COMPUTER AIDED ANALYSIS OF PARASPINAL ELECTROMYOGRAPHY

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ABSTRACT

Back pain is responsible for British employees taking 5 million sick days per year. Low back pain (LBP) has a controversial aetiology, with 95% of cases caused by mechanical, non-pathological causes. Current medical treatment for mechanical LBP is an exercise regime designed to restore lumbar stability. Unfortunately this is often a painful process, and therefore difficult to complete.

Electromyography (EMG) variables have been shown to be able to discriminate between subjects with and without mechanical LBP. If these variables could be shown to have discriminatory abilities before the actual onset of LBP they could be used to predict future episodes of LBP in currently otherwise asymptomatic individuals and allow the rehabilitation process to begin before the onset of symptoms. However a number of problems persist with EMG measurement. The test must be administered under closely controlled conditions in order to record clean signals, and interpretation of this data requires special tools and training.

This thesis aims to make contributions in three main areas;

AUTOMATED ANALYSIS

Manual analysis of a large store of EMG raw data files is a time consuming process. If outcome variables that require manual interpretation are included this effect is magnified, with necessary questions being raised as to the accuracy and consistency levels that can be maintained. A successfully implemented automated system would reduce analysis time and improve confidence in the outcome variables recorded. Investigations will also be carried out into the addition of error detection and correction algorithms that could be performed during the analysis procedure.

ECG CONTAMINATION REMOVAL

Previous studies have identified ECG as a potential source of contamination of lumbar EMG signals. Compensation for this effect is non-trivial as the ECG frequencies overlap an area of interest in the EMG spectrum, and the ECG signal characteristics would change over a fatiguing EMG test. The Independent Component Analysis method will be used to attempt to extract and remove the ECG component of a recorded signal whilst preserving the underlying EMG data. If this is successful an analysis of the effect that removing ECG contamination has on EMG outcome variables will be presented.

COLOUR MAP DIAGNOSTIC METHOD

Colour maps are an excellent method of presenting a large amount of signal data to a researcher, and have been used to discriminate between LBP and non-LBP subjects. The usefulness of this diagnostic display too has been somewhat limited however by the difficulty in producing such maps. Investigations will be carried out into methods that will be able to quickly and accurately produce these colour maps to the same specification as earlier studies. Colour maps of subjects that did not report LBP at the time of testing, but who then did report LBP at their next presentation, will be examined to assess whether or not EMG colour maps can be used as a predictor for low back pain.

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CHAPTER 1

INTRODUCTION

1.1 CONTEXT

This thesis deals with a subject area that crosses both the engineering and medical fields. As such the first parts of this chapter can be considered a primer for those who are not overly familiar with either topic. After this the aims of the thesis in detail will be discussed.

1.1.1 BACK PAIN

Back pain is a growing problem within, but certainly not limited to, the United Kingdom (UK). Back pain usually has a non-serious cause and sufferers will recover with no medical intervention. However, the sheer number of people affected by the condition makes it a costly one. In 1994, the Clinical Standards Advisory Group (CSAG) reported that the prevalence of LBP was 16.5 million people in the UK, and the report estimated the costs to the National Health Service (NHS) to be £480 million. This figure did not however include costs external to the NHS; the study stated these costs to be £1400 million (CSAG 1994). Another study performed in 2000 (Maniadakis & Gray, 2000) showed that in 1998 the direct cost of back pain was estimated at £1632 million, that is cost relating to the healthcare of people with back pain. However the cost of informal care, and the associated costs related to this, was estimated at £10668 million. These two figures combined corresponded to around 2% of the British GDP in 1998.

Back pain is a common condition, but again is rarely a serious medical problem. A patient with LBP will often be concerned by the issue, as the experience of pain might cause them to assume that it has the potential to be a major medical problem. An episode of chronic LBP would also have an impact on their everyday activities and may limit their ability to do simple tasks at home, at work, or socially. This effect

is likely to be extended to family, friends, or colleagues. The dimensions of the condition can therefore be seen to extend beyond the physical symptoms.

A study conducted in 2000 (Palmer et al, 2000) showed that almost half the adult population (49%) reported Low Back Pain (LBP) lasting for more than 24 hours. The authors also estimated that four out of five adults will experience back pain at some point in their lives. It has been suggested (Andersson 1999) that the occurrence of LBP should be accepted as a fact of life and that efforts should be directed towards anticipating LBP and preventing it from becoming chronic rather than at prevention of first time occurrence. However the currently prescribed method for dealing with non-specific low back pain (LBP) in the UK is exercise. This presents a problem regarding patient compliance as the exercise would be painful for people who already have LBP. A system that could identify a person's susceptibility to LBP before the onset of symptoms would be beneficial.

This work only concerns itself with non-specific back pain, in the lumbar region. Indeed, subjects with any of the specific conditions were excluded. The definition of LBP for the purposes of this study was described as "Ordinary Backache" (Waddell, 2004). This identifies that the pain is in the lumbar/sacral region, buttocks and thighs, and that it varies with time and activity. It is described as 'mechanical' and the patient is usually well.

1.1.2 SPINAL MUSCLES

The term muscle corresponds to groups of fibres held together by connective tissue. These fibres can be classified into Fast and Slow Twitch Fibres. Fast twitch muscle fibres respond quickly to the demands of the nervous system, but are also fast to fatigue. Slow twitch muscle fibres develop tension two to three times slower than the

fast twitch muscles, but have a higher resistance to fatigue. The slow twitch muscles fibres are also known as Type I muscle fibres. The fast twitch muscles fibres can be further grouped into Type IIa and Type IIx. Individual muscles are a mixture of these three groups, with the exact proportion varying according the role of the muscles.

A motor unit consists of a single motor neuron, along with all of the muscle fibres it activates. The point at which the motor neuron enters the muscle is called the innervation point. Very briefly, an electrical signal is conducted from the central nervous system, along this motor neuron, and into the muscle, which causes the contraction of the muscle. An important note is that a motor unit only contains one type of muscle fibre. This means that examining which motor units are being activated (by analysing the EMG power spectrum) identifies the muscle fibre types that are in use.

1.1.3 ELECTROMYOGRAPHY

Computer-aided Electromyography (EMG) is fast becoming an indispensable tool for examining and recording data concerning the activation of muscles. It uses sensors to detect electrical signals generated by muscles when activated. These sensors consist of either needle electrodes inserted into the muscle itself, or standard surface electrodes placed on the skin, overlying the muscle.

Needle EMG (NEMG) electrodes (provided they are correctly placed) provide the researcher with a good view of the electrical products of a particular muscle fibre. Probes are inserted into the actual muscle where they can record data about the electrical activity present. However, experiments are difficult to set up and can be uncomfortable for the subject. The benefit of this method is that it provides a clear picture of the electrical activity in a specific, single muscle.

Conversely surface electrodes provide a much broader view of underlying muscle function and are far less uncomfortable. The electrodes do not need to be in direct contact with a muscle, they detect the action potential propagation along the muscle fibres which can be conducted to the skin surface. However, by the time the signal has reached the sensor it has passed through fat and skin layers and is usually measured in microvolts (approximately one million times smaller than mains electricity). Due to the necessary amplification needed to counter this, and the issue of collecting signal data from surrounding muscles (crosstalk) this method is more susceptible to interference than the needle electrode techniques. The main benefit of Surface EMG (SEMG) is that the tests are far simpler to set up and much less unpleasant for the subject. Also less clinical skill is required, which would reduce training times.

As this research is aiming towards assessing the viability of clinic based EMG analysis, SEMG provides the only realistic method of fulfilling the ‘quick and easy’ criteria.

Despite the shortcomings in achievable levels of accuracy and in the interference levels experienced, SEMG has been reported as a valuable and objective method for the assessment of general muscle function (Pattichis and Elia, 1999; Pattichis et al, 1999). However SEMG, when used with relation to the erector spinae muscles, is slightly more problematic due to the underlying anatomy. The relevant details are discussed in greater detail in the next section.

1.1.4 DIGITAL SIGNAL PROCESSING

As compared to electromyography, Digital Signal Processing (DSP) is a much more recent field. It is concerned with representing signals as a sequence of numbers, and the processing of these signals. It is a subset of the more general Signal Processing.

With the advent of usable digital computers in the 60's and 70's DSP began to take root. Due to the prohibitive cost of computer equipment DSP was limited to only a few critical application areas; Radar and sonar for national defence, oil exploration where large sums of money could be made, space exploration where data is irreplaceable and medical imaging where lives are at risk. The computer revolution of the 80's and 90's produced a shift in application areas that now encompasses commercial ventures such as mobile phones and digital music systems.

Within the context of this project, DSP generally is what happens once the analogue-to-digital converter is attached to the computer and has recorded some real world data. DSP processes and analyses this data in order to present useful values to an end user. Specifically, the EMG recording system culminates with the creation of files containing a series of voltages corresponding to EMG readings. DSP techniques are used to process and display this data.

1.2 BACKGROUND

As previously stated, the management of LBP has impact on the NHS as it is a high volume activity, there are various treatment options and members of a number of groups are involved in service provision. During 1999 a number of staff in the Middlesbrough area became interested in providing a more co-ordinated approach to how services were organised and how patients were able to access them. At the outset this was a fairly large group and included members of primary and secondary care working in general practice, neurosurgery, nursing, orthopaedics, pain management, psychology, physiotherapy, radiology and rheumatology.

The initial meetings were held over lunchtime, and discussion ranged around the provision that existed, research on the topic, and the growing consensus that new ways of triage and fast tracking to treatment was the way forward. These meetings provided an insight into the diversity of information available to each professional group and utilisation of the literature in all the groups. It became obvious during this stage of discussion that although most of the people in the group were keen to move forward, practical constraints made this difficult as each member also had a full-time post, or 'day job'.

The group was particularly keen to;

- Influence how the evidence base used to support options for treatments was developed. This would need to be linked into some understanding of the way the professional groups acquired information and applied it in practice.
- Investigate what happened to outcomes if the type of intervention for a new episode of back pain presenting in primary care was altered at the point of triage.

- Extend some initial work that had been done on a group of volunteers that predicted who might get back pain and investigate this across a wider community base to evaluate if a programme of prevention teaching would have some benefit.

It became obvious that to move this work forward would require some increased funding that would facilitate some of the initial ideas shared in the group to be expanded and underpin this with increased research. A bid was prepared that was submitted under the provision of Health Action Zone (HAZ) funding. The government launched the HAZ initiative in 1997. Twenty six HAZs were set up with a view to “explore mechanisms for breaking through current organisational boundaries to tackle inequalities and deliver better services”. Their aim was to improve health outcomes and current services, along with developing new ways of local working. They have now been incorporated into the local primary care trusts.

This bid was successful and early in 2000 the group was notified of three-year funding of £135,000 annually to proceed with the work. It was at this point that the group became known as the Teesside Back Pain Partnership (TBPP).

The partnership moved these early ideas forward with research but needed some additional staff employed specifically for the project. There were four distinct areas for investigation;

- The Expert System
- The Evidence Base
- EMG Testing
- Early Intervention in Primary Care

Of these areas, the EMG Testing component is the relevant section to this thesis and so the other three will not be discussed in further detail.

Earlier EMG research within the South Tees Acute Trust had focused on being able to evaluate if it is possible to predict who would be likely to suffer an episode of back pain in the future. This work investigated a number of factors and has been linked to previously validated outcome measures, in this case the Low Back Outcome Score (LBOS) (Greenough & Fraser, 1992). This method of using an outcome score system enables sequential measuring of items and can be widely applied to a large group of volunteers. It is of a suitable nature to be stored on a computer and so a database of information can be generated.

This initial work had been conducted on a cross section of staff working in the Trust and had been successful in using the patterns from EMG recordings to indicate which individuals would in the future be more likely to develop an episode of back pain.

The aim of the next stage of the project was to evaluate if such patterning could be demonstrated in volunteers from a wider community base, and if so, would extra intervention alter the individual's behaviour to decrease future problems? This aspect of the research was keen to access volunteers from a variety of sources with some emphasis on people who did not normally attend health care. The staff involved in this project spent a lot of time in community-based activities to publicise the project under the auspices of a 'roadshow' to encourage involvement. This also provided an opportunity to initiate some health promotion advice and increase awareness of the reality of back pain and promote aspects of empowerment and partnership.

In addition to casting a wider net where subject participation was concerned, this stage of the EMG research was the first time that the tests were not carried out by trained medical professionals. This provided a double test for the procedure: are the tests still reliable on a wider population, and can they be carried out by persons with

a minimum of training? Investigation of the second part required closer inspection of the recorded EMG data than had been previously carried out, leading to the discovery of the various signal contamination issues. The research involved in this thesis picks up from this point.

1.3 JUSTIFICATION

The answer to the question “Could lumbar EMG testing be used to improve LBP outcomes?” is a valuable one, both to society as a whole due to the huge costs of the condition, and to the individual in question who is in pain. This is rather a nebulous topic however, hence the requirement of this multi-disciplinary approach.

No one project could hope to gain the amount of new knowledge needed to definitively answer that question, this thesis concerns itself with the acquisition and analysis of EMG signal data. Specifically this will be methods for removing signal interference, methods for batch processing EMG data and potential methods for discriminating between back pain and no back pain subjects using EMG variables.

The test data required for this project (EMG raw test data and subject questionnaires) have already been acquired as previously described. There will be no extra costs due to additional data collection, and no additional risks to research subjects.

The units of analysis have been identified from the literature review. They have all been published in relevant journals and have demonstrated evidence of being fit for purpose. They are all also fully repeatable and quantifiable.

Care has been taken to ensure that the following hypotheses have been set up so that more than one result is possible, that is that the working hypothesis can be refuted.

This research will extend the knowledge both of how EMG signals can be better gathered and examined, and how the same signals can be interpreted with a view to their discriminatory potential.

1.4 CONTRIBUTION TO KNOWLEDGE

The following sections will be discussed fully in their relevant chapters. However, a short summary of each area is useful to note at this point.

1.4.1 AUTOMATION OF ANALYSIS

The conversion of raw EMG signal data into a format that can be usefully examined is not a simple one. In addition, the output traces must be interpreted by a trained observer and any recording errors must be identified and compensated for. A system that could automate this process would be advantageous as it would not only save time, but ensure that test data could be re-examined with the identical results.

The hypothesis is;

A system can be created to automatically replicate the outcome scores currently generated manually by researchers

If such a system could be proven to work accurately, it would mean that testing procedures would be faster and more reliable, and that batch processing of previous test data would become possible. This means additional analysis methods could be tested routinely.

1.4.2 ECG REMOVAL

A known source of sEMG contamination is crosstalk, whereby the electrodes collect signals from muscles other than the intended group. A major contributor to crosstalk

when recording signals from the lumbar spine region is the heart. The power spectrum of ECG overlaps an area of interest in the EMG spectrum and as such has an impact on the interpretation of results. This work will be in two sections, can the ECG be reliably removed from the EMG data, and what effect does this have on the outcome scores?

The hypotheses are;

It is possible to remove ECG signal contamination from recorded signal data whilst preserving the underlying EMG components

Removing ECG contamination from recorded EMG data will have a measurable effect on EMG outcome scores

Obviously, the second hypothesis is dependent on the first. If a method is not successfully located that will achieve the stated goal then work on identifying any effect will be impossible. The successful completion of this stage of the research will enable a higher level of confidence in EMG variables.

1.4.3 COLOUR MAPS

Previous work (Greenough et al, 1998) has identified that spectral colour maps detailing EMG data over time have some use in discriminating between subjects with LBP and subjects without LBP. The research however was hampered due to the difficulty in creating these maps, and the interpretation methods chosen when analysing said maps. Again, there will be two components to this area of the project.

The hypotheses are;

Modern computing and graphical techniques will be able to produce EMG Spectral Colour Maps quickly and reliably.

EMG Spectral Colour Maps will be able to be used to discriminate between back pain, no back pain and future onset of back pain subject groups.

Even if the first part is unsuccessful it is hoped that using the previous methods of colour map generation will allow some analysis of discrimination ability for the second part.

The areas of contribution would be in the efficient and repeatable creation of the maps, and whether or not these maps can be used for the discrimination purpose.

1.5 THESIS OUTLINE

The work in this thesis falls into four main areas. Firstly a general introduction to the medical and technical fields appropriate to this project is presented, followed by a short overview on the data collection methods. The next area is the literature review where current work in the EMG/Low back pain field will be described, so as to put this project into a useful context. The third stage details the actual research work carried out and finally there is a conclusion section. A chapter listing follows;

Chapter One – **Introduction**

This chapter provides an overview of the thesis, and the general background to the research area and hypotheses to be examined.

Chapter Two – **Literature Review**

The literature review chapter presents a detailed view of the literature surrounding the EMG/Low Back Pain fields, with a view to putting the proposed research into context. It evaluates current views on the aetiology of LBP along with effective treatments, the general use of EMG, the use of EMG with respect to LBP and various signal processing techniques currently in use in this field. More detailed literature reviews on the areas of research carried out are included in the relevant chapters.

Chapter Three – **EMG Machine, Measurement and Display**

Here the technologies used in gathering, recording and analysing the EMG data are described. This covers the machine itself, the raw data types and electronic file formats, any digital filters used, the mathematical transforms utilised, and the methods used to interpret the final results.

Chapter Four – **Original Project**

This thesis builds on previous work carried out at this centre. This chapter will detail this work and indicate the boundaries between projects. The data collection methodologies are described and any relevant background information listed.

Chapter Five – **Automated Analysis**

The issues behind the analysis and interpretation of EMG raw data are examined in this chapter. This is followed by an investigation into methods that can be used to facilitate the automation of this process. Finally the effectiveness of these methods is evaluated.

Chapter Six – **ECG Removal**

This chapter explains a method of removing ECG contamination from EMG signals. It then goes on to examine the effect that this removal has on the EMG outcome measurements. Finally other potential uses for this technology are discussed.

Chapter Seven – **EMG Spectral Colour Maps**

Methods suitable for creating colour maps based on EMG data are examined. The potential role of these maps in discriminating between LBP and no-LBP subjects is assessed and discussed.

Chapter Eight – **Conclusion**

The final chapter revisits the thesis with a view to reassessing the work completed. Special mention is made with regards to contributions to the field. Study limitations are identified, along with directions for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 POTENTIAL CAUSES OF LOW BACK PAIN

LBP remains a difficult condition to accurately diagnose since many people with LBP lack a specific pathology. Also, objective indicators of pathology (X-Ray, MRI) are not specific to persons with LBP (Boden et al, 1990; Jensen et al, 1994; Weishaupt et al, 1998). Furthermore, after several decades of research, the aetiology of LBP is still a controversial issue (Adams et al, 1999). Indeed, the usage of the term “Non-specific Low Back Pain” to describe the condition that affects 95% of back pain sufferers speaks volumes. If a confirmed aetiology exists for this condition (or, more likely, set of conditions) then this term would not be used. This has led efforts to concentrate on methods that aid the diagnostic process.

However, a suggested source of LBP that is gaining some evidential support in the literature is structural instability in the spinal column. This theory suggests that the loss of normal pattern of spinal motion can cause pain and/or neurological dysfunction. Assuming this is the case, it is of some benefit to assess the stabilisation system of the spine.

The following is a hypothesis regarding the cause of some cases of non-specific back pain developed by orthopaedic surgeons treating LBP, and was the basis for the usage of EMG as a predictor for this condition.

The human spine is an ‘active structure’. This means that the only thing keeping a person upright is the muscles surrounding the spinal column. Without this support the person would simply collapse.

The spine, or Vertebral Column, protects the Spinal Cord. It comprises of vertebrae, the bony part of the structure, and intervertebral discs, cartilaginous joints that allow small movements of the vertebrae.

When some people age, their intervertebral discs lose some of this fluid pressure, rather like a tyre deflating. The result of this is that the vertebrae around the joint are allowed to move a little more than is ideal. When this happens, the burden of keeping the person upright and stable is passed onto the muscles surrounding the spine. If these muscles are insufficient to the task then a degree of spinal instability occurs. It is proposed that this instability is what causes at least a good portion of Mechanical Low Back Pain. Along with aging other processes, such as minor endplate damage, can contribute to depressurisation of the discs.

Taking that this loss of pressure in the intervertebral discs is an unavoidable component of the aging process, assessing a subject's spinal musculature would provide evidence to how well that subject could resist the eventual onset of spinal instability. Reliable EMG measurement techniques should provide good indication of a subject's susceptibility to this condition.

There is little evidence in the literature to support this directly. However, other work in related areas adds weight to the hypothesis.

It has been suggested (Panjabi, 2003) that the functional stabilisation system of the spinal column can be divided into three subsystems;

- The passive subsystem consists of vertebrae, intervertebral discs, ligaments, joint capsules and zygapophyseal (facet) joints. This system exerts some passive resistance at the limits of voluntary movement, but in a neutral position its stabilisation capabilities remain limited. In vitro studies have demonstrated that the load bearing capability of this subsystem is limited to less than 90 Newtons (N) (Crisco & Panjabi, 1991).
- The active subsystem is the muscles and tendons that contribute to spinal stability. In vivo studies (Nachemson & Morris, 1964) indicated that this subsystem provides mechanical stability for loads exceeding 1500 N. The

active subsystem appears particularly effective in the neutral position, where the passive subsystem assumes only a minor role.

- The third component is the neuromuscular subsystem, the nerves and central nervous system. It is this subsystem which co-ordinates the actions of the active subsystem.

It is clear from this work that the active subsystem provides the far greater proportion of stabilisation force to the spine, and does so across a wider range of movements. Other studies examined the effect the passive lumbodorsal fascia has on overall lumbar stability. One group examining this (Dolan et al, 1994) concluded that between 16 and 31% of the peak extensor movement generated during lifting was unrelated to EMG activity in the spine, i.e. caused instead by the passive subsystem. A different study (McGill & Norman, 1988) suggested that the potential for the lumbodorsal fascia to contribute significant extensor movement has been overestimated. However taking the higher number shown by Dolan still leaves 69% of the extensor movement to be caused by non-passive means.

Assuming that spinal instability is a cause of LBP, and that fatigued muscles are less able to maintain this stability, leads to the presumption that an association exists between muscle fatigability and LBP.

