefact a special set of short leads 20cms long were made for the link between the surface electrodes and pre-amplifier. Filter settings were determined for the low filter at 3Hz due to the ECG artefact. As long as there was no movement from the subject no visible disturbance of the real time electromyogram oscilloscope monitor was seen.

Signal recording and processing

Purpose designed software programs were written to process the electromyogram data.

Electromyogram to personal computer transfer program

Digitised electromyogram data from the Medelec® electromyogram machine was stored onto 720 Kbyte floppy discs and processed as desired. The digitised electromyogram signal required to be in a form that could be interpreted by the spectral analysis program. The electromyogram to personal computer transfer program converted the data into a readable digital format. No direct RS232 link was written between the electromyogram machine and the personal computer.

Spectral analysis program

A composite program was written to perform the following tasks for each of the two channels of the electromyogram machine:

1) Fast Fourier transforms of the raw electromyogram data in one second epochs
2) Plot the power spectra for each one second epoch. The *Y* axis autoscaled amplitude for each plot whilst frequency would be plotted from 0Hz to 300Hz in 1Hz intervals
3) Calculate the median frequencies, peak amplitude and peak amplitude frequency of each power spectrum
4) Plot regression lines of total power or median frequency for the thirty second duration of each subject test
5) Plot initial total power and initial median frequency from the intercepts of the regression lines.
6) Produced data files of regression and spectrum data for each subject and test.
7) Calculate students t test values for significance of slope of regression line
8) Calculate correlation statistics for the degree of fit of regression line slopes
9) Provide an interface with the loadcell program

The software code for the fast Fourier transforms routine was obtained from a Turbo Pascal® library routine. Validation of a frequency analysis device that uses a fast Fourier transforms can be tested by feeding a pure sine wave into the device to be tested. Pure sine waves can be obtained from a frequency generator or by a computer software generated program. The frequency spread of the power density spectrum has been measured by (Luciani 1983, DeAngelis 1990). The narrower the frequency spread the more accurate the device will be. Digital algorithms have been written to produce band-limited noise (pink noise, band limited white noise 20 to 40 Hz) with adjustable median frequency and amplitude to produce test signals with spectral characteristics typical of those of the surface myoelectric signals encountered in muscle fatigue studies (DeAngelis 1990). These synthesised signals can provide a basis for standardised evaluation of the performance of various spectral analysis techniques and research equipment in muscle fatigue.

Frequency testing was performed by using a sine wave generator checked with a frequency counter to produce sine wives into the spectral analysis program. Results are shown in table 3. The error at above 100Hz of 1% was attributable to 'impure' sine waves being generated by the frequency generator.

Table 3. Testing fast Fourier transform Input-Output Frequencies

Input signal (Hz)	Output signal-fast Fourier transform Peak Amplitude Frequency (Hz)
5.0	5.0
10.0	10.0
20.0	20.0
50.0	50.0
100.0	101.5
200.0	202.0

File management program

This program was written to place the regression data files into a spreadsheet for subsequent analysis. The destination of each data file could be chosen. Commercial packages were used to manipulate the spreadsheet files (Stanford Graphics®, Microsoft-Excel® and SPSS®).

Sampling program

The conventional approach of representing the results of spectral analysis as initial median frequency, initial total power spectra and respective regression lines are simplistic and represent only a limited amount of the total data. The regression lines of power and median frequency were not found to be not particularly reliable. To represent the entire data more fully a new technique of three-dimensional and spectral colour mapping was developed. In the past scanning electromyograms have been used by Stalberg (1991) but only give a stacked two-dimensional image of successive electromyograms. Colour is a very powerful tool for illustrating apparent differences and similarities between cohorts. To represent the electromyogram data, three-dimensional plotting of the data in colour; *X, Y, Z*: frequency/amplitude/time was performed. Plotting all the spectrum files in three-dimensional would take ten minutes if the 7500 data points were plotted in an Excel® three-dimensional graph on a 386SX 33Mhz computer.

A peak-average sampling and smoothing software program was written which only used 900 data points and would take 30 seconds to plot each spectral colour map. A commercial software package (Stanford Graphics®) plotted the results as a three-dimensional graph. The spectral map could be colour mapped. Colour mapping would delineate the amplitude range over twelve, equal width colour bands. The colour banding transitions were all blended and autoscaled. Colour mapping allows a much larger amount of the data to be represented.

The sampling program degraded the data from a resolution of 1Hz to 2.5Hz so some information would be lost. The gain obtained from plotting the spectral colour maps much faster was at a small loss to reducing the resolution of the three-dimensional graphs and spectral colour maps.

Electromyogram amplitude values between subjects varied so a *'birds-eye view'* two-dimensional spectral colour mapping was used to normalise intraindividual differences in amplitude. An *X*-time, *Y*-frequency colour map was produced. The same twelve band colour mapping scheme was used as in the three-dimensional surface maps. The scaling method was automatically set between the minimum and maximum amplitude range for each graph.

Halfwidth measurement

It was observed from the spectral colour maps that the pattern of frequencies and the width of the spectra did not vary greatly over the 30 second duration of each test. It was also observed that the modal frequency did not vary greatly. Because of this lack of variation in frequency pattern and modal frequency all thirty power spectra from each test were averaged to produce a composite averaged power spectra of each test. The spectral halfwidth was then measured automatically. Spectral halfwidth was calculated at 50% of the peak amplitude. No smoothing of the spectra was performed.

Reliability and repeatability method

It is crucial to the development of a new technique of assessment of muscle function that the technique can be shown to be reproducible. Nine normal male subjects (age 26 to 50 years) were tested on three separate occasions within a thirty-five day period with at least twenty-four hours rest between tests. It must be noted however that low frequency fatigue has been recorded to last up to three days in some subjects. Fresh surface electrodes were used on each occasion. Frame and load settings were the same for each subject between tests. Tests were performed at 2/3 maximum voluntary contraction and observations made for the left side of the back. Initial median frequency values, initial total power, spectral halfwidth, respective and regression line slope plots were calculated for each load.

Statistical analysis

Statistical analysis was performed with Excel®, Minitab® and SPSS® standard spreadsheet and statistical packages. The z test was used to compared means with an adjustment for unequal variance. Significance values were set at the 0.05 level in all tests. In all tests * denotes a significant difference between populations, ns denotes no significant difference between populations. Intraclass correlation coefficient (Fleiss 1986) was used for the reliability and repeatability study. A reliability of repeatability of above 80% is satisfactory in a biological experiment (Fleiss 1986).

Artificial intelligence data collection

Data collection

Electromyogram power spectra data from sixty subjects were used. Thirty-three normal control subjects and twenty-seven chronic back pain subjects. Subjects were classified from their clinical history (without physical examination) into groups of normal subjects who had never had chronic back pain at any time of their life and secondly into chronic back pain subjects with a recurring history of chronic back pain (> six months), at time of testing. The same population of subjects used to collect the data for the spectral colour maps was used for the neural network investigation. The subject set was reduced to 60 subjects because of concern about the processing power of the personal computer due to the huge volume of data involved.

The details of the electromyogram collection from the patient were the same as that for the collection of data for the spectral colour mapping.

The joint time-frequency transform

For analysis of the electromyogram with the neural network data, a joint time-frequency transform was used. The joint time frequency analysis transform enables looking at changes of the frequency contents of a signal in time. A way to do this is by dividing the signal in segments of equal duration, and calculate the Fourier transform for each segment. A better resolution is achieved when a sliding analysis window is used. The Fourier transform is calculated for the part of the signal "in the window", and is assigned to its centre point. The window is moved over the time axis, to get a complete representation of the signal. This is the basic idea of the short-time Fourier transform. The advantage of a joint time frequency analysis is that information about frequency content is retrieved, while at the same time transient phenomena are preserved. A short time Fourier spectrum lacks this quality. The short-time Fourier transform is sufficient if the rate of change in the signal is low. Problems arise when signals with rapidly changing spectral contents are analysed. Finding an appropriate short-time analysis window is problematic since there may not be any time interval for which the signal is more or less stationary. Also, decreasing the time window so that one may locate events in time reduces frequency resolution (Cohen 1989).

The transformation of the electromyogram data was performed with an icon driven programming software package, LabVIEW® for Windows, with a supplemental joint time-frequency analysis toolkit both supplied by National Instruments. The adaptive joint time frequency analysis was chosen because this transforms combines reasonably fast computation with, the best time-frequency resolutions of all the transform algorithms. The joint time frequency analysis package was not available at the time of the initial analysis of results in 1993. (See Appendix for the settings used for transforming the data.) Transformation of a 30 second time signal, sampled at 1000 Hz, yielded a two-dimensional array of 129 points (frequency) by 469 points (time). The 128th point on the frequency axis corresponds to half the sampling frequency: 500 Hz, and the 469th point on the time axis corresponds to 30 seconds.

Data reduction

Before feeding the data into the neural network, the size of the frequency time spectrograms was reduced. First, the part with frequencies higher than 270 Hz was discarded. For higher frequencies the spectrogram contained virtually no energy. The resulting matrix was 70 columns by 469 rows. Both the frequency and the time axis were divided in bands. The frequency band was divided in ten bands, seven points each; the time axis was divided in thirty bands, approximately sixteen points each. This banding of the axes yielded 300 oblong areas in the spectrogram. In each area the average of the points in it was calculated, which produced 300 values in a matrix of ten columns by thirty rows. This matrix then was normalised and stored. This pre-processing of the data performed for three reasons. If the original spectrogram were to be loaded into a neural network, training the network would require a very large amount of computation and time. Secondly, averaging areas in the spectrum has the effect of a spatial low pass filter. The spectra of electromyogram signals are known to be noisy, which is now reduced. This makes training the neural network easier. Finally, the data is normalised. The classification is based on changes in the shape of the spectrogram. The matrix is mapped on a [0..1] interval, which is required for the neural network. All the pre-processing was performed with LabVIEW®. The values are stored as single precision floats.

Backpropagation neural networks

A suitable design neural network was implemented. The most important feature of a neural net is the ability to learn. For supervised learning, a set of input patterns of which the proper outputs is known is necessary. During one epoch, all the training patterns are loaded into the network. Next, the weights are adjusted to decrease the error at the output. This is repeated until the network performance is satisfactory. To train a network a learning algorithm is needed. One of the most often used is backpropagation. While training, the algorithm tries to find network weights that minimise a criterion function. This criterion function is the *sum-of-squared-error* criterion function:

$$J(\overline{w}) = \sum_{p=1}^{P} J_p(\overline{w})$$

Where P is the number of training patterns. J_p is the total squared error for the p^{th} pattern:

$$J_p(\overline{w}) = \tfrac{1}{2}\sum_{q=1}^{N}(u_q(\overline{x}_p) - d_q(\overline{x}_p))^2$$

Where N is the number of outputs, $u_q(x_p)$ is output q for training pattern p, and $d_q(x_p)$ is the desired output for training pattern p. Minimising $J(w)$ for a training set will set the decision boundaries. If the training set is large enough and representative for the patterns that can be expected, then after training the net will be able to generalise the learned behaviour. To minimise the error the weights have to be adjusted. This is performed iteratively:

$$w_{l,j,i}(k+1) = w_{l,j,i}(k) - \mu\sum_{p=1}^{P}\frac{\partial J_p(\overline{w})}{\partial w_{l,j,i}}$$

$$\text{or } w_{l,j,i}(k+1) = w_{l,j,i}(k) - \mu\frac{\partial J(\overline{w})}{\partial w_{l,j,i}}$$

where $w_{l,j,i}$ is the weight connecting the i^{th} node of layer l-1 to the j^{th} node of layer l, μ is a positive constant called the learning rate. It can be seen that a weight's adjustment depends on its influence on the total error. If the gradient is positive then the weight has

to be decreased, if negative then the weight is increased, to diminish the error. The learning rate μ determines the proportion of the gradient to the adjustment made in every iteration. The partial derivative can be rewritten as:

$$\frac{\partial J_p(\overline{w})}{\partial w_{l,j,i}} = \frac{\partial J_p(\overline{w})}{\partial u_{l,j}} \frac{\partial u_{l,j}}{\partial w_{l,j,i}}$$

Where $u_{l,j}$ is the output of the j^{th} node in layer l. The third term is a derivative of the relation between output value and weights of a single node, which involves differentiating the activation function. This is why the non-linear activation function must be differentiable.

Another factor available for training the net is the momentum. The momentum determines the proportion of the last weight change that is added to the new weight change. This parameter is needed because large learning rates often lead to oscillation of weight changes and learning is never completed, or the network converges to a solution that is not optimal. Momentum provides a smoothing effect to the weight changes and allows a larger learning rate (Ward Systems 1993).

Tralning and testing a neural network

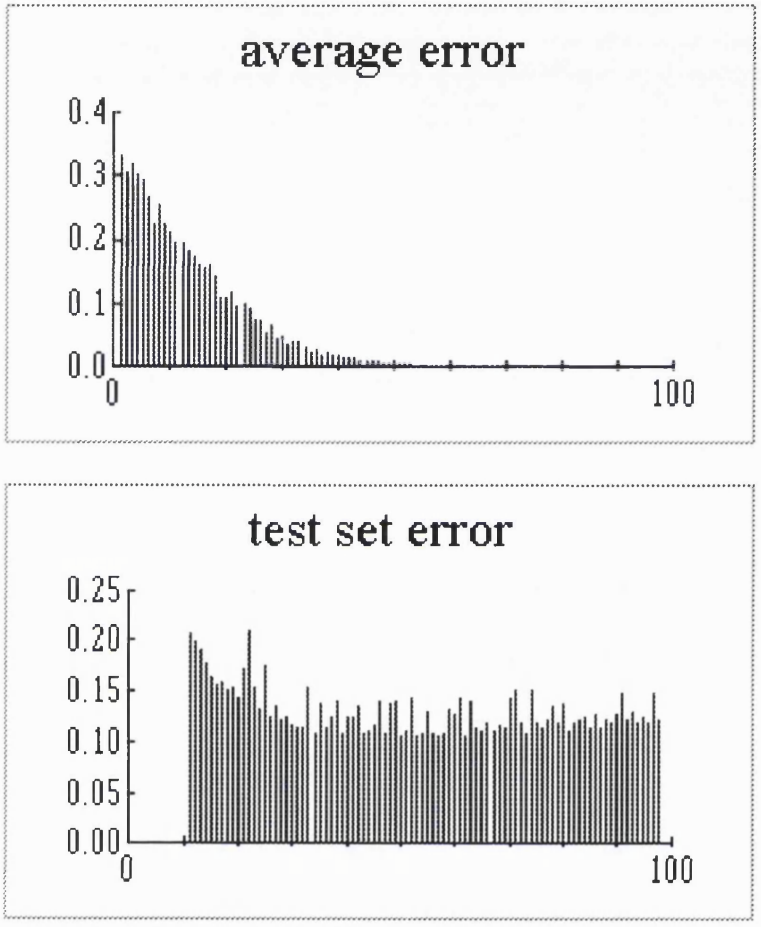
To train a network and then evaluate its performance, two sets of input patterns are needed: a train set and a test set. Of all patterns the desired output of the net must be known. The train set is used to teach the network to generate the proper output for the input patterns. If the train set is a good representation of all the possible input patterns and the network was well trained, then what was learned from the training set can be generalised. After training, the patterns in the test are fed into the network and the output produced by the network is then compared with the desired output. If the test set is a good representation of all possible input patterns, the results of testing will give a good indication of network performance. To make the test valid, it is required that none of the patterns in the test set are present in the train set. Before starting with training, all the weights in the network are initialised with random values. If this is not performed and all weights have the same value when training starts, then adjustments made through backpropagation will be the same for each weight. The result is that the net will never

converge, that is the weight adjustment will never result in a decreasing error at the output.

A problem is deciding when to stop training. If training is continued too long, the network may become overtrained. This happens when the network becomes "too good" and has specialised on the training set, which deteriorates the ability to generalise. If training is terminated too soon, the network will not have adapted sufficiently to the training set and the net performance will be poor. There are several criteria for terminating training. One can train until the error for each training pattern, ($(J_p(w))$, falls below a threshold. Alternatively, training can continue until the *sum-squared-error* falls below a threshold. Another method, which is used here, is *test-set-error-comparison*, which is the most common method used to evaluate a neural network (Ward systems 1993). During training, the network's ability to generalise is evaluated periodically. This is done by feeding the test set into the network and see how well the outputs approximate the desired values. Every time the network performs better, all the weights are stored. Training is terminated when no improvement occurred for some period of time. Added to this scheme the test-set-error-comparison would not start before the average error for the training set reaches a threshold value. This was done to ensure that the network has already partly converged to the train set before it is tested. This way the chance at accidentally finding a low error for the test set, before performance for the train set is good enough, is small. This is thought to be particularly important for relatively small test sets. The addition of a threshold for the average error of the train set also speeds up training. The average error e_{av} is defined as: $e_{av} = \frac{1}{P}\sum_{p=1}^{P} J_p(\overline{w})$

During training the same average error is calculated for the test set and is used as an indicator for the network's ability to generalise. When a test yields a lower average error than any test before, the network is stored. Figure 9 shows a typical example of the development of the average error for the train set (top) and the test set (bottom). In this example the test-set-error-comparison starts when the average error for the train set goes below 0.2. The average error for the test set converges with the train set's error at first, then stabilises and then gradually will increase when training continues.

Figure 9: Typical curves for the average error of the train set (average error) and the test set (test set error) during training for the electromyogram data. The X axis is the epoch, the Y is the average error.



Training and testing the neural network

Commercial software programs were developed in Visual Basic™ for program development with additional runtime libraries from NeuroWindows™. NeuroWindows™ provided functions and data structures that facilitated simulating a neural network with a digital computer. All the nodes have the logistic function as activation function. The user has control over the number of nodes in each layer and learning rate and momentum in the input and the hidden layer. The input layer of the network has one node for each input, which is 300. Each input feeds into one node of the input layer. The number of outputs is equal to the number of classes in input patterns. There are two classes of input patterns: twenty-seven chronic back pain subjects and thirty-three normal controls, so the

number of nodes in the output layer is two. With the application a train and a test set can be generated. The user has to specify the percentage of the total number of patterns in each class that will be in the test set. Next, the test set is generated by random selection. The remaining patterns are the training set. Test sets of 20% and 40 % of the available input patterns were generated for the network. A test set of 10% of the available input patterns is generally considered appropriate (Ward Systems 1993), which would produce a test set of six patterns: three chronic back pain subjects and three controls. This is considered too few for evaluating the network performance. A test set of 20% contains twelve input patterns: five chronic back pain subjects and seven normal controls. A test set of 40% holds twenty-four: eleven chronic back pain subjects and thirteen controls. A consequence of having a larger test set is that the train set now is smaller and this might have a negative influence on the ability of the network to generalise after training. The network was trained with fifteen, ten, five, three nodes and one node in the hidden layer, to investigate the effect of network size on convergence and generalising ability. The network with one node in the hidden layer is functionally similar to a single perceptron, and will therefore try to implement a linear decision boundary. The training and testing of the network with different numbers of nodes in the hidden layer were done with the same train and test set. This was repeated four times with different compositions of train and test set for both 20% and 40% test sets, to find out how dependent the results are on the patterns present in the test set and those in the train set.

The values of training parameters were chosen after some experimenting. For the networks with ten and fifteen nodes in the hidden layer a learning rate of 0.3 and a momentum of 0.1 was used for both layers. For the other networks these settings were 0.6 and 0.2 respectively. The threshold for starting the test-set-error-comparison was 0.05. The test-set-error-comparison was performed for every five epochs. Training was terminated if no new low was found for the test set error for one hundred epochs. All settings are summarised in table 4

Table 4 Neural Network Training Parameters

Test-set-error-comparison:
Threshold for train set error: 0.05
Test interval: 5 epochs
Stop training if no new low was found during: 100 epochs
With 15 or 10 nodes in the hidden layer:
Learning rate in input and hidden layer:
0.3, Momentum in input and hidden layer: 0.1
With 5, 3 or 1 node(s) in the hidden layer:
Learning rate in input and hidden layer:
0.6, Momentum in input and hidden layer: 0.2

After training has completed the network performance must be tested. For this, each pattern in the test set is fed into the network. The final classification by the neural network is determined by comparing the two outputs. The input pattern is assigned to the class with the largest output. This result is then compared with what the class should be. The software generates an output that is stored in ASCII text format. This output contains the number of correct categorisations, and the number of patterns that were classified wrong, for each class.

Chapter Four - Results

A total of one hundred and three subjects was tested, fifty-two males and fifty-one females. Each subject performed bilateral testing at L4/L5 under 2/3 and 1/3 maximum voluntary contraction. Due to the electromyogram sampling rate of 1024 Hz approximately 140 Megabytes of raw electromyogram signal were collected on individual subject floppy discs.