Other work in the literature appears to back this up. It has been demonstrated that fatigue reduces neuromuscular control of trunk movement (Parnianpour, et al, 1988). In addition to this, epidemiologic studies suggest that fatigability and endurance contribute to Low Back Disorders (Jones et al, 1993; Macfarlane et al, 1997; Taimela et al, 1999). The study conducted by Taimela was examining proprioception rather than back pain specifically, but did note that lumbar fatigue impairs proprioception in LBP subjects and controls, and that LBP patients had poor proprioception even when not fatigued. Finally, a model proposed by (Granata et al,

2004) indicated that it is more difficult to achieve muscle recruitment patterns necessary to maintain spinal stability as muscle force generating capacity declines with fatigue.

The current treatment recommendations for non-specific LBP within the UK are for exercise regimes designed to improve the fitness of the lumbar spinal musculature (NICE Guideline, 2009). This was supported by a large scale literature review (Henchoz & So, 2008) which concluded *"Exercise is effective in the primary and secondary prevention of low back pain. When used for curative treatment, exercise diminishes disability and pain severity while improving fitness and occupational status in patients who have subacute, recurrent or chronic low back pain."*

There still remains a great deal of work to be conducted before even a portion of the current non-specific LBP cases can be attributed to stability issues. However, the evidence found in the literature leans more towards supporting the previously mentioned hypothesis, rather than not.

Once, at least for the purpose of this thesis, the hypothesis that non-specific LBP can be caused by lumbar instability is accepted, the next stage is to identify a suitable method that allows the quantifiable assessment of the lumbar musculature.

2.2 PREVIOUS WORK IN PARASPINAL ELECTROMYOGRAPHY

2.2.1 GENERAL SEMG UTILITY

A huge body of work has been created dealing with SEMG generally and a good amount of work has been published relating to lumbar SEMG specifically. Opinion is divided regarding to what extent clinical usage of lumbar SEMG can be achieved.

A large review (Pullman et al, 2000) was carried out with the aim of examining the scope of SEMG utility. This review reinforced the view that Needle Electromyography (NEMG) is a superior technique to SEMG for general analysis of a single muscle, but also comments that SEMG is a more useful technique for clinical analysis of the erector spinae. Overall this review is pessimistic about the suitability of SEMG usage in clinical areas, saying *"even if the reports are accepted at face value, the findings suggest only that SEMG can identify patients who have low back pain"*. The further point is made that *"it would be easier and cheaper simply to ask the patient whether his or her back hurts"***.** The question of whether or not SEMG can actually predict LBP, that is, return a positive result before the patient begins to experience the pain, was not considered by the authors. They did however suggest that SEMG would be a useful tool for contrasting between back pain from muscle sources and back pain from other sources (such as nerve-root compression). Presumably if a person who was complaining of back pain returned a negative EMG reading they would warrant further examination. Their final comment

was the emphatic *"SEMG is considered unacceptable as a clinical tool in the evaluation of patients with low back pain at this time"*.

A meta-analytic review (Geisser et al, 2005) examined previous work done on SEMG with respect to analysing LBP. Compared to the previously mentioned review, the authors presented a more positive view of the potential of SEMG with regards to LBP. Also, in addition to physiological factors, the amount that psychological factors could have an effect on LBP was also considered. The comment was made that *"given that insincere effort is common in some LBP populations, one might also consider choosing a SEMG method for which insincere effort, due to pain or other factors, biases the SEMG measure in a direction that is characteristic of a person with LBP"*. This poses a potential problem however, that some patients may find it advantageous to themselves to feign an episode of LBP, for a variety of reasons. The authors admit this, saying that *"if one were using SEMG in a medical-legal context, choosing the latter type of measurement makes it possible for a subject to "feign" having LBP through insincere effort"*. Common exploitation of this knowledge could very well render such a testing system, at best, untrustworthy. Again, no mention was raised whether or not SEMG of the lumbar regions could be used as a predictor for LBP. This report concluded that *"SEMG measures hold promise as an objective marker of LBP"*. However, the comment was also made that *"Further research is needed to determine the combination of measures that are cost-effective, reliable, valid, and discriminate with a high degree of accuracy between healthy persons and those with LBP"*.

Both of these reviews note that SEMG can be used to distinguish between subjects with and subjects without LBP in a blinded trial, although they differ in views on how useful that fact is. The question of whether or not lumbar EMG can be used as a predictor for back pain is raised by neither of the studies.

They also both say much work remains to be done before such analysis of lumbar EMG could begin to be used on a day-to-day clinical basis for diagnostic purposes.

When examining differences in muscle recruitment patterns during trunk flexion exercises between LBP and healthy control subjects (Nelson-Wong et al, 2012), the authors said that *"Individuals predisposed to LBP development during standing exhibited altered neuromuscular strategies prior to pain development"*. Another study (Ng et al, 2002) said that *"reduced levels of activity of the multifidus muscle during axial rotation exertion in LBP patients may indicate that spinal stability could be compromised."* When assessing paraspinal EMG test variables generated from subjects undergoing fatiguing assessment (Heydari et al, 2010), the authors noted that *"Based on self-assessment data, subjects with no history of LBP with a half-width of greater than 56 Hz were at a threefold greater risk of developing LBP as compared with the remainder of the population"*. Finally, when examining torso muscle EMG profile differences between patients of back pain and control (Kumar & Prasad, 2010), the authors stated that *"SEMG can be used in discriminating between LBP patients and controls"*,.

2.2.2 SURFACE ELECTROMYOGRAPHY MEASUREMENTS

SEMG signals can be represented by two variable types – amplitude and frequency (Conforto & D'Alessio, 1999; Kamen & Caldwell, 1996; Lehman & McGill, 1999).

Amplitude measurement has been used extensively in many different studies and has shown ability in evaluation of back pain patients by reflecting on the symmetry of muscular activities (Finneran et al, 2003).

Frequency measurement has been used in discriminating individuals with low back pain (LBP) from those without (Beidermann et al, 1991; De Luca, 1997; Fuglsang-Frederiksen, 2000), identifying back muscle impairment (Roy et al, 1995), assessing and monitoring rehabilitation (Roy et al, 1995) and muscle fatigability (Mannion et al, 1997).

A large body of work exists within the literature that shows the SEMG provides valuable information that can be utilised as an important outcome assessment tool in the treatment and rehabilitation of LBP. The advantages of this method are that it provides a non-invasive, and therefore relatively simple to set up, method of assessing a patient. The downsides are that this method is prone to signal interference from external and non-relevant internal sources, making day-to-day application of the technique problematic.

With a view to improving this situation, work has been carried out with the aim of creating suitable tools for analysing SEMG lumbar data. This work can be broadly split into two areas, work which creates new analysis techniques, and work aimed at cleaning up raw signals.

Various measurement strategies were evaluated (Larvière et al, 2002) with a view to identifying how various EMG indices could have their reliabilities improved. This review also noted that the sex of a subject would play a part in EMG diagnosis, as females present different back muscle composition and reduced back muscle endurance.

A description of the various EMG variables can be found in section 4.4

2.2.3 GENERAL BACK PAIN PREDICTION

MAXIMUM VOLUNTARY CONTRACTION

It has been shown in many studies that subjects with chronic LBP have weak paraspinal muscles (Arena et al, 1991; Mayer et al, 1989). A true Maximum Voluntary Contraction (MVC), that is one not subject to a self-limiting effect by reduced effort from a subject, can be predicted from anthropometric data (Oddsson et al, 1997). Also, it has been shown that back muscle strength is correlated with body mass and lean body mass (Mannion et al, 1999).

BODY FAT

Body mass index (BMI) has previously been linked with variance of MF (Median Frequency) slope results (Roy et al, 1995). This was attributed to spatial filtering of higher frequencies, which reduces values derived from the MF and the half-width (Roy et al, 1986). Back pain patients have higher IMFs (Initial Median Frequency), half-widths and percentage body fat. This would suggest that spatial filtering is not significant, or that IMF and half-width would be even better discriminators if correction for spatial filtering could be achieved. Fat percentage was not found to be a significant factor in predicting LBP (Humphrey et al, 2005).

2.2.4 SEMG ANALYSIS FOR BACK PAIN PREDICTION

ROOT MEAN SQUARE (RMS)

The power spectrum of EMG increases with fatigue (Edwards & Lippold, 1956). It has been suggested that this increase is greater in chronic LBP subjects (Lee et al, 1992). This information points to the RMS variable being suitable for use as a discriminator.

MEDIAN FREQUENCY (MF) SLOPE

It has been commented that MF slope is a suitable technique for monitoring back muscle fatigue (Mannion & Dolan, 1994), and also that the change of MF over time is thought to be one of the defining characteristics of fatigue (Edwards & Lippold, 1956).

It is not surprising therefore that much recent work comparing EMG of chronic LBP with EMG of no LBP groups has focused on this variable.

Using IMF and the fatigue slope, a sensitivity of 0.91 and a specificity of 0.83 was achieved (Roy et al, 1989). However some methodological shortcomings in this study have been identified (Beidermann et al, 1991); namely a lack of evidence that the selected muscle recording sites were actually related to those muscles under investigation, and the poor identification of the direction of muscle fibre direction. Another study achieved a sensitivity of 0.88, and a specificity of 1.0 (Klein 1991), but only studied university rowers, who cannot be considered to be typical of either LBP or no LBP groups. Roy et al attempted another study, achieving a sensitivity of 0.85 and a specificity of 0.86 (Roy et al, 1995). These figures indicate that this technique shows promise in discriminating between LBP and no LBP subjects.

It is worth noting that classifications using the MF slope start to deteriorate significantly below 55% of their predicted MVC (Oddsson et al, 1997). Also a recent study showed no significant difference between LBP and no LBP groups (Humphrey et al, 2005) using the MF slope variable.

INITIAL MEDIAN FREQUENCY (IMF)

A number of studies have shown that the IMF is a variable that is reliable and relatively independent of load (Humphrey et at, 1998; Nargol et al, 1999).

Other research groups however have shown that it is load-dependent at low loads (Mannion and Dolan, 1996). This is particularly relevant in this area as low loads are the ones more likely to be achieved by chronic LBP subjects.

Significant differences in the proportions of different fibre types between LBP and no LBP groups were demonstrated (Mannion AF, 1999). This study did not however demonstrate different fibre sizes occurring in a given fibre type. Consequently, how IMF discriminates remains obscure.

Another study (Humphrey et al, 2005) found IMF to be one of the most accurate discriminators. However again, questions were raised regarding its ability to discriminate at lower loads (Oddsson et al, 1997).

COLOUR MAPS

As this section concerns work done towards completion of the thesis, this will be covered in greater detail in Chapter 6. However, a brief overview is appropriate at this point.

A spectral colour mapping technique has been devised (Greenough et al, 1998). The technique consists of taking a Fast Fourier Transformed (FFT) spectrum and plotting it onto a 2D image. In this case the signal was recorded over 30 s, and

instead of transforming the whole of the recorded signal, the signal was split into 1 second epochs. This allowed observation of how the transformed spectra changed over time. On the colour map image, the x axis represents time, the y axis frequency, with pixel colour being used to show signal amplitude. The visual sorting of these images by an experienced operator proved capable of distinguishing between no pain ever and chronic pain groups, but proved less capable of identifying the group that had a previous history of LBP (Greenough et al, 1998). It is possible that with modern image analysis methods these results can be improved upon. This colour mapping technique provided rich information on how amplitude and frequency change over time, but was time consuming to create and required an expert observer for analysis. Work in this area lead to the development of the use of the half-width variable with respect to EMG analysis (Nargol et al, 1999).

HALF-WIDTH

The half-width variable shows the possibility of being used as a predictor for future onset of LBP (Humphrey et al, 2005, Heydari et al 2010). Also, the half-width has been shown to be a variable that is reliable and relatively independent of load (Humphrey et at, 2005; Nargol et al, 1999).

As well as the notion that fatigability of the paraspinal muscles is significantly different between LBP and no LBP groups, back pain sufferers have a greater proportion of type II fibres and more pathological fibres (Mannion AF, 1999). The half-width may be a good discriminator as it reflects not only how the muscle fatigues (fibre type distribution) but also the initial state of the fresh muscle (fibre size).

As conduction velocity is proportional to muscle fibre diameter, the spread of the power spectrum is therefore narrower in a homogeneous control group, which is reflected in a narrower spectral half-width.

A broader spectral half-width would suggest that recruitment was taking place across more than one fibre type, meaning that that person was experiencing a higher fatigue level than that of the control group.

A muscle's fibre-type composition is largely under genetic control, although with appropriate training this can change to some extent (Goldspink et al, 1992). Training can also change the diameters of individual fibres (Saltin & Gollnick, 1983) and could result in a more heterogeneous set of muscle fibres.

2.3 BIOFEEDBACK

Presenting data on a subject's physiological functions to an end user is known as Biofeedback. Biofeedback is a clinical modality in which technology or instrumentation is used to allow a patient to gain awareness of, and control over, physiologic processes. Successful treatment employing biofeedback can be beneficial for several stress-related and pain conditions, as well as other forms of somatic disturbance (Glick & Greco, 2010).

It must be said that typically biofeedback is a "live" system, whereby a subject is asked to perform a task and then they see the results of the task immediately. This enables them to reattempt the task in a different manner until satisfactory feedback is obtained. The proposed system described in this thesis would present results to a subject, at which point it is anticipated they would perform certain exercises and return after a number of weeks for another test. Whilst this system is not a typical biofeedback system, the fact that a subject is being shown visual feedback and asked to modify their behaviour based on this means that it is close enough for the term to remain relevant.

The biofeedback technique itself is based on the fundamental learning principle that individuals learn to perform a particular response when they receive feedback on information about the consequences of that response, and then make the appropriate compensatory behaviour adjustments. This is how individuals have learned to perform the wide variety of skills and behaviours utilised in everyday life (Gatchel et al, 2003). It is hoped that this reinforcement would be beneficial in raising exercise regime compliance probabilities in LBP patients.

Biofeedback can be a valuable tool in the treatment of chronic pain. In addition to being an effective method for directly addressing physiological processes that cause chronic pain symptoms, biofeedback facilitates psychological interventions that aid the chronic pain patient in developing greater skills for coping and improved functioning (Jepson 2008).

The technique has been used in treating patients with low back pain, with mixed results. Several studies (Flor et al, 1986; Flor et al, 1983; Nouwen & Solinger, 1979) have demonstrated pain reductions in LBP subjects, whilst others (Fordyce et al, 1976; Turner, 1982) only obtained minimal or no pain relief. However these types of studies were using a live feedback system, and as such are only of slight relevance to this thesis.

2.4 SIGNAL PROCESSING

2.4.1 DOMAIN TRANSFORM METHODS

FOURIER TRANSFORMS

Traditionally, Fourier transforms have been used to aid in the production of EMG outcome values (Pope et al, 2000; Sparto et al, 1999). The limitation of using this technique is that the Fourier transform requires a stationary signal (Beck et al 2005; Karlsson et al, 1999; Karlsson et al, 2000), i.e. one that will not experience any change in frequency content over time (see Chapter 3).

With regards to this, there is some agreement that this stationary condition is not met with regards to EMG testing during dynamic contractions, due to changes in muscle force and length, velocity of movement, and electrode placement changing relative to the muscle fibres (Knaflitz & Bonato, 1999; Roy et al, 1998).

In contrast to this, various studies have indicated that, dependent on the muscles tested and the force exerted, the EMG signal from isometric contractions can be seen as wide-sense stationary over time epochs between 0.5 and 2 seconds (Karlsson et al, 1999; Karlsson et al, 2000; Knaflitz & Bonato, 1999).

Another study (Merletti et al, 1992) attempted to define this property of wide sense stationarity more precisely. The authors indicated that the condition holds true during short contractions (20-40 s) at low intensity levels (20-30% of MVC), and for contractions of shorter length (0.5-1.5 s) for higher intensity levels (50-80% of MVC).

SHORT TERM FOURIER TRANSFORM

A method previously described (Karlsson et al, 2000) as being suitable to get around this non-stationary issue is the Short Term Fourier Transform STFT. With this method a window function (of size corresponding to the signal window time frame) is slid along the time axis. This results in a two-dimensional representation of the original signal. With specific respect to EMG, the problem of non-stationarity can be solved by dividing the recorded signal into appropriate lengths and applying the Fourier transform to each independently, resulting in a series of short segments where wide sense stationarity can be assumed i.e. a STFT (Karlsson et al, 2000).

The downsides to the STFT are that short window segments allow good temporal resolution but poor frequency resolution, whilst long window segments allow good frequency resolution, but poor temporal resolution (Beck et al, 2005; Karlsson et al, 2000). Also, as the window segment is of a fixed width, the frequency resolution will also be of a fixed width (Beck et al, 2005; Karlsson et al, 2000; Ng et al, 1997).

WAVELETS

Wavelets are of a similar nature to the STFT in that a windowing function is used to assess individual sections of a recorded section. However in this case, a recursive algorithm is used to make multiple passes of the recorded signal whilst altering the window size based on a mother wavelet. As such, this technique provides the highest possible resolution in both the temporal and frequency domains (Hostens et al, 2004). This technique has been successfully applied in analysing complex non-stationary signals in other scientific fields (Pope et al, 2000), along with studies conducted on EMG variables (Hostens et al, 2004; Karlsson et al, 1999).

COMPARISON BETWEEN WAVELETS AND STFT

Other than general commentary about Fourier transforms being suitable in the case of non-stationary signals, very little actual evidence is presented to actually quantify the error levels introduced into results obtained using this method. Some work has been completed however, including that which has been conducted in comparing the two techniques in other areas.

One study (Houtveen & Molenaar, 2001) compared these methods whilst examining heart rate variability data using the power spectra. In this study the authors demonstrated high correlation coefficients and small differences between both methods. They indicated that the errors were larger for non-stationary signals. Based on these results the authors stated that they believed the wavelet method to be the correct one when using non-stationary data as opposed to the STFT.

Another group (Zhang et al, 2003) used both methods to create independent models simulating the Doppler blood flow signal of the carotid artery. Again the authors indicated that the wavelet model better fitted the theoretical spectra than the STFT, concluding that the wavelet method was to be preferred in this area.

Moving onto synthetic EMG signals, lower error levels were demonstrated with the wavelet method as compared to the STFT (Isson et al, 2000). The disadvantage of using synthetic signals in this case was outweighed by the benefit that the results obtained by both methods can be compared to known ideal answers.

Using real EMG signals, it was found that wavelets provided less noisy estimates than when using the STFT (Karlsson et al, 2000). This study used EMG recordings obtained during dynamic contractions.

Despite the previously mentioned studies indicating that the wavelet transform is to be favoured over the STFT, other work has been published showing that the STFT

can still be used, even in non-stationary conditions. It was suggested (MacIssac et al, 2001) that Fourier transforms are useful for assessing fatiguing dynamic contractions as the method was able to identify a decrease in the mean power spectrum during the test. High correlations were also noted between wavelet and Fourier transforms whilst assessing non-stationary isometric contractions (Beck et al, 2005).

SUMMARY

When assessing what method to use to create the power spectrum of recorded data, it is obviously not as simple as just automatically selecting the ‘best’ method. One must take into account the location the tests are being performed on, the type of muscle activity being used to invoke the EMG data, and the outcome variables that are to be examined. As the tests performed in this project were fatiguing, isometric tests examining the lumbar region, the STFT provides ample resolution to clearly examine the necessary outcome variables, without needing to resort to the more complicated wavelet transform.

2.4.2 NOISE ELIMINATION STRATEGIES

GENERAL NOISE FILTERING

Surface EMG signals are invariably contaminated with extraneous signal data from a variety of sources. These can be from the electronics that comprise the testing equipment, the skin/electrode interface, or from various biological sources. Band pass filters are typically used to remove certain portions of a recorded signal. However as the noise components can overlap the EMG components when examined in the power spectrum care is needed to preserve as much of the signal data as possible. Calculating appropriate band pass frequencies is a compromise between these areas as these methods will remove all signal data at a given frequency range, irrespective of the source of said data.

HIGH FREQUENCY NOISE SOURCES

Depending on muscle type, fatty tissue levels between the signal sources (muscles) and skin, electrode spacing, and the shapes of the action potentials, the frequency spectrum of surface EMG signals ranges from 0 to 400 Hz (Basmajian and De Luca, 1985). It has been suggested (De Luca et al, 2010) that the high frequency cut-off should be set where the amplitude of the noise components outweighs that of the EMG signal. The range identified was 400-450 Hz.

LOW FREQUENCY NOISE SOURCES

There are several kinds of low frequency noise that possess the potential to corrupt recorded EMG signal data, both from external and internal sources.

EXTERNAL SOURCES

Wires leading from electrodes to the recording hardware, and to a certain extent human skin, act as fairly efficient aerials (Sherman, 2003). This has the effect that any electromagnetic sources in the area (such as fluorescent lights or radio waves) will get picked up and added to the signal mix.

An additional source of external noise is the cable motion artefact (De Luca, 2010). The external wires connecting the electrodes to the recording hardware have a metallic core, and when these wires sway a movement is produced relative to the Earth's magnetic field. In a similar manner to the principles of electricity generation, this produces a small but measurable voltage.

Both of these signal sources are of a very low intensity, but their impact is magnified by the fact that they are introduced to the system before the amplification process, thereby greatly increasing the effect. However modern electronics technology and circuit design can almost completely eliminate these noise sources from recorded data (De Luca, 2010).

INTERNAL SOURCES

Two internal noise sources are from the electronics in the amplifier (thermal noise) and from the skin-electrode interface (electrochemical noise) (Huigen et al, 2002). These noises form a base line noise and can be seen whenever the electrode is attached to the skin. As they can be produced independently from EMG signal data, filtering them is a relatively simple process.

An additional internal noise source is movement artefact noise. This noise is produced when a muscle moves relative to the electrode on the skin above it. As has been pointed out in a previous study (Beck et al, 2003), the amplitude of the signal can vary considerably according to the proximity of the electrode to the

innervation point of the muscle. This noise source becomes less relevant when examining the frequency spectra of isometric contractions, as the frequency components of a source signal are not affected by their amplitude, and isometric contractions reduce the amount of movement experienced by a muscle. This noise source can also be minimised by placing the electrodes at some distance from the innervation zone (De Luca, 1997).