Anthropometric results

Age and sex

A total of one-hundred and three subjects was tested. Normal was defined as no back pain at the time of testing but may have had a minor back pain episode at any time of their lives. Back Pain was defined as any subject with chronic back pain more than six months. Table 5 shows the age, sex and back pain status of subjects.

Table 5. Subject Age (years) and Sex

	Normal		Back Pain	
Sex				
Male	33		19	
Female	29		22	
Age (mean (range))				
Male	34.9	(15-52)	44.6	(25-65) *
Female	34.2	(18-54)	44.0	(23-62) *

z test

Body weight and lean body mass

There were no significant differences between the body weight, body mass index, percentage body fat and lean body mass between normals and back pain subjects. The expected differences between the sexes for these parameters were observed. Body weight, body mass index, percentage body fat and lean body mass are shown in table 6.

Table 6. Subject Anthropometrics spectral analysis and colour mapping

	Normal	Chronic Back	
Body Weight (Kg)			
Male	77.4	74.8	ns
Female	63.5	61.6	ns
Body Mass Index ($Kg/m^{2)}$			
Male	29.9	29.5	ns
Female	29.0	28.5	ns
Percentage Body Fat			
Male	19.8	21.6	ns
Female	30.6	32.5	ns
Lean Body Mass (Kg)			
Male	61.6	58.7	ns
Female	43.8	41.2	ns

z test

Maximum voluntary contraction

Subjects maximum voluntary contraction is shown in table 7.

Table 7. Subject Maximum Voluntary Contraction Kg
(mean (range) sd = Standard Deviation)

	Normal	Back Pain
Male	115.1 (68-200) sd 27.9	56.4 (11-105) * sd 30.2
Female	60.7 (18-110) sd 21.8	39.2 (8-65) * sd 18.4

z test

Back pain males were on average 49% weaker than their normal cohort. Back pain females were 65% weaker than their normal cohort.

Maximum voluntary contraction plotted against lean body mass is shown in figure 10. The correlation between maximum voluntary contraction and lean body mass in normal subjects and chronic back pain subjects was found to be 0.85 and 0.56 respectively. The regression line equation for males and females with no pain at the time of testing was: $y = 1.2 + 2.68x$. The regression line equation for males and females with back pain was: $y = 35.1 + 0.59x$

Exercise history

Exercise history was recorded as each exercise episode per week that caused the subject to sweat. Exercise history is shown in table 8.

Table 8. Subject Exercise History

	Normal	Back Pain
Male	2.32	1.91 *
Female	1.83	1.59 ns

z test

Functional assessment

Low back outcome score

Low back outcome score is shown in table 9. The maximum score possible 75

Table 9. Low Back Outcome Score

	Normal	Back Pain
Male	72.3 sd (7.9)	59.4 sd (17.2) *
Female	72.4 sd (3.4)	51.2 sd (17.8) *

z test

All subjects were in full time employment and none were pursuing a medicolegal claim for back injury.

Psychological results

Modified somatic perception questionnaire and Zung

Maximum score possible modified somatic perception questionnaire = 39

Maximum score possible modified Zung = 66

Modified somatic perception questionnaire + Zung - Psychologically disturbed: Male >32, Female >36

Psychometric scores for all subjects are shown in table 10.

Table 10. Psychometric Scores (mean (sd))

	Normal	Back Pain
Modified somatic perception questionnaire		
Male	1.9	3.0
Female	2.3	6.1
Zung		
Male	5.6	9.6
Female	8.4	13.7
Modified somatic perception questionnaire + Zung		
Male	7.5 sd (5.5)	12.6 sd (8.7)
Female	10.7 sd (8.8)	19.8 sd (15.8)

Job satisfaction

The sum of four questions relating to job satisfaction scored on a visual analogue scale (Maximum score possible 40) are shown in table 11.

Table 11. Job Satisfaction (mean)

	Normal	Back Pain
Male	32.4	31.2 ns
Female	32.3	30.6 ns

z test

Reliability results

The anthropometric, disability and psychometric scores of the subjects in the reliability study are shown in tables 12 and 13

Table 12. Subject Anthropometrics Surface electromyogram Reliability (Nine Subjects)

Age	34.6 years	(range 26-50)
Body Mass index	27.3 Kg/m^2	(sd 12.1)
Weight	74.7 Kg	(sd 10.4)
Height	166.5cm	(sd 12.1)
Percentage body fat	20.2%	(sd 3.9)
Lean body mass	59.6Kg	(sd 8.1)
Maximum voluntary contraction	112.6Kg	(sd 23.7)

Table 13. Disability and Psychometric Scores

Low back outcome score	73.2	(sd 3.7)
MSPQ	1.6	(sd 0.8)
Modified Zung	7.4	(sd 5.5)

MSPQ = Modified somatic perception questionnaire

Initial median frequency at the beginning of each test showed a variation in normal individuals of 2.5Hz (2.5%) average variation from the mean. The initial median frequency at 2/3 maximum voluntary contraction of erector spinae was found to have a subject to subject range of 45.0Hz to 76.4Hz, mean 61.7Hz. Median frequency gradients at 2/3 maximum voluntary contraction all declined by an average of 6.8% variation from the mean. The average median frequency regression slope at 2/3 maximum voluntary contraction decreased by 0.23Hz/s with a range 0.07 to 0.48 Hz/s. Total power spectra at 2/3 maximum voluntary contraction all increased by an average of 21.8% and had a 20.3% average variation from the mean.

Intraclass correlation coefficients (Fleiss 1986) were used to demonstrate the reliability and repeatability of the results. Percentage reliability is the simple replication reliability statistic and gives a measure of the reliability between each of the three trials. Repeatability is the 95% confidence limit for each test. The intraclass correlation coefficient for normal subjects tested on three separate occasions with fresh electrodes are shown in table 14.

Table 14. Intraclass correlation coefficients in normals

	Reliability	Repeatability
2/3 maximum voluntary contraction		
Initial median frequency (Hz)	92%	10.3
Regression median frequency (Hz/s)	49%	0.32
Initial Power (uV^2)	86%	10658
Regression Power (uV^2/s)	57%	278
Halfwidth (Hz)	89%	23.5

Breath holding results

In common with other observers (Dolan, personal communication) it was noted that the median frequency regression line has an apparent periodicity as illustrated in figure 11. It has been postulated that the periodicity was associated with breathing. One subject on three separate occasions held his breath for 30 seconds whilst being tested. A similar pattern of periodicity was seen with the breath holding tests to the normal breathing tests as shown in figure 12.

Power spectrum results

The right versus left side results of the lumbar spine showed that in both the normal and back pain subjects of both sexes that there was no difference between the two sides in all the following parameters of median frequency (z test). However, between normal and back pain groups there was a significant difference for all parameters (z test). Initial Median frequency, median frequency regression line slopes, initial total power and total power regression line slopes are shown in tables 15, 16, 17 and 18.

Table 15. Males Median Frequency Parameters (mean)

Initial Median Frequency 2/3 maximum voluntary contraction (Hz)		
	Normal	Back Pain
Left	67.0	77.1
Right	67.5	78.1
Median Frequency Regression Line Gradient 2/3 maximum voluntary contraction (Hz/second)		
	Normal	Back Pain
Left	-0.27	-0.08
Right	-0.21	-0.07

Table 16. Females Median Frequency Parameters (mean)

Initial Median Frequency 2/3 maximum voluntary contraction 2/3 maximum voluntary contraction (Hz)		
	Normal	Back Pain
Left	68.4	71.9
Right	70.6	73.5
Median Frequency Regression Line Gradient 2/3 maximum voluntary contraction (Hz/second)		
	Normal	Back Pain
Left	-0.08	-0.02
Right	-0.10	-0.04

Table 17 Males Power Spectrum Parameters (mean)

Initial Total Power 2/3 maximum voluntary contraction (uV^2)		
	Normal	Back Pain
Left	23836.1	15269.6
Right	23951.5	15511.7
Total Power Regression Line Gradient 2/3 maximum voluntary contraction (uV^2/s)		
	Normal	Back Pain
Left	180.2	11.7
Right	149.9	26.3

Table 18. Females Power Spectrum Parameters (mean)

Initial Total Power 2/3 maximum voluntary contraction (uV^2)		
	Normal	Back Pain
Left	17785.0	12618.0
Right	15854.7	12477.5
Total Power Regression Line Gradient 2/3 maximum voluntary contraction (uV^2/s)		
	Normal	Back Pain
Left	53.0	19.5
Right	64.6	26.7

Relationship of power spectrum to loading

As there has been shown to be no statistical difference between the right and left side of the back only results for the left side of the back will be quoted. One normal subject was asked to deliberately twist his pelvis to the right on the test frame, the results from this subject were known previously to be symmetrical. The initial median frequency on the right side of the lumbar spine was observed to be 5Hz lower than on the left. One subject with chronic back pain was tested with a leg length discrepancy (due to a previous malunited femoral fracture) of 4cm. The median frequency on the side of the leg shortening was found to be 4Hz lower than the normal side. The subject with leg length discrepancy was excluded from this series.

A composite of average mean values of spectral parameters in relation to loading and sex is shown in table 19. Table 20 gives the z test values comparing normal to back pain subjects in males and females.

Table 19. Average Mean Values of Spectral Parameters (mean (sd))

		Lumbar Condition	Initial Median Frequency (Hz)	Median Frequency Regression Line Gradient (Hz/s)	Initial Total Power (uV^2)	Total Power Regression Line Gradient (uV^2/s)
Male	2/3 MVC	Normal	67.0 (12.3)	-0.27 (0.21)	23836.1 (9703.8)	180.2 (187.0)
		Back Pain	78.1 (11.8)	-0.08 (0.15)	15269.6 (5770.9)	12.7 (47.8)
	1/3 MVC	Normal	66.7 (12.2)	-0.13 (0.36)	17482.2 (7039.7)	12.5 (55.6)
		Back Pain	77.3 (12.5)	-0.03 (0.11)	14045.8 (5230.8)	4.8 (45.0)
Female	2/3 MVC	Normal	68.4 (12.3)	-0.08 (0.33)	17785.0 (7880.9)	53.0 (105.4)
		Back Pain	71.9 (11.2)	-0.02 (0.1)	12618.0 (5410.2)	19.5 (43.5)
	1/3 MVC	Normal	65.7 (12.6)	-0.06 (0.36)	14263.8 (7878.4)	-2.6 (132.4)
		Back Pain	73.0 (12.5)	-0.01 (0.09)	10813.6 (4730.5)	-5.01 (28.7)

All figures are for the left lumbar paraspinals

MVC = Maximum voluntary contraction

Table 20. Back Pain versus '*Normals*' Significance Values (z test)

2/3 maximum voluntary contraction left paraspinals	Males P value <	Females P value <
Initial Total Power (uV^2)	0.001	0.001
Initial median frequency (Hz)	0.001	0.008
Total Power Regression Line (uV^2/s)	0.002	0.002
Median frequency Regression Line (Hz/s)	0.007	0.009
Low Back Outcome Score	0.001	0.001
Maximum Voluntary Contraction (Kg)	0.001	0.001

Age and power spectra results

Initial median frequency was plotted against age for normal subjects. Figure 13 shows the regression line plots for age. In males the regression line equation was: $y = 64.2 + 0.07x$. This gradient shows an increase of initial median frequency over the age range of 50 years of this population of 3.5Hz (7%). In females the regression line equation was: $y = 64.1 + 0.12x$. This gradient shows an increase of initial median frequency over the age range of 50 years of this population of 6.0Hz (12%).

Spectral colour mapping results

It was found that very clear differences could be observed between the subject groups. Spectral colour maps were produced to represent characteristic subjects: figure 14 normal subjects three-dimensional graph, figure 15 normal spectral colour map, Figure 16 chronic back pain spectral colour map, figure 17 athlete with no past history of back pain spectral colour map.

The relationship of isometric load to spectral colour mapping for a normal subject at 2/3 and 1/3 maximum voluntary contraction is shown in figure 18. The spectral colour maps in figure 19 have been autoscaled over their own ranges and appear to show similar bandwidths at 2/3 and 1/3 maximum voluntary contraction.

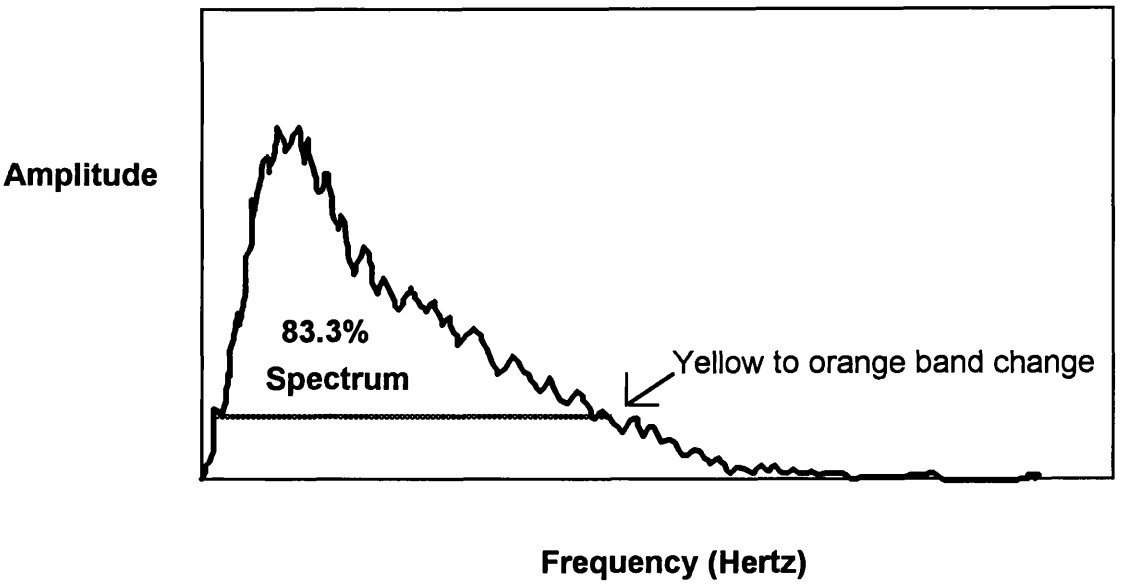
Measuring spectral colour map shape

Before computer software was developed to measure the colour maps scoring was performed by visual inspection. Spectral colour maps were produced from twenty-one subjects with chronic low back pain and twenty-six normal volunteers. Nineteen other maps were produced from normal volunteers with a history of low back pain. The observer was unaware of the numbers of normals, chronics and others. Using a protocol depending on the bandwidths, a blinded observer arranged the maps in the order he believed represented a range from 'normal' to 'chronic' and identified the point he believed separated 'normal' from 'chronic'

Twenty-three of the twenty-six 'normals' were correctly identified (Sensitivity of detecting normals 88%). Fourteen of twenty-one chronics were identified (specificity 67%). Using a refined protocol depending on the quality of the modal frequency and widened low frequency bands the specificity was increased to 76% but at the expense of reducing the sensitivity to 81%. The volunteers with a history of back pain divided equally into normal and chronic patterns.

Computer sorting of halfwidth by computer for the same population gave a sensitivity of detecting normals of 80% and a specificity of 80%. An attempt at visually objectively scoring the colour maps was made by measuring the bandwidth at 15 seconds through the spectral colour map. The bandwidth chosen was the point where the colour changed from orange to yellow. This orange to yellow inter-change bandwidth represented 83.3% of the total spectrum amplitude above the orange to yellow colour. The bandwidth measurement is shown in figure 20.

Figure 20. To show method of visual estimation of spectral bandwidth for colour mapping

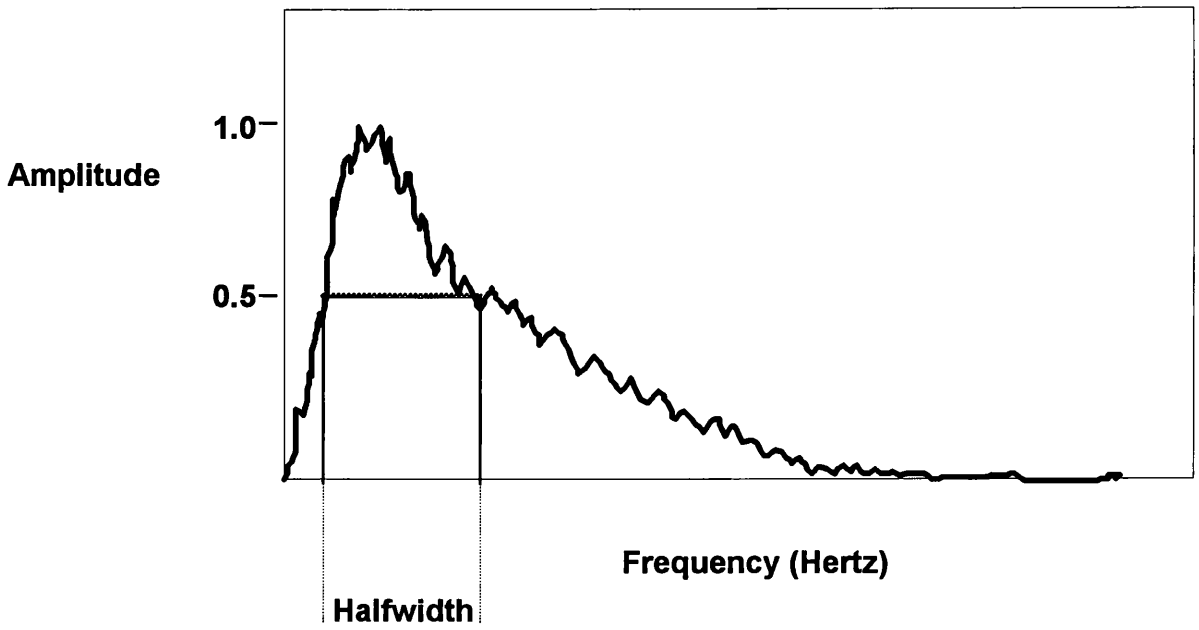


Frequency bandwidths of lumbar paraspinal spectral colour mapping by visual measurement is shown in table 21

Table 21. Frequency bandwidths of lumbar paraspinal spectral colour mapping-visual measurement Hz. (mean (sd))

	Male	Female
Normal	86.6 (17.1)	84.7 (7.2)
Chronic Back Pain	109.6 (11.4)	110.5 (13.9)

Figure 21 To show method of computer estimation of spectral halfwidth for colour mapping



Frequency halfwidths of lumbar paraspinal spectral colour mapping by computer measurement are shown in table 22

Table 22. Frequency halfwidths and modal frequency of lumbar paraspinal spectral colour mapping-computer measurement Hz. (Mean(sd))

	Male		Female	
Half Width				
Normal	65.6	(23.9)	71.7	(20.3)
Chronic Back Pain	91.0	(18.9)	84.4	(21.7)
Modal Frequency				
Normal	33.9	(5.9)	35.0	(6.8)
Chronic Back Pain	33.5	(9.6)	32.0	(6.8)

Halfwidth measurements of spectral bandwidth by computer measurement compared are shown in table 23.

Table 23. Halfwidth population means compared

Population means were compared using the Z test	
	P (two tails)
Normal Male versus Chronic Male	<0.01
Normal Female versus Chronic Female	<0.01

Maximum voluntary lumbar isometric paraspinal extensor contraction of subjects visual and computer measurements are shown in table 24

Table 24. Maximum voluntary lumbar isometric paraspinal extensor contraction of subjects visual and computer measurements
Kg. (mean (sd))

	Male	Female
Normal	112.7 (30.6)	56.5 (26.8)
Chronic Back Pain	62.6 (31.6)	39.0 (19.8)

The regression line plot of spectral halfwidths is shown in figures 21. There was only a small effect on halfwidth with increasing isometric load. The equation for normal subjects was: $y = 65.6 - 0.03x$.

The relationship between increasing isometric load is shown in figure 22 from 0Kg to 140Kg the whole spectrum is autoscaled over its own range. The same graph as figure 22 is split into 3 second blocks that corresponded to the increasing 20Kg increments of increasing isometric load is shown in figure 23.

Neural network results

Subject anthropometrics for neural network

Anthropometric details of subjects tested by the neural network are summarised in Table 25.

Table 25 Anthropometrics of all subjects to train and test the back propagation neural network (mean (range))

	Normal Back	Chronic Back
Sex		
Males	16	14
Females	17	13
Age		
Males	37.8 (22-65)	39.4 (18-65) NS
Females	38.1 (18-62)	40.0 (26-52) NS
Body Mass Index (Kg/m^2)		
Males	29.2	29.6 NS
Females	29.7	29.8 NS
Maximum Voluntary Contraction (Kg)		
Males	77.6 (14.0 SD)	54.8 (11.2 SD)
Females	62.4 (8.6 SD)	45.9 (13.5 SD)

Body mass index = Weight (Kg) / Height^2 (m)
(t test $P < 0.05$) NS = Not significant - SD = Standard Deviation

Network sensitivity and specificity

For network size the results are summarised in tables 26 and 27 for a test set of 20% and 40% respectively of the available patterns. In the left most column the different composition of test and train set used for each row is indicated. The second column from the left indicates what class the test patterns on that row belong to. The second row from the top shows what number of nodes the network that produced the results in that column. The third row from the top indicates the classifications made by the network after testing. For example in table 26, for the first test and train set composition (run 1) and a network with fifteen nodes in the hidden layer, six of the normal controls and four of the chronic back pain subjects were classified correctly. Of both groups, one was classified falsely. Specificity is defined as the percentage of the normal control group that

is classified correctly. Sensitivity is defined as the percentage of the chronic back pain subjects that is classified correctly. N stands for normal, C for chronic back.

Table 26 Results with a test set of 20% (12 subjects) of the total available input patterns.

		Classifications									
Number of nodes:		15 nodes		10 nodes		5 nodes		3 nodes		1 node	
Run:	Class:	N	C	N	C	N	C	N	C	N	C
1	Normal	6	1	6	1	6	1	6	1	6	1
	Chronic	1	4	1	4	1	4	1	4	1	4
2	Normal	7	0	6	1	7	0	7	0	6	1
	Chronic	1	4	1	4	1	4	1	4	0	5
3	Normal	6	1	6	1	6	1	6	1	6	1
	Chronic	0	5	0	5	0	5	0	5	0	5
4	Normal	6	1	6	1	5	2	5	2	5	2
	Chronic	1	4	2	3	0	5	0	5	0	5

Table 27: Results with a test set of 40% (24 subjects) of the total available input patterns.

		Classifications									
Number of nodes:		15 nodes		10 nodes		5 nodes		3 nodes		1 node	
Run:	Class:	N	C	N	C	N	C	N	C	N	C
1	Normal	10	3	10	3	10	3	9	4	9	4
	Chronic	3	8	3	8	4	7	3	8	2	9
2	Normal	9	4	7	6	9	4	9	4	8	5
	Chronic	1	10	0	11	1	10	2	9	2	9
3	Normal	12	1	12	1	12	1	12	1	11	2
	Chronic	3	8	3	8	3	8	3	8	3	8
4	Normal	11	2	10	3	10	3	10	3	10	3
	Chronic	1	10	1	10	1	10	1	10	1	10

Tables 28 and 29 show that better classification was achieved with the 40% test set (24 patient) input set and the spread between the results for the four runs are fairly small. The same results are presented in as sensitivity and specificity in tables 28 and 29. Specificity is defined as the percentage of the normal control group that is classified correctly. Sensitivity is defined as the percentage of the chronic back pain subjects that is classified correctly.

Table 28: Results with a test set of 20% of the total available input patterns. Results are presented as specificity and sensitivity percentages.

		Classifications				
		Number of Nodes				
Run		15 nodes	10 nodes	5 nodes	3 nodes	1 node
1	Specificity	85.7	85.7	85.7	85.7	85.7
	Sensitivity	80.0	80.0	80.0	80.0	80.0
2	Specificity	100.0	85.7	100.0	100.0	85.7
	Sensitivity	80.0	80.0	80.0	80.0	100.0
3	Specificity	85.7	85.7	85.7	85.7	85.7
	Sensitivity	100.0	100.0	100.0	100.0	100.0
4	Specificity	85.7	85.7	71.4	71.4	71.4
	Sensitivity	80.0	60.0	100.0	100.0	100.0

Table 29 Results with a test set of 40% of the total available input patterns. Results are presented as specificity and sensitivity percentages.

		Number of Nodes				
Run		15 nodes	10 nodes	5 nodes	3 nodes	1 node
1	Specificity	76.9	76.9	76.9	69.2	69.2
	Sensitivity	72.7	72.7	63.6	72.7	81.8
2	Specificity	69.2	53.8	69.2	69.2	61.5
	Sensitivity	90.9	100.0	90.9	81.8	81.8
3	Specificity	92.3	92.3	92.3	92.3	84.6
	Sensitivity	72.7	72.7	72.7	72.7	72.7
4	Specificity	84.6	76.9	76.9	76.9	76.9
	Sensitivity	90.9	90.9	90.9	90.9	90.9

The results in tables 28 and 29 show the results achieved with the 20% test set and the spread among the four runs is small. The results in tables 27 and 29 for the 40% test set are not as sensitive or specific and the spread between the runs are larger.

Neural network convergence

Almost all network configurations converged well with each train and test set, both for the 20% and the 40% test set trials. Only during the training of the networks with one and three nodes in the hidden layer a plateau in the average error curve occurred for an average train set error of approximately 0.03. In all the training trials the average error of the train set went below 0.05 within 50 epochs. The rapid convergence of the network indicates that the two classes, normal and chronic back pain, are separable. The plateaux that occurred in the curve of the average error during training of the networks with one and three nodes in the hidden layer, indicate that the error function reached a local minimum. This could mean that the separation of the two classes is harder to achieve with these smaller networks. This hypothesis is supported by the observation that the plateau occurred more often for the network with one node in the hidden layer (four times), than for the network with three nodes in the hidden layer (two times).

Network size

A surprising finding is, that changing the network size has no apparent influence on network performance. The general observation is that if a network is too small, it will be incapable of forming a good model of the problem. On the other hand, if the network is too large, it may be able to implement numerous solutions that are consistent with the training data, but most of these are likely to be poor approximations to the actual problem (Hush 1993). It might be that the larger networks are in fact too large and that the test-set-error-comparison method for finding an optimal weight set keeps the network from specialising on the train set. This is unlikely however, even if too large a network could generalise from the train set during the initial phase of training. It was observed that after the lowest value for the average error of the test set was reached the test set error increased only very slightly, while the network continued converging on the train set. This behaviour was seen in all the network configurations. If the network had indeed been too large, this should have resulted in bad generalisation after prolonged training, in which case, the test set error would have increased more rapidly.

Another possibility is that the larger networks pick up more features in the input patterns than the smaller ones do. The similar performance of all the network configurations might be due to the fact that only a few dominant features provide a good basis for distinction between the normal and the chronic class. Also, the larger networks could have groups of neurons that converge on the same feature, which would not influence the network performance except for the fact that the network is not utilised optimally. The networks with one and three neurons in the hidden layer demonstrated some difficulty in converging, which means that these may be less suitable for the problem.

Generalising abiiities of the trained neural network

The ability of the net to generalise is evaluated by testing the network. The train set must be a representative sample of all possible input patterns, or the network will not perform well. The test set must fulfil the same condition, or the test results will not be appropriate. In tables 30 and 31 the average and extreme values for specificity and sensitivity for each network size are shown. The spread in the results shows that the ability to generalise after training depends on the composition of train and test set. Poor generalisation results can be due to poor training, because the train set is not a good representation of the possible input patterns. Very good results can be a misleading, because the test set may be a poor representation of the possible input patterns.

Table 30: Average and spread of specificity and sensitivity percentages for the test set of 20% of the available patterns

		Number of nodes:				
		15 nodes	10 nodes	5 nodes	3 nodes	1 node
Specificity	Average	89.3	85.7	85.7	85.7	82.1
	Highest	100.0	85.7	100.0	100.0	85.7
	Lowest	85.7	85.7	71.4	71.4	71.4
Sensitivity	Average	85.0	80.0	90.0	90.0	95.0
	Highest	100.0	100.0	100.0	100.0	100.0
	Lowest	80.0	60.0	80.0	80.0	80.0

Table 31 Average and spread of specificity and sensitivity percentages for the test set of 40% of the available patterns.

		Number of Nodes				
		15 nodes	10 nodes	5 nodes	3 nodes	1 node
Specificity	Average	80.8	75.0	78.8	76.9	73.1
	Highest	92.3	92.3	92.3	92.3	84.6
	Lowest	69.2	53.8	69.2	69.2	61.5
Sensitivity	Average	81.8	84.1	79.5	79.5	81.8
	Highest	90.9	100.0	90.9	90.9	90.9
	Lowest	72.7	72.7	63.6	72.7	72.7

The probability of poor results due to a limited train set is smallest for the trials with a test set of 20%. In these trials the train set is 80% of the available patterns, which is a larger sample and thus is more likely to be a good representation of the possible input patterns. Indeed it can be seen from the lowest values for specificity and sensitivity in table 30 and 31 that the 20% test set trials do better. Because of the limited size of the test set the reliability of the test results is low. One normal subject has an influence of 14.3% on the specificity, a chronic back pain subject has an influence of 20 % on the sensitivity.

The chance at misleadingly good results due to a limited test set is smallest for the trials with a test set of 40%, because here the larger test set is more likely to be a good representation. This can be seen from the results in tables 30 and 31 that show that the highest values for specificity and sensitivity are lower for the 40% test set trials. The larger test set makes the reliability of the results in better. One normal subject now has an influence of 7.7% on the specificity. A chronic back pain subject has an influence of 9.1% on the sensitivity. The train set in these trials is 60% of the available patterns, which is less then for the 20% test set trials. This can be a reason for the network to perform less well, because the train set can be a poor representation of the possible input patterns.

Chapter Five - Discussion

Electromyography is an attractive investigation tool as it provides easy access to physiological processes and by using surface electrodes it is non-invasive. There are limitations on the use of electromyogram and confounding factors must be controlled to make the technique reproducible and reliable. Electromyogram recording and analysis has its limitations such as the great inter-individual variation of the amplitude of the myoelectric signals, differences in the electrical conductivity of tissue, electrode geometry about muscles, muscle length, fibre size, posture and isometric load (Rosenburg 1989, Basmajian 1984, DeLuca 1993). These factors are important to control within subjects and must be controlled in long term studies. This study shown that using the technique of spectral analysis the behaviour of the median frequency power spectra and spectral shape of the monitored muscles in the lower back is different in individuals who have no dysfunction induced by injury, pain, or possibly congenital defect than among those who do. There may be some compensation from normal muscles to the dysfunctional muscles.

Psychometric scoring

The results of the psychometric measurement tools of modified somatic perception questionnaire and Zung (Main 1984 and 1992) demonstrates in this working population of hospital employees that there was no gross psychological disturbance in the population tested. The low back outcome score of Greenough (1992) demonstrated that the population tested with back pain were functionally impaired as compared to the normal population tested. Psychological disturbance has been shown to effect dynamometric performance in low back testing (Hirsh 1991).

Exercise history and job satisfaction

The results showed that in males there was a correlation ($P < 0.05$) between a reduced level of exercise and back pain, however, this however is not evidence for a cause. This

observation was not seen in females. The exercise question was subjective and as a single question may appear to be a poor method of assessing exercise history and personal fitness.

The job satisfaction score did not demonstrate any difference between back pain and normal subjects and this is not unexpected as the population tested were all in full time employment.

Reference frame

There are several positions that could have been employed for testing. Limburg (1991) has used dynamometer lying prone, this position is cumbersome. Biering-Sorensen (1984) has described a testing position where the trunk is positioned unsupported and held horizontal from a couch. The Biering-Sorensen position was not used as it was thought that the chronic back pain subjects would not be able to sustain the test position, however Cooper (1993) usefully employed this position. Roy (1989) has used an erect frame with a seat to isolate the pelvis and a harness around the chest through which a subject pulls backwards. This kind of frame is complicated to use and requires a great deal of customisation for each subject. Muscle length will be different using an erect frame so comparison of results from an erect frame to a frame with stooped postures may be misleading. The frame design was a compromise between controlling posture and employing a coupled lift throughout; hands-arms-neck-spinal-column-legs-feet. The stooped frame design has been shown to produce satisfactory results in the reliability study.

The use of a paper template enabled accurate reproduction of posture. A similar method of recording lordosis has been used by Tillotson (1991) who bent a flexicurve to record lumbar posture, this method does not have the advantage of the body contour formulator fixed on a rigid reference frame. More sophisticated methods of controlling and recording posture could have been used such as the Isotrac® (electromagnetic three-dimensional spatial reference system) but would have complicated the experiments and may not have added any benefits of additional reliability. The test frame position in the standing position has other limitations:

Functional testing of the body in lifting as a whole using the link of: hands-arms-shoulders-thorax-trunk-thighs-legs-feet to determine if a specific task is possible has the disadvantage that there may be a failure anywhere along the chain rather than in the specific muscle group that is being tested. For example the limiting factor in lifting may be the strength of the finger flexors and it would be difficult to implicate the trunk muscles in such a test. Specific muscle group weakness may be a problem when initial maximum voluntary contraction is established. Weakness of the finger flexors was seen in only athletes whose back muscles were much stronger than their finger flexors. Disease conditions such as rheumatoid arthritis where hand grip is weak may make lumbar muscle testing difficult.

The lumbar forward flexion position of 30 degrees does not eliminate gravity from the upper body during testing. The forward flexion position of 30 degrees was chosen as at that angle there is the maximum electrical signal arising from the unloaded erector spinae muscles (Schultz 1985). Schultz who studied the flexion-relaxation phenomenon in the trunk extensor muscles and found that measured myoelectric signal level was greatest in 30 degrees of forward flexion and smallest at forward flexion angles greater than 70 degrees and 0 degree's flexion. The myoelectric activity begins to markedly decrease beyond forty degrees of flexion so would have a significant effect on any posture used in extensor muscle testing at these angles. The flexion-relaxation phenomenon was hypothesised as the mechanism for the fall off in myoelectric signal on forward flexion. The mechanism is said to be due to secondary passive resistance of stretching of the ligamentous tissues of the back that substitutes for active muscle contractions in flexed trunk positions. Unfortunately no recordings were made at thirty degree's forward flexion with the spine unloaded and therefore it cannot be said if the flexion-relaxation response was different between normal and low back pain subjects.

Not only will the isometric force cause fatigue during testing but the added effects of gravity increase the moment arm of the upper torso arms and head. An independent fatigue process due to gravity will be observed in all tests. An erect seating posture similar to Roy (1989) would eliminate gravity. Erect type frames are clumsy to test large number of subjects on as they require a higher degree of individual customisation than the standing type frames.

The simple method of positioning the pelvic rest bar 6cm below the anterior superior ilaic spines will cause the pelvis to rotate sagitally forwards on testing. Although

the isometric load will pass through the lumbar spine during testing the combined loading posture may allow for other muscles, especially if the arms are allowed to bend to compensate for fatigue by voluntary increased effort. As different muscles are substituted during the test the posture of the back and muscle length may change. A more sophisticated reference frame in an erect posture with a more rigid pelvic restraint and isolating forces to only the lumbar spine (L1 to L5) may give more reproducible and reliable results.

The ergonomic lifting position of the testing apparatus is not ideal. Firstly the lifting position and does not mimic every day lifting. Secondly an isometric load would not be held for such a long duration with normal lifting and thirdly a knee bent position for lifting is much safer and has a lower incidence of injuring the lumbar spine. Shochina (1986) rationalised that in real life that isometric contractions are only rarely sustained until fatigue and were resumed after a brief period of rest. Shochina however found that in the biceps brachii in two small groups of subjects that for short 20 or 40 second periods of rest did not differ significantly from an uninterrupted isometric contraction control group, spectral analysis was however not used in this study. The multiple spinal motion segments involved also make it difficult to standardise body position or body movement to a particular task. It is also very difficult to exactly mimic the task in the workplace. Little is known about the transferability of isolated muscle function to occupational and non occupational activities (Smidt 1988).

The rest period between tests was dictated by the known patterns of signal restitution. After a sustained isometric contraction the signal has been observed to recover and come back to their normal value within four to five minutes (Petrofsky 1980b). Kadefors (1968) found that recovery was most rapid in the first 30 seconds after an isometric contraction. Siedel (1987) looked at the lumbar spine and found that breaks of twenty minutes were sufficient for a complete restitution of fatigue induced electromyogram changes. Funderburgh (1974) found that recovery of endurance took close to half an hour. Hara (1980) found that the electromyogram spectra returned to normal more quickly than did the muscle force.

Electromyographic recording

Electromyography is the accurate display of the electric signal present at the active electrode. However, the electric signals are only tiny perturbations superimposed on mountains of noise. Therefore the purpose of electromyogram signal recording equipment is to accurately record and display the signals that are physiologically relevant and discard everything that is not relevant. Much consideration has been given by Basmajian (1985) to signal acquisition and filtering. It is important when filtering a signal not to distort it. The high pass filter is the one set at a low frequency, for example 20Hz since it allows high frequencies through and stops the low frequencies. Filter settings have been set by some early workers above 60Hz (Hoyt 1981) to eliminate mains electricity (50Hz) interference, but this is unfortunate as the most interesting spectrum lies below 60Hz, Shochina (1989) analysed the frequency range of 15Hz to 5000Hz in fatiguing isometric contractions and found that there are a high density of slow motor units and at high frequency range (200 to 5000Hz) there are numerous small fast motor units. Largo and Jones (1977) have shown that synchronisation of the motor unit activity and intramuscular spike interval statistics can significantly alter the lower frequencies of the power spectrum where the effects of muscle fatigue would be most likely to occur. The signal processing frequency needs to be at least twice the sampling frequency to fulfil the Nyquist Criteria. Guld (1970) has previously described standards of electromyogram recordings and Barry (1991) has given a full explanation of terminology.

Specificity and reliability

Any new technique that is introduced as a method of evaluation must have its reliability demonstrated. This is particularly true for surface electromyogram techniques as there is a need to overcome the bias that has evolved from a history of unfulfilled expectations (Roy 1989). There have been no large reliability studies of spectral parameters on median frequency and power spectra published to date. Two issues must be addressed; specificity and reliability.

The specificity of the muscle generating a detected signal and the location of the surface electrodes on the muscle is important. Surface electrodes may be criticised as

they only detect signals from surface muscles when in fact there are muscles in deeper layers located about the spinal column that contribute to extension and rotation of the trunk. Although this is a factor the longer surface muscles have a greater moment arm about the centre of rotation of the spine, thus they contribute the major share of the monitored torque during extension.

Few published electromyogram studies of back function have examined the reliability and repeatability of measurements. Lee (1992) showed satisfactory reliability for lumbar paraspinal testing using integrated electromyography. Cooper (1993) using integrated electromyogram signals found reliability of 4.9% and 2.6% for normal subjects and back pain patients respectively. Results from this thesis of the average variation from the mean initial median frequency and median frequency slope were 3.2% and 6.8% respectively which favourably compared with 2% and 6% found by Roy (1989) using 'similar' test equipment. No trial has been performed that used fresh electrodes on three separate occasions. The intraclass correlation coefficient at 2/3 maximum voluntary contraction of 92% for initial median frequency, 86% for initial power and 89% for halfwidth are statistically acceptable. The regression line slopes of median frequency and power are not reliable. No data are available for 1/3 maximum voluntary contraction. The intraclass correlation coefficient is the most appropriate method of assessing reliability and has only been used by Daanen (1990) in the biceps who found that the intraclass correlation coefficient for the median frequency was 99% for two tests five days apart. The precautions taken in controlling posture, electrode placement, electrode resistance and isometric force are important to give long term reliability and repeatability. The relatively stable determinant of initial median frequency and halfwidth can be contrasted with the more unpredictable processes of metabolite production, re-utilisation and vascular flow that are the primary determinants of the median frequency and total power slope (DeLuca 1985). These physiologic correlates may explain the differences in reliability between initial median frequency and halfwidth as compared to and median frequency and power slope parameters.

The back analysis system described by Roy (1989) using six channels and averaging the results of initial median frequency and regression slope may be a more reliable system. Due to six channels being averaged there could be a smaller total signal error. The reliability data presented from this thesis, however, shows the regression line

slope to be unreliable. The method of calculating halfwidth uses thirty averaged signals and this may be why bandwidth measurement at low loads has such a high reliability.

The reliability tests were recorded with at least twenty-four hours between tests, it must be noted that low-frequency fatigue can last up to three days and that twenty-four hours may not be sufficient to confidently exclude fatigue induced electromyogram changes. It is not known what the reliability and repeatability would be in chronic back pain subjects. Halfwidth reliability and repeatability in chronic back pain subjects will depend on spectral shape being as consistent as in normal subjects.

Normal back muscle performance

There appeared to be a wide range of normal muscle function between individuals. The high interindividual differences in results stress the importance of using subjects as their own controls if the results were to be used for assessment of rehabilitation. During the isometric stress test an increase in signal amplitude was seen in both the normal and back pain subjects. Increased electromyogram activity during fatiguing contractions have been also been observed by DeVries (1968a), Jayasinghe (1978), Sherman (1985), Soderberg (1983) and Cooper (1993). The electromyogram changes in normal and back pain subjects reflect the increasing central drive required to maintain the isometric force in the face of increasing peripheral fatigue resulting from activity induced metabolic and electrical disturbances from within the muscle (Edwards 1981).