Various recommendations have been put forward in respect for choosing a low frequency cut-off. As a part of Standards for recording EMG data (Merletti, 1999), a cut-off value of 5 Hz is recommended. The Surface EMG for Noninvasive Assessment of Muscles (SENIAM) (Stegeman and Hermens, 1998) recommends cut-off values between 10-20 Hz. The recommendation of the International Society of Electrophysiology and Kinesiology (Winter et al, 1980) is for a cut—off value of 20Hz. Finally, for publication in the Journal of Electromyography and Kinesiology, it is required that a report use a cut-off of 10 Hz.

The 20 Hz cut-off will remove a portion of the EMG signal of some significance along with the associated noise in that frequency range. If more intelligent methods are available that specifically target noise, rather than the whole area the noise exists in, a lower general cut-off can be used.

ECG CONTAMINATION REMOVAL

As this section concerns work done towards completion of the thesis, this will be covered in greater detail in Chapter 6. However, a brief overview is appropriate at this point.

Due to the spatial proximity of electrode sites to the heart, EMG signals collected from trunk musculature are often contaminated with heart muscle activity (ECG)

(Allison, 2003). This effect is worsened when taking into account that the EMG and ECG power spectra overlap. The EMG signal spans from 10-500 Hz, with the majority of the signal intensity occurring in the 20-200 Hz range. The ECG signal spans from 0-100 Hz, with the majority of the signal intensity falling below 35 Hz. A key indication that this contamination has occurred is a peak in the lower frequencies (10-25 Hz) of the EMG power spectrum (Coxon et al, 2011).

Various methods have been examined to assess their use in removing this contamination. An area that has attracted much assessment is using various filters to remove affected frequency ranges. One study (Redfern et al, 1993) examined a range of finite impulse response high pass filters, and concluded that a cut-off of 30 Hz was optimal from the examined choices. Two studies (Levine et al 1986, Bloch et al 1983) examined a subtraction template technique with mixed results. In a partial response to these studies, another group (Bartolo et al, 1996) compared those results to their own based upon amplitude gating, which they found to be superior. This finding was supported in another piece of work (Black and Lovely, 1997) which compared the technique to clipping and noise cancellation methods. While these methods all have shown at least some ability to reduce the effect of ECG contamination of the EMG signal, the fact that power spectrum and frequency based subtraction methods will inevitably remove underlying EMG data is unavoidable.

A technique that avoids this limitation is Independent Component Analysis (ICA). Whilst the previously mentioned transformation methods (FFT, wavelet) take a time domain input and return a frequency domain output, this method orders the output based on mutual statistical independence. ICA is a multi-dimensional signal processing technique to separate signals from different sources into a series of additive subcomponents, based on their mutual statistical independence.

The ICA technique is fully described in Chapter 6. However, very briefly it is a subset of Blind Source Separation, and the framework for the technique was first formulated in 1986 (Herault & Jutten, 1986). It is a technique that allows for the separation of underlying signals from a signal mix, given the assumption that these signals are non-Gaussian, and that they are independent of each other.

CHAPTER 3

ORIGINAL PROJECT

3.1 INTRODUCTION

This thesis represents a continuation of work performed at James Cook University Hospital (JCUH) towards creating a system to act as a predictor towards Low Back Pain (LBP). Other research has been conducted at this centre before the work described in this thesis was commissioned, and this chapter aims to discuss this with a view to putting the current work into context beside it.

The current work can be seen as the third stage of the overall EMG project at JCUH. The first stage started in 1997 and consisted of doctors working under The Back Care Project, which was a part of South Tees Hospitals NHS Trust. This group was interested in producing a tool that discriminated between Low Back Pain (LBP) and non-LBP subjects. Identifying that using EMG variables which monitor the total strength of a subject's back muscles was a less than optimal tool to discriminate between Low Back Pain (LBP) and non-LBP subjects, they looked to how the spectral frequencies change over time. In addition to this they examined various techniques for analysing and displaying this EMG data from lumbar muscles.

A weakness to the first stage was the limited subject sample size, along with all of these subjects being in full time hospital employment. As previously described in Chapter 1, Health Action Zone (HAZ) funding was received in 2000 which allowed EMG research to be performed on a larger, more heterogeneous population. This was therefore a larger research project, but analysis methods were concentrated around the half-width variable, which had been identified as useful in the first stage.

This second stage had some success, showing that the half-width variable was indeed useful in discriminating between LBP and non-LBP groups. However, this second round of analysis revealed that more issues had arisen, namely the difficulty in repeatedly and consistently analysing large datasets, the requirement for trained

observers to interpret the results, and the large number of signal artefacts present in the test data. The necessity of evaluating methods to overcome these difficulties led to this thesis.

A more in-depth discussion of these initial stages follows.

3.2 FIRST STAGE

3.2.1 BACKGROUND

This study was grounded in the increasing awareness of a correlation between disability, deconditioning and lumbar trunk strength. It was suggested that suboptimal, or impaired, muscle control could permit abnormal motion segment movement, which would predispose a subject to pain.

At the time of work, dynamometric methods were gaining somewhat in popularity, despite a lack of validation. However this kind of testing had been shown to be vulnerable to influence from psychological factors and growing evidence was suggesting that a stronger back is not predictive of future back injury. A search for a more objective method led to the examination of EMG techniques to measure the shifts of the power spectrum during fatiguing isometric contractions.

Two areas were examined during this phase;

- Are surface EMG measurements reproducible over a period of time in healthy volunteers?
- How useful would a graphical representation of the variables established in the Section 2.2. be in discriminating between LBP and non-LBP groups.

3.2.2 VARIABLE EXAMINATION

METHODS

Ten healthy male subjects were recruited from the local hospital community. All of these subjects gave informed consent and ethical approval was granted. Anthropometric details are given below;

Variable	Mean	
Age	38.0 years	(range 26-50)
Weight	70.1 Kg	(SD, 11.6)
Height	1.618 m	(SD, 0.119)
Body Mass Index	27.3 Kg/m^2	(SD, 4.9)
Percentage Body Fat	22.4%	(SD, 4.6)
Lean Body Mass	46.1 Kg	(SD, 18.6)
Maximum Voluntary Contraction	87.5 Kg	(SD. 33.2)

Table 3.1 Anthropometric details of subject group.

Each subject underwent three rounds of testing, with each round being between five days and four weeks apart. Each test round consisted of two EMG tests, with the subject having at least one day's rest between them. In each round of testing the subject's Maximum Voluntary Contraction (MVC) was asessed and the subjects were then asked to achieve levels of 1/3 and 2/3rds of this amount for 30 s whilst EMG recordings were made. The data acquisition and analysis process is as described in Chapter 4.

RESULTS

Five variables were recorded at 1/3 and 2/3rds of MVC;

- Initial Median Frequency (MF)
- Initial Power
- The Regression Slope of the MF
- The Regression Slope of the Power
- Half-width

The reproducibility of the measured variables over the three occasions was assessed using estimates of reliability. They give the proportion of the variance of an observation due to true inter-subject variability, the proportion being termed as the intra-class correlation coefficient (ICCC). A figure of 0.75 or above may be considered excellent (Fleiss, 1986).

The results are tabled below;

	1/3 MVC	**2/3 MVC**
Initial MF	0.92	0.96
Initial Power	0.60	0.66
Regression Slope MF	0.44	0.72
Regression Slope Power	0.18	0.43
Half-width	0.92	0.94

Table 3.2 Reproducibility of measured variables.

These data clearly indicate the reproducibility of the Initial MF and half-width variables.

DISCUSSION

The reproducibility of the Initial MF and half-width variables can be classified as excellent. The regression slopes for MF and Power, along with the Initial Power, were not satisfactorily reproducible between tests. The suggestion was raised that a contributing factor to this is the relatively stable determinants of Initial MF and half-width, as opposed to the more stochastic processes of metabolite production, re-utilisation and vascular flow that are the primary determinants of the MF and Power slopes.

This work provided evidence that the of technique of using surface EMG to examine the spectral characteristics of the erector spinae is reliable with respect to certain variables, giving encouragement to its use in future studies.

3.2.3 GRAPHICAL REPRESENTATION OF VARIABLES

METHODS

Ninety nine people, all in full-time hospital employment, were recruited. All of these subjects gave informed consent and ethical approval was granted. They were divided into four categories; those with “no pain ever” had never had an episode of back pain sufficiently severe to lose time from work, those with “history” had previously had such an episode but not in the past two years, those in the “chronic” group had recurring pain with time off work within six months of testing but were without pain on the day of testing, and finally those with “acute” pain had a history of pain and had pain on the day of testing. There were 48 men (24 no pain ever, 5 history, 16 chronic, and 3 acute) and 51 women (17 no pain ever, 15 history, and 19 chronic). Anthropometric details are given below;

		No Pain Ever	History	Chronic
Number	**Males**	24	5	16
	Females	17	15	19
Age - yr	**Males**	35.4 (16-52)	32.2(20-43)	45.1(25-65)
(range)	**Females**	39.8 (25-62)	34.5 (18-59)	40.3 (23-57)
Body Mass Index - kg/m^2	**Males**	28.2 (5.50)	27.2 (3.49)	29.2 (3.41)
(standard deviation)	**Females**	30.3 (5.70)	26.8 (4.12)	28.9 (4.94)
Body Mass - kg	**Males**	77.8 (13.6)	68.7 (9.14)	74.9 (10.7)
(standard deviation)	**Females**	62.8 (10.7)	61.3 (6.19)	65.5 (11.2)
Lean Body Mass - kg	**Males**	61.7 (9.74)	57.3 (6.32)	58.1 (8.73)
(standard deviation)	**Females**	43.1 (5.69)	42.9 (4.94)	43.1 (5.26)

Table 3.3 Anthropometric details of subject group.

Each subject underwent a single round of testing which consisted of two individual tests, with a minimum of four minutes rest provided between. In a similar manner to the previous project, the first test took place with the test subject aiming for 1/3 MVC, with the second test being at 2/3rds MVC, each for 30 s. The data acquisition and analysis process was the same as is described in Chapter 4.

A three-dimensional image was created representing time on the x-axis, frequency of EMG on the z-axis, and signal amplitude on the y-axis.

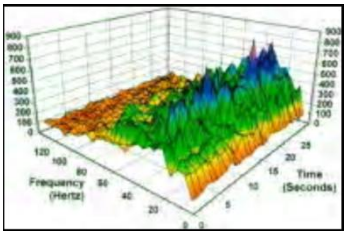


Figure 3.1 - 3 Dimensional Spectral colour map

For the two-dimensional image the signal amplitude is divided into 12 equal bands, and each band is represented by a different colour on the two-dimensional plot of time versus frequency. This produced a contour map of the data.

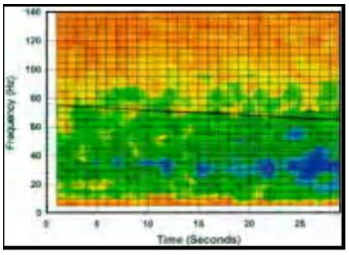


Figure 3.2 -2 Dimensional Spectral colour map

Spectral colour maps were produced from a randomly selected subset of 66 people (21 with chronic pain, 26 with no pain ever, and 19 with a history of pain), and were visually sorted by a single observer. This observer was unaware of the number in each category. The observer then arranged the maps in the order thought to represent a range from no pain ever to chronic pain, using the width of the green band averaged by eye for the duration of the test. For maps of similar widths the amount of variation in the colour bands was assessed, with maps with more variation being placed towards the chronic end.

RESULTS

Marked differences were observed in the colour spectral maps among people with no pain ever, people with a history of pain and those with chronic pain. Subjects with chronic pain had a wider disorganised spectrum, and data for those with acute pain appeared almost chaotic.

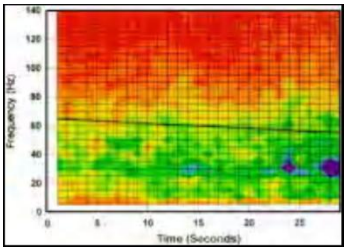


Figure 3.3 – Spectral colour map for person with no pain ever

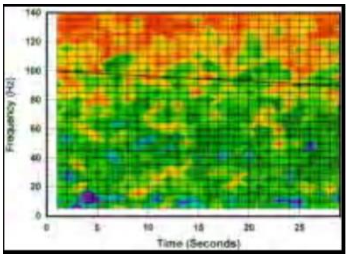


Figure 3.4 – Spectral colour map for person with a history of pain

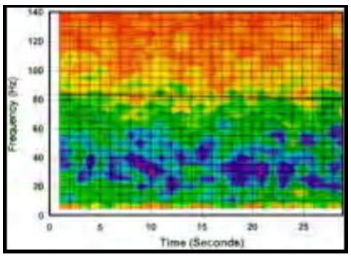


Figure 3.5 – Spectral colour map for person with chronic pain

Sorting the spectra visually had a high degree of sensitivity and specificity for detecting subjects with no pain ever, and those with chronic pain. The method was less successful at differentiating subjects with a history of pain. The colour maps did not appear to be dependent on load or laterality (possibly as they were normalised to the maximum value), and the ability to discriminate on a blinded basis between

people provided powerful evidence of a correlation between muscular control and low back pain.

3.3 SECOND STAGE

Building on the promising results described in the previous section, a further data collection exercise was carried out. For this exercise efforts were aimed at recruiting from the general population, rather than from only hospital staff. In addition to this the EMG tests were carried out by the researchers rather than trained medical staff. It was hoped that these recruiting/testing methods would provide more robust results that could be repeatable on a clinical basis.

Unfortunately, due to a number of reasons, this research was not carried out to its natural conclusion. Nevertheless the data collection was completed, and this provided a valuable resource for future projects.

3.3.1 RECRUITMENT

Initial recruitment techniques utilised health promotion roadshows, which were held in prominent locations throughout Teesside (UK). A large-scale media campaign was also initiated. These roadshows aimed to promote a positive message relating to the importance of exercise with regards to LBP. Each person was told they would be given the opportunity to obtain unique individual information relating to their back muscle function from EMG testing. This was designed as a motivator to encourage subjects to participate.

Secondary recruitment took the form of approaching selected professional groups (teachers, police, prison officers) through their work. Testing took place at their workplace, but the same research message was employed.

This recruitment aimed to recruit at least 300 test subjects. Unfortunately, after extensive efforts, only 192 subjects were eventually recruited. The initial demographic details are listed below.

	Male	**Female**
N	90	102
Age - yrs	43 ± 10	42 ± 10
Weight - kg	83 ± 11	67 ± 11
% Body Fat	22 ± 5	33 ± 5

Table 3.4 Anthropometric details of subject group.

3.3.2 METHODS

Each subject was to be tested on three separate occasions; on first appointment, after one year, and then finally two years after the first appointment. The test started with the subject completing a questionnaire, which contained questions pertaining to the LBOS, MSPQ, ZUNG, and BBQ scales. Next the EMG test was performed, the data acquisition and analysis process was the same as is described in Chapter 4. The subject was asked to maintain a load of 70% of their lean body mass for 30 s, whilst EMG variables were recorded. Finally a fitness test, consisting of a two minute step test, was performed after the subject had rested sufficiently. Once a subject had completed all three tests, data was available detailing their fitness, level of back pain (if any), and their lumbar EMG measurements across the two years.

Unfortunately, along with subject recruitment, an issue emerged of subject retention. Not all of the subjects initially recruited stayed for the full three tests over the two years. Details of subject retention are shown below.

	Number
Completed 1st Test	192
Completed 2nd Test	142
Completed 3rd Test	109

Table 3.5 Subject retention data.

3.3.3 DISCUSSION

Due to the researcher in charge of this project leaving prematurely these data were never analysed. Despite this, and the recruitment and retention issues, the data produced in this time period have since proven extremely useful. The test subjects come from a wide range of backgrounds and all of the tests were performed by non-medically trained individuals. This enables assessment of the suitability of the Lumbar EMG test to be used in a clinical environment amongst the general population. The fact that the subjects were examined across two years enables the testing of any predictive factors that might exist. Finally, possibly due to the relatively untrained nature of the researchers, it was during this testing phase that the amount of errors potentially present in the EMG data began to be quantified. All of these factors provided a very good starting point for the research contributing to this thesis.

CHAPTER 4

EMG MACHINE,

MEASUREMENT AND DISPLAY

4.1 SYSTEM COMPONENTS

4.1.1 EMG TESTING MACHINE

The EMG testing machine is the apparatus that connects the human test subject to the computer; it comprises all of the equipment used to record the signals that reach the skin from the subject's muscles. The key components are listed below;

ELECTRODES

In the case of medical usage, an electrode transfers the energy of ionic currents in the body into an electric current that can be measured and recorded using the appropriate equipment. In the case of EMG, the electrodes are part of a passive system, i.e. they are simply monitoring the impulses, not contributing to them, meaning there is no chance of electric shock to the patient.

Proper procedure was followed in the choice of, and the preparation of, the placement location. As previously mentioned this is of vital importance while recording lumbar spine EMG data. The electrodes are connected to the amplifier by wires.

WIRES

Wires are the part of an electrical circuit that are used to connect the various components to each other. Within the context of EMG testing it is the wires that connect the electrodes to the amplifier that are of interest as they are a source of potential error in the system.

As the signals being analysed are very weak, background noise becomes an issue. A common problem is the 50 Hz spike obtained when a test is conducted near to a 'leaky' electrical device (fluorescent lights for example). This is observed as a small

current in the connecting wires and is intermingled with actual EMG data. Radio waves can also contribute to this form of error.

Swaying wires also cause errors to enter the system. A swaying wire will move relative to the Earth's magnetic field, generating a small current in much the same way large scale electrical generation works.

These errors are small but are encountered before the amplification stage of the recording process and therefore amplified along with the original signal.

AMPLIFIER

An amplifier is a device which increases the amplitude of the voltage, current or power of a source signal. In this case an amplifier is used to boost the EMG signals so they can be read by the Analogue to Digital Converter (ADC).

Amplifiers are usually found in audio applications. In sound reproduction, sound waves move a microphone diaphragm back and forth. The microphone translates this movement into an electric signal which represents the rarefactions and compressions of the sound wave. This electric signal is used by a recorder to encode the pattern in some sort of medium, such as magnetic impulses on a tape or pits and grooves on a CD. A player reinterprets this pattern as an electric signal and uses this electricity to move a speaker cone back and forth. This movement of the speaker cone recreates the sound waves initially picked up by the microphone.

The microphone only produces a small current, due to its sensitive nature, and while this is fine for most stages of the process it is insufficient to move the speaker cone. Amplifiers are used to boost the audio signal whilst preserving the overall pattern.

Rather than simply boosting the original signal, amplifiers produce a completely new signal, albeit obviously one based on the original. It is best to consider these two signals as two separate circuits. The output circuit is the amplified signal and is

generated by the amplifier's power supply. The load on the output circuit is moving the speaker cone. The input circuit is the electrical audio signal, taken either from a storage medium or directly from a microphone. The load on the input circuit is to apply a variable resistance to the output circuit, thereby enabling the output circuit to resemble the input circuit.

Amplifiers are used in a similar way in the EMG field. Due to the nature of the received signal (initially small and insulated from the electrode by fat and skin layers) amplification is needed so the signal can be recorded and interpreted by the ADC. Considering the example above, the microphone corresponds to the electrodes and the speaker corresponds to the ADC.

ANALOGUE TO DIGITAL CONVERTER

Analogue to Digital Converters are used in almost all signal processing applications. They are basically electronic circuits that convert analogue signals into digital ones, a process which facilitates input into a computer. Many systems designed to measure physical properties such as temperature or pressure produce analogue readings in the form of voltages. These readings must pass through an AD Converter before computer processing of the information is possible.

When utilising an ADC it is important to consider the overall accuracy of the device. This accuracy dictates how closely the discrete digital values follow the continuous analogue values. Two values determine the accuracy of an ADC, the sampling rate and the bit rate.

The sampling rate is how many times per second a snapshot of the analogue signal is taken. Obviously the higher the sampling rate the higher the level of accuracy achieved, the downside being the increased amount of storage space needed to store this information. To decide upon an appropriate sampling rate Nyquist

Theorem is used. This says that a signal must be sampled at twice the value of the highest frequency aimed to be captured. A real life example of this is in CD audio. The human ear can handle sounds of up to 20 KHz; therefore the sampling rate used in CD audio is 44.1 KHz.

The bit rate denotes the level of accuracy available to record each snapshot taken. Likewise with the sampling rate, the higher the bit rate, the more accurately the digital signal can correspond to the analogue one. The overall data requirements of the digital signal are the sampling rate multiplied by the bit rate.

There are several sources of error intrinsic to ADCs;

Quantisation Error is the error that results from the difference between an analogue value and the corresponding digital one. Increasing the sampling rate of the ADC, as well as increasing the number of bits per sample, will reduce this error source.

Non-Linearity is the difference between input and output signals caused by tiny imperfections in the ADC's hardware. This affects all ADCs but can sometimes be reduced by calibration.

Aperture Error results from a non-consistent sampling rate. The ADC gets the exact moment to record each sample from the system clock. This can be inaccurate due to clock jitter. Obviously the higher the sampling frequency the higher the level of error that is experienced which leads to quite significant errors at higher frequencies.

ACTUAL TEST CONFIGURATION

EMG recording sites were carefully prepared in order to ensure a constant inter-subject level of impedance. Surface electrodes were placed bilaterally over the erector spinae muscles at the L4/L5 and T5/T6 levels, with the inter-electrode distance being 10 cm.

A Medelec 2ME EMG system was used to amplify and filter the EMG signal (band pass 3-300Hz). The analogue output of the EMG system was digitised on a laptop computer using a National Instruments DAQ-Card-700 PCMCIA analogue-to-digital converter. Four channels of EMG and the output of the load cell were sampled at 1024 Hz using a continuous double-buffered process.

To reduce interference, wires were insulated and taped down, and the tests were conducted away from any obvious sources of noise (mains electricity, fluorescent lighting).