Normal subjects had lower initial median frequency compared to back pain subjects. At the 2/3 maximum voluntary contraction loading the slopes of the median frequency regression lines had steeper gradients than at 1/3 maximum voluntary contraction. This may suggest that smaller size muscle fibres are recruited at higher forces. This observation is consistent with type II muscle fibres that are later recruited have smaller mean diameters than type I muscle fibres (Bagnall 1984, Sirca 1985, Sulemana 1972). A trend towards increasing fatigue rates with increasing force of contraction was characteristic of the low back muscles tested and was similar to that observed by Roy (1989). This relationship is most likely due to the increased rate of metabolite accumulation associated with an increasing contractile force level. This can occur when a predominance of type II motor units are active and the pressure within the muscle reduces the blood flow to the muscle (DeLuca 1985).

Although there was a minor trend to increased frequency to the side of the back that had back pain in both normal and back pain subjects there was no statistical difference between the sides of the back. It was not surprising that in the subject with leg length inequality that a lower frequency was recorded on the shortened side due to a shortened muscle length. The subject who twisted their back deliberately had a 5Hz difference between the sides of the back and this could be attributed to alteration in muscle length (Bazzy 1986).

The effect of an isometric load at 50Kg and at 100Kg would only alter halfwidth by 3.5Hz so isometric load level does not totally account for the altered spectral halfwidths between the two populations.

The results have shown that the surface recordings provide considerable information that can be used to construct statistically significant discriminations between normal and abnormal behaviour.

Muscle performance associated with low back pain

The normal and back pain populations for both initial median frequency and initial total power in both sexes were statistically validated. These findings imply that normal and back pain subjects can be classified objectively according to spectral parameters that do not directly involve the psychological aspects of performance. The contribution made to alteration of spectral halfwidth by increasing isometric load was found to be 7% for back pain suffers.

Visual sorting of spectral colour maps had comparable sensitivity and sensitivity to computer halfwidth measurement for detecting normals and chronic back pain subjects. Neural network sorting of he subjects into back pain and non back pain subjects appeared better than visual or simple computer halfwidth measurement. It must be noted that the database for the spectral analysis subjects was small and that only a clinical history of back pain was recorded. The reliability of subject's history could account for some subjects being misplaced into wrong categories.

Different normative databases would be required for each sex and a careful back pain history needs to be recorded before testing as spectral colour mapping appears to be a very sensitive instrument at detecting abnormality. The two groups selected were closely matched and the lower maximum voluntary contraction observed in back pain

subjects was as expected. It is however difficult to set a target maximum voluntary contraction and how much central control affected the results cannot be determined from these experiments. One possibility is to set the maximum voluntary contraction from the lean body mass, the correlation between maximum voluntary contraction and lean body mass in normal subjects and chronic back pain subjects was found to be 0.85 and 0.56 respectively.

The three methods of assessing the spectral colour maps: visual sorting, visual manual measuring bandwidths and computer measurement of halfwidth all appeared to separate back pain subjects from subjects with no back pain. The current sorting may not however, be able to separate subjects who had a minor back pain history from chronic back pain subjects.

Gandevia (1978) attributes the perception of effort to be related to the degree of motor unit recruitment. Therefore it can be argued that back pain subjects would have experienced a greater muscle effort perception during their fatigue tests. The subjects may thus have discontinued their tests 'centrally' because of increased perception of effort rather than because of the energy or metabolic status of their muscles.

In low back pain it has been hypothesised by Biedermann (1991) that in personality testing of twenty-two 'confronters' and twenty-four 'avoider's that in their group of 'avoider's had a greater shift towards lower frequencies, reduced variability and higher values of estimated initial frequencies of the power spectrum. 'Confronters' were seen to engage in fewer self protective behaviours that may result in more appropriate use of their trunk and back muscles. The frequency shift was attributed to the 'avoider' group displaying a deficient endurance capacity because of either a lower ratio of slow twitch to fast twitch muscle or, a degeneration of type I slow twitch muscle fibres. An increased presence of slow twitch muscle action potentials with concomitant lower conduction velocity would add lower frequency components to the to the surface myoelectric signal, thus reducing the median frequency values. The same effect would also be to flatten the peak of the spectrum. Unfortunately there are no biopsy studies at present to base this hypothesis on. This also raises the question of constitutional, perhaps genetically based insufficiency of spinal musculature that may predispose to back pain later in life. Alternatively it may be that the 'avoiders' never took regular exercise.

Age

Only a small effect of age was observed on this relatively young population of 7% (0.14Hz/year) in males and 12% (0.24Hz/year) in females over the population age range of fifty years. The change with age is related to progressive muscular weakness of old age and is associated with shrinkage of muscle mass and cross-sectional area. The loss of muscle mass is associated with a decrease in fibre size and fibre number (Merletti 1992). A loss of motor units within the muscle is due to the loss of alpha motor neurons within the central nervous system. These decreases are more relevant in type II fibres than type I fibres (Merletti 1992). As age increases the relative proportion of type I fibre increases and it would be expected that as maximal voluntary contraction force decreases isometric endurance would increase. Merletti (1992) found that when voluntary contractions are increased from 20% to 80% in the elderly (65 to 84 years) there was a significantly smaller increase in conduction velocity and spectral variables than younger subjects (18 to 43 years). These spectral changes in conduction velocity reflect age and fibre composition of the muscle and must be considered when studying different populations of lumbar muscles. Normative databases must take into account age differences of populations.

Relationship to temperature and Ischaemia

No attempt was made to control the temperature of the paraspinal muscles. All the subjects were tested in a warm room. The core tissues of the human body are closely regulated at around 37 degrees centigrade but the shell tissues are not so closely regulated. Between 28 degrees centigrade and 38 degrees centigrade the maximum isometric strength that can be developed by muscles varies very little (Petrofsky 1977). Changes of the median and mean frequencies have been shown to be effected by temperature by Petrofsky (1980a), Bigland-Rithcie (1981), Merletti (1983).

When blood flow is reduced or occluded toxic metabolites such as lactic acids accumulate in the internal environment of muscle and as hydrogen ion concentration increases, pH reduces. Petrofsky (1981) showed as intramuscular pressure increases when a muscle contracts the arterioles become occluded and blood flow diminishes

Barcroft (1932) estimated that when skeletal muscle contracts more than 30% of its maximum voluntary contractile force, ischaemia results from intramuscular compression. It is not known if Barcroft's estimate can be directly extrapolated to paraspinal muscle. It is known, however, that the rate of blood flow in the muscle can affect the behaviour of electromyogram spectral variables (DeLuca 1993). Changes in integrated electromyogram (Dietz 1978) and median and mean frequencies have been shown to be affected by ischaemia within the muscle (Alfonsi 1991, Barnes 1987). There may be cellular events other than lactate such as changes in the sodium to potassium sarcolemmal concentration ratio that can be responsible for spectral shifts in muscle fatigue (Jones 1979, Bigland-Ritchie 1979).

In the hand, blood flow peaked at 25% maximum voluntary contraction and decreased to below resting values for contractions performed above 50% maximum voluntary contraction. In a non fatiguing surface electromyogram 25% maximum voluntary contraction test in the opponens pollicis muscle of the hand no changes in local venous lactate could be observed but at 50% maximum voluntary contraction lactate was significantly increased and was related to the mean power frequency shifts of the surface electromyogram (Alfonsi 1991). Thus lactate appears to play a role in fatigue only at higher levels of contraction. Muscle restitution following fatigue depends in part on lactate removal, in the forearm mean power frequency failed to recover in the absence of circulation but did so within 5 minutes if circulation was normal (Barnes 1987). How much muscle ischaemia and what load level are required to produce fatigue in the lumbar muscle is unknown. The test period had been arbitrarily set at thirty seconds after trials with normal and back pain subjects. No tests were performed on subjects at a greater duration than thirty seconds and such data may have been useful to further understand paraspinal muscular fatigue. It has been observed by Cooper (1992) that integrated electromyogram does not rise more rapidly after forty seconds and falls precipitously. The fall-off phenomenon is difficult to explain and suggests that it is unlikely that electromyogram changes are just only related to loading.

Cooper (1993) has suggested that some patients because of their greater masses would have to start and continue their contractions using a higher percentage of their maximal contractile force. Intramuscular ischaemia would thus have been greater in back pain subjects and precipitated more rapid ischemic peripheral fatigue, thereby requiring

greater central drive to maintain force. However, as in this and Cooper's (1993) study the chronic back pain subjects as a whole were not significantly more obese.

Relationship to type of muscle composition

No studies of fibre types were performed in this thesis but it is known that fibre type composition of muscle can affect the electromyogram signal. Relative proportions of fibre types within a muscle are important characteristics of the fatiguability of muscle.

The congenital myopathies and nemaline rod myopathy are characterised by a generalised type I (Red muscle, slow twitch, oxidative) fibre preponderance and are a useful clinical model to study fibre types. The power spectrum fatigue characteristics of these muscles have been studied in the quadriceps muscle by Linssen (1991) who found that type I fibres had a lower force generating capacity than type II (White muscles, fast twitch, glycolytic IIB) fibres. Muscle conduction velocities were slower in subjects with 95-100% type I fibres, however during the isometric exercise test 95-100% type I fibres showed less fatiguability than type II fibres, which was reflected by a nearly absent decrease of the muscle membrane excitability as measured by the muscle fibre conducting velocity and only a slight increase in the surface electromyogram amplitude compared with subjects having 80% type I fibres and controls.

Three subjects with McArdles disease, a congenital muscle disorder with a deficiency of the enzyme myophosphorylase who are characteristically unable to endure muscular fatigue, was tested under maximal sustained isometric conditions by Mills (1984). It was found that the spectral shift in these subjects was greater than in normal subjects thus rendering lactate as the sole cause of spectral compression unlikely. The mechanism of excessive fatiguability in McArdles disease is thought to be due to failure of excitation of the muscle membrane and it is postulated by Mills that accumulation of potassium ions may explain the phenomena of spectral shift in normals and myophosphorylase deficient subjects and the excessive fatiguability in the latter.

Paraspinal muscle denervation is known to occur and may persist for very long periods after spinal surgery (MacNab 1977). As well as causing wasting, denervation also leads to fibre grouping owing to reinnervation changes (Cancilla 1984). Cooper (1993) suggests that back pain patients may have developed 'non-physiologic' central activation patterns. Back pain subjects may have preferentially activated different parts of

the same muscles, such as type I fibres or larger than normal groups of either fibre type, or activated more of the available muscles. This phenomenon could account for the electromyogram changes seen in the spectral colour maps.

Relationship to muscle biochemistry

Electromyogram testing requires the subject to perform a submaximal constant-force isometric contraction. The electromyogram spectral colour mapping results appear to show only minimally affects by isometric loading and age. The electromyogram under specific rules appears to be substantially free of influence by motivation. However the relationship between the spectral variables and the physiology and biochemistry occurring during muscle contractions is unresolved. The electromyogram spectral variables have been causally related to the pH of the extra cellular fluid and possibly to the intracellular fluid (Merletti 1992). The exploitable aspect of these relationships is that through an analysis of the electromyogram signal detected painlessly on the surface of the skin above the muscle it is possible to obtain useful information on the time course of the processes that are fatigue dependant during muscle contraction.

Given that the electromyogram spectral variables and the force variable of the contractile mechanisms undergo changes during the progression of fatigue, it is inevitable to ask if a relationship exists between the two. There may be a inter-relationship but its nature is not currently understood and research is required to ascertain a causal link.

Relationship to muscle neurophysiology

Although the shift towards lower median frequencies of the power spectrum provides an estimate of fatigue development in the muscle (Basmajian 1985) the conventional representation by using regression lines is simplistic. Three-dimensional and spectral colour mapping gives a fuller representation of events occurring within paraspinal muscle and shows apparent differences between normal, athletically trained and chronic back pain subjects.

Autoscaled split-range spectra plotted from data obtained during increasing isometric loading, demonstrates (in one normal subject) the relationship of muscle recruitment and firing rates. The whole range spectral map, shown in figure 22 demonstrates increasing muscle recruitment and motor unit firing with force. The split-range autoscaled banded spectral map, shown in figure 23 demonstrates that muscle recruitment and firing over a specific bandwidth for 40Kg to 140Kg is independent of force. Testing at lower force levels than 2/3 maximum voluntary contraction may be possible but reliability at low loads may become difficult. Two subjects with no past history of back pain were tested both at high load 100Kg and low load 10Kg, there appeared to be little difference in spectral half width but the numbers are too small to extrapolate any useful information at very low loads, it is not known from this present study that the reliability of halfwidth and initial median frequency at maximum voluntary contraction are acceptable.

Analysis of the spectral colour maps is complex. The relationship of the control properties (either central or peripheral) of motor unit recruitment and firing rate interactions may control the patterning of the data. It is known that both the central (Bigland-Ritchie 1981, Cooper 1993) and peripheral nervous system affects the performance of muscle or a group of muscles. Basmajian and Deluca (1985) propose the ideal concept of a '*common drive*' that modulates the firing rates of all motor neurons of a homonymous pool. Basmajian's and Deluca's (1985) common drive theory indicates that central nervous system does not control the motor units individually. The peripheral nervous system is centred on the motor neuron pool and is the centre of excitatory and inhibitory inputs. The principal (efferent) outputs of the motor neuron pool are the α and ψ motor neurons. The (afferent) input to the motor neuron pool consists of the peripheral receptors, aspects of the Renshaw cell system in the anterior horn (Renshaw)

and drive from higher centres. The peripheral receptor muscle spindles are generally regarded as servo controllers and provide information on muscle length with load. Golgi tendon organs provide no information on length but are sensitive to muscle tension. In normal muscle the contribution of Golgi tendon organ and muscle spindle is complementary. The contribution in back pain subjects is not known. The Renshaw cell system (Renshaw 1946) forms a feedback system with *'recurrent inhibition'* onto the motor neuron pool. It has been shown that Renshaw cells mutually inhibit other Renshaw cells (Ryall 1970) and ψ motor neurons (Ellaway 1971). It is difficult to identify a clear functional role of Renshaw cells but Hultborn (1979) has suggested the supra-spinal inputs that converge on Renshaw cells enable recurrent inhibition to serve as a variable gain regulator at the motor neuronal level. The role of Pacinian (pressure) and joint receptors in muscle have not been clearly identified in the common drive mechanism. It has been show however by Sabbahi (1981) that cutaneous afferents may also have important inhibitory effects on α motor neurons. The average firing rate of motor units has been reported by Holonen (1981) to be greater than normal in deconditioned muscles with myopathic disorders and this may explain the wider halfwidths in subjects with back pain. The widened spectral halfwidths may be explained in dysfunction of some aspect of the common drive. Current research does not identify the exact site or sites.

The issue of causality is still unresolved after the present arguments. It has been demonstrated that there is an association between performance of back muscle and the presence of pain. In the presence of a soft tissue injury, does the presence of pain cause the muscles to work differently? Does prolonged muscle deconditioning eventually cause a physical disturbance that causes chronic pain? The spectral colour mapping technique is unable to discriminate these different aetiologies without prospective studies.

Application of neural networks to power spectra data

The results of both 20% and 40% trials indicate that neural networks can be used to developed a system to distinguish between subjects with chronic back pain and healthy subjects. The network converges well with only five nodes in the hidden layer, with an average specificity of 85.7% and an average sensitivity of 90.0%, with a train set of forty-eight patterns (80%) and a test set of twelve patterns (20%). When a train set of

thirty-six patterns (60%) and a test set of twenty-four patterns (40%) is used, this network had an average specificity of 78.8% and an average sensitivity of 79.5%.

The weights in the trained network can be investigated further to isolate the inputs and input combinations that contribute most to distinguishing between the two classes. With this information the number of inputs could be reduced and the pre-processing of the data optimised, to produce more distinct input patterns.

Neural network classification of electromyogram power spectra appears to be better than either visual sorting of power spectra or simple halfwidth measurement. Artificial intelligence interpretation therefore appears to be the best method of interpreting automatically back muscle electromyogram signals. However it must be noted that even with the sophisticated neural networks used no diagnosis of the cause or neurological level of the back pain can be made. It is worth noting that the sensitivities and specificity's of all these techniques are dependant on the clinician correctly labelling each subject used in training. This may explain some of the observed error since the subjects' recall is not always accurate. Classification generalisation would improve as more training patterns are added and sensitivity and specificity may also be improved.

Contemporary developments and future research in muscular fatigue

Spectral analysis may have future roles in pre-employment screening of a work force (DeLuca 1985), athletic training (Sward 1990), ergonomics (Lacuna 1983), (Hosea 1986), diagnosis of neuromuscular disorders (Boruta 1981), (Linssen 1991) and rehabilitation (Smidt 1988). However, before spectral analysis is used in the workplace a large population of subjects need to be tested to establish a normative database and statistical reliability must be established.

The present spectral analysis experimental set up is laboratory based but simple ambulatory recording of surface electromyograms has been developed by Remes (1984) 375g weight and Sherman (1991) 616g weight recorders. Sherman developed a recorder that would fit into the canteen belt of a soldier and record every second for 18 hours, the signal would subsequently be analysed back at base. Ambulatory recorders would allow study of muscle function almost anywhere.

Instead of using electromyogram Stokes (1991), Lee (1992) has used acoustic myography to study isometric force and fatigue by listening to muscles.

Surface stimulation of motor units and recording cerebral somatosensory evoked potential is a complex method of investigating lumbar muscle fatigue (Merletti 1992). Zhu (1993) employed the technique of magnetic stimulation of paraspinal muscles unilaterally and recorded potentials over the scalp. Both normal subjects and those with muscular spasm were tested. Components of the evoked potential in subjects with unilateral muscle spasm were significantly altered by vibration of the back muscles. This technique may have potential for investigating paraspinal muscle fatigue.

Whole body vibration at low frequency (3-10Hz) vertically and sinusoidally in conjunction with electromyogram-torque measurements of the paraspinal muscles as described by Serrousi (1989) showed that there was more average peak to peak estimated torque at almost all frequencies for vibration. The degenerative changes that may occur in the vibration exposed spine could be a fatigue phenomenon analogous to the fatigue of engineering structure subjected to oscillatory loads. Vibration studies in conjunction with surface electromyogram spectral analysis could give information about fatiguability and endurance of back muscle.

Ivanova-Smolenskaya (1987) used spectral analysis clinically to differentiate between essential tremor, physiological tremor and Parkinsonian tremor and used the analysis to treat subjects with the appropriate drug therapy and then to monitor therapy. Ivanova-Smolenskaya postulated that the mechanisms responsible for generating pathological tremors have different localisations within the nervous system. Spectral analysis could have a role in diagnosing and treating muscle disorders from a central or peripheral origin.

It has been possible to reverse recruitment order of single motor units by electrical stimulation during voluntary muscle contraction in the human being (Stephens 1978). It may be possible in back pain to electrically modify recruitment order by afferent input into an orderly fashion and regaining the lost muscle control and restoring muscle function to normality.

There has been a considerable amount of work in the basic science of the electro-biomechanics of fatigue. Most of this work has been performed on data from isometric constant force contractions and little work has been performed under dynamic conditions. Dynamic electromyogram has great technical problems in the lumbar spine

due to difficulties of securing satisfactory electrode placement and eliminating movement artefacts. However dynamic electromyogram has been used to some success with human gait analysis (Wooten 1990) using video motion analysis in conjunction with principal component analysis to study patterns of muscle activation with walking. The data produced from this kind of analysis is very complex and requires statistical pattern recognition techniques. This kind of gait and postural analysis has not been used in the lumbar spine and could be useful in determining abnormal muscle activation in the lumbar spine as a result of fatigued muscles. This kind of data would be well suited to interpretation by artificial intelligence

Clinical applications

Rehabilitation and screening

Deluca (1985) suggested that spectral analysis could be applied to rehabilitation programmes to assess the effectiveness of a prescribed treatment program. Manual muscle tests and tests of subjects function are currently the primary tests of progression or regression of muscle strength. These tests are often subjective and depend on training, skill, and experience of the health care worker performing the evaluation. Costs have now become a major importance. It is not only the effectiveness of the rehabilitation but it also the efficiency of these programmes themselves that are being evaluated by many workers; Bly (1986), Haig (1990), Frymoyer (1991), Harris (1991a), Harris (1991b). Spectral analysis and colour mapping techniques may only help in providing baseline objective evidence of lumbar paraspinal electromyograms and an objective measure of progress. More so spectral analysis could only be used to detect or exclude back pain and could not help in giving any form of diagnosis. Some individuals work all their lives with back pain with either none or infrequent work absences. In its current form spectral analysis has no medic-legal application unless greater reliability is shown..

If it could be shown in future studies that when impaired back muscles are exercised the initial median frequency or halfwidth decrease it may indicate that a muscle power spectrum is changing from a back pain power spectral pattern to a 'normal' power spectral pattern. This measure may objectively quantitate functional improvement. Spectral analysis could therefore be a useful tool in assessment of rehabilitation. If the

frequency does not change the muscle may not be being exercised and a more successful method of rehabilitation used. When muscles are injured, synergistic muscles in that group may substitute for the injured muscle and change the pattern of muscle activity and may deprive a muscle of its unintended exercise. '*Muscle substitution*' is difficult to detect by current manual testing. If a characteristic frequency from a muscle may change without any alteration in loading it may indicate other muscles are generating more force. The effectiveness of a prescribed treatment programme could be determined by changes of behaviour of characteristics of the lumbar spine muscles. During therapy there may be a percentage decrease in the characteristic frequency obtained during a sustained contraction that may increase as therapy progresses. If a muscle is atrophied or damaged at the start of a rehabilitation programme monitoring the power spectrum may show a pattern similar to back pain.

With refinements spectral analysis could be useful, but would need to validated in several centres to show reproducibility before being applied to the general population.

Chapter Six - Summary

Lumbar muscle function is considered to be an important component of chronic lower back pain. It has been demonstrated in this study that wider spectral colour maps and halfwidths appear to be related to back pain. Wider spectral halfwidths are also seen in subjects who have had a prior back pain episode. Recurrence of back pain is explained by the apparent widening of spectral halfwidths that may be related to altered motor unit firing rates or recruitment patterns.

Although the mechanism associated with muscle insufficiency is poorly understood, spectral analysis can demonstrate apparent differences between normal and deconditioned cohorts. Surface electromyogram spectral analysis provides an objective method of measuring paraspinal muscles. Spectral analysis may be of practical importance for the assessment of muscle deficits associated with low back pain. Median frequency and halfwidth parameters of the electromyogram can discriminate healthy subjects from those suffering chronic low back pain. Three-dimensional and spectral colour mapping provides a new method of demonstrating lumbar muscle fatigue and endurance and may reflect motor unit firing rates and recruitment patterns within the underlying muscle. The implementation of artificial neural networks appears to be a promising method of differentiation of spectral colour maps from normal and chronic back pain subjects. Artificial intelligence analysis of electromyogram signals shows good sensitivity and specificity and may have future uses in analysis of paraspinal muscle activity.

The evidence presented validates the use of surface electromyograms as an objective measure of back muscle function in normal and chronic low back pain subjects. However, large normative databases would need to be constructed before electromyogram spectral analysis is applied clinically in rehabilitation, screening and medico legal cases.

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Appendices

Disability assessment questionnaires

This questionnaire has been designed to help us understand the problem you are having with your back and how much trouble it is causing you. Please complete the form as completely as possible.

Answers to these questions are confidential to the BACK CARE PROJECT and will be only used for the clinical management of your case and research purposes.

Low back outcome score

Surname _____ Forenames _____

Date of Birth _____ Age ____ Sex M/F Toady's Date _____

Daytime Tel no: _____ Home Tel no: _____

Are you-Married/Single/Widowed/Divorced or separated

Are you-Non-smoker/smoker

Please mark on the line below how much pain you get from your back on an average day.

no pain at all	0 1 2 3 4 5 6 7 8 9 10	maximum pain possible

What is your usual occupation? _____

Workplace _____

At present, are you working ? -

Full time at your usual job	( )
Full time at a lighter job	( )
Part time	( )
Not working	( )

At present, can you undertake household chores or odd jobs ?

Normally	( )
As much as usual but more slowly	( )
A few but not as many as usual	( )
Not at all	( )

At present, can you undertake sports or active pursuits ?
(for example dancing)

As much as usual	( )
Almost as much as usual	( )
Some but much less than usual	( )
Not at all	( )

Do you have to rest during the day due to pain ?

Not at all	( )
A little	( )
Half the day	( )
Over half the day	( )

How often do you have a consultation with a doctor or have any treatment (eg physiotherapy) for your pain ?

Never	( )
Rarely	( )
About once a month	( )
More than once a month	( )

How often do you take pain killers for your pain ?

Never	( )
Occasionally	( )
Almost every day	( )
Several times a day	( )

How much does your back pain effect the following activities ?

	no effect	*mildly/not much*	*moderately difficult*	*severely impossible*
Sleeping				
Walking				
Sitting				
Dressing				
Sex life				
Travelling				

Modified somatic perception questionnaire

Please describe how you have felt during the PAST WEEK by ticking the appropriate box.

Please answer all questions do not think too much before answering.

	Not at all	A little	A great deal	Could not have been worse
Feeling hot all over				
Dizziness				
Blurring of vision				
Feeling faint				
Nausea				
Sweating all over				
Pain in stomach				
Churning in stomach				
Mouth becomes dry				
Neck muscles aching				
Legs feel weak				
Muscles twitching/jumping				
Tense feeling across forehead				

Compensation

Have you had any operation to your back in the past ? Yes/No

What was it ? _____ Date _____

Are you claiming compensation for your back pain ? Yes/No

If so has the case been settled ? Yes/No

Are you receiving any sickness benefit ? Yes/No

Have you had to retire on medical grounds Yes/No

Did you injure your back on this occasion at work or outside work ?

At work ( ) Outside work H/W

Modified Zung

Your general Health will have an effect on your sense of well being and your enjoyment of life. The next section is concerned with this. Back Pain may cause feelings of sadness and depression. For each statement tick the box that most closely describes how you feel.

	Rarely or none of the time (less than 1 day per week)	Some or little of the time (1-2 days per week)	A moderate amount of time (3-4 days per week)	Most of the time (5-7 days per week)
I feel downhearted blue and sad				
I find it easy to do the things I used to				
Morning is when I feel best				
I have crying spells or feel like it				
I eat as much as I used to				
I still enjoy sex				
I notice I am loosing weight				
I have trouble with constipation				
My heart beats faster than usual				
I get tired for no reason				
My mind is as clear as it used to be				
I am restless and can't keep still				
I am hopeful about the future				
I am more irritable than usual				
I find it easy to make decisions				
I feel that I am useful and needed				
My life is pretty full				
I feel others will be better off if I were dead				
I have trouble getting to sleep at night				
I feel quite guilty				
I tend to wake up too early				
I feel nobody cares				

Job satisfaction

Please mark on the line-if you manage to complete your daily tasks at work ?

Never _____ All of the time
0 1 2 3 4 5 6 7 8 9 10

- how contented you feel at work ?

Very unhappy _____ Very happy
0 1 2 3 4 5 6 7 8 9 10

- how you feel about your work mates ?

I dislike them _____ I like them
0 1 2 3 4 5 6 7 8 9 10

- how do you feel about your supervisor ?

Very unsatisfactory _____ Very
satisfactory
0 1 2 3 4 5 6 7 8 9 10

Exercise

How much exercise do you take

I never exercise : ( )

I exercise enough to make myself sweat:
- Once per week ( )
- Twice per week ( )
- Three times per week ( )
- More than three times per week ( )

Electromyogram recording equipment

Electromyogram equipment

Medelec® Sapphire 2ME

Supplier: Vickers Medical Division, Medelec Ltd, Manor Way, Old Woking, Surrey. GU22 9JU

Environment

Sapphire 2M designed to operate within the following ranges

temperature	:	+ 10°C to + 40°C
relative humidity	:	30 % to 75 %
atmospheric pressure	:	700mB to 1060mB

Voltage 240V/50Hz supply
Two Input Channel Recording Option
RS232 Port to link to microcomputer not used-transfer via diskette DS,DD

Pre-amplifier

Input Impedance 100MΩ < 30pF
Common Mode Rejection Ratio > 100dB with no impedance imbalance
Noise : < 5μV peak-to-peak when inputs are connected to neutral through 4.7kΩ
Input Offset Tolerance ± 500mV differential

Impedance test

LED display on preamplifier to indicate < 2, 4, 8, 16, 32 and > 32kΩ
Accuracy to ± 0.5k between 2kΩ and 8kΩ
Test current < 10μA
Electrode selection at the pre-amplifier by push buttons positioned adjacent to input sockets

Amplifier sensitivity

Set at 200μV/division

Filters

Low frequency filter-Roll off: 6dB/octave Set at-3Hz
High frequency filter-Roll off: 12dB/octave Set at-200Hz
Notch filter (50Hz)-not activated throughout all tests

Analogue/digital Conversion

Resolution-12 Bits at all sampling rates
Sampling rate-Maximum 10μs (200kHz) for two channels
Display gain maximum sensitivity 100nV/division
Analysis times-1 second epochs on cascade display mode
Resolution-1000 points/channel

Data storage

Data Memory -1 Mbyte 32 Stores 100 Cascades
Disc Storage and Recall MS-DOS compatible
3.5" Floppy Disc Drive
Program memory user defined program parameters are stored in battery backed Non Volatile RAM

Safety

Sapphire 2ME complies with:
British Standard BS5724 part 1.
IEC601-1 international standard for medical electrical equipment, defined by the International Electrotechnical Commission.
Due to significant mains leakage, the personal computer and loadcell were connected to an isolating transformer.
The reference frame had a common earth via the Sapphire 2ME

Micro-computer

In Middlesbrough
386SX: 25 MHz 100 MB Hard Disc
4 MB RAM 387 Maths CoProcessor
Supplier: Elonex

In Oswestry
Pentium 60 MHz 0.5 GB Hard Disc
16 MB RAM
Supplier: Dell

Software

1. Program software for processing fast Fourier transform written in Turbo-Pascal®
   Borland

2. System software MS-DOS 6.2® and Word 6.0® for Windows 3.11®
   Microsoft

3. Program for Database management written in Turbo Pascal®
   Borland

4. Sampling and smoothing programs written in Visual Basic®
   Microsoft

5. Three-dimensional colour and spectral mapping written in Stanford Graphics®
   3-D Visions

6. Spreadsheet management Microsoft Excel®
   Microsoft

7. Statistical processing SPSS®
   SPSS

8. Data reduction for Neural Network Visual Basic®
   Microsoft

9. Joint Time Frequency Analysis for Neural Network LabVIEW®
   National Instruments

10. Neural Network implementation Neurowindows®
    Ward Systems

Surface electrodes

Biotrace® Bio-Adhesive Neonatal ECG Electrodes (Ag/AgCl)
Biotrace-NS 0713
Supplier: MSD Ltd, River Road, Shalbourne, Wiltshire

Loadcell

200Kg Modified AFG6 Electronic force gauge with continuos RS232 output

AFG6 0 to 200Kg LCD and Digital readout loadcell (special request)

Safety limit 1000Kg

Supplier: TWL Force Systems Ltd, 15 Old Farm Lane Stubbington, Fareham, Hants 0329-665186

Body contour formulator

Body Contour Formulator: TEM Formatron 93 parallel freely moving aluminium needles mounted between rollers. Active Width 305mm. Weight 2Kg

Supplier: TEM instruments Ltd, Gatwick Road, Crawley Sussex

Software programs

Please contact the author if access to these programs is required

Loadcell program

Electromyogram transfer Program

Spectral analysis program

File management program

Halfwidth measurement and sampling program

Neural network settings

The following settings were used to produce the adaptive spectrograms of the data:

Time increment: 64

Window length: 256

Error tolerance: 0.01

The effects of these parameters on the transform are discussed below[1].

Time increment is the time spacing, in samples, between each row of the spectrogram. If the sampling frequency is f_s then the spacing ΔT between the rows of the spectrogram is given by:

$$\Delta t = \frac{time\ increment}{f_s}$$

Increasing the time increment decreases the computation time and memory requirements, but also reduces time-domain resolution.

Window length controls the frequency spacing of the columns of the spectrogram. If the time signal was sampled with sampling frequency f_s, the spacing Δf between the columns of the spectrogram is given by:

$$\Delta f = \frac{f_s}{window\ length}$$

increasing the window length improves frequency resolution, but increases computation time and memory requirements. The window length must be a power of two.

---

[1] From: LabVIEW® Joint Time-Frequency Analysis Toolkit Reference Manual; 1993; part number: 320544-01

The **error tolerance** is the maximum normalised error in the energy in the time waveform and the spectrogram. Decreasing the error tolerance improves accuracy, but also increases computation time. The error tolerance is defined as follows:

$$error\ tolerance \geq \frac{\sum_{i=0}^{\infty}|s(i)|^2 - \sum_{i=0}^{\infty}\sum_{k=0}^{\frac{L}{2}} AS(i,k)}{\sum_{i=0}^{\infty}|s(i)|^2}$$

Where: *i* is the time index; *k* is the frequency index; *s(i)* is the i^{th} sample of the time signal; *L* is the window length and *AS(i,k)* is a point in the adaptive spectrogram. The number of rows (time axis) in the spectrogram is equal to the number of elements in the time waveform divided by the time increment, and then rounded up. The number of columns (frequency axis) is given by:

$$\frac{window\ length}{2} + 1$$

The sampled electromyogram signals consisted of 30000 points, so the adaptive transform with the settings of above yields a matrix of 129 columns by 469 rows.

Scientific Abstracts

HOW SHOULD COST EFFECTIVENESS OF A BACK CARE PROGRAM BE ASSESSED ? - A DISCUSSION PAPER

Oliver C, Greenough C

OBJECT OF INVESTIGATION

Back pain costs South Tees Acute Unit Trust approximately £1 million per year from litigation and sick pay costs for its health care workers alone. As part of a newly implemented early rehabilitation, training and prevention program for the health care workers, performance indicators of the program are being assessed. It is important that any business activity be monitored so that the funds expended on the activity produce a net benefit for the trust. Failure to account for costs and benefits on the premise that the program is '*clearly a good idea*' is unacceptable to management. The issue of costing is complex (1) although it is easy to decide what major performance indicators can be tracked some of the more attractive back care program benefits seen as '*total quality care*' are much harder to quantify.

METHOD

Data from potentially quantifiable performance indicators has been identified against 'non quantifiable' indicators in terms of cost-benefit (2) analysis for a back care program. These indicators can be also split into cost-benefit for the employer (The Trust) versus the employee (worker).

RESULTS

* = a quantifiable performance indicator ie £ lost/gained, days lost/gained.

Employer

BENEFITS	COSTS
Reduction in costs of loss due to back pain illness:	Employee time lost to:
Medical costs*	Screening*
Wage costs*	Treatment*
Replacement costs*	Participation*
Decreased productivity due to disability*	Facilities cost*
	Contractor costs*
	Hospital integration*
	Communication*
Reduction in costs of loss due to back injury:	Supplies*
Sick pay*	Staff salary*
Litigation*	Maintenance*
Insurance*	Utilities*
Improvement in:	
Patient treatment*	Risk
Morale	
Productivity	
Corporate 'Trust' Esteem	
Safety	
Recruitment ?/*	
Job satisfaction ?/*	
Continuity of care	
Total Quality (Patients Charter)	

Employee

BENEFITS	COSTS
Reduction in:	Longevity !
Injury rates*	Lifestyle !
Sick Leave*	Life cover
premiums*	
Wage loss*	
Disability*	
Increase in:	
'*Value of Life*'	
Morale/Esteem	
Work Quality	
Job Satisfaction*	
Fitness*	

CONCLUSIONS

Aggressive early management of musculoskeletal spine injuries has been shown to reduce number of lost days and enhance workers satisfaction of their hospital (3). The cost benefit-analysis has been evaluated longitudinally in the Johnson and Johnson's, health promotion 'Fitness for Life' (4) programs but did not focus on back related problems. Cost-benefit analysis of back care programs is very complex to evaluate and the more attractive benefits such as boosted corporate 'Trust' esteem and elevated morale may not be easily quantifiable. Financial and non-financial cost-benefit effectiveness results are awaited from the South Tees Trust Back Care Program.

References

(1) Harris JS (1991) Watching the numbers: Basic Data for Health Care Management.
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J. Occupational Medicine 33 (3) 327-329
(3) Haig AJ et Al (1990) Aggressive Early Medical Management by a Specialist in Physical Medicine and Rehabilitation; Effect on Lost Time due to Injuries in Hospital Employees.
J Occupational Medicine 32 (3) 241-244
(4) Bly JL et Al (1986) Impact of Worksite Health Promotion on Health Care Costs and Utilisation
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SURFACE ELECTROMYOGRAM MEDIAN FREQUENCY FATIGUE OF LUMBAR PARASPINAL MUSCLES: REPRODUCIBILITY

C. W. Oliver, R.A. Royall, C G Greenough

Although spectral analysis of electromyogram signals from lumbar muscles have been in increasing use, little data has been published on reproducibility. Spectral compression and reduction of the median frequency of lumbar erector spinae (LES) Electromyogram was investigated with regard to reproducibility at a standard isometric load.

Ten healthy male volunteers (age 26 to 50) were fixed on a reference frame in 30 degrees of lumbar flexion. An isometric load of 2/3 maximum voluntary contraction was held constant for 30 seconds whilst surface electromyograms were recorded at the left and right 3rd/4th Lumbar interspace. Subjects were retested on three separate occasions (within 35 days) with at least one days rest between tests with fresh electrodes. The median frequency and total power were determined by fast Fourier transform of a filtered and digitised signal.

Initial median frequency at the beginning of each test showed reproducibility within individuals of 2.5Hz (3.2%) average variation from the mean. The initial median frequency of LES was found to have a subject to subject variation of 38% (range 53.4Hz to 85.7Hz, mean 67.1Hz). Median frequency gradients all declined and were reproducible within individuals with 6.8% average variation from the mean. The average median frequency decreased by 0.21Hz/s (range 0.09 to 0.48 Hz/s). Total power spectra all increased by an average of 21.8% (range 2% to 48%) and had a 20.3% average variation from the mean.

The data suggest that the median frequency of surface electromyogram are reproducible in individuals, but total power spectra shows a greater variation. There is considerable variation between individuals. median frequency fatigue phenomena may be useful as a measure of spinal muscular fitness and could have a role in pre-employment screening and assessment of spinal rehabilitation programs.

3-D AND SURFACE SPECTRAL COLOUR MAPPING OF LUMBAR PARASPINAL MUSCLE FIBRE TYPES AND RECRUITMENT PATTERNS

Oliver C, Jones P, Greenough C

OBJECT OF INVESTIGATION

Although spectral analysis of the surface electromyogram has been in increasing use to give an objective measure to paraspinal muscle fitness (1), little information has been published on the shape of power spectra and their possible relationships to muscle fibre types and motor unit recruitment patterns. The technique of monitoring the shift of the median frequency and increase in the power spectra gives only a simplistic representation of fatigue changes. By colour mapping the electromyogram power spectra in 3-D this new technique may allow a dynamic representation of fibre type firing and recruitment.

METHOD

Four populations of volunteers were studied: 'Normal' backs, acute back pain, chronic back pain and elite athletes. Subjects were placed on a reference frame in 30 degrees of lumbar flexion. An isometric load of 2/3 maximum voluntary contraction was held constant for 30 seconds whilst surface electromyograms were recorded from the level of the left and right 3rd/4th Lumbar interspace. During this period raw electromyogram was recorded at 1024Hz, the signal was digitised, filtered and power spectra plotted by fast Fourier transform. 3-D colour plots of the power spectra over 30 seconds were plotted using a sampling and smoothing computer program. Smoothed and un-smoothed colour surface spectral plots of frequency against time were drawn to normalise for power spectra amplitude.

RESULTS

The four populations of volunteers had distinctly different visual patterns of colour 3-D spectra and surface spectral plots (table).

	Normal Back	Acute Back	Chronic Back	Athlete
Spectrum amplitude	middle	low	low	high
Spectrum width	middle	very wide	wide	narrow

Normalisation of spectral amplitude by colour surface plotting showed the range of frequency of firing of muscle fibres was greatest in acute back > chronic back > normal back > athletes back.

CONCLUSIONS

High spectrum amplitude and the narrow firing frequency in the athlete infer a well-trained '*fit*' back comprising of slow fibres and an orderly muscle fibre recruitment profile. In contrast the acute back has a low spectrum amplitude and wide firing frequency of fast and slow fibres firing inferring a disordered '*chaotic*' recruitment pattern. 3-D and surface spectral colour mapping also give

a fuller representation of fatiguability and endurance and further studies are ongoing to match these results to histological biopsies.

SURFACE ELECTROMYOGRAM MEDIAN FREQUENCY FATIGUE OF LUMBAR PARASPINAL MUSCLES: RELATIONSHIP TO ISOMETRIC LOAD.

C. W. Oliver, R.A. Royall, C G Greenough

Object of Investigation

Although spectral analysis of electromyogram signals from lumbar muscles have been in increasing use, little data has been published on reproducibility or relationship to loading. The technique of monitoring the shift of the median frequency of lumbar erector spinae (LES) Electromyogram was investigated with regard to reproducibility and isometric load. Other influencing factors on the median frequency were controlled. Lumbar isometric loading was standardised at two loads and a normalised ratio of the gradient of decline of the median frequency (MF_{ind}) was measured.