4.1.2 TEST CONFIGURATION

SUBJECTS

This is a brief summary of the second round of EMG testing, described fully in Chapter 3.

One hundred and ninety two subjects were tested in total; these were recruited from members of the general public. Each of the subjects tested on three occasions, initial contact, after 12 months and finally after 24 months. In addition to the EMG test, the subjects were asked to fill out questionnaires designed to enable calculation of their LBOS, ZUNG and MSPQ scores at each visit. After subject drop outs, 455 data sets were generated.

Subject height and weight were recorded, along with the percentage body fat. This was recorded using a skin fold calliper and from this the subject's lean body mass was calculated by subtracting the percentage of their body weight corresponding to their body fat from their total body weight.

ISOMETRIC LUMBAR EXTENSOR TESTING

The subject was placed on a stand, facing a computer screen. A pelvic rest was set in front of them, set at 6 cm below the anterior superior iliac spines. They were given a bar to hold, which was attached by a chain to a load cell fixed on the floor. With the subject leaning against the pelvic rest, a trunk angle of 30° (measured by a goniometer) was achieved by altering the length of the chain with the subject's arms fully extended.

Loading was performed by the subject pulling upwards with straight arms on this bar. The target load was set at 70% of the subject's lean body mass (the subject's weight minus the percentage figure of their body fat) and this was measured by the

load cell. The subject was asked to exert this force for 30 s whilst the surface EMG was recorded. Feedback relating to the actual load the subject was achieving and how much time was remaining for the test was indicated on the computer screen facing the subject. This display was to help the subject achieve the test targets, and to ensure a degree of accuracy was maintained across the test subjects. A degree of deviation of no greater than 10% was considered accurate for these tests.

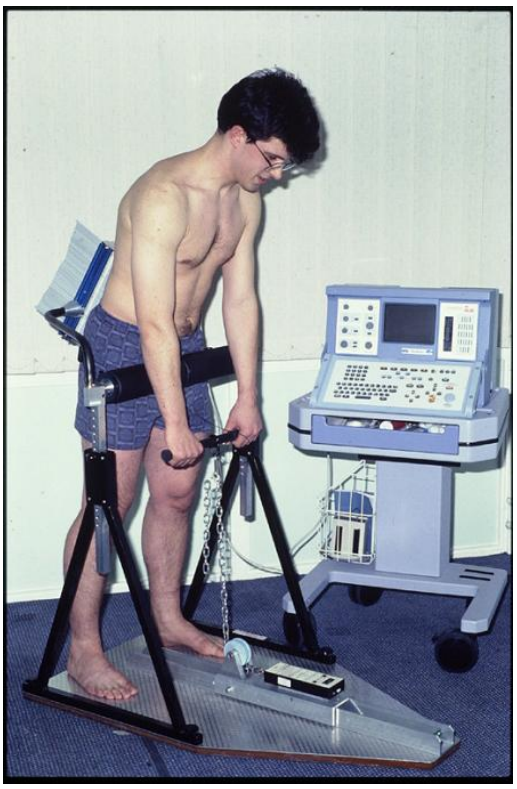


Figure 4.1 – An example test configuration

SIGNAL ACQUISITION

EMG recording sites were carefully prepared using skin abrasion in order to ensure a constant inter-subject level of impedance. Surface electrodes were placed bilaterally over the erector spinae muscles at the L4/L5 and T5/T6 levels, with the inter-electrode distance being 2 cm. A Medelec 2ME EMG system was used to amplify and filter the EMG signal (band pass 3-300 Hz). The analogue output of the EMG system was digitised on a laptop computer using a National Instruments DAQ-Card-700 PCMCIA analogue to digital converter. Four channels of EMG, and the output of the load cell, were sampled at 1024 Hz using a continuous double-buffered process, while the acquisition software maintained the real-time feedback to the subject regarding remaining time and current load achieved.

4.2 DATA ANALYSIS

4.2.1 DATA PROCESSING

This section of the chapter details the process that occurs once the signal reaches the laptop. A significant amount of processing is required before the results can be assessed; the steps are detailed below;

RECORDED DATA

Once the signal has been processed by the ADC, it is saved onto the computer used to perform the test. The file contains some data about the test participant, along with five columns of tab separated data corresponding to the four electrode locations, and the load the subject was pulling. Each column contains 30,720 data points (30 seconds multiplied by the 1024 Hz sampling rate). The file name is used to indicate the code number of the test subject, along with the test number. No identifiable data is present in the test files, the code number of the test subject can be looked up in a secure database if this information is needed. This was in order to comply with the 1998 Data Protection Act.

The recorded data is in a raw format, i.e. no processing (other than the 3-300 Hz band pass filter in the acquisition hardware) has been performed on it. Along with EMG data from the spinal muscles there will also be EMG data from other muscles, ECG from the heart, and other external sources of interference (as described in the wires section). Digital filters can be used to clean up some of this noise.

DIGITAL FILTERS

Digital filters are used for two main purposes; the separation of signals that have become combined, and the restoration of signals that have been distorted in some way. Both of these applications will be of some use to this project.

Signal separation is used when additional signal data is recorded on top of the signal that is of interest. Due to the nature of EMG recording this is an almost inevitable occurrence. Along with irrelevant EMG data from surrounding muscles being present at a surface electrode site, experiments have shown that ECG data is also present at these sites. All of this extraneous data needs to be removed from raw data before accurate testing can commence.

The first, simple digital signal filter applied to the data is a band pass filter. This filter passes frequencies within a certain range (3-300 Hz in this case) and attenuates (blocks) frequencies from outside this range. Anything outside this range will not be EMG so does not need to be recorded.

Another method used for removing unwanted data is Independent Component Analysis. This is a subset of blind source separation, used for separating an input signal into additive subcomponents based on mutual statistical independence. This method was applied in order to eliminate ECG contamination (Coxon et al, 2009), and is described fully in Chapter 6.

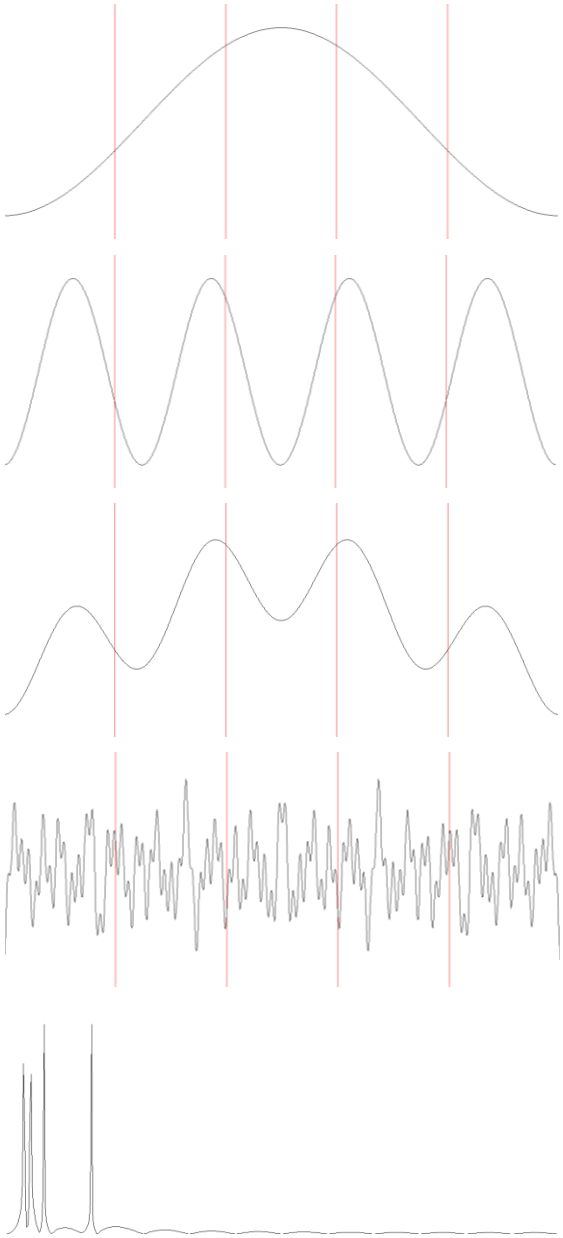
Signal distortion is also a large issue when recording EMG data. As the recorded EMG surface signal can be a million times weaker than mains electricity, significant amplification is needed to provide a useable signal to an analogue-to-digital converter. Any noise or distortion present is subject to the same amplification and can seriously corrupt recorded raw data. Digital filters provide a means to go some way towards correcting this.

A general error correcting filter used on the recorded data is the moving average filter. This filter is a type of finite impulse response filters, sometimes called a boxcar filter. For this study it is used as a smoothing algorithm.

A final type of filter used in the post recording, analysis phase is the notch filter. This filter is the opposite of the band pass filter and is used to reject a certain frequency range. In this case it is ideal to remove 50 Hz noise (i.e. from mains electricity) from recorded data.

4.2.2 MATHEMATICAL TRANSFORMS

Mathematical transformations are applied to signals to obtain further information from that signal that is not readily available in the raw signal. In this context a time domain signal is a raw signal, whilst a frequency domain signal is the transformed one. To explain why mathematical signal transforms are so useful and have so many applications it would be appropriate to include some illustrations;



The image to the left shows a 1Hz signal. In this one period takes one second.

This image shows a 4Hz signal. Here there are four periods to the second.

This more complex signal is a 1Hz signal with a 4Hz signal overlaid on top of it. The base signals are still apparent however.

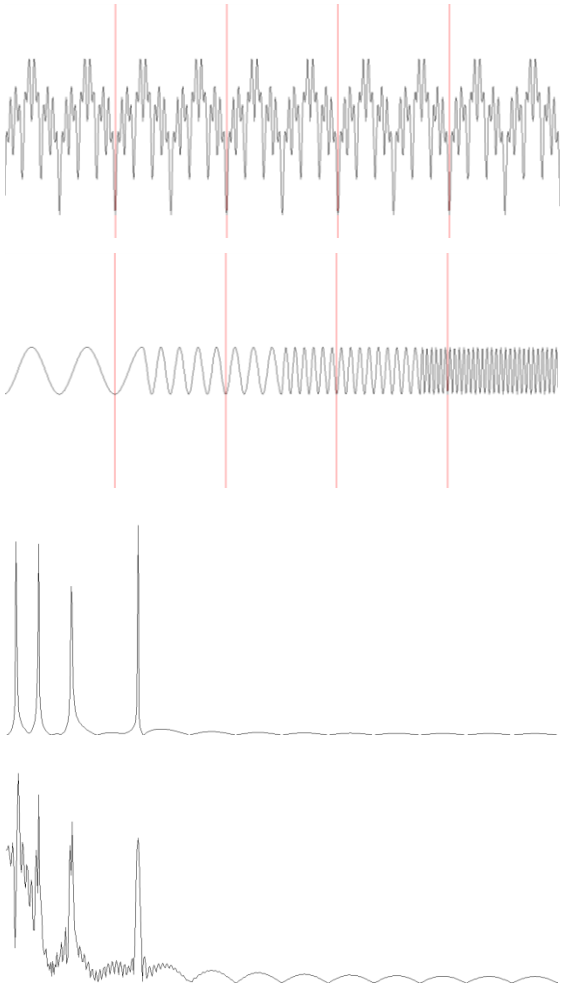
This is a much more complex signal made of four different, non-harmonic components. It is much harder to discern the individual components.

This shows the Fourier Transform of the complex signal. The peaks correspond to the individual components, making it a simple matter to identify them.

Figure 4.2 – Sample Signals

The Fourier Transform is an effective signal analysis method and with the advent of more powerful computers and the Fast Fourier Transform algorithm it has found many uses. A problem it has however is that it is only of use in situations where the signal to be analysed is a continuous one, i.e. it doesn't change over time. There is no time domain information present in the FFT spectra so it is impossible to tell

whether or not a signal was present for the whole of the test period, or just a part of it. The following diagrams illustrate this.



This is a continuous signal with four individual components. It doesn't change over time.

This is a discrete signal. It has the same four components as the previous signal but they now occur one after the other.

The FFT of the continuous signal shows the four signal components that make up the original signal.

The FFT of the discrete signal shows the same four peaks as the previous one.

Figure 4.3 – Signal diagrams detailing stationarity issue with FFT analysis

For this project, the most relevant data that can be taken out of a FFT spectrum is the peak location, peak height is an indication of how much signal energy exists at the specified frequency ranges. This means that, again for this project, the two FFTs are for all intents and purposes identical while the initial signals clearly are not. This is a simplified example but a real world example could be running vibration tests on a car engine. In this test vibrations from the starter motor would be visible on the

FFT even though they would not be present for the majority of the test. So for situations where a non-continuous signal will be encountered a simple FFT is not a suitable analysis tool.

Due to the reasoning described in Chapter 2, it was decided to use the Short Term FFT to analyse the recorded data. The 30 s EMG recordings were divided into 30 epochs, each containing 1024 samples of data, which were then subjected to an FFT.

4.2.3 CALCULATING THE FAST FOURIER TRANSFORM

The FFT was calculated using the Cooley-Tukey algorithm (Cooley & Tukey, 1965), which is based on the discrete Fourier transform (DFT) algorithm, shown below;

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i 2\pi k \frac{n}{N}} \qquad k = 0, \ldots, N-1.$$

Figure 4.4 – The Discrete Fourier Transform

This algorithm was chosen as it is the most common FFT algorithm and therefore could be implemented using well supported methodologies.

It should be noted that in retrospect the algorithm had been discovered some time before. Carl Friedrich Gauss, the German mathematician, had used that method over a century earlier. Unfortunately since he lacked the appropriate tool to implement this fully, i.e. a computer, the work was largely forgotten. This work was "re-discovered" by Cooley and Tukey just as digital computing was becoming capable of performing such complex tasks and as such they are rightfully honoured for it.

The FFT is a “divide and conquer” algorithm that recursively breaks down a DFT of size $N = N_1N_2$ into multiple smaller Discrete Fourier Transforms (DFT) of sizes N_1 and N_2, along with $O(N)$ multiplications by complex roots of unity. It is used in this case to break down the transform into two pieces of size $N/2$ at each step, which limits the window length to sizes of power of two. The sampling rate of 1024 Hz means that any epoch length being of a number of whole seconds will be sufficient to meet this criterion.

$$X_k = \begin{cases} E_k + e^{-\frac{2\pi i}{N}k} O_k & \text{if } k < N/2 \\ E_{k-N/2} - e^{-\frac{2\pi i}{N}(k-N/2)} O_{k-N/2} & \text{if } k \geq N/2. \end{cases}$$

Figure 4.5 – The Cooley-Tukey Fast Fourier Transform Formula

The formula takes an input signal array of length *N* (where the size of *N* is of a power of two) and returns an array of length *M* (where the size of *M* is the sampling rate of *N*). The second half of this resultant array should be discarded as it will be a mirror image of the first half, supporting the Nyquist Theorem assertion that a signal should be sampled at twice the rate of the highest frequency of interest.

The options for viewing and interpreting this resultant data are now described in 4.5.

4.3 TEST COMPUTATIONAL PROCESS

4.3.1 SIGNAL ACQUISITION

Once the electrical signals from the electrodes and the load cell have been amplified sufficiently and sent to the A/D converter, the output voltages produced are saved into a text file.

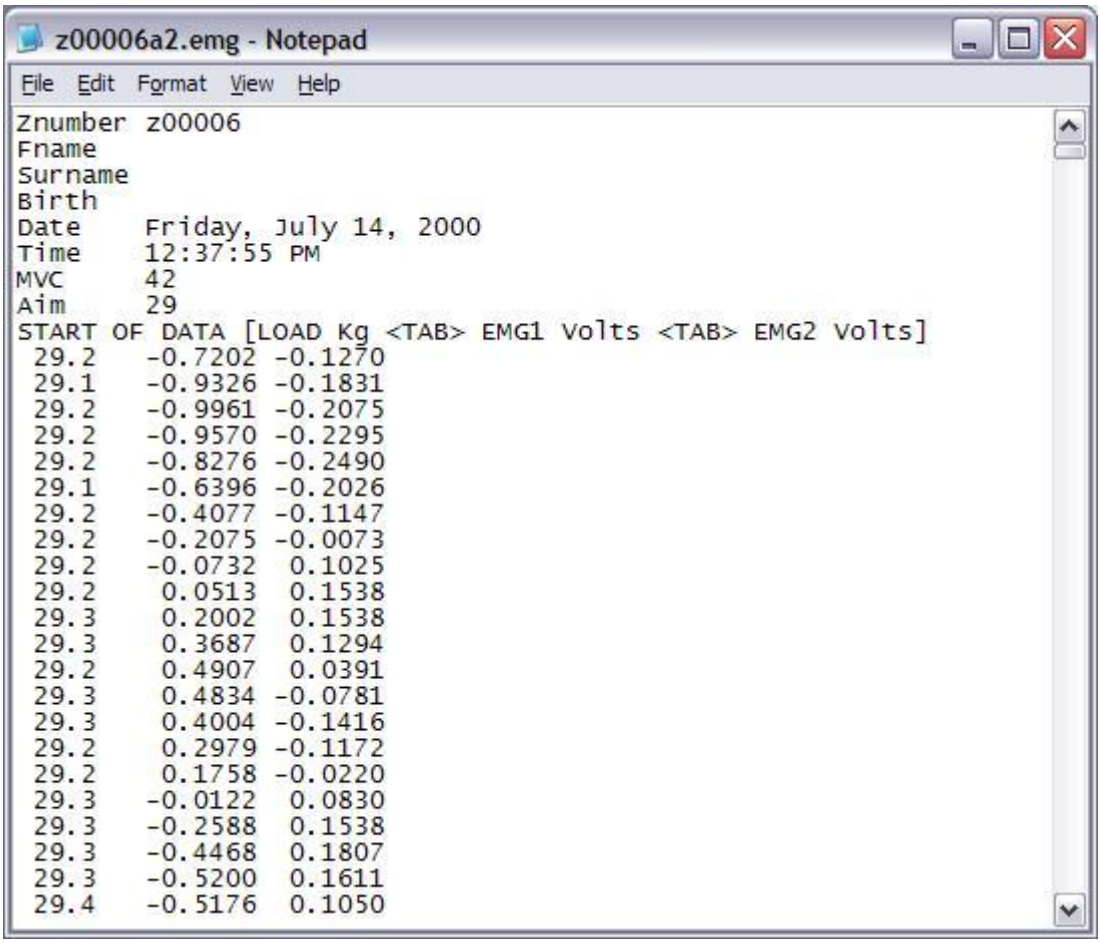


Figure 4.6 – Sample EMG Raw Data File

The above image details the header data included in the EMG raw data file, along with the formats of the signals recorded. The data was anonymised.

Each test produces two data files; the second file is identical to this one, apart from the load cell data being omitted.

In each test session, usually containing the tests of several subjects, the raw data files were saved and analysed later. This proved to be a less than ideal method as errors in test configuration often only became apparent at a point at which they could not be rectified. In the original test procedure, no error checking was carried out at this stage.

4.3.2 SIGNAL ANALYSIS

The signal analysis section starts by reading the contents of the EMG raw data files into memory, and splitting the EMG voltages into epochs 1024 data points (one second) long. An FFT (as previously described) is applied to each epoch, and the resulting data is also stored in memory.

The 30 FFTs are averaged to create a composite spectrum, representing the whole of the test. A three point moving average filter is applied to this composite spectrum to smooth it slightly, and a 50 Hz notch filter removes any mains electricity noise.

The composite spectrum is analysed in order to create values for the variables described in 4.4. This is done automatically in order to aid repeatability (see Chapter 5).

In addition to this a series of error flags are also checked and recorded if present. These errors are;

- Low Frequency Peak height: Normal Range Peak height > 3
    - Is the ratio of the peak height below 25 Hz to the peak height above 25 Hz higher than 3?

- Highest peak height over 500.
    - Is the height of the highest peak (above and below 25 Hz cut-off) over 500?

- Peak below 25 Hz above 300.
    - Is the height of the peak below 25 Hz above 300?

- Peak location at 49-51 Hz.
    - Is there a peak in the 49-51 Hz range? This would suggest mains electricity contamination has occurred.

- Peak location at 0-4 Hz.
    - Is there a peak in the 0-4 Hz range? No significant EMG data is expected here so this would be an indication of an error occurring.

Once the analysis and error checking is complete, the results are saved into an Access database in order to aid statistical analysis.

4.4 VARIABLES RECORDED

Each EMG test recorded four datasets, one per test location. A listing of the pertinent variables with a brief description follows.

- Date
    - The date the test took place.

- Time
    - The time of day the test took place. There were some questions to the effect this variable has on EMG repeatability so it was felt best to record this data.

- Maximum Voluntary Contraction
    - The maximum voluntary contraction (MVC) is the maximum load the test subject was able to exert on the load cell.

- Aim
    - The load the test subject was asked to maintain for the duration of the test. The actual load they achieved was sampled at the same time and rate as the EMG data, which allows the removal of tests conducted with sub-optimal effort on the part of the subject.

- Peak Height
    - This is the height of the highest peak in the FFT spectrum above 24 Hz.

- Low Peak Height
    - This is the height of the highest peak in the FFT spectrum at 24 Hz or lower. The additional constraint was added that the signal must drop by 10% of the peak height within this range for it to qualify as a low frequency peak.

- Peak Centre
    - The peak centre is the frequency at which the highest peak above 24 Hz occurred at.

- Low Peak Centre
    - The low peak centre is the frequency at which the highest peak at or below 24 Hz (if any) occurred at.

- Peak Ratio
    - This variable is the ratio of the peak height above 24 Hz to the peak height at or below 24 Hz.

- Half-Width
    - This variable refers to the width of the spectrum at half the height of the highest peak above 24 Hz, centred on this location, as previously described (Section 2.2.4).

- Root Mean Square
    - The Root Mean Square (RMS) is a figure relating to a statistical measure of the variation in the magnitude of the FFT of the

composite spectrum. It is the square root of the mean of the squares of the FFT values.