Method

Healthy volunteers were fixed on a reference frame in 30 degrees of lumbar flexion. An isometric load of 2/3 and 1/3 maximum voluntary contraction was held constant for 30 seconds whilst surface electromyograms were recorded from the level of the left and right 3rd/4th Lumbar interspace. During this period the power spectrum median frequency was determined by fast Fourier transform of a filtered and digitised signal. The rate of decline of the median frequency index (MF_{ind}) was calculated by the equation:

MF_{ind} = (Gradient of decline of median frequency/Initial median frequency) x100

Results

No difference in average initial median frequency was observed between 2/3 and 1/3 maximum voluntary contraction. Similarly no difference between right and left sides was seen. Consistency within individuals was satisfactory on three separate occasions with fresh electrodes. The MF_{ind} at 1/3 maximum voluntary contraction was reduced by 61.2% as compared to 2/3 maximum voluntary contraction (MF_{ind} for 2/3 maximum voluntary contraction was 0.329 and 1/3 maximum voluntary contraction was 0.128, $P< 0.001$). No difference in MF_{ind} was observed between right and left sides. Measurements of MF_{ind} within individuals showed little variation.

Conclusions

The data suggest that median frequency fatigue is dependant on isometric load. In this study the load levels were set as a proportion of the maximum voluntary contraction. The initial maximum voluntary contraction, however, depends on subject motivation and the maximum voluntary contraction may not be a useful parameter when deciding on isometric load levels especially in the deconditioned spine. Isometric spine loading may be better set by deriving a force level from Lean Body Mass and further research is ongoing.

THE ROLE OF LUMBAR PARASPINAL SURFACE ELECTROMYOGRAPHY IN LOW BACK PAIN

C. W. Oliver, C. G. Greenough

Although spectral analysis of the surface electromyogram has been in increasing use to give an objective measure of spinal muscular fitness the technique has not been applied to the clinical diagnosis of patients.

One hundred and three patients (age 15 to 62) 41 with chronic back pain and 62 normal volunteers were tested. Subjects were placed on a test frame in 30 degrees of forward flexion. An isometric load of 2/3 maximum voluntary contraction was held constant for 30 seconds whilst surface electromyograms were recorded at the level of the left 3rd/4th interspace. The raw electromyogram was filtered, digitised and median frequency and power spectra were plotted by fast Fourier transform. Median frequency regression lines were plotted to give gradient of median frequency fatigue. 3-D and surface spectral colour plots of the power spectrum were plotted.

Average maximum voluntary lumbar extensor contraction was 115.1 Kg in the normal male and 60.7Kg in the normal female whilst in the back pain male was 56.4Kg and 39.2Kg for the back pain female. Initial median frequency was found to be significantly higher in both sexes of the back pain sufferers ($P < 0.05$). Initial Power Spectra area in both sexes was significantly lower in the back pain sufferers ($P < 0.05$).

Spectral colour maps were produced at varying loads. Spectral patterns were found not to vary with load over the range tested. On surface spectral colour plots the width of the power spectrum was significantly greater in chronic back pain (10-100 Hz) than controls (10-70 Hz).

It was concluded from the present study that it has proved possible to distinguish chronic low back pain sufferers from normal volunteers by electromyographic techniques of median frequency fatigue and 3-D surface spectral colour mapping. The technique has been previously been shown to be reliable and repeatable. Surface electromyography may have an important role in the future diagnosis and management of chronic back pain, especially in pre-employment screening and monitoring of rehabilitation programs.

ELECTROMYOGRAM COLOUR SPECTRAL MAPPING CORRELATES WITH CHRONIC LOW BACK PAIN

C.G. Greenough, C.W.Oliver

A technique of recording electromyogram signals from the spinal muscles during a fatiguing contraction has been previously reported to the society. It has been shown to be reproducible from occasion to occasion. A new technique for displaying the power spectrum has been developed. A three-dimensional image is created representing time on the X axis, frequency of fibre firing on the Y axis and signal amplitude on the Z axis. The signal amplitude is divided into twelve equal colour bands and each band is represented by a different colour on a two-dimensional plot of time versus frequency, producing a 'contour map' of the data.

The pattern of the colour spectral map was found to be reproducible from individuals with no intervening incident. Although the amplitude varied markedly with load, when the maps were scaled to their own maximum the pattern was found to be independent of load within the range tested.

Twenty one patients with chronic low back pain and twenty six normal volunteers were tested and spectral colour maps were produced. Nineteen other maps were produced from normal volunteers with a past history of low back pain. The observer was unaware of the numbers of normals, chronics and others. Using a protocol depending on the bandwidths, a blinded observer arranged the maps in the order he believed represented a range from 'normal' to 'chronic' and identified the point he believed separated 'normal' from 'chronic'

Twenty three of the twenty six 'normals' were correctly identified (Sensitivity of detecting normals 88%). Fourteen of twenty one chronics were identified (specificity 67%). Using a refined protocol the specificity was increased to 76% but at the expense of reducing the sensitivity to 81%. The volunteers with a past history of back pain divided equally into normal and chronic patterns.

This new technique has for the first time allowed differentiation between patients with chronic low back pain and normal subjects. The protocols will be outlined and discussion will be welcomed on the possible physiological basis of the patterns seen and methods of improving discrimination.

SURFACE ELECTROMYOGRAM POWER SPECTRA IN CHRONIC BACK PAIN

C. W. Oliver, C. G. Greenough

Spectral analysis of the surface electromyogram has been in increasing use to give an objective measure of spinal muscular fitness but little data has been produced from chronic back pain subjects.

One hundred and three subjects (age 15 to 62), 41 with chronic back pain and 62 normal volunteers were tested. Subjects were positioned on a test frame in 30 degrees of forward flexion. An isometric load of 2/3 and 1/3 maximum voluntary contraction was held constant for 30 seconds whilst surface electromyograms were recorded at the level of the left and right 3rd/4th interspace. The raw electromyogram was filtered, digitised and median frequency and power spectra were plotted by Fast Fourier transformation. median frequency and power spectra regression lines against time were plotted to give a fatigue gradient of median frequency and power spectra. All subjects were assessed for Low-Back Outcome (LBO) score, and controlled for psychological disturbance using modified somatic perception questionnaire and modified Zung.

Initial median frequency was found to be significantly higher in both sexes of the back pain sufferers ($P < 0.05$). Initial Power Spectra area in both sexes was significantly lower in the back pain sufferers ($P < 0.05$). There was no significant difference between the two sides of the back. Median frequency and power spectra regression lines showed significant differences between the sexes and between volunteers and back pain subjects ($P < 0.05$). Regression lines of median frequency and power spectra were isometric load dependant. LBO showed significant difference ($P < 0.05$) between normal and back pain groups but modified somatic perception questionnaire and Zung showed no significant difference.

It was concluded from the present study that it has proved possible to distinguish chronic low back pain sufferers from normal volunteers by electromyographic techniques of initial median frequency and initial total power. It may not be necessary to plot regression lines of median frequency and power to distinguish these groups. The technique has been previously been shown to be reliable and repeatable. Surface electromyography may have an important role in the future diagnosis and management of chronic back pain, especially in pre-employment screening and monitoring of rehabilitation programs.

CHOICE OF NEURAL NETWORK ALGORITHM TO DIFFERENTIATE ELECTROMYOGRAM POWER SPECTRA IN LOW BACK PAIN

C.W. Oliver, P. Jones, C.G. Greenough

Accurate clinical diagnosis and prognosis of back pain is difficult. As an aid to diagnosis two forms of neural networks were compared. A Probabilistic Neural Network (PNN) and Back Propagation Neural Network (BPN) was used to differentiate categories of paraspinal muscular fitness. Previously, spectral colour mapping has been used to differentiate diagnostic categories but sensitivity and specificity have been each only 80% by simple spectral halfwidth measurement.

The power spectra from 65 subjects with a range of spinal muscular fitness were used to train the PNN. The power spectral data from 33 subjects, diagnosed by a single clinician (12 with no back pain history ever, 9 with a history of back pain at any time of their lives, 12 chronic back pain sufferers) were used to test the PNN.

Subjects were placed on a test frame in 30 degrees of forward flexion. An isometric load of 2/3 maximum voluntary contraction was held constant for 30 seconds whilst surface electromyograms were recorded at the level of the left 4th/5th interspace. The raw electromyogram was filtered, digitised and power spectra were plotted by Fast Fourier transform. A three layer neural network was designed with: a 250 unit input layer, 65 cell neuron Probabilistic (or 25 cell neuron Back Propagation) 'hidden' middle layer and a three level output layer. The output layer defined the power spectra as normal, history or back pain. For the PNN two thirds of subjects were used to train the PNN and one third to test it. In the BPN there were only 25 neurons in the middle layer. A probability of 10% difference in spectral shape defined output probability.

The PNN had a specificity of 92% of detecting 'normals' and a sensitivity of 75% of detecting chronic back pain. The BPN had a specificity of 100% of detecting 'normals' and a sensitivity of 83% of detecting chronic back pain.

Diagnosis of low back dysfunction using a PNN or BPN has been shown to be an accurate method of categorising 'normal' and chronic back pain subjects. The networks were unable to correctly classify subjects who had back pain at any time of their lives. BPN and PNN techniques may be useful indicators to identify subjects at high risk or of developing chronic back pain in the workplace. Larger databases are required to test this hypothesis.

Figures

Figure 5 Reference frame and test subject

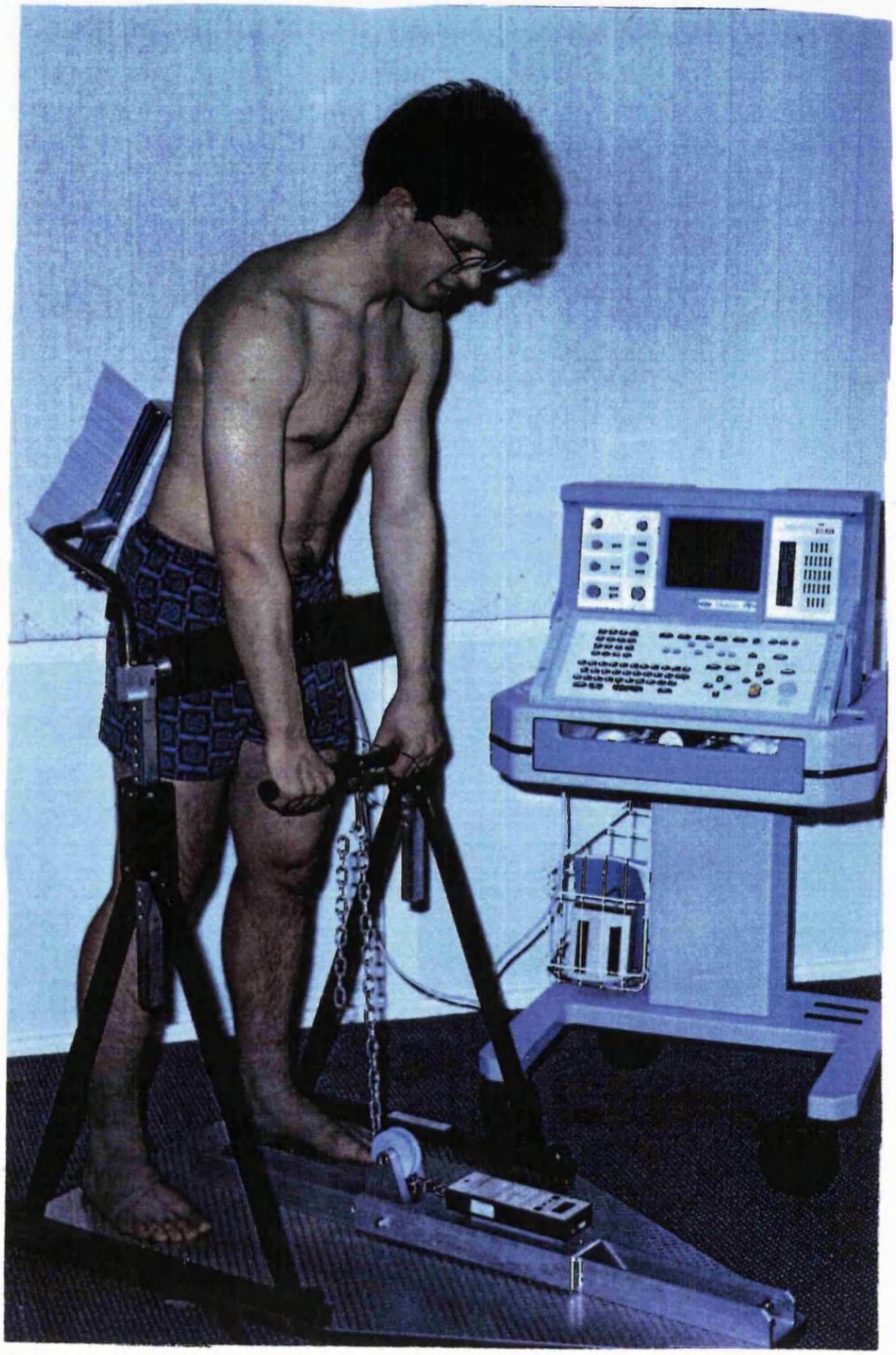


Figure 7 Typical positioning of surface electrodes

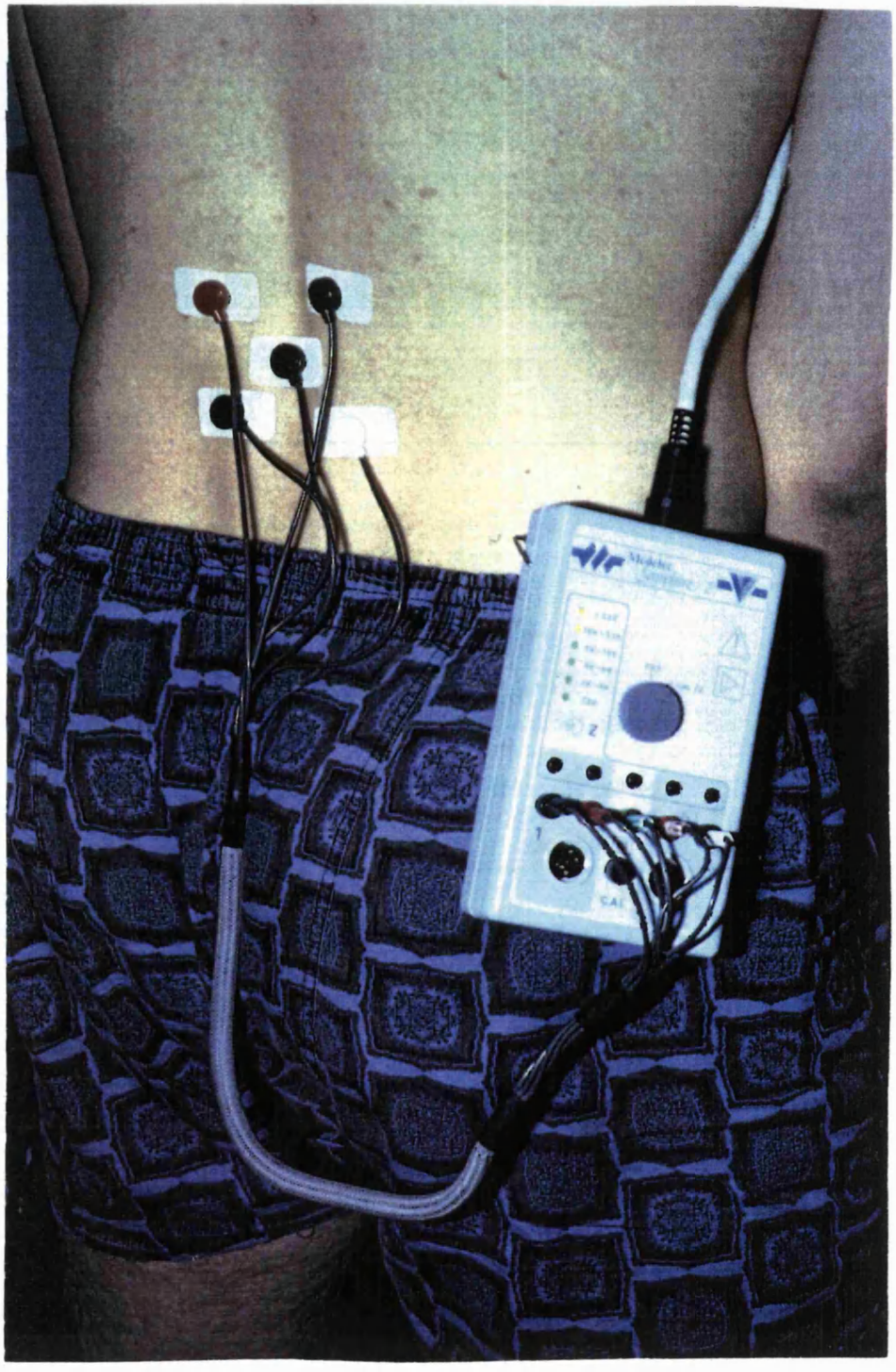


Figure 10 Relationship of lean body mass versus maximum voluntary contraction

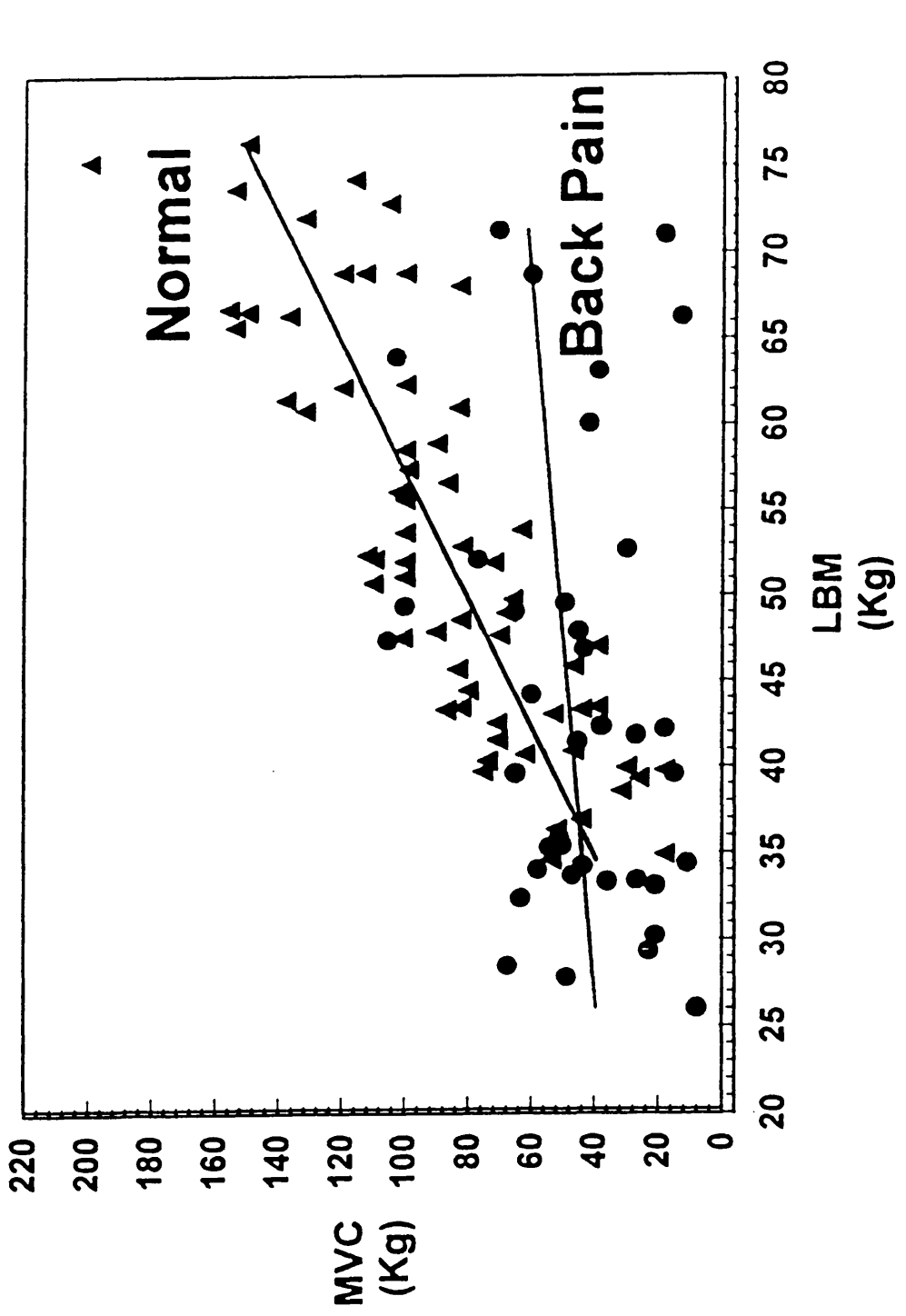


Figure 11 Apparent Periodicity of median frequency regression line slope normal breathing

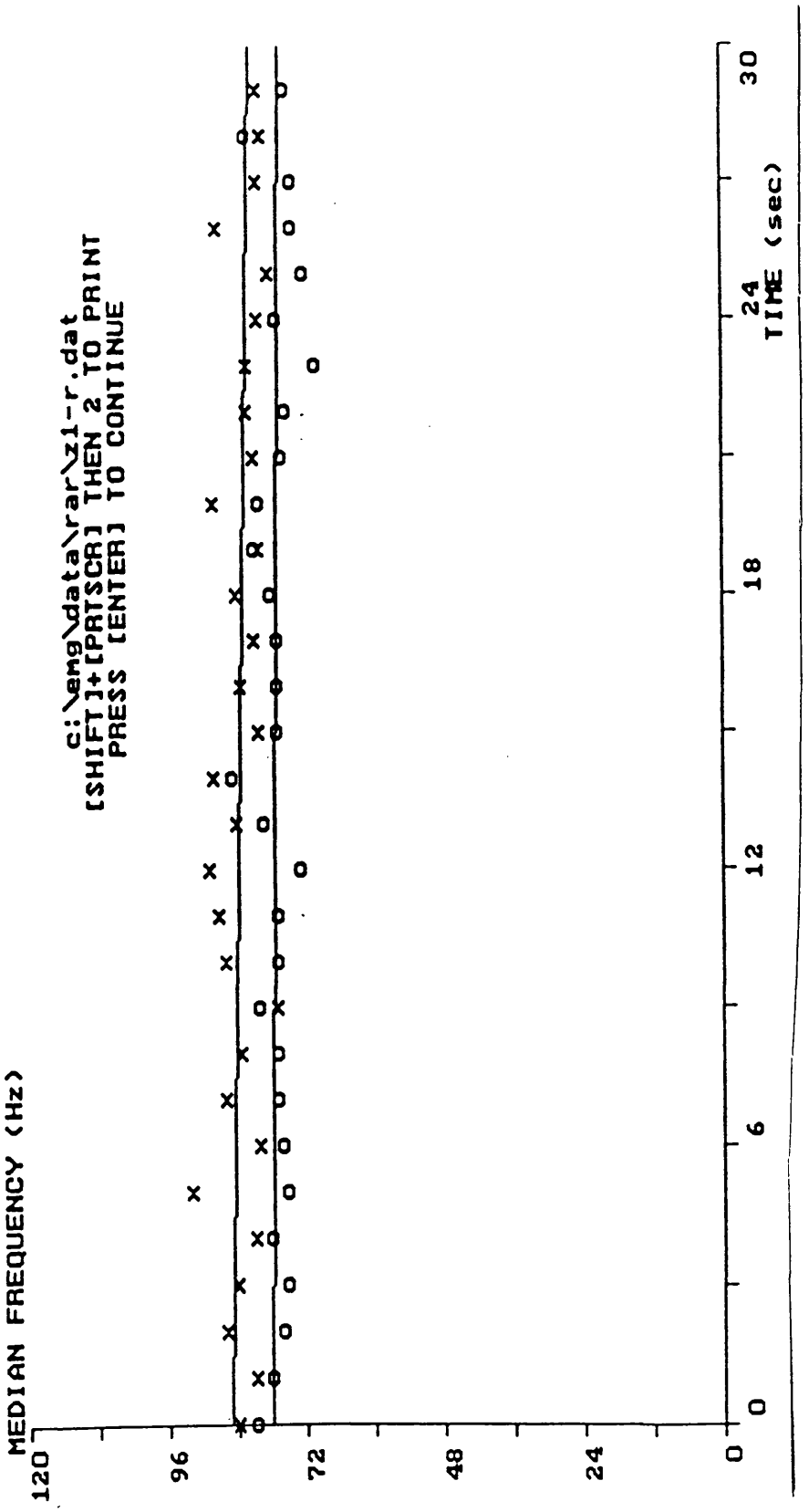


Figure 12 Apparent Periodicity of median frequency regression line slope breath held for duration of test

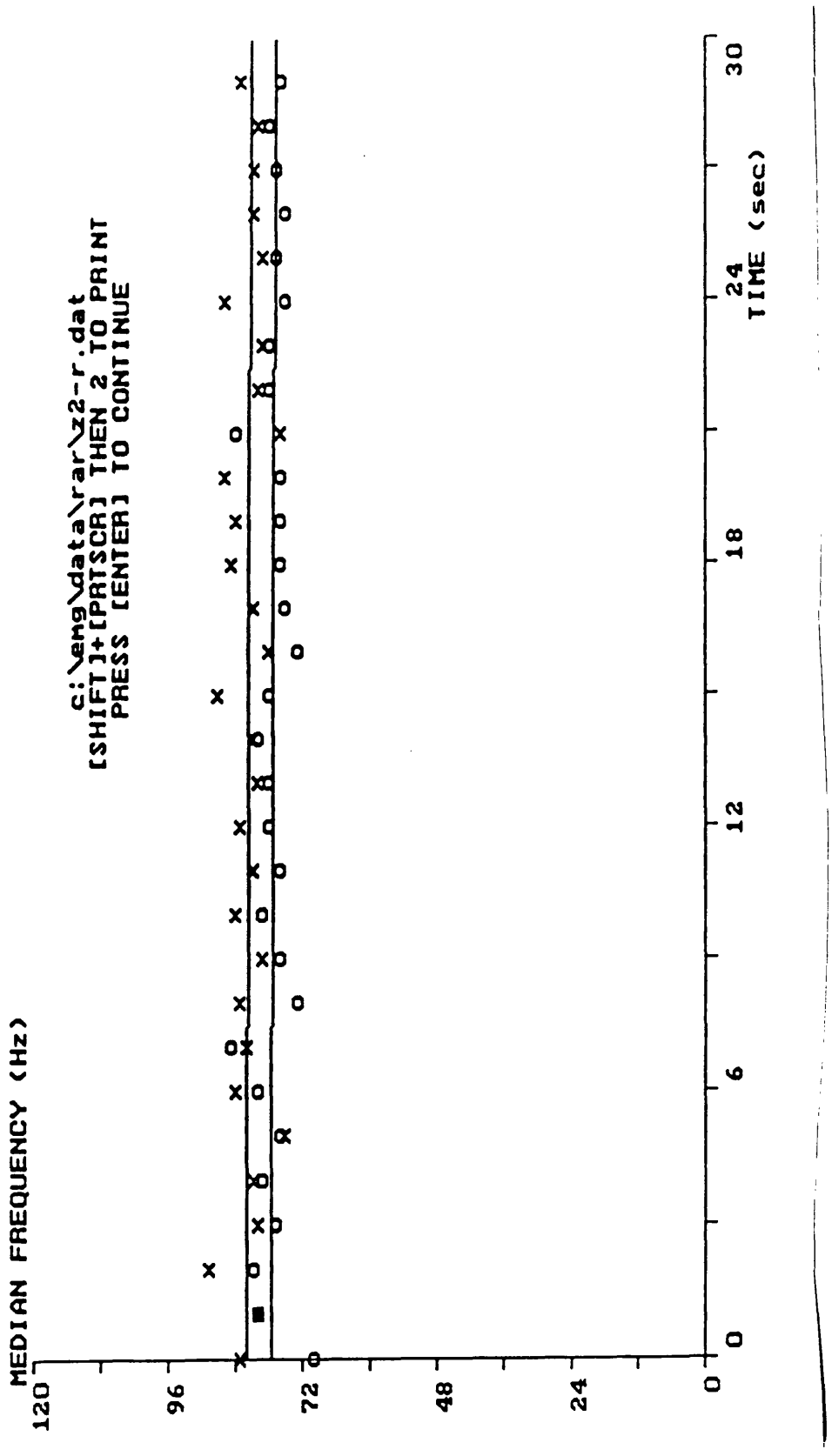
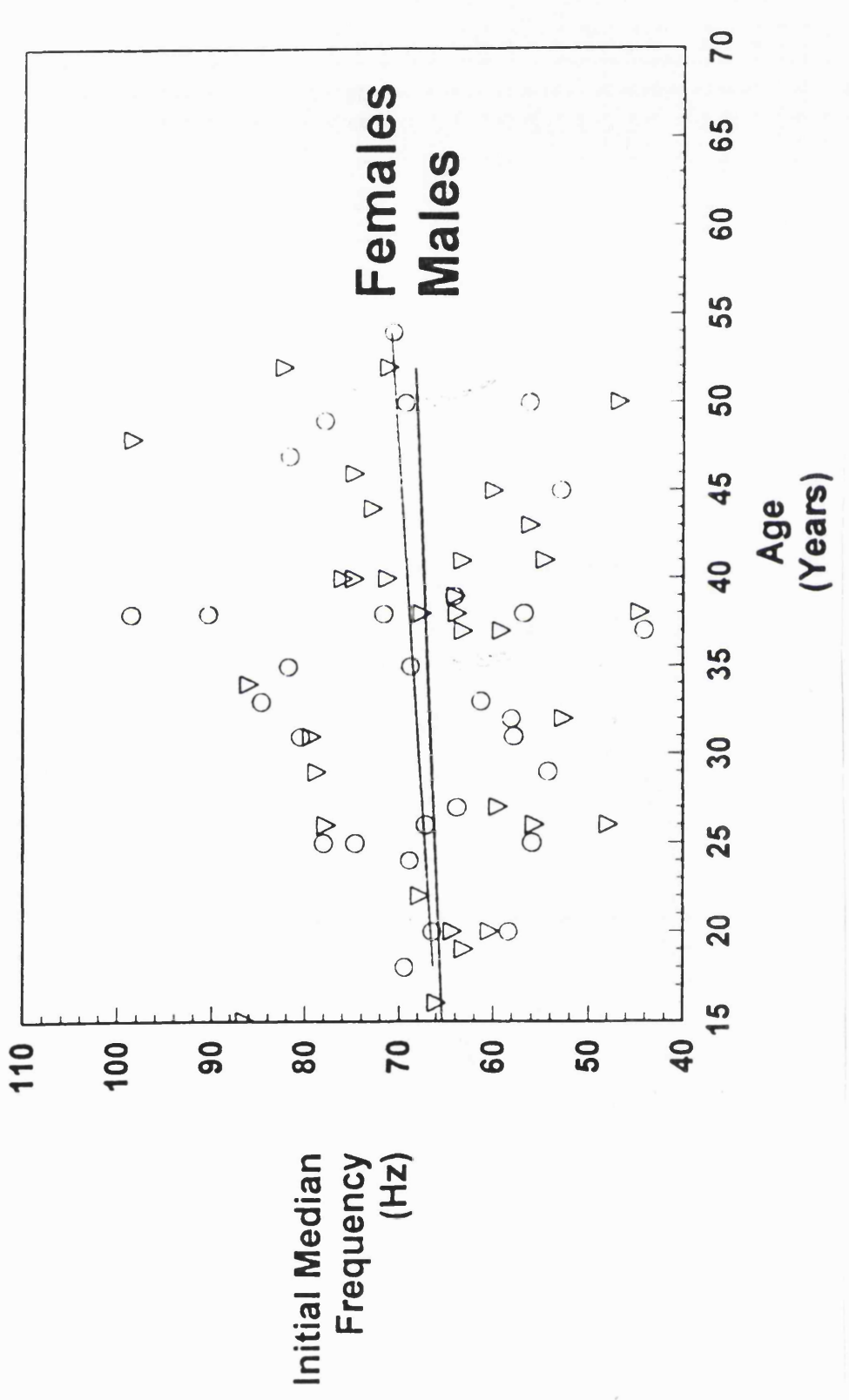