- Root Mean Square Slope
    - The RMS slope is the line of best fit slope relating to how the RMS value of each of the FFT epochs varies during the test period. The slope was calculated using the “Least Squares” method. Further information on this method can be seen in Section 7.2.6.

- Root Mean Square Intercept
    - The RMS intercept is the level of where the RMS slope crosses the zero seconds mark if calculated for the whole of the test, and then plotted backwards.

- Median Frequency
    - The median frequency (MF) of a spectrum is the point at which half of the spectral energy occurs below that point, and the other half occurs above the point. Here it is the MF of the composite spectrum.

- Median Frequency Slope
    - The MF slope is the slope of the MF value of each of the FFT epochs varies during the test period. Again, this slope was calculated using the ‘Least Squares’ method in order to find the line of best fit.

- Initial Median Frequency
    - The MF recorded in the initial epoch of the EMG test.

- Error Code
    - If certain types of errors (as described in 4.3) were detected during the analysis process, the relevant code relating to the error type was stored here.

4.5 SPECTRAL DISPLAY

As the project was created with the goal of identifying usable EMG variables to distinguish between LBP and non-LBP subjects, a brief discussion of the systems used to view recorded EMG data follows.

4.5.1 COMPOSITE SPECTRUM

The composite spectrum shows an average of each of the 30, 1 s epochs. In other words, the spectra height at 1 Hz for each of the individual epochs is added up, and then the total divided by 30. This is done for each frequency point, 1-512 Hz (from the sampling rate of 1024 Hz divided by 2). An example of the outcome is shown below, taken from the original analysis suite.

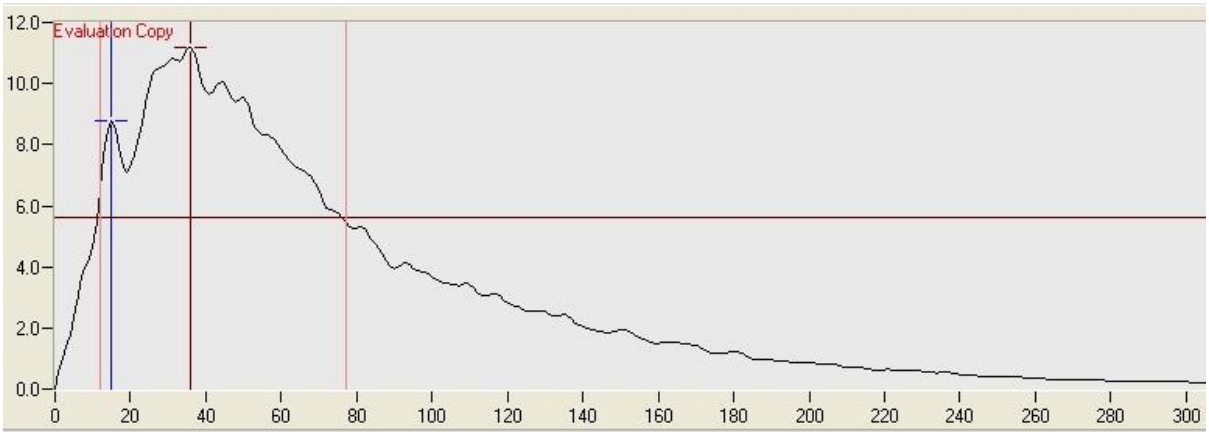


Figure 4.7 – Composite Spectrum

In this diagram, the X axis denotes the frequency, and the Y axis indicates the level of energy present at that frequency. The coloured lines are configured in order to

calculate the highest peak above 25 Hz (the darker red vertical line), the highest peak below 25 Hz (the blue vertical line), and the half-width boundaries (indicated by the two lighter red vertical lines).

This diagram shows a recording taken from one electrode site. There would be three other diagrams of this nature produced per test.

The half-width is calculated by firstly identifying the highest peak above 25 Hz. A horizontal line is placed across the spectrum at half the height of this peak, as shown in Fig 4.7. Where the spectrum crosses this line, either side of the highest peak, is marked as the edges of the half-width. The value is calculated on how much of the frequency spectrum this area spans. As this image is a composite of 30 one second images this can be interpreted as the wider the half-width, the wider the range of frequencies detected. The implications of this were discussed in Chapter 2.

Also note the low frequency component. At the time this software was in use there existed some controversy regarding the source of this signal data, and how to best deal with it regarding the half-width. As can be seen from the above image the half-width is increased by the presence of this artefact.

This method of examining the resulting composite frequency spectrum of the recorded EMG data had the advantage of being easy to produce and fairly simple to interpret. However the amount of actual information shown is relatively limited. In an effort to improve this, alternate information display methods were investigated.

4.5.2 3D VIEWER

The short term FFT produces a series of output spectra ordered by time. The composite spectra method described previously averaged these into one spectrum; the decision was made that it would be advantageous to investigate methods of displaying the data at once. A 3D viewer seemed the natural choice.

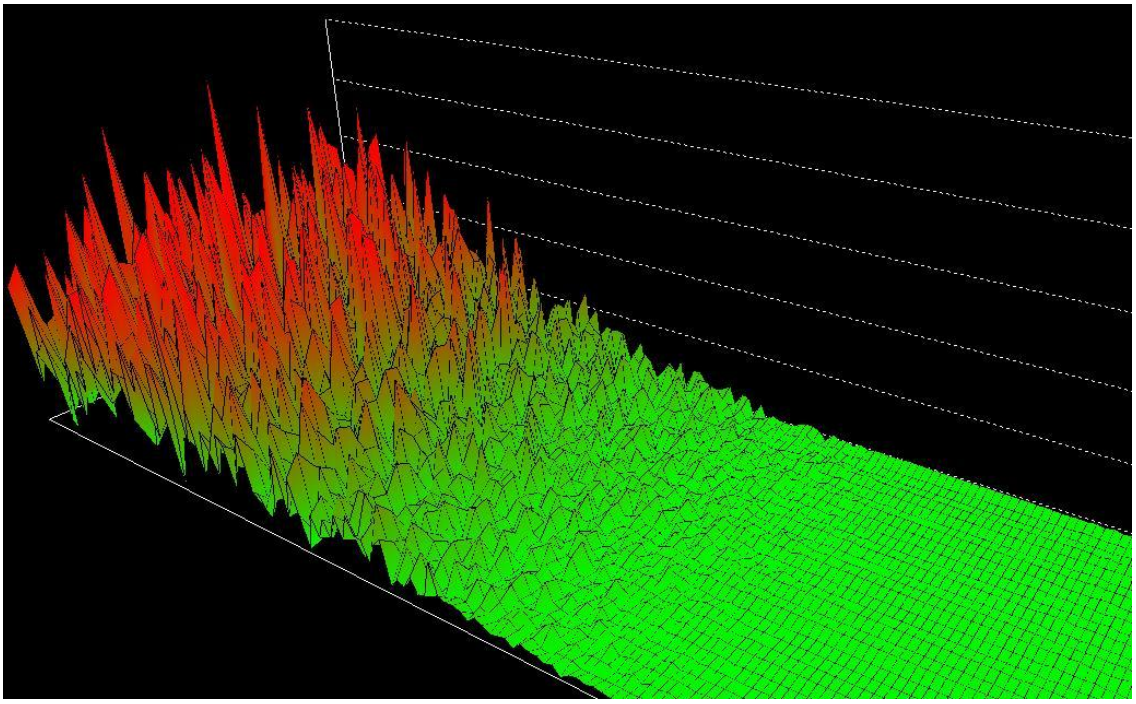


Figure 4.8 - 3D Display of EMG Data

The above diagram represents the 30 epochs, placed next to each other in time order, with second number 1 being at the back of the image and second number 30 being at the front. The height of the surface at a given point represents the signal energy present at a given epoch/frequency level, and the frequency increases from left to right. The images were created using OpenGL libraries and were fully interactive, allowing the viewer to rotate, pan, and zoom the image.

In an effort to aid and speed up comprehension, the surface was coloured between red and green dependent on the height of the surface. The maximum and minimum values used to calculate the colours were taken per individual test rather than from all of the tests combined. This was done both because the inter-subject height variation was quite large, and to enable repeatable individual testing i.e. the same spectra will always be the same colour regardless of how many others are being tested at the time.

This method of displaying the EMG data produced mixed results. It does indeed show more signal information than the previous method. This enabled researchers, at least at this centre (Coxon et al, 2010), the ability to view the EMG signal as it evolves across the 30 s test period. It also allowed viewing of the low frequency noise component to indicate it does indeed occur throughout the entirety of the tests.

The disadvantages of this method are that analysing and interpreting the data takes longer and requires more training. Visually separating the subjects between groups proved difficult with this method of viewing the EMG signal and reference to numerical data values were needed, somewhat negating the point of visualising the data. Also the display is necessarily large, making it difficult to view more than one spectrum at a time.

4.5.3 COLOUR MAPS

With a view to reducing the complexity of the 3D viewing method, efforts were directed to 2D colour maps. This method indicates energy levels at a given time/frequency purely by using colour. These images were also rendered using the OpenGL graphics libraries.

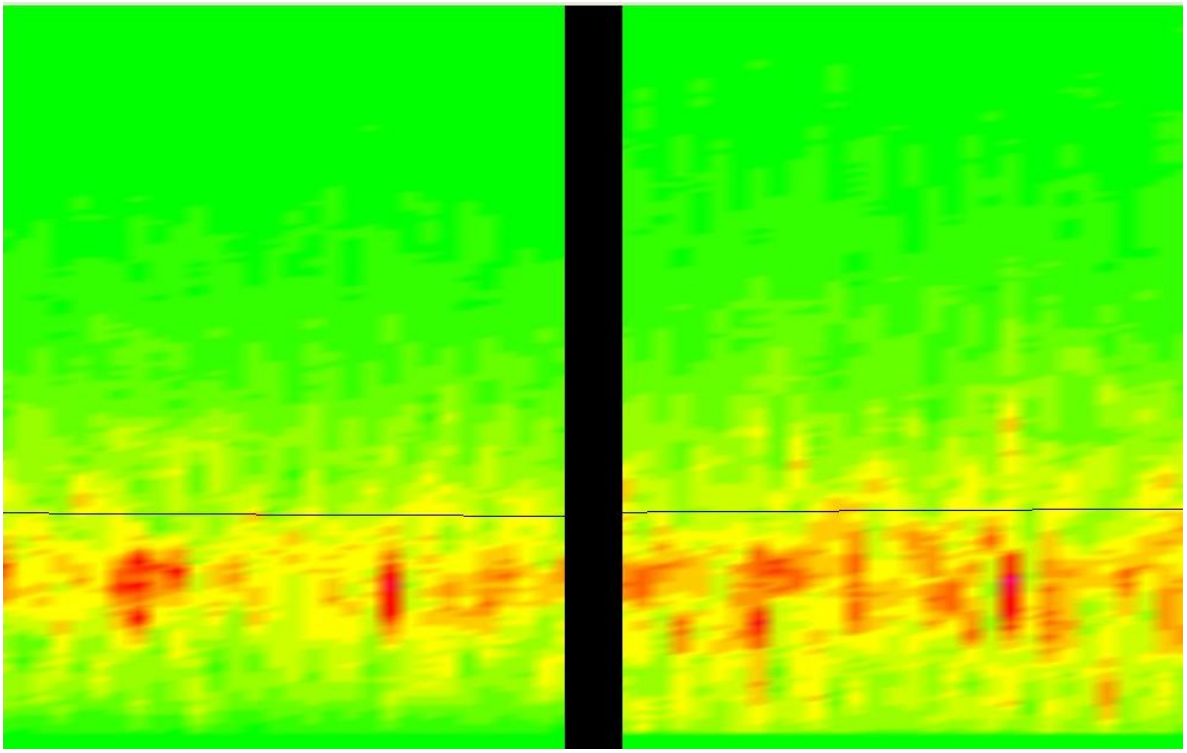


Figure 4.9 – Spectral Colour Map of EMG data

The above image is split into two halves, these relate to EMG signals recorded from the left and right sides of the back. However lumbar and thoracic regions must still be viewed separately. For each side, the X axis relates to the epoch (1 to 30 s) and the Y axis relates to the frequency (0-200 Hz). This frequency range was chosen as the spectrum tends to level off after this point, and only including a smaller frequency range allows it to be shown in greater detail.

The signal frequency levels (the “height” component of the 3D system) are split into 12 levels, with each level having a colour assigned to it. These colours range from green for the lower energy levels to red for the higher energy levels.

The horizontal black line across the images is a line of best fit relating to the median frequencies of the EMG signal at each epoch.

This method does not allow simple viewing of the half-width variable. However it does show a great deal of information about other aspects of the EMG signal. Initial

tests of this method's discriminatory ability between LBP and non-LBP subjects were promising and a larger study was commissioned (Coxon et al, 2010). This is described further in Chapter 7.

CHAPTER 5

AUTOMATED ANALYSIS

5.1 BACKGROUND

5.1.1 HISTORY

The experimental work in this project can be divided into two parts; data acquisition and data analysis.

The data acquisition component concerns itself with the generation of the raw signal data, along with the questionnaire answers and fitness test results from the subject. It is important that the test configuration procedures are carried out correctly so as to ensure accurate data collection. Once all subjects have been seen and tested a library has been built up of the raw EMG data along with the other subject data. In the case of the final data collection there were 455 data sets consisting of four channels of raw data along with the demographic information about the subject.

Data analysis varies according to the nature and requirements of the particular project. The raw data needs to be manually inspected and the relevant variables populated (half-width, initial median frequency, peak height etc). This data analysis could very well prove to be a difficult procedure and accuracy could not be guaranteed with a human observer.

5.1.2 DATA ANALYSIS

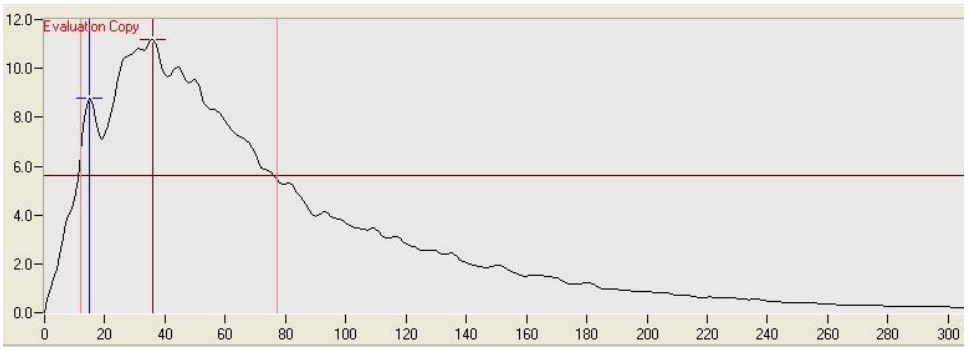


Figure 5.1 EMG Frequency Spectrum indicating half-width, maximum peak height and low frequency peak height

As an example, the above figure details how the half-width variable is generated. The researcher would initially select the highest point the spectrum achieves and then, using this as a guideline, draw a line across the spectrum at half the height of this peak (the two dark red lines). Next the two lighter coloured red lines are placed at the points where the horizontal dark red line crosses the spectrum outline. The distance between these two light red lines (in Hz) is the half-width. This is obviously a monotonous and time consuming operation, especially when one considers a full data analysis would require the analysis of 1828 (4 channels multiplied by 455 data sets) spectra. A point of concern would be how long a human observer would be able to maintain an appropriate level of accuracy. This effect is magnified when considering that the task may reasonably be expected to be split amongst a group of people. Finally, the magnitude of this task precludes the option of re-analysing the data in the future should the need arise, for example if it became desirable to examine results from the power spectrum, or new filters were devised to remove various contaminations.

5.1.3 ERROR DETECTION

During the course of the initial (manual) data analysis, it was noticed that some of the EMG spectra had aberrations from normal in their shape. After further analysis it became apparent that various errors had occurred during the data collection process. The main form that the symptoms of these errors occurring took was that there was additional signal data present. Rarely, for example in the case of a faulty electrode, there would be signal data missing. Due to the nature of the test and equipment, these errors could come from three different places;

- From the subject - EMG from non-related muscles. ECG
- Outside the test room - Radio waves.
- Inside the test room - Fluorescent lights, mains electricity, swaying wires.

Obviously if a recording was irretrievably contaminated it would be necessary to note this and exclude that particular dataset from overall analysis. Therefore a series of rules would need to be created that identified when errors had occurred, and what caused them.

5.1.4 AUTOMATED ANALYSIS

The issues raised in the previous section indicated that it would be beneficial if a system could be created that would be able to autonomously analyse the EMG raw data, produce the required outcome variables, indicate if an error had occurred, and if so what type. This would ensure that results were accurate and repeatable. The successful implementation of such a system would have the added bonus that the re-analysis of the data would become trivial, enabling a much wider array of analysis techniques to be examined.

As projects would rely heavily on this system for their outcome variables it is essential that this is a transparent system, and is carefully tested. Therefore, the various stages of the system development are now detailed.

5.2 METHODOLOGY

5.2.1 CREATE MANUALLY ANALYSED DATA

An existing EMG study was used to provide the dataset comprising of manually analysed data. This dataset was chosen for two reasons. The first was one of simple convenience, the dataset already existed and was of an appropriate size (n = 455 x 4 electrodes per test = 1820). The second reason was that it had been generated by experienced EMG research staff and would therefore provide a good gold standard manually analysed dataset.

5.2.2 CREATE AUTOMATICALLY ANALYSED DATA

The raw data test files for the 455 tests that had been manually analysed were located. The automated analysis software was given the location of these files and then used to batch process them. The results were stored in a database designed to be identical to the one used for the manually assessed data.

5.2.3 SELECT COMPARISON OUTCOME MEASURES

It was decided to use the half-width for a comparative measure. This variable is one that could not be calculated mathematically and so was created manually according to the instructions provided to the researchers. If the results created by the experienced researchers were to be replicated by the automated system, then this automated method could be said to be successful. Other variables, such as the median frequency and its related slope, were mathematically generated and as such are less useful as comparison measures. Also, the half-width is by far the most

time consuming variable to generate (as it currently has to be done manually) and so this is the most useful to use in order to test the efficacy of the new system.

5.2.4 COMPARE DATASETS

After the automated system has completed the analysis process and produced its dataset, this can be compared with the manual dataset. The Pearson Product Moment Correlation Co-efficient (PPMCC) (Pearson, 1896) can be used along with the F-Test, to establish what degree of variance occurred between the half-widths recorded by the two methods.

5.3 DESIGN

5.3.1 RAW DATA FILES

The EMG test produces raw data files. When the testing process was first conceptualised, the process of performing a Fast Fourier Transform and evaluating the resulting spectra in order to produce the outcome variables was a long and involved task. Storing the raw data variables meant that process could be completed after the EMG tests, thereby increasing the proportion of testing time that could be spent on acquiring new data. An unfortunate side effect was that any test errors were only identified at a point when a re-test was impossible, resulting in a higher than ideal number of sets of data being discarded.

Two files were created per test. The initial component of each file was a series of headers containing information about the patient and the test configuration. This was followed by columns of data containing voltages from the lumbar left and right electrodes, the thoracic left and right electrodes, and a weight in kilograms referring to the load the test subject was applying to the load cell. These values were split across the two files.

5.3.2 DATABASES

Data from the analysis of the EMG signals were recorded in an Access database. The disadvantages of this method, namely slow operation and a limitation on simultaneous connections, did not significantly apply in this scenario. The advantages that the Access database provides simple methods of connecting to

other software such as Excel and SPSS for data analysis, and is easy to back up, more than outweighed the negatives.

The results were split up by test number, and within this separation again by location (lumbar or thoracic), creating six sets. An extra dataset was created per test number which consisted of averaged values from the lumbar and thoracic region. Therefore, as each dataset was stored in its own table, in total the database contained nine tables.

In addition to the test data, subjects also completed questionnaires which created data that needed to be stored. These data points were stored in the same database, within a separate table. Each subject was assigned a unique identifier (the letter ‘z’ followed by five numbers, e.g. z00007) which was used as a primary key and used to link the tables together.

5.3.3 VISUAL BASIC

The software for this project was written in Visual Basic (VB) 6, as the project started before the various .Net technologies were available. VB6 is an event based language designed to create programs based upon Windows Forms. Event based languages differ from procedurally based languages by the order that the source code is executed.

Procedurally based languages (for example, C or Pascal) are executed like the following of a flow chart, starting at the beginning and working through to the end, providing functionality for branched execution and iteration. This type of language is suitable for systems that require little in the way of human interaction and typically are faster to execute than event based languages.

Event based languages consist of smaller code snippets that are executed in response to events triggered by the user. An extra layer of abstraction is added by the software constantly listening for event triggers, which tends to slow down code execution. The advantage of this type of language is that it takes much less time to create useable software, and its close integration with the Windows operating system aids connecting to objects such as Access databases. In addition, the speed penalties have been somewhat negated with the advent of more powerful computer hardware.

5.3.4 COLLECT FILES

The first part of the process to automatically analyse a group of EMG raw data files would be for the software to identify the files that were to be part of the batch. To reduce the scope for errors on this part, a folder was created to contain a copy of the raw EMG files that were to be analysed. This had two advantages; firstly that the single location made coding the relevant sections of the software much simpler, and secondly that working from copies reduced the chance of irreplaceable data being lost.

When the user indicated that a new analysis project was to commence the software scanned the AutoRun folder and stored the file paths and names of all of the EMG raw data files present. These were stored as a series of records in a temporary database. As each file was analysed, and the outcome variables saved to the main database, the record containing the file location was deleted. The next file could then be selected and analysed. Using this method meant that the process could be stopped and started again as the un-analysed files were still listed in the temporary database.

5.3.5 FILTERS

MOVING AVERAGE FILTER

$$y[i] = \frac{1}{m} \sum_{j=-(M-1)/2}^{(M-1)/2} x[i+j]$$

Figure 5.1 The Moving Average Filter

The Moving Average Filter (MAF) is one of the most common filters used in the Digital Signal Processing (DSP) area, a fact helped by its simplicity of construction and use.

In the above example, x[ ] is the input signal and y[ ] is the output signal. The number of points the algorithm uses for the smoothing process is denoted by M. For example to work out point 60 of an output signal for a three point MAF the equation is;

$$y[60] = \frac{x[59] + x[60] + x[61]}{3}$$

Figure 5.2 Implementation of one point of the MAF

The MAF is used primarily to remove random background noise from recorded signals in the time domain. As the algorithm possesses very little ability to resolve one set of frequencies from another it is wholly unsuited for this task when considering signals in the frequency domain. The MAF algorithm has a second use however, which is that of a general smoothing algorithm. This usage is suitable for use within both the time and frequency domains.

It is for this second usage that the algorithm is applied in this project. Three passes are made of the transformed spectra, with a filter kernel width of 3, in order to smooth the spectra slightly. This was done in order to make the half-width variable easier to calculate.

BAND PASS FILTER

$$h[i] = \frac{\sin(2\pi fci)}{i\pi}$$

Figure 5.3 The Low Pass Filter

Band pass filters are used to remove signal information above or below a certain frequency from time domain signals. In the above equation, fc refers to the cut-off frequency and should be given as a fraction of the sampling rate (i.e. if the sampling rate was 1024 Hz and one wished to remove frequencies above 512 Hz, the value used for fc would be 0.5).

In the case of this project, the raw EMG signals were band pass filtered to remove frequencies below 3 Hz and above 300 Hz.

WINDOWED-SINC FILTER

$$h[i] = K\frac{\sin(2\pi fc(i - M/2))}{i - M/2}\left[0.42 - 0.5\cos\left(\frac{2\pi i}{M}\right) + 0.08\cos\left(\frac{4\pi i}{M}\right)\right]$$

Figure 5.4 The Windowed-Sinc Filter

The Windowed-Sinc Filter (WSF) is a special case of the band pass filter. Where the band pass filter allows the removal of signal information above (low pass filter) or below (high pass filter) a given frequency; the WSF allows the selection of a window of frequencies to be removed, whilst preserving the signal information above and below these values. An inverse of this filter kernel can be calculated which would preserve signal data between two frequencies, and remove signal data from outside them.

In the above diagram, the cutoff filter (fc) should be given as a fraction of the sampling rate (0 to 0.5). M corresponds to the length of the filter kernel and should be an even integer, and i moves from zero to M.

These filters were used to remove raw EMG signal data from the lower ends of the frequency spectrum in an attempt to compensate for low frequency peaks (Chapter 6).

NOTCH FILTER

A notch filter is used to remove a single frequency component from a recorded signal, for example 50 Hz noise caused by mains electricity. There are two ways this can be accomplished. The first is to use the previously described Windowed-Sinc Filter to remove the specified frequency from the signal whilst preserving the information either side of it. The other is to use a Fourier Transform. To use the example of 50 Hz mains electricity contamination, first of all the signal data is transformed into the frequency domain. The data structure holding the signal magnitude figure at 50 Hz is then set to zero. Calculating and performing the inverse of the original Fourier Transform will return the signal data to the time domain, without the 50 Hz component.

In the case of this part of the project it is only the frequency spectrum that is of interest. Therefore it was sufficient to simply remove the signal magnitude information at the point of 50 Hz, and then replace it with the averages of the magnitude information at 49 and 51 Hz.

5.3.6 FAST FOURIER TRANSFORM

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i 2\pi k \frac{n}{N}} \qquad k = 0, \ldots, N-1.$$

Figure 5.5 The Discrete Fourier Transform

As described in Chapter 4, the Fast Fourier Transform is based on the Cooley-Tukey algorithm (Cooley & Tukey, 1965).

$$X_k = \begin{cases} E_k + e^{-\frac{2\pi i}{N} k} O_k & \text{if } k < N/2 \\ E_{k-N/2} - e^{-\frac{2\pi i}{N}(k-N/2)} O_{k-N/2} & \text{if } k \geq N/2. \end{cases}$$

Figure 5.6 The Cooley-Tukey Fast Fourier Transform Formula

So to be able to observe how the frequency domain of the recorded EMG signal changed over time, the recordings were split up into 30 individual epochs, each being of one second in length. The sampling rate of the testing equipment was 1024 Hz, meaning that each epoch contained 1024 data points. This allowed the epochs

to meet the FFT algorithm criterion that each window must be of a length equivalent to a number to the power of two.

The individual epochs were stored and used to calculate the Median Frequency Slope and Root Mean Square Slope. They were then averaged to create one composite spectrum for the whole test, which was used to create the other outcome variables. As each test recorded EMG data from four sites there was a total of four composite spectra produced per test.

5.3.7 INTERPRET SPECTRA

AUTOMATED ANALYSIS

In the original system there were four variables that required manual intervention to calculate; Low Peak Height, Maximum Peak Height, Half Peak Height, and the Half-Width. If a system was to be created to batch process multiple raw EMG files, the criteria for assessing these variables must be formalised.

The method for discerning the location, if any, of a genuine low frequency peak (LFP) is split into two parts; identifying the highest point and assessing if it can be classified as a peak. Identifying the highest point simply involves checking each of the intensity values of the composite spectra at the 0-25 Hz points of the particular channel in question. In order for this to be classified as a genuine LFP, the rule created stated that the spectral height had to decrease by 20% of the height of the LFP within the 0-25 Hz zone. The spectra was examined from the location of the potential LFP to 25 Hz, and if the spectral height at any of these locations was 80%

or less than the value of the spectral height of the LFP, then this peak was classified as a genuine LFP and recorded as such.

The maximum peak height and the half peak height are used to calculate the half-width. The maximum peak height is the frequency at which the spectral height reaches its highest point, measured across the 26-512 Hz range. The half peak height variable is the signal intensity at this frequency, divided by two. The half-width is calculated by first of all marking the points where the overall EMG spectra rises above half the height of the maximum peak, either side of the location of the maximum peak frequency. In an attempt to reduce the effect of LFPs, if the spectrum height passes this half maximum height more than once on a particular side (usually the lower frequencies side) the measurement is taken from the crossing at the frequency nearest to that of the maximum peak.

After these measurements were taken and the outcome measure variables produced they were stored in the appropriate table in the database.

ERRORS

An unfortunate side effect of performing the spectral conversion and analysis of the raw EMG data at a later date from the actual test was that errors that took place during the testing process could not be corrected with a re-test. This led to the stockpile of raw EMG test data files containing some unsuitable data. Without modification the automatic analysis system would still produce outcome measure variables from these data and so a system would have to be implemented to indicate in the database if a test had been contaminated.

A list of five rules were drawn up that would indicate if an error had occurred during the testing process, or at least that this particular set of test data would benefit from human analysis.

- Is the ratio of the low frequency peak to the peak above 25 Hz larger than three?
- Is the height of the peak above 25 Hz larger than 500?
- Is the location of the peak above 25 Hz between 49 and 51 Hz?
- Is the low frequency peak larger than 300?
- Does a peak exist in the 0-4 Hz region?

Each of these rules was given a letter, and this letter was saved in the test data table if the appropriate rule was triggered. The more rules that were triggered, the more letters were added to the error identification variable. Using this method rather than a simple yes/no meant that certain errors could be ignored for the purposes of statistical analysis if they were thought to be unimportant in that case.

5.4 RESULTS

The half-widths from a database containing manually calculated data were extracted. The raw EMG files corresponding to these half-widths were identified and batch processed using the new automated method. The scatter graph below shows a comparison between half-widths generated manually and half-widths generated automatically.

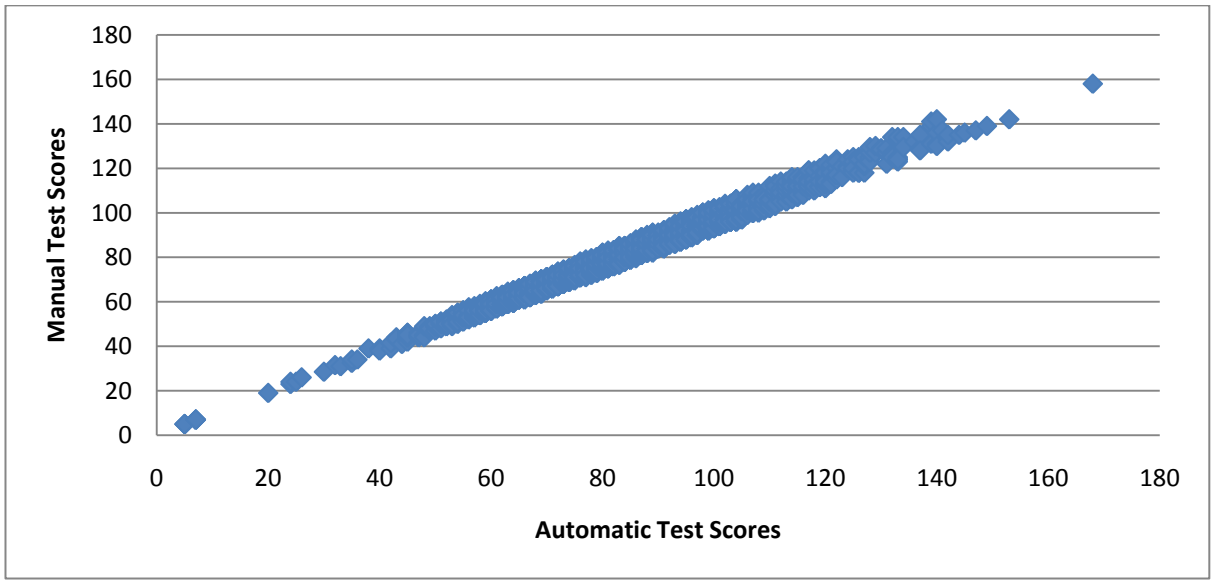


Figure 5.7 Comparison between automated and manual half-widths.

N = 1780	Score
F-Test	0.083
PPMCC	0.99

Table 5.1 Comparison between automated and manual half-widths. PPMCC is the Pearson Product-Moment Correlation Coefficient.

As can be clearly seen, the two datasets are highly correlated. The PPMCC (r = 0.99) value indicated that there is an extremely high linear dependence between the two half-width variables. The F-Test value (f = 0.083) is above the 0.05 threshold, meaning there is no significant degree of difference in the variance between the two groups.

In this case the manual dataset took two researchers just over two weeks to produce, whilst the automated dataset took just under 10 minutes to complete the batch process. The automated system produced highly similar results, in a fraction of the time.

5.5 CONCLUSIONS

The act of manually examining the frequency spectra of the EMG tests was long and tedious. In the case of this project there were 455 individual tests performed, each containing four sets of signal information, giving a total of 1780 spectra to be assessed. Optimistically assuming that each manual analysis would take one minute to complete would mean that the process of analysing this data set would take just under 30 hours. This is obviously a significant investment in research time.

When partaking in a monotonous task that takes such a long time to complete, a question must be raised about the levels of accuracy, and consistency, that can be attained. This issue is worsened if the natural step of spreading this monotonous workload across several researchers is taken. Without randomly re-testing raw data files, and performing extensive cross checking against other people's results if more than one person was involved, it would be impossible to know for certain if there could be full confidence in the produced results.

Using an automated system negated these issues with the added benefit of analysis time dropping from the aforementioned 30 hours to just over 10 minutes. As can be seen from the results, the automated analysis system has proven it's facility in batch processing large numbers of EMG raw data files and accurately reproducing the various required outcome measures.

A further factor to be taken into account is that the automated analysis system enables re-testing the entire dataset to become a trivial exercise.

5.6 IMPLEMENTATION

5.6.1 FILTERS

Within the source code each filter was constructed separately, within its own function. This code compartmentalisation methodology aids testing and allows the filters to be used in other projects. This second point was an important one as it allowed the exact same filter methods to be used in different projects; ensuring accurate comparisons can be made.

Having the filters contained in a separate function means the function requires some data to be passed to it in the form of parameters. This data varied according to the type of filter that was being programmed. In the case of this software, the exception was the actual signal data. In the case of this information two global arrays, that is arrays that can be accessed both by the main program code and the filter function code were created. The process was that the signal data that was to have the filter applied to it was copied into a global array called ‘input’. The filter was then called, and the appropriate parameter values passed to it. The filter function performed the necessary calculations and then recorded the outcomes into another global variable, this time called ‘output’. The main program code could then proceed with access to the filtered signal information.

Global variables can be considered bad practice as, unless they are protected, they can potentially be modified from anywhere in the software. As an example, using the design described above, if the moving average filter function was called it would put the output into the ‘output’ array. Unless care was taken to save this value to a

different location immediately after this, a different function could modify this ‘output’ array and corrupt the values stored within it. This was considered an unlikely occurrence in the case of this system as there is a fairly linear code progression with little concurrency. The advantage of using global arrays was a reduction in the amount of data that needed to be passed from the main code to the function as the signal data to be filtered could be saved an a mutually accessible area. Therefore the advantage of the reduced complexity of the functions outweighed the potential disadvantages of global variables.

MOVING AVERAGE FILTER

The definition for the Moving Average Filter function is;

```
Public Sub movingAverageFilter(     ByVal passes As Integer,
                                    ByVal points As Integer,
                                    ByVal signalLength As Integer)
```

For the three parameters, 'passes' refers to the number of times the filter is passed across the input signal, 'points' denotes the number of points around the current point in the input signal to be used for the averaging, and 'signalLength' is the length of the array containing the input signal.

The code used to call this function, with example parameters is *movingAverageFilter(3,11,1024)*. This would pass the filter three times across an input signal of 1024 points, taking an average of the five points either side of the current point (five points either side plus the current point).

BAND PASS FILTER

The definition for the Band Pass Filter function is;

```
Public Sub lowPassFilter(    ByVal type As String,
                             ByVal freq As Double,
                             ByVal kernelLength As Integer,
                             ByVal signalLength As Integer)
```

The 'type' parameter allows the function to perform either as a low pass or a high pass filter, the two string options being "high" and "low". The decision was made to use a string for this option to aid code clarity. Using a Boolean variable rather than a string would perhaps have been algorithmically preferable, but less readable to a human observer. The 'freq' parameter is the cut-off frequency that is required and the 'kernelLength' denotes the length of the filter kernel to be constructed, this is similar to the 'points' option on the Moving Average Filter. A larger kernel length value creates a more accurate filter output, but destroys a larger section of the original signal and increases computation time. Finally the 'signalLength' parameter indicates the length of the signal that is to be processed.

An example of how this filter would be called is *lowPassFilter("high",0.25,25,4096)*. This would call the function requesting that the signal stored in the input array be subjected to a high pass filter with a 25 point kernel, and that the signal is 4096 data points long. The frequency component is expressed as a fraction of the sampling rate. Therefore if the sampling rate was 1024 Hz, passing the 'freq' parameter with a value of 0.25 would result in the filter cut-off being 256 Hz. To fulfil the Nyquist criterion this number must be between 0 and 0.5.

NOTCH FILTER

The notch filter simply removes a certain single frequency from a given signal. It would indeed be possible to create such a filter using the Windowed-Sinc Filter described previously; however this is unnecessary if one is purely concerned with observing a signal in the frequency domain. If this is the case then it is simply a case of removing the signal data at the appropriate frequency mark. Indeed, it can be suggested that a notch filter can be implemented by performing a FFT on a given signal, removing the signal information from the appropriate frequency on the frequency domain spectra, and then performing the inverse of the original FFT to retrieve the original signal, minus the filtered frequency.

In the case of this project the notch filter was only applied to a certain frequency (typically 50 Hz, i.e. mains electricity in the UK) and observed in the frequency domain. To implement this the frequency component data at (using the mains electricity example) point 50 would be removed and replaced with the average of the data at point 49 and point 51. This averaging was performed so to preserve an element of consistency in the presented frequency domain spectra. This also had the benefit of aiding the automatic selection of the half-width. If the 50 Hz data had been simply removed, the spectra would drop to zero at that point, thereby crossing the height indicating half of the maximum peak height, meaning the half-width would have been measured from that point.

WINDOWED-SINC FILTER

The definition for the Windowed-Sinc Filter is;

```
Public Sub windowedSincFilter(    ByVal freq1 As Double,
                                  ByVal freq2 As Double,
                                  ByVal bandType As String,
                                  ByVal kernelLength As Integer,
                                  ByVal signalLength As Integer)
```

The 'freq1' and 'freq2' parameters contain frequency values that correspond to the upper and lower bounds of the window that is to be created in the specific signal. Again they are to be expressed as fractions of the sampling rate (0 to 0.5). The 'bandType' parameter is to contain a string value of either "pass" or "reject". Using "pass" would preserve the signal information between the frequency values from the provided 'freq1' and 'freq2' parameters whilst removing the information from outside that area. Passing the value "reject" in 'bandType' parameter would have the opposite effect, preserving the signal information from outside the specified window and removing the information from within. The 'kernelLength' parameter contains an integer value relating to the number of signal points the filter kernel should encompass. Finally the ‘signalLength’ parameter identifies the number of data points that comprise the total length of the signal to be filtered.

An example of how this function would be called is *windowedSincFilter(0.125,0.25,”pass”,25,10240)*. This would take a signal that was ten seconds long (assuming a sampling rate of 1024 Hz) and remove all signal data outside of the window covering 128 Hz to 256 Hz, using a 25 point filter kernel.

5.6.2 HALF-WIDTH CALCULATION

The half-width refers to the distance (in Hz) between the points where the frequency spectral height drops below half the maximum height present, either side of this maximum height. To generate this variable, four individual figures are needed; the maximum spectral height present, the frequency value this height is recorded at, and the frequency values where the spectral height drops below half the maximum height recorded above and below that frequency.

The maximum height, and the position it is recorded at, are calculated as a part of the same calculation. A comparison variable is created and seeded at an initially extremely low value, for example -10000, a figure well below what would be expected anywhere in the spectrum. Starting from element number 25 (i.e. at 25 Hz), each element in the array containing the spectral values is selected. If the value stored in this element is greater than the value stored in the comparison variable (which it would be for the first element) then the comparison variable value is replaced by the value in the current element and the array element number is recorded. This process continues until the entire array has been checked, after which the comparison variable will contain the highest peak value and the recorded array element number will correspond to the frequency at which this occurred.

The frequency at which the highest peak is located is used as the starting point for calculating the points where the spectrum drops below half the height of this highest peak. In a step by step fashion each frequency point above the highest peak location is examined. Once the spectral intensity at a certain point drops below half the maximum peak height, that location is recorded as the upper component of the half-width. Those steps are repeated, this time starting from the maximum peak location and moving step by step below it. Starting the search from the centre location and moving outwards ensures that the cross-over points selected are those

nearest the centre in the case of spectra that have multiple cross over locations, especially when a low frequency peak is present.

Once these calculations have been successfully carried out all that remains is to simply subtract the frequency value the lower cross-over was located at from the frequency value the upper cross-over was located at. This resultant figure is the half-width.

5.6.3 ERROR DETECTION

The method of recording the number and type of errors was to assign the details to a string, or a group of letters. After the error processing had taken place the presence of a certain letter in this string would indicate that particular error had occurred.

Several functions were created, each to assess a given frequency spectrum for the presence of known error characteristics. Each function was passed an array containing a frequency spectrum, and returned an error code letter if the error specific to that function was found. If no error was found an empty string was returned. An example of this is shown below;

errorString = *errorString* & *lowPeakAbove300*(*frequencySpectrum*)

In the above example 'errorString' is the string designed to hold the error code, 'lowPeakAbove300' is the error checking function (in this case checking to see if the low frequency peak intensity is above 300), and 'frequencySpectrum' is an array holding the frequency spectrum to be examined (512 elements). The shown code takes the current contents of 'errorString', appends (the '&' symbol) the value returned by the function to it, and then stores the resultant string in the errorString variable. For example, if 'errorString' already held the string "AC" (from other

checking functions) and this function returned "D", 'errorString' would now hold "ACD". This would allow the researcher to look up which errors correspond to those letters.

There were five separate functions created to evaluate a given frequency spectrum for the presence of certain errors. These errors were;

- Is the ratio of the low frequency peak to the peak above 25 Hz larger than three?
- Is the height of the peak above 25 Hz larger than 500?
- Is the location of the peak above 25 Hz between 49 and 51 Hz?
- Is the low frequency peak larger than 300?
- Does a peak exist in the 0-4 Hz region?

Each function checks the frequency spectra that is passed to it and then returns a string, the contents of which depends on if the error is found. This is then appended to the existing error string. An example error checking function (in this case is the low frequency peak larger than 300?) is shown below;

```
Private Function lowPeakAbove300(byRef spectrum() as double) as string
        dim max as double = 0.0
        For i = 0 To 24
                If spectrum(i) > max Then
                        max = spectrum(i)
                End If
        Next i
        If max > 300 Then
                Return "D"
        Else
                Return ""
        End If
End Function
```

This function is passed an array holding the frequency spectrum from one electrode pair of an EMG test. A variable called 'max' is created and assigned the value zero. The spectrum array is then assessed to find out the highest value, as this function is checking for a low frequency peaks only the first 25 array locations (representing the values at 0-24 Hz) need to be examined. If this highest value is above 300 then it can be said that an error has occurred and so the function returns the string "D". If this value is below 300 then the function returns an empty string, denoted by "". As appending an empty string to an existing string will leave the existing string unchanged, the function return value can always be appended to the errorString regardless of its outcome.

CHAPTER 6

REMOVAL OF ECG CONTAMINATION

6.1 BACKGROUND

6.1.1 HISTORY

During the course of the previous automated analysis work (Chapter 5) it became apparent that some of the frequency domain EMG traces contained a low frequency peak (LFP) that did not correspond to any known underlying physiological cause (Heydari et al, 2009). This peak is indicated by the blue vertical line in the figure below.

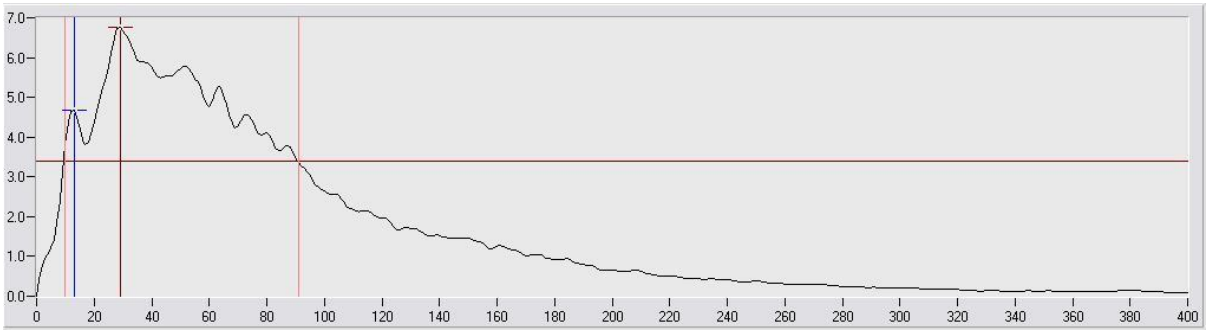


Figure 6.1 EMG Frequency Domain Spectrum with Low Frequency Peak

As can be seen the presence of this peak had implications when calculating the half-width variable, as it would seem to extend the left hand side of the spectrum. The decision was made that if the left hand side of the spectrum was to descend past the half-width height indicator (the horizontal dark red line) before ascending up towards the low frequency peak, then the half-width variable would be recorded from the innermost crossing of the spectrum. This is shown below.

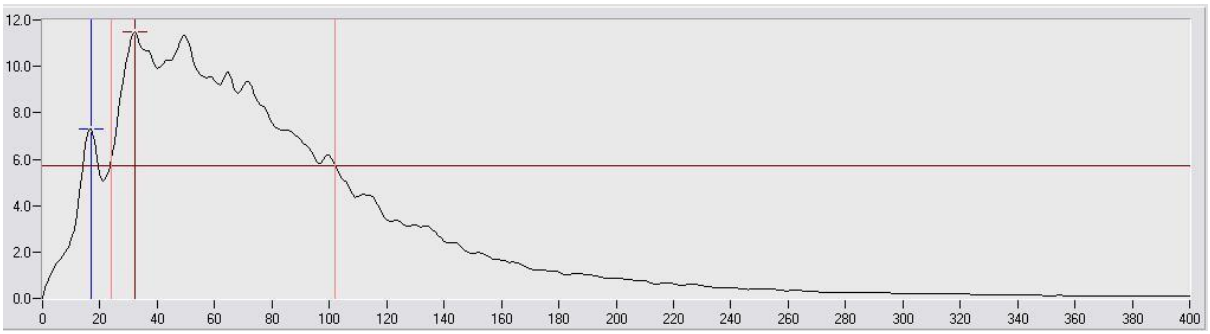


Figure 6.2 Demonstration of Innermost descending slope selection criterion

Obviously this was not an ideal solution, not in the least that unknown spectral information in an area of interest in the EMG spectrum should not simply be discounted. Also, as can be seen in Figure 6.1, the size and location of the LFP sometimes meant that it was still included in the half-width measurement.

It was entirely possible that this signal data could provide useful discriminatory variables and so for this research to continue the source of this contamination would have to be identified. Once this had been accomplished decisions could be made on how best to utilise, or remove, this information.

6.1.2 POTENTIAL SOURCES OF CONTAMINATION

EXTERNAL

It was unlikely that external electrical signals would be causing this contamination as sources such as fluorescent light bulbs and radio waves would have a much tighter frequency band, rather than the broad area the LFP covers. Contamination due to current induced by swaying wires was easily replicated and discounted by manually contaminating the data to see if this produced the appropriate LFP. The LFP corresponded to no known amplifier noise profiles.

INTERNAL

As the presence of LFPs tended to be consistent by subject, it would seem to indicate that this contamination is of a biological origin. Previous studies (Allison, 2003) have indicated that surface EMG recorded from the trunk and neck can often contain noise from strong ECG signals. This has an effect on the accurate interpretation of this surface EMG data for diagnostic results. As the ECG power spectra spans from 0 to 100 Hz, with the majority being found in the 0-20 Hz range (Conforto & D'Alessio, 1999), it is likely that this low frequency signal data could indeed be ECG contamination.

As seen in Figure 6.3, examining the raw, non-transformed, EMG data from a test that exhibited a low frequency peak in the signal domain would show evidence of a faint ECG trace. It was this, and the previous evidence that lumbar EMG tests are prone to contamination from ECG within those specific spectral frequencies, that allowed the use of the hypothesis that the low frequency peak was caused by the presence of an ECG artefact.

6.1.3 POTENTIAL REMOVAL STRATEGIES

BAND REJECT STRATEGIES

Band Reject Strategies work by removing signal frequency components from a signal. It is possible to remove frequencies above or below a given value, or to remove frequencies between two values. Various studies have analysed different methods of selecting which frequencies are suitable for removal with respect to ECG contamination of the EMG signal. One study (Redfern et al, 1993) examined a range of finite impulse response high pass filters, and concluded that a cut-off of 30 Hz was optimal from the examined choices. Two studies (Levine et al 1986, Bloch

et al 1983) examined a subtraction template technique with mixed results. In a partial response to these studies, another group (Bartolo et al, 1996) compared the results from Levine and Bloch to their own based upon amplitude gating, which they found to be superior. This was due to Bartolo's group using an average ECG waveform as a pattern template rather than a single ECG waveform. The advantage of this is that the average waveform compensates somewhat for the issue of the ECG waveform altering slightly between beats; the averaged template is not reliant on a single datapoint. This finding was supported in another piece of work (Black and Lovely, 1997) which compared the technique to clipping and noise cancellation methods.

These methods were considered, but were inappropriate for two reasons;

Firstly they are only to be used on signal data in the time domain. If the experiment calls for the data to remain in the time domain for examination then this remains an appropriate tool. If time domain data has a band reject filter applied and then is transformed into the frequency domain, one simply sees the rejected frequency components as a flattened line on the spectra. For example, if one of the above EMG spectra had a <20 Hz band reject filter applied to it before transformation into the frequency domain, the spectra would contain no energy for the first 20 Hz, i.e. it would be a flat line at zero until 21 Hz was reached. All underlying data would have been deleted.

Secondly this LFP (0-25 Hz) overlaps an area of interest in the EMG (10-500 HZ) spectrum (Chapter 2.4). Simply deleting signal data below 25 Hz would also remove EMG data. Until more is known, this method cannot be recommended.

BLIND SOURCE SEPARATION

Blind source separation, sometimes known as blind signal separation, is a group of techniques used to separate a set of signals from a set of mixed signals, without the aid of information about the original data. This group of techniques relies on the assumption that the signals to be separated out do not correlate with each other, that is, they are mutually statistically independent or simply decorrelated. It is this statistical independence that is used as the basis for separation.

One type of blind source separation is Independent Component Analysis (ICA). This is a computational method used to separate a multi-dimensional signal into a series of additive subcomponents, assuming the source signals are non-Gaussian and possess a mutual statistical independence. In the case of this project the assumption of mutual statistical independence was that the electrical activities from the lumbar and cardiac muscles are separate, non-Gaussian, processes. It is this independency that will be taken advantage of for the application of the ICA method.

The ICA algorithm has been utilised for its abilities in artefact removal in several areas; magnetoencephalographic data (Barbati et al, 2004), ictal scale EEG (Levan et al, 2006) and EEG recordings in small animals (Tong et al, 2001). Detailed discussions and views on the requirements, assumptions and limitations of the ICA method are beyond the scope of this project, but can be found in many publications detailing the implementation of the ICA method (Hyvarinen et al, 2001; Lee, 1998; Stone 2004).

Very briefly, ICA is a subset of blind source separation. It is a computational method used to separate a multivariate signal into a series of additive subcomponents. Its two main assumptions are that the signals are non-Gaussian (i.e. they do not consist of ‘white noise’, they are caused by a physical process) and that the signal mixes contain mutually statistically independent data (there are different processes

causing each signal to be extracted). A real life example of ICA algorithm would be the ‘cocktail party problem’.

Consider a room containing eight people talking to one another, who are being recorded by eight microphones placed around the room. Playing back the recordings from each of the microphones will reveal a mixture of all of the voices present in the room. If the eight individual recordings are considered to be a matrix (containing a grid of eight by time elements) the ICA algorithm calculates a de-mixing matrix which is multiplied by the source matrix containing the voice recordings. The outcome of this calculation results in a new matrix (again a grid of eight by time elements) which can now be separated into individual rows of signal data, each containing an individual voice of a person in the room. The ICA method will only return a number of de-mixed signals equivalent to the number of sensors (e.g. microphones, electrodes, etc) present. That is, if only four microphones were present there would be only four sets of de-mixed data. Clearly, sufficient numbers of sensors must be used according to the application.

This technique was used in a study (Hu et al, 2005) to examine its effectiveness for removing ECG contamination from trunk EMG. This work used eight sensors and the ECG component was artificially created and then added to a clean EMG signal. This was obviously not a ‘real world’ test; however this method of analysis does allow accurate comparison of before and after signals, as the ideal answer is already known. The test was successful and the authors identified 30 Hz as the ideal cut-off point to remove the ECG component from the contaminated de-mixed signal trace.

The continuation of this work (Hu et al, 2007) examined the effect the removal of the ECG contamination has on the Root Mean Square (RMS) and Median Frequency (MF) variables. This time, EMG signals contaminated with real ECG noise were

used, again with eight sensors, and the subjects were asked to perform dynamic, non-fatiguing tasks. The authors reported a reduction in the RMS values, and an increase in the MF values.

This study has two goals;

- To identify whether or not the ICA technique can be used to remove ECG contamination from lumbar EMG signals recorded during a fatiguing, isometric contraction.

- To identify what effect this process has on the following outcome measures;
    - Half-Width
    - Root Mean Square
    - Root Mean Square Slope
    - Root Mean Square Intercept
    - Median Frequency
    - Median Frequency Slope

6.2 METHODOLOGY

6.2.1 SUBJECTS

One hundred and ninety two subjects were tested. Subjects were recruited from members of the general public. They were each tested on three occasions; initial contact, after 12 months and finally after 24 months. In addition to the EMG test, subjects completed questionnaires designed to enable calculation of their LBOS, ZUNG and MSPQ scores at each visit. After drop-outs, a total of 444 data sets were acquired.

The height and weight of all the subjects were recorded. Percentage body fat was estimated with a skin fold calliper and from this the lean body mass was calculated.

6.2.2 ISOMETRIC LUMBAR TESTING

With the subject standing, a pelvic rest was set 6 cm below the anterior superior iliac spines. The subject was positioned with a trunk angle of 30^{o} using a goniometer. Loading was performed by the subject pulling upwards with straight arms on a bar attached to a load cell fixed to the floor. The target load was to be 70% of the subject's lean body mass. The subject exerted this force on the bar for 30 s while surface EMG was recorded.

6.2.3 EMG RECORDING

EMG recording sites were carefully prepared in order to ensure a constant inter-subject level of impedance. Surface electrodes were placed bilaterally over the erector spinae muscles at the L4/L5 and T5/T6 levels, with the inter-electrode distance being 10 cm. The lumbar recordings would be used to create the half-width variables, whilst the thoracic recordings were taken to provide additional input signals for the ICA method.

A Medelec 2ME EMG system was used to amplify and filer the EMG signal (band pass 3-300 Hz). The analogue output of the EMG system was digitized on a laptop computer using a National Instruments DAQ-Card-700 PCMCIA analogue to digital converter. Four channels of EMG and the output of the load cell were sampled at 1024 Hz using a continuous double-buffered process, while the acquisition software maintained a real-time bar graph display of load centred at 70% of the subject's lean body mass. This clear display helped the subjects maintain a steady and accurate force for the 30 s duration of the test.

6.2.4 EMG ANALYSIS

The 30 s EMG recordings were divided into 30 epochs containing 1024 voltage samples. In order to calculate the half-width variable (as described in Chapter 2) a Fast Fourier Transform was applied to each epoch to obtain a power spectrum. The power spectrums of the 30 epochs were averaged and this composite spectrum was smoothed by applying a three-point moving average in three passes. The peak amplitude was taken as the greatest amplitude and the modal frequency was taken as the frequency at which this peak occurred. The half-width was taken as the width of the spectrum at half the maximum amplitude.

6.2.5 APPLYING INDEPENDENT COMPONENT ANALYSIS

ICA belongs to a class of blind source separation methods used for separating data into underlying informational components. It is based on the assumption that if signals are generated by different physical processes they will be statistically independent. This leads to a new assumption that if statistically independent signals can be extracted from input signal mixes, these independent signals must be from different physical processes.

The ICA method was applied to the recorded data from each subject. This method was based on the following model:

x = As

x=[x1,x2,x3.....xn]T is an output matrix of independent components,

s=[s1,s2,s3.....sm]T is an input matrix of signal mixes.

A is a (n x m) de-mixing matrix.

A was generated using the JADE algorithm (Cardoso & Souloumiac, 1993; Cardoso, 1999) and when this was multiplied with (s), the independent components (x) were created. The four source signals were multiplied by a mixing matrix in order to produce four sets of signals from statistically independent sources. When viewed in the time domain one of the outputs from this method would contain a clear ECG trace (component 3 in Fig 6.4), with the power spectrum demonstrating the typical features in the 0-20 Hz range (Seen in Fig 6.7).

A previous study (Hu et al, 2005) indicated that a cut-off frequency of 30 Hz was the most suitable for removing the ECG component from the relevant de-mixed signal output. However, as this study is using fewer sensors, it would be advantageous if a

smaller number could be successfully used. It had previously been indicated that the majority of the ECG power spectrum occupies the 0-20Hz range in the power spectrum (Conforto & D'Alessio, 1999). Initial tests of this value indicated that this number was suitable and so it was used across the whole dataset. As such, a high band pass filter (>20Hz) was applied to the component containing the ECG noise.

The inverse of the mixing matrix (A) was then calculated using the Gauss elimination method to create (A^{-1}) and this used to return the output signals to their original state, minus the ECG contamination, using the following model:

$$\mathbf{s = A^{-1}x}$$

(s) now contains the original four, spatially separated input signals, minus ECG contamination.

6.3 RESULTS

6.3.1 ICA ILLUSTRATION

This section contains an illustration of how the ICA algorithm affects the recorded signal information. Fig 6.3 shows 3 seconds of unmodified EMG data in the time domain.

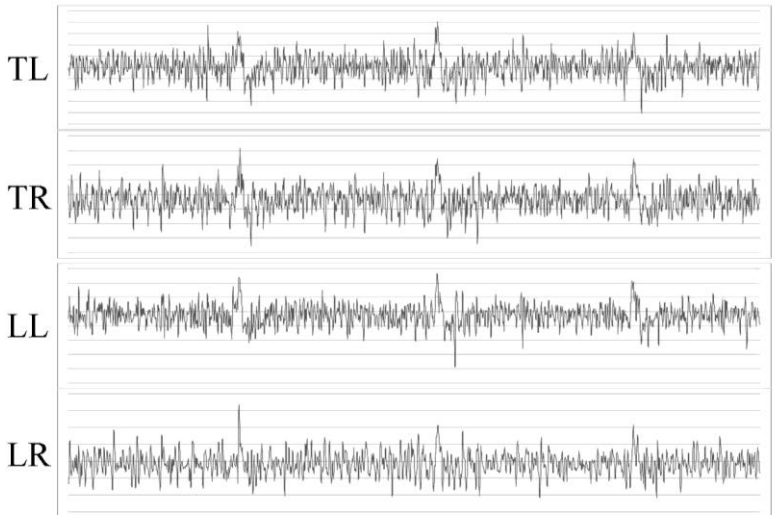


Figure 6.3 Three seconds of unaltered EMG data in time domain.

Note the apparent ECG outline that occurs across all four channels. As this image shows 3 seconds of data the ECG peaks would appear to be approximately 1 second apart, which is to be expected. Next the ICA algorithm is applied. This algorithm attempts to separate the signal data into a series of additive subcomponents by the mutual statistical independence of components in the source signal. The output remains in the time domain.

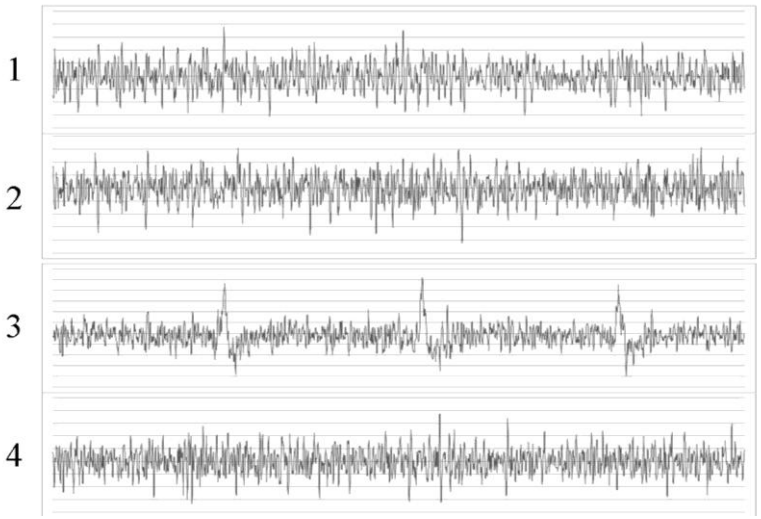


Figure 6.4 The same signal data after application of the ICA method.

Fig 6.4 shows that the ECG component of the signal has been constrained into a single output channel, in this case the channel labelled 3. Now that the ECG component is in this one channel, a band pass filter can be applied to this single channel, rather than all of them. The results of the application of a filter removing everything below 20 Hz from channel 3 are now shown in Fig 6.5.

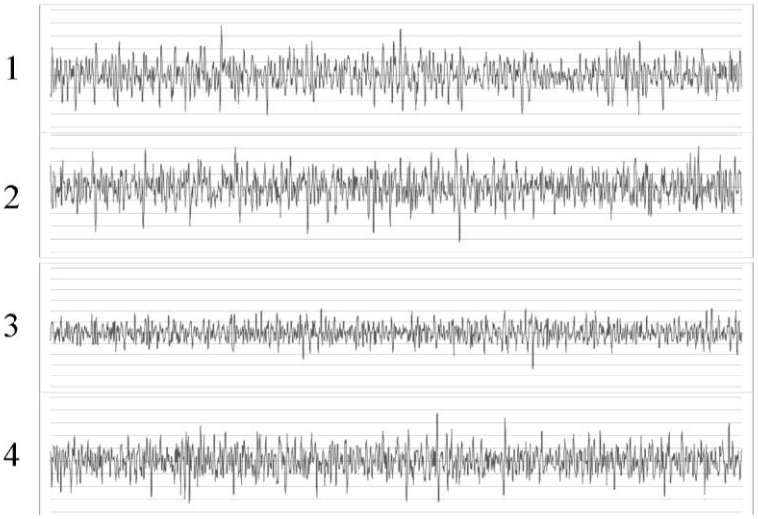


Figure 6.5 The independent component data after application of band pass filter to channel 3

As can be seen, the ECG component had been removed from channel 3 by the filter. The next stage is to recombine the independent components using the inverse of the matrix generated to separate them.

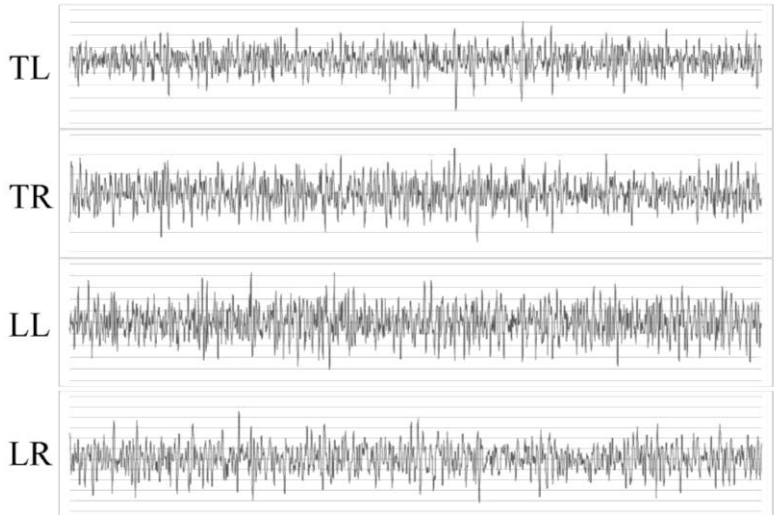


Figure 6.6 The EMG raw data after the independent components have been recombined.

Finally the signal data has been restored to its original state, minus the ECG artefacts (Fig 6.6). By isolating the ECG component to a single channel and only applying the filter to this one area, most of the 0-20 Hz underlying EMG data has been preserved. The effect of this on the frequency domain signal is clear, as the next illustrations demonstrate.

These images appear less smooth than the ones in Figs 6.1 and 6.2. This is because no smoothing algorithms have been applied. Figs 6.7 and 6.8 demonstrate a pure FFT of the signal data in Figs 6.3 and 6.6 respectively.

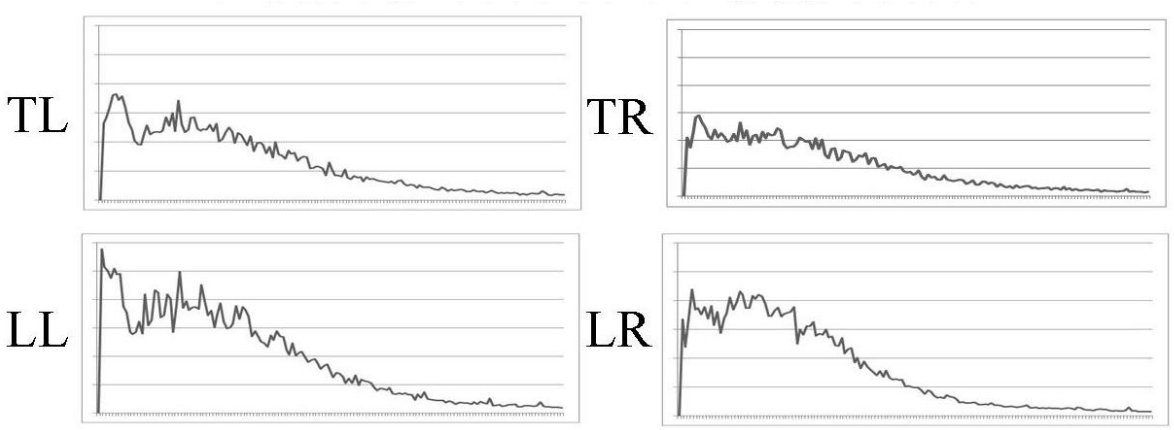


Figure 6.7 The FFT spectra of the recorded EMG signals, showing a LFP on all channels

Fig 6.7 shows the original FFR spectrum of the EMG signals. The letters indicate thoracic left/right and lumbar left/right. Low frequency peaks can be seen on all channels.

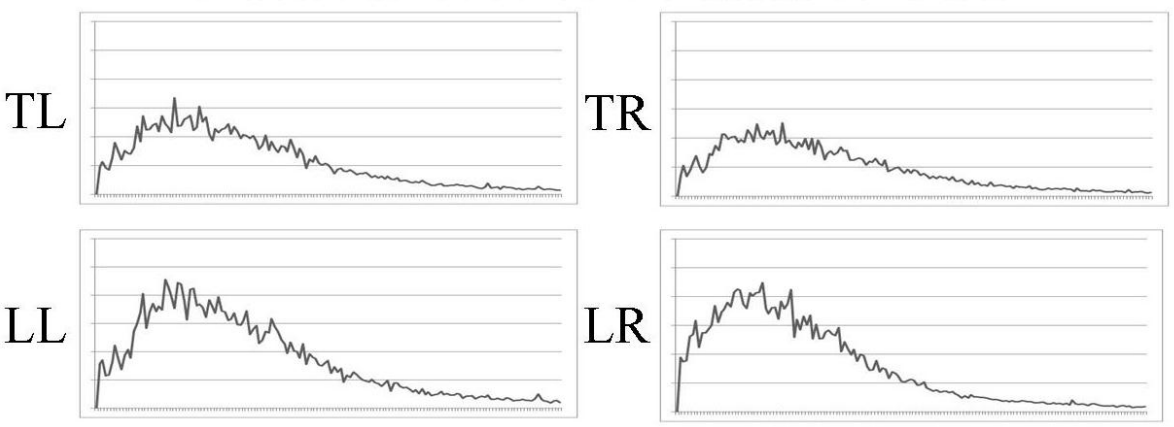


Figure 6.8 The FFT spectra after the application of the described ICA methods.

Fig 6.8 now shows the frequency domain spectra after the independent components had been re-integrated using the inverse matrix. The LFP that had been present in all of the 4 spectra has been removed, whilst the underlying 0-20 Hz signal data has been preserved. The very slight changes in the shape of the spectra in the areas over 20 Hz are caused by the rounding errors intrinsic in operations involving multiple matrix transformations.

This work indicates with some confidence that the low frequency peak component of frequency domain EMG spectra is caused by ECG contamination. It shows that even with only four channels of real data, the ICA algorithm can separate the ECG contamination from the EMG data, allowing it to be filtered out whilst preserving the underlying EMG signals (Coxon et al, 2011).

6.3.2 EFFECT OF ECG REMOVAL ON EMG VARIABLES

Once all of the previously recorded EMG raw data files had been examined, significant ECG contamination was found to have occurred in 33 of them out of a total of 455. This is an incidence of 7.3%.

Tests were conducted to examine the effect that the ECG artefact removal had on six key variables that had previously been identified as being of interest (Chapter 2), the lumbar half-width, the RMS, the RMS slope, the RMS intercept, the median frequency slope and the median frequency intercept. These were expressed as averages taken from the left and right sides. For both before and after ECG artefact removal, variable averages and standard deviations were calculated for a simple comparison. The Pearson Product Moment Correlation Coefficient (PPMCC) was used to examine how relative any differences were to the initial values. Next the average and standard deviation of any change in the variables was calculated. Finally a graph was produced to demonstrate the differences visually. This graph was ordered by magnitude of the unaltered variable to aid clarity.

HALF-WIDTH

	Original	No ECG
Avg	87.12	75.03
SDev	21.45	20.70
PPMCC	0.82	
Change Amounts Avg	12.10	
Change Amounts SDev	12.79	

Table 6.1 - Changes in Lumbar EMG Half-Width values.

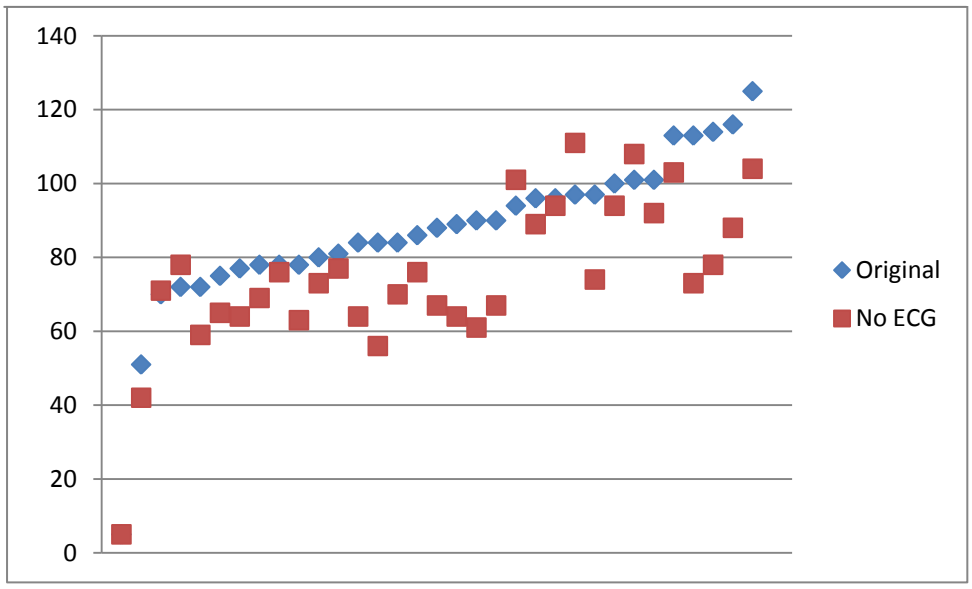


Figure 6.9 - Graph comparing Lumbar EMG Half-Width variables before and after ECG removal, ordered by original values.

These results show that removing the ECG contamination does have an effect on the lumbar half-width variable, on average making it smaller.

This is to be expected as the presence of a low frequency peak would extend the left hand side of the half-width, thereby increasing its value. The effect is not constant however. It is possible that whilst the spectral frequencies of the ECG are constant the spectral areas covered by the half-width change per subject. A more likely cause for this effect is the algorithm used to set the left hand side of the half-width measurement. As shown in Section 6.1 the algorithm used will often remove the low frequency component from the half-width (Figure 6.2), but this is dependent on the spectral height dropping sufficiently after the low frequency peak, which is not always the case. This could result in the inconsistency demonstrated in the above graph.

However despite this uncertainty, experiments based on half-width values would benefit from the use of this method to remove the ECG artefact from the EMG data.

ROOT MEAN SQUARE

	Original	No ECG
Avg	44.98	39.37
SDev	16.76	15.10
PPMCC	0.96	
Change Amounts Avg	5.61	
Change Amounts SDev	4.80	

Table 6.2 - Changes in the Lumbar EMG RMS values.

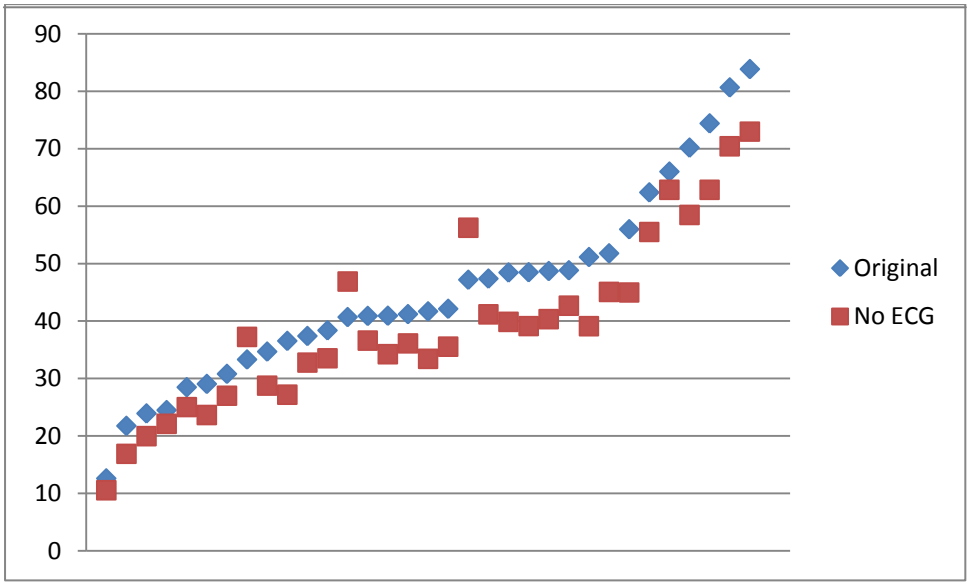


Figure 6.10 - Graph comparing Lumbar EMG RMS variables before and after ECG removal, ordered by original values.

Removing the ECG artefact from the EMG data does have some effect on the RMS variables, making them slightly lower. The PPMCC figure, and the graph, indicates that this is a very consistent change.

The outliers in these results could be to do with how the shape of the low frequency peak relating to ECG is not always consistently proportioned to the shape of the rest of the EMG spectrum. These proportions will affect the consistency of the spectrum once the low peak is removed.

As the RMS is a measure of the consistency of the shape of the transformed spectra, the cause of this effect could simply be that removing a large peak at the start of the spectrum would result in it having a more homogenous shape.

Nevertheless, removing the ECG artefact has altered this variable.

ROOT MEAN SQUARE SLOPE

	Original	No ECG
Avg	0.14	0.15
SDev	0.24	0.25
PPMCC	0.86	
Change Amounts Avg	-0.01	
Change Amounts SDev	0.13	

Table 6.3 Changes in the Lumbar EMG RMS Slope values.

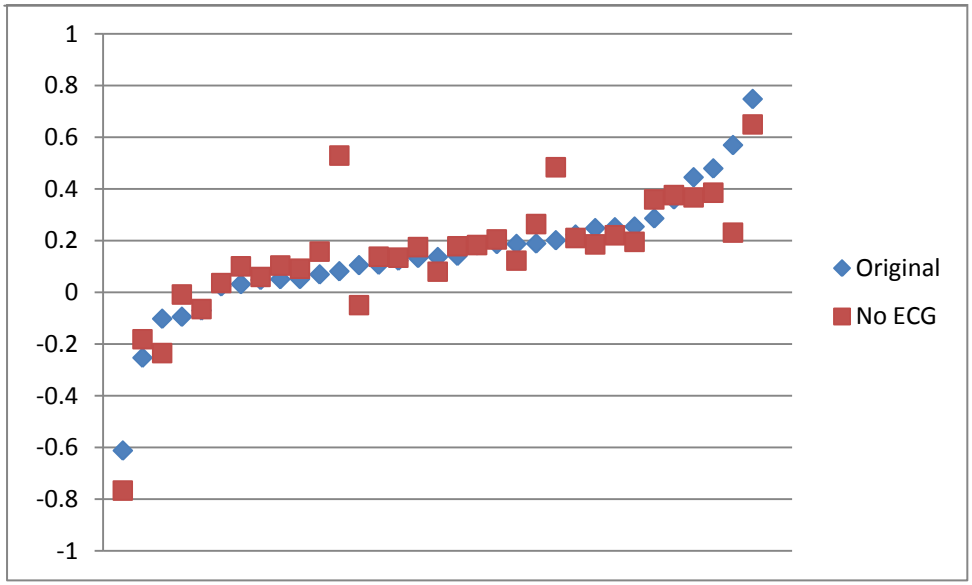


Figure 6.11 - Graph comparing Lumbar EMG RMS slope variables before and after ECG removal, ordered by original values.

There is little change evident in the RMS slopes after removal of the ECG artefact.

This variable indicates how the homogeneity of the EMG frequency spectrum changes from each one second epoch to the next. As the ICA algorithm was applied evenly to each epoch, it is to be expected that this level of difference would be constant across the tests.

Again the outliers are possibly caused by some low frequency peaks having a greater impact on the overall spectral shape than others.

It is suggested that the ECG artefact had little effect on the RMS slope values.

ROOT MEAN SQUARE INTERCEPT

	Original	No ECG
Avg	42.29	36.64
SDev	14.36	13.76
PPMCC	0.96	
Change Amounts Avg	5.65	
Change Amounts SDev	3.78	

Table 6.4 - Changes in the Lumbar EMG RMS Intercept values.

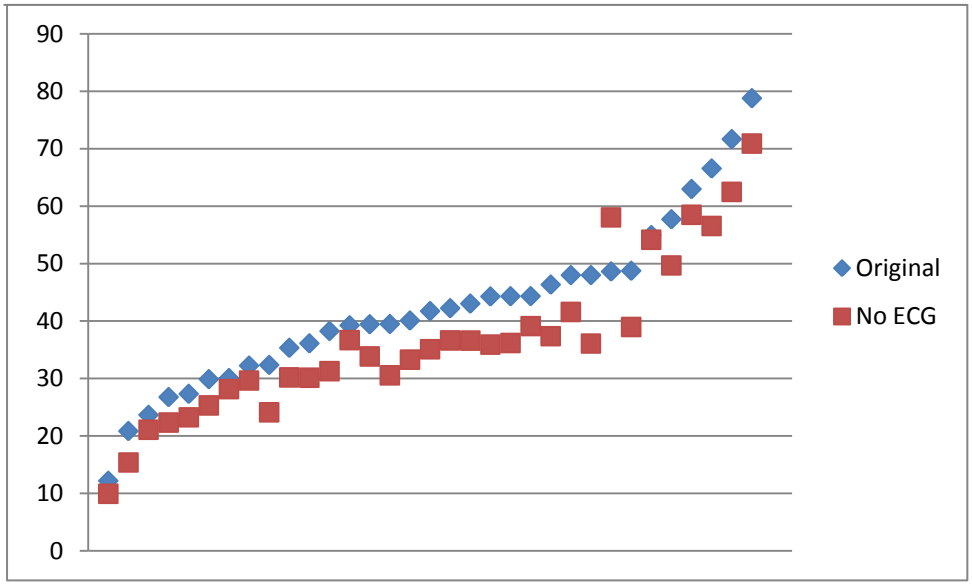


Figure 6.12 - Graph comparing Lumbar EMG RMS Intercept variables before and after ECG removal, ordered by original values.

Again there is a slight, consistent difference between the values before and after ECG artefact removal when considering the RMS Intercept variable. The new values show a high correlation with the old (0.96 PPMCC), with the difference being a slight reduction in magnitude.

Removing spectral content from the lower frequency areas of the spectrum, consistently over time, would not change the slope of the RMS value. It would however shift it to the left, resulting in a lower RMS Intercept value.

This evidence would suggest that the RMS Intercept variable is affected by ECG contamination.

MEDIAN FREQUENCY SLOPE

	Original	No ECG
Avg	-0.11	0.04
SDev	0.17	0.48
PPMCC	-0.75	
Change Amounts Avg	-0.16	
Change Amounts SDev	0.62	

Table 6.5 - Changes in the Lumbar EMG Median Slope values.

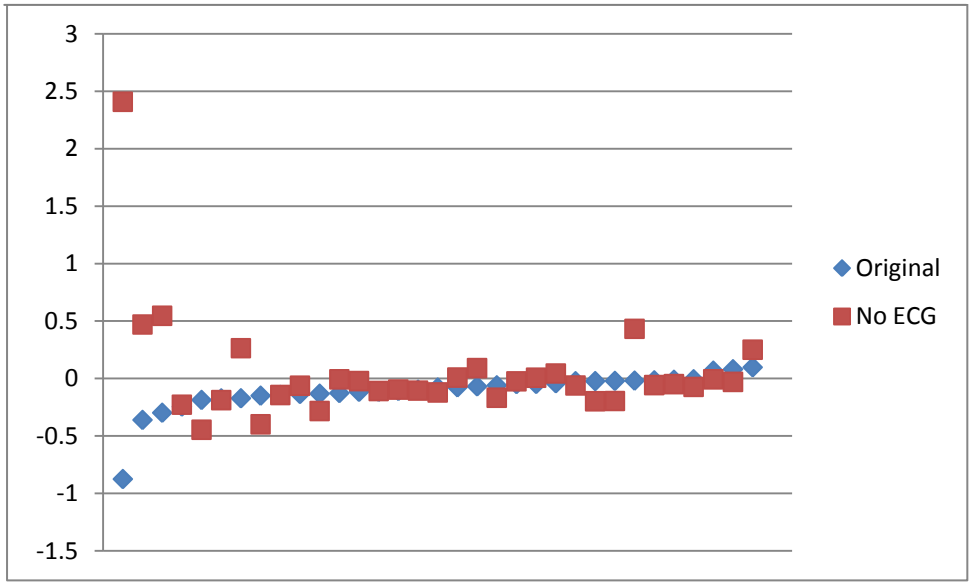


Figure 6.13 - Graph comparing Lumbar EMG Median Slope variables before and after ECG removal, ordered by original values.

Other than in the case of the outliers, the Lumber EMG Median Slope variable undergoes very little change after removal of the ECG artefact. It is suggested that the negative correlation indicated in the PPMCC score (-0.75) is a consequence of these outliers rather than an indication that the higher an initial Median Slope value, the lower the new value would be.

Again, the value of the slope not being affected is to be expected. The ECG artefact removal strategy was applied evenly over time for the test data and so would affect each epoch equally.

The Lumbar EMG Median Slope variable is not affected by the presence of an ECG artefact.

MEDIAN FREQUENCY INTERCEPT

	Original	No EMG
Avg	62.15	89.62
SDev	10.47	14.44
PPMCC	0.68	
Change Amounts Avg	-27.47	
Change Amounts SDev	10.68	

Table 6.6 - Changes in the Lumbar EMG Median Frequency Intercept values.

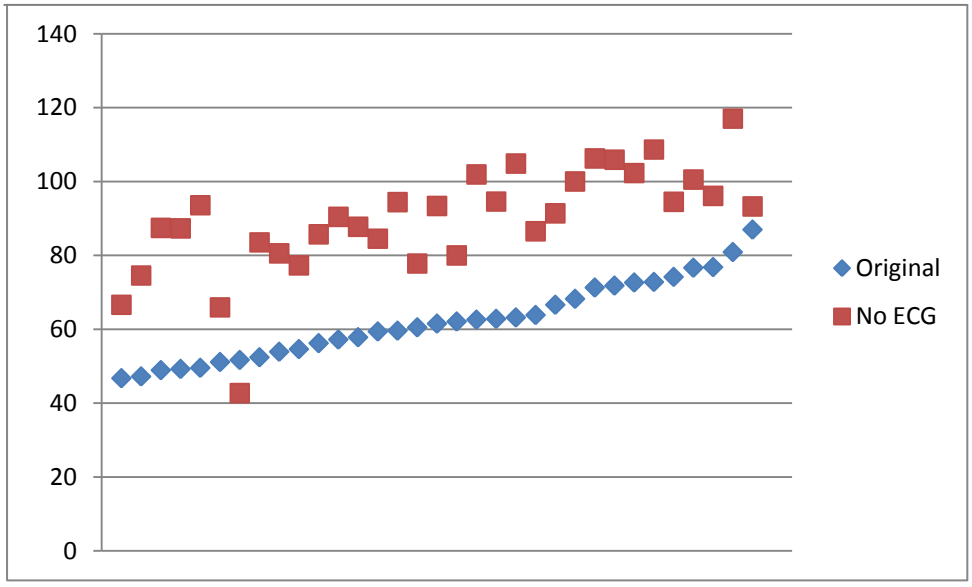


Figure 6.14 - Graph comparing Lumbar EMG Median Frequency Intercept variables before and after ECG removal, ordered by original values.

The Lumbar EMG Median Frequency Intercept value is increased markedly by removal of the ECG artefact. The PPMCC figure is not as high as for previous variables (0.68), but still indicates a strong correlation between the before and after removal figures.

An increase in the Median Frequency intercept value indicates that the median frequency shifts to the higher ends of the frequency spectrum after removal of the ECG artefact consistently across each epoch. This is supported by the Median Frequency Slope being unchanged by removing this artefact, demonstrated previously. Naturally one would expect that removing a quantity of signal information from the lower ends of a spectrum would result in the median shifting away from that end.

Removing the ECG artefact has a strong effect on the Lumbar EMG Median Frequency Intercept variable.

6.4 DISCUSSION

6.4.1 EFFECTIVENESS OF INDEPENDENT COMPONENT ANALYSIS METHOD

As can be clearly seen in Figures 6.3 to 6.8 the ECG component in the time domain series, along with the low frequency peak in the frequency domain series, are removed after application of the ICA method. It is important to state that without an ideal answer, that is something that the cleaned up EMG signals can be compared to; this study was limited to ‘eyeballing’ the output spectra to evaluate its efficacy.

However visual analysis of the spectra provided clear and obvious evidence that the ECG contamination had been removed. Further confidence can be gained by noting that similar results were obtained by this research with respect to the RMS and MF slope outcome scores as had been previously presented (Hu et al, 2007).

A cut-off of 20 Hz was high enough to remove the ECG component in this project, despite the higher figure of 30 Hz being recommended previously (Hu et al, 2004). The main difference between that study and this one is that this study was examining lumbar EMG data from a fatiguing test. It is unlikely however that this is why the lower figure proved suitable in this case, if anything one would expect the ECG power spectrum representing a fatiguing test to be wider, and therefore require a higher cut-off. The answer is possibly that as the authors from that study were working with eight sensors instead of four, they felt that the outcome de-mixed signal component that contained the ECG artefact would contain so little EMG data, a higher cut-off was justified to ensure all of the contamination was removed. In the case of this study, using four sensors meant that a greater proportion of the EMG

data would remain in the contaminated de-mixed outcome trace and so greater care needed to be used.

In conclusion it can be stated