Figure 13 Relationship of age versus initial median frequency in normal subjects



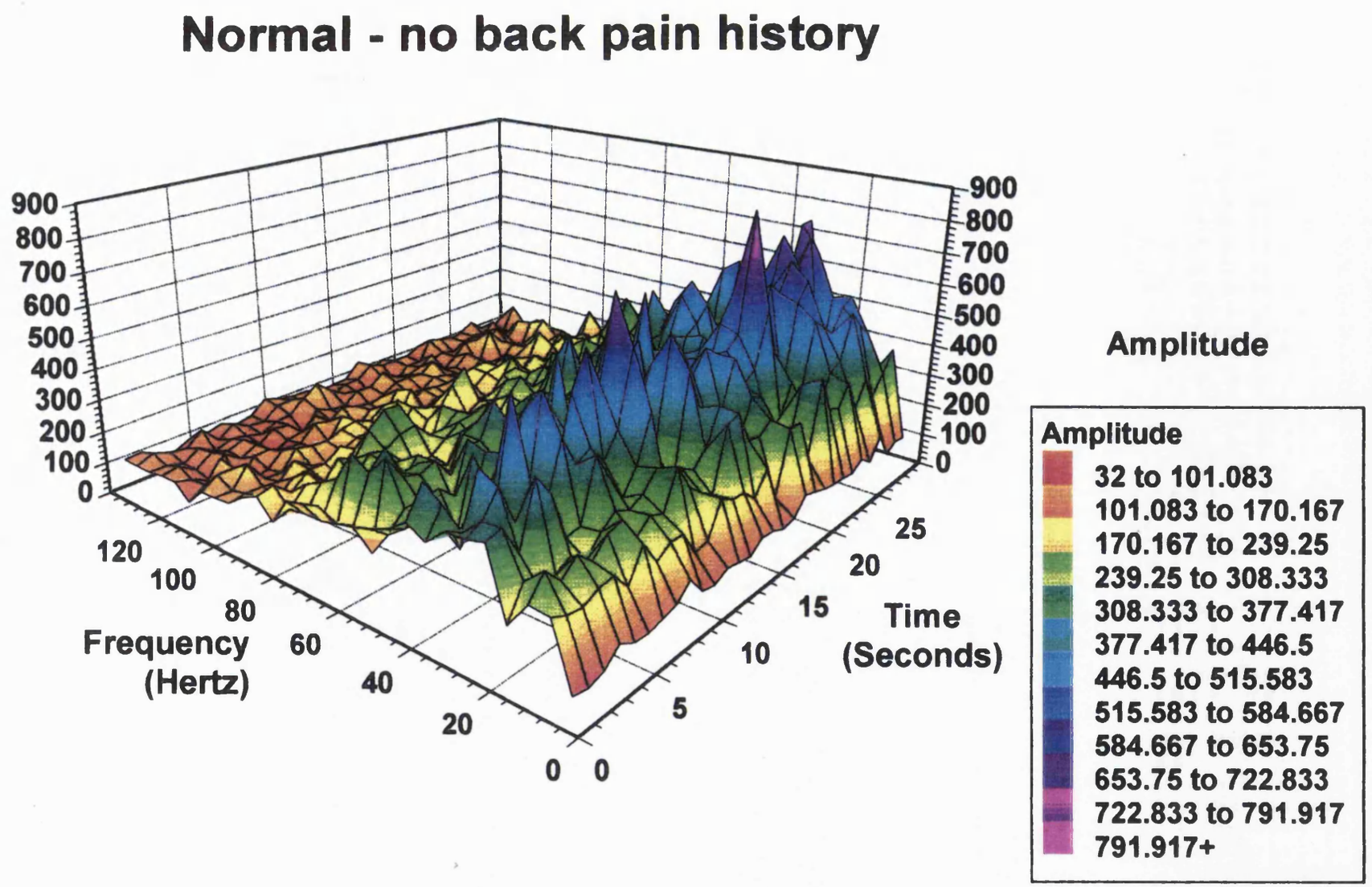


Figure 14 Normal three-dimensional graph

Figure 15 Normal spectral colour mapping

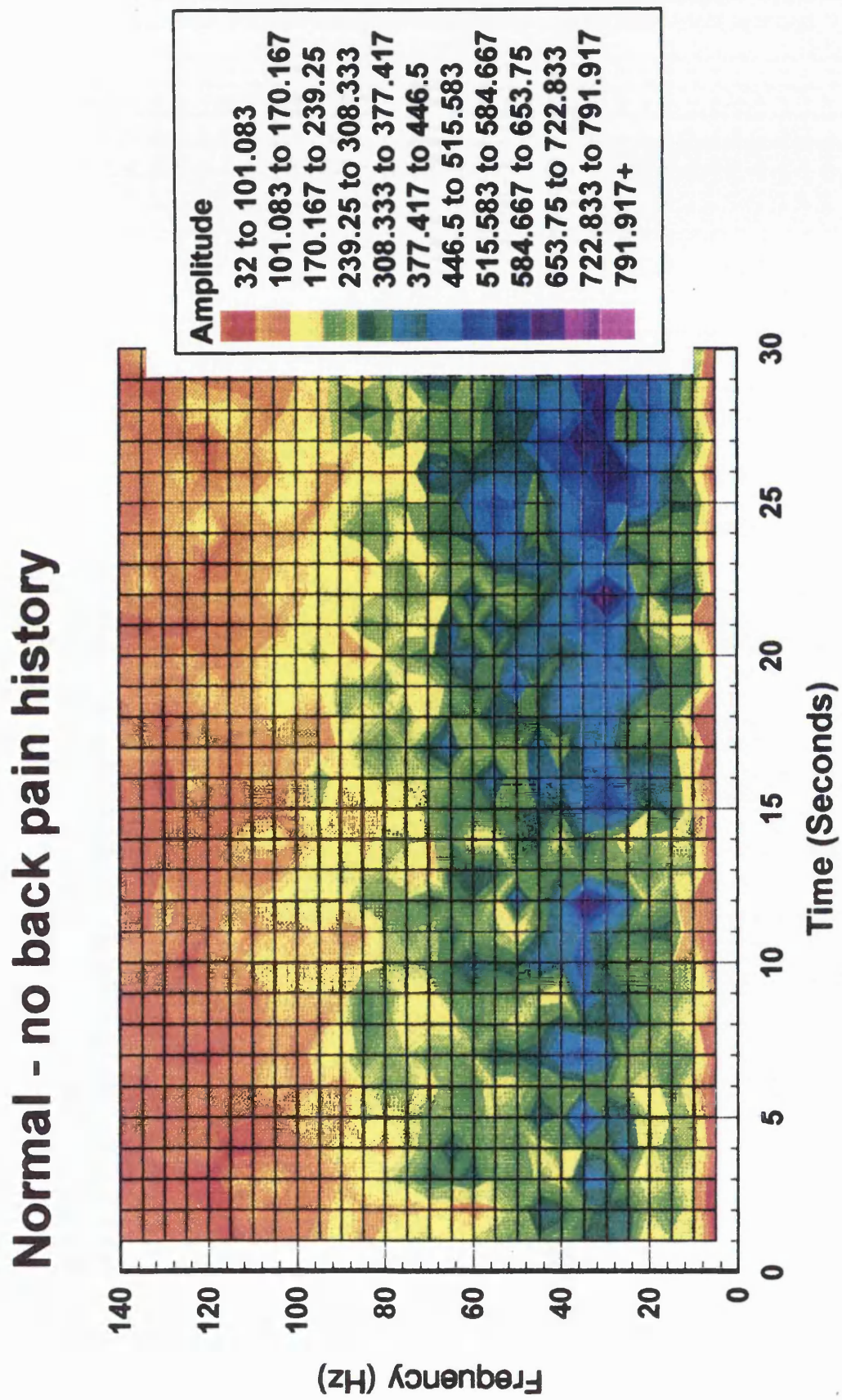


Figure 16 Chronic back pain spectral colour mapping

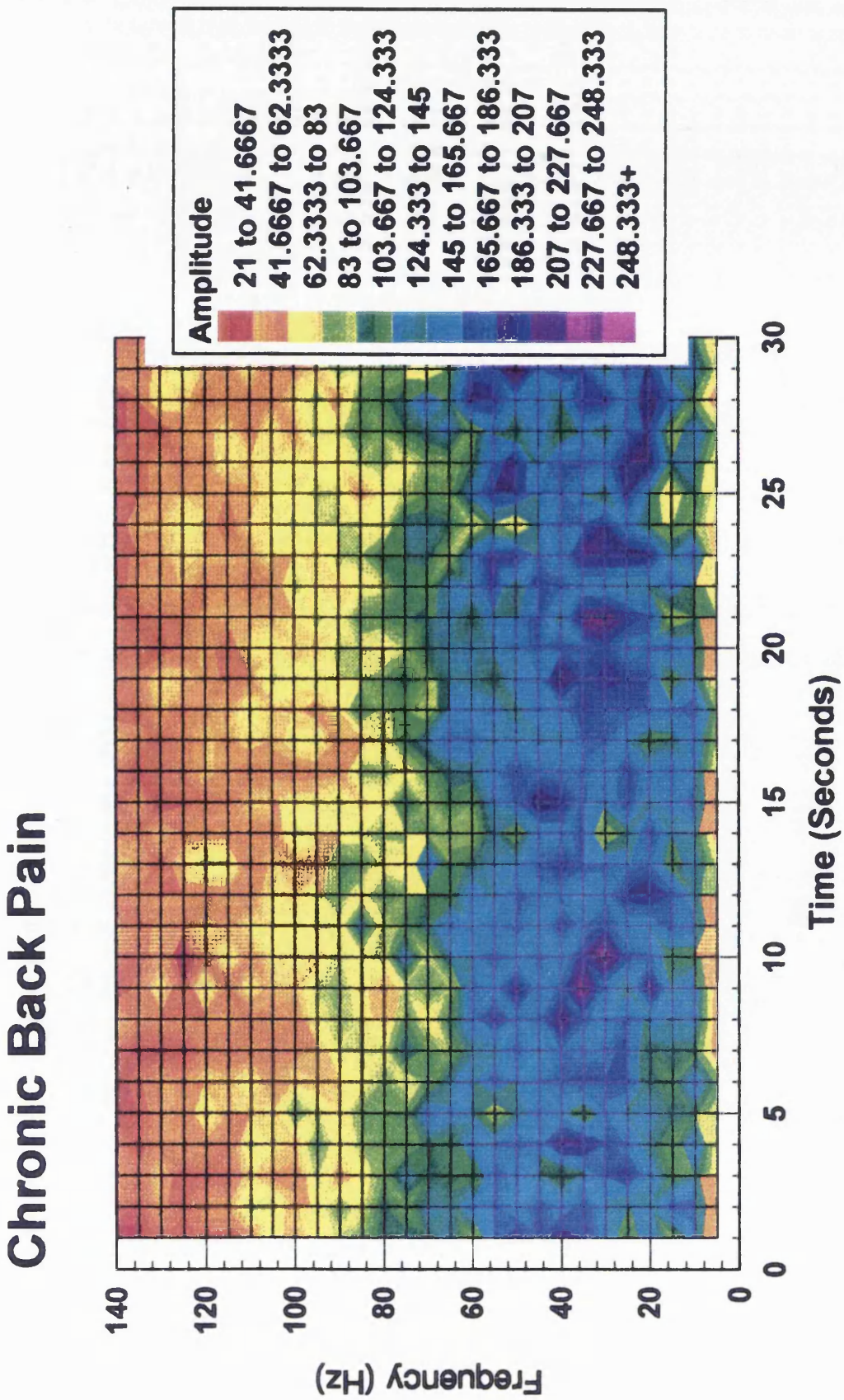


Figure 17 Athlete no past history of back pain spectral colour mapping

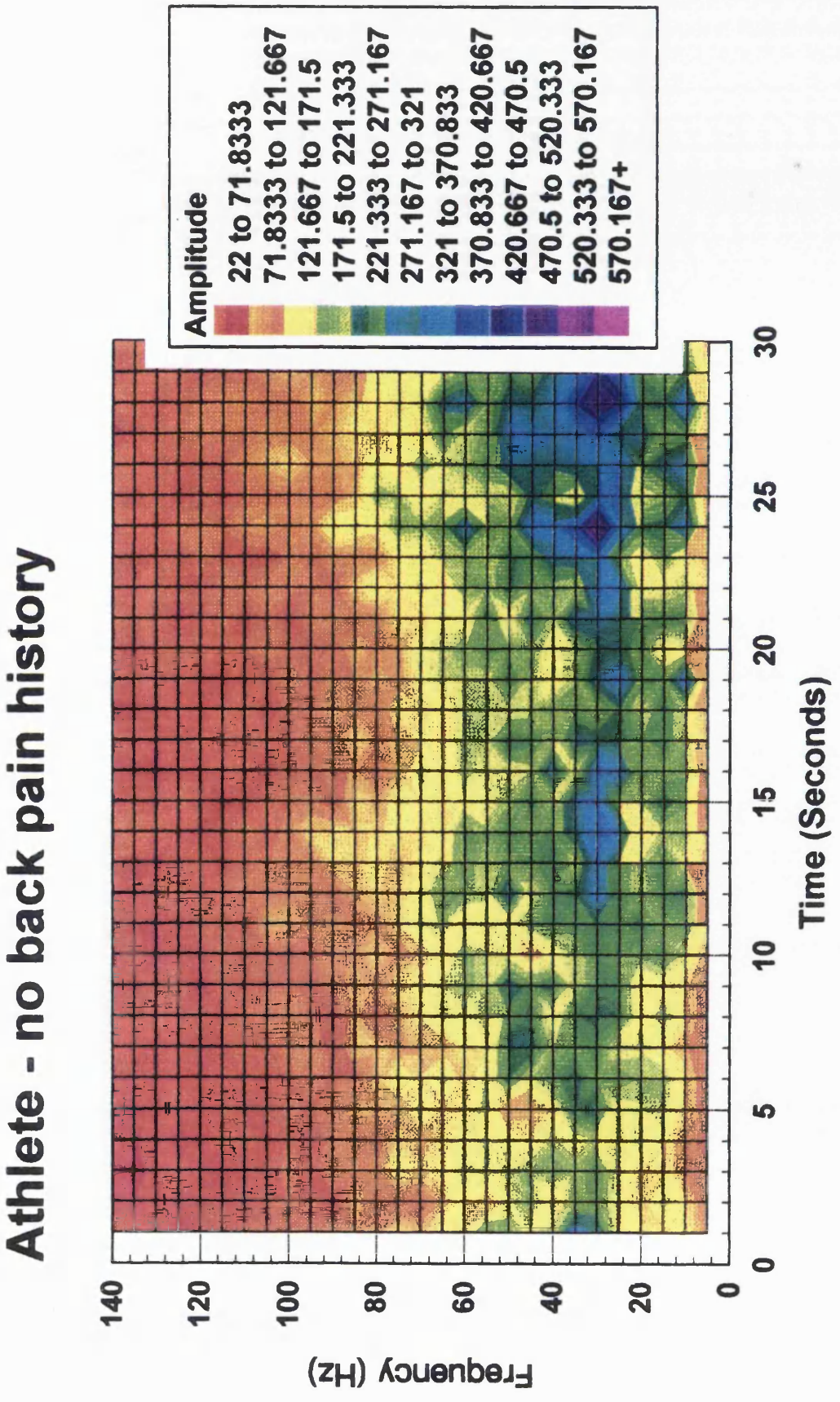


Figure 18 Normal scaled spectral colour map left side 2/3 and 1/3 maximum voluntary contraction normal subject

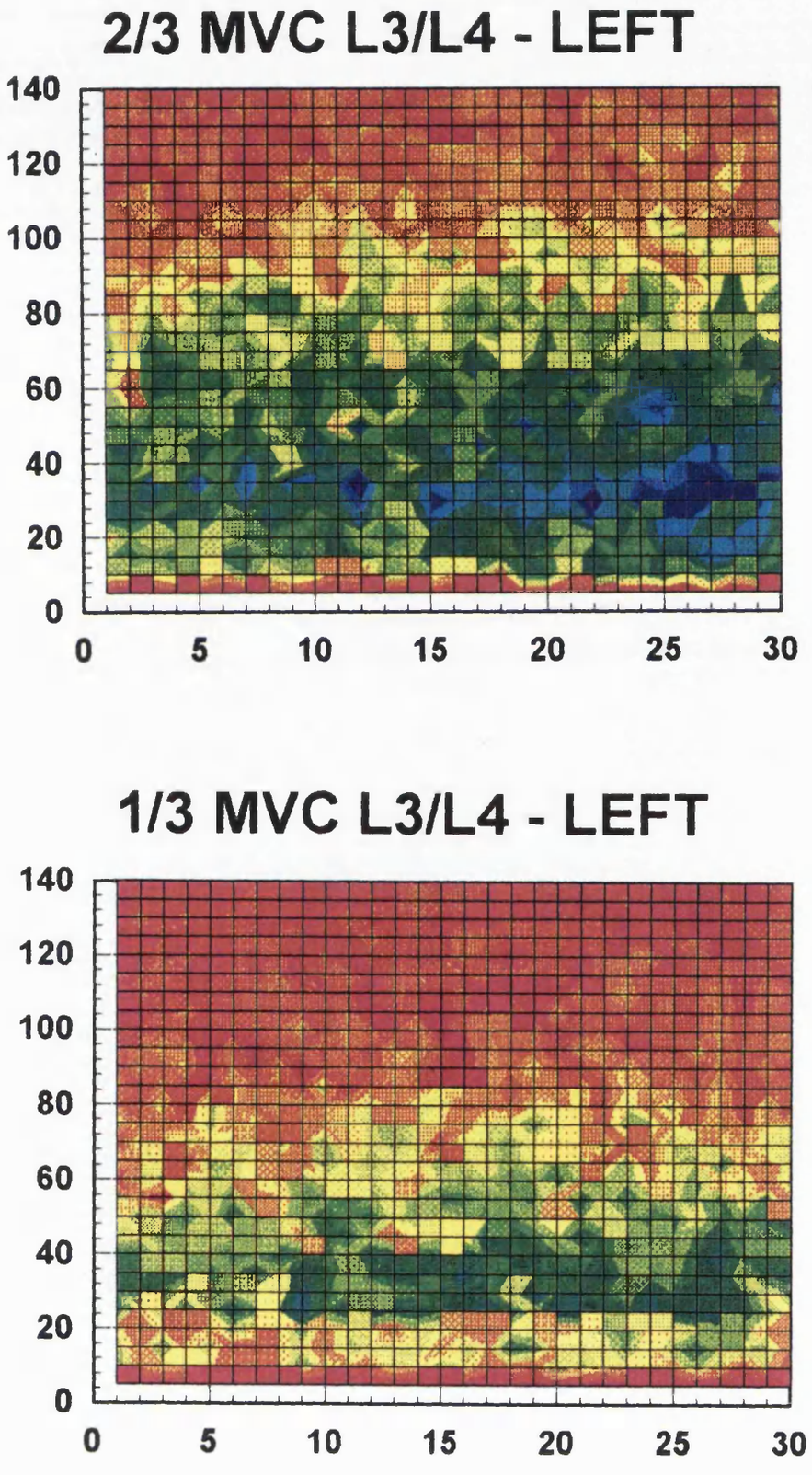
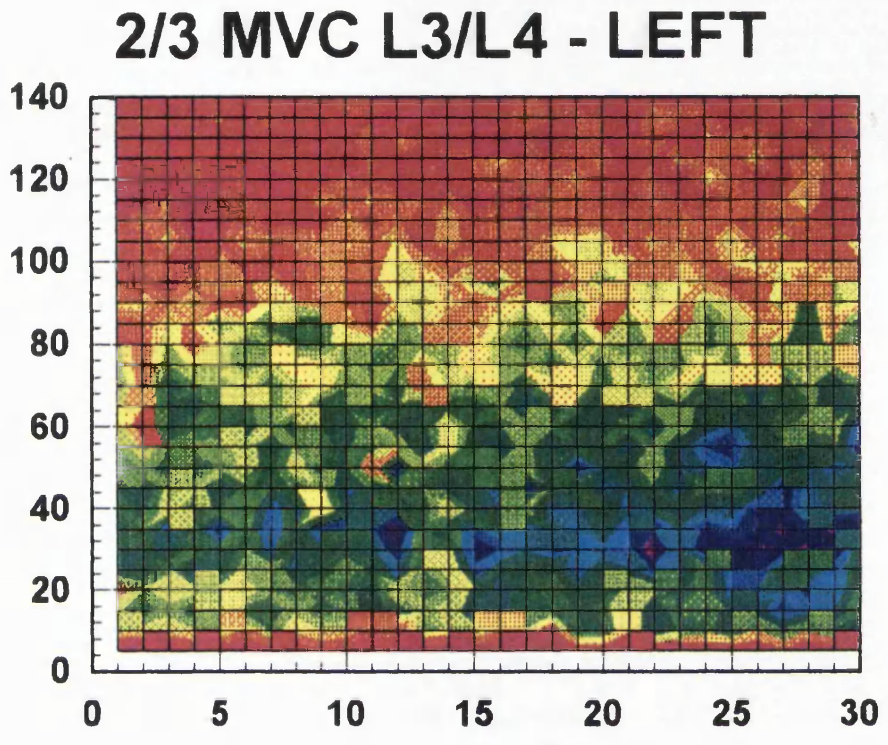
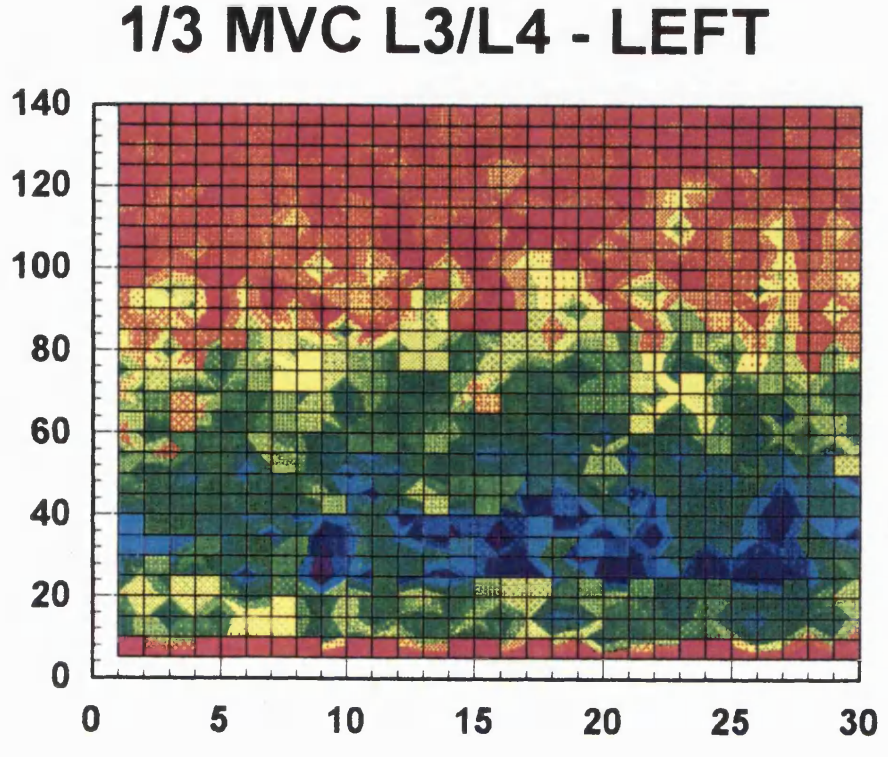


Figure 19 Autoscaled spectral colour map left side 2/3 and 1/3 maximum voluntary contraction normal subject





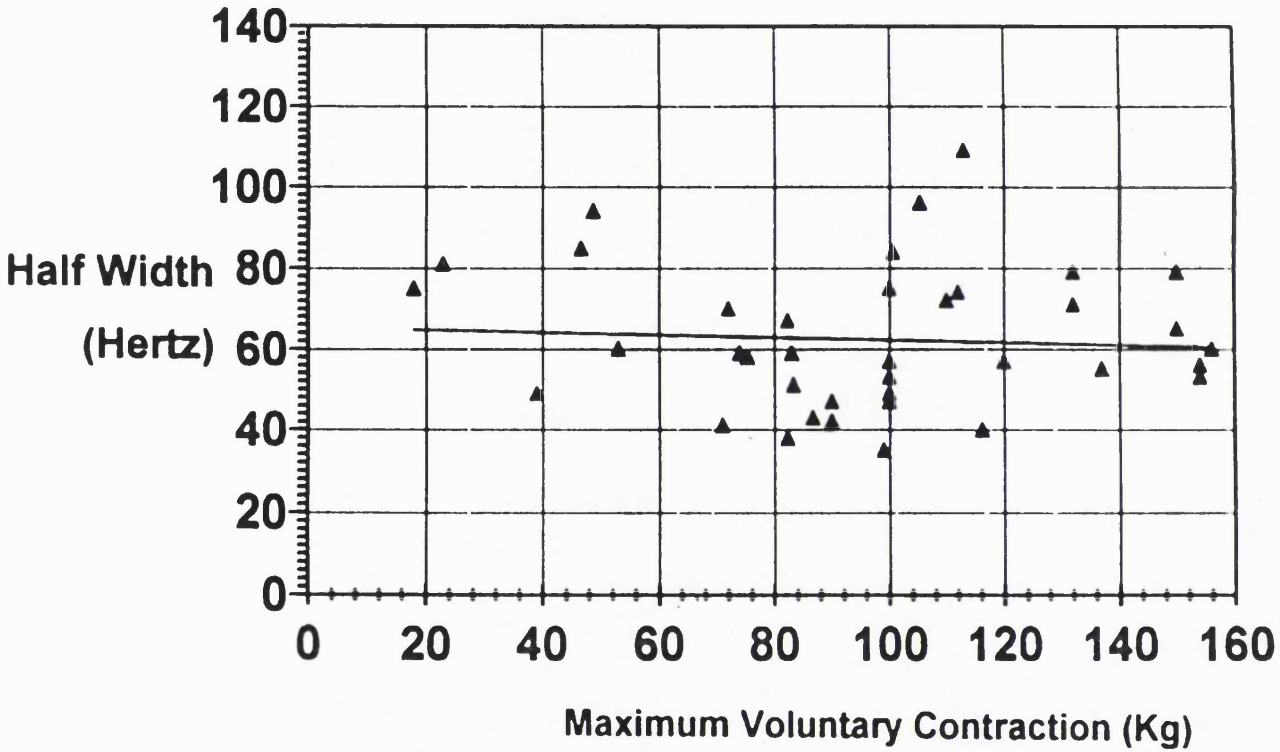


Figure 21 Relationship of spectral half width to loading-normal subjects

Figure 22 Increasing isometric load spectral colour map

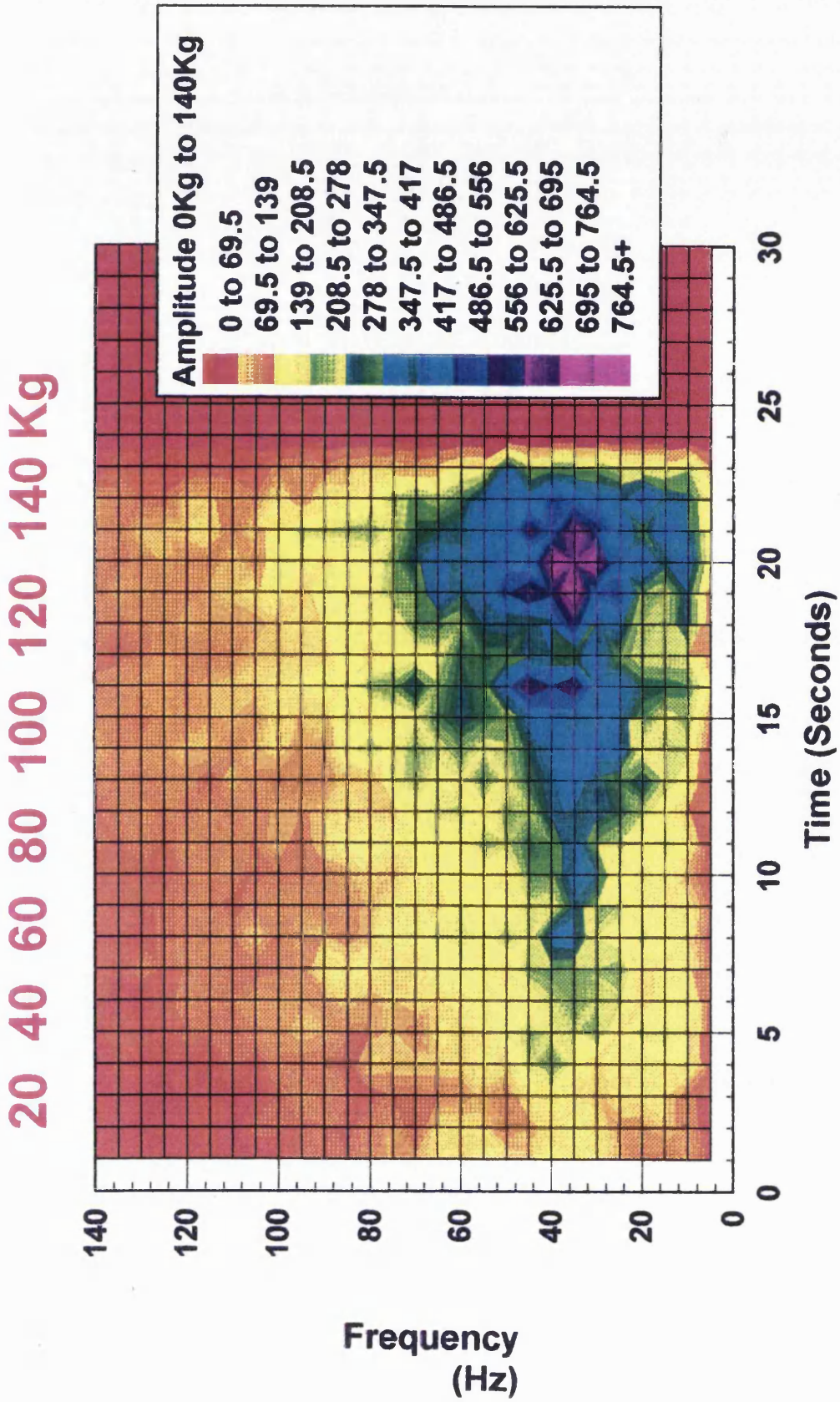


Figure 23 Increasing isometric range split-range separately autoscaled spectral colour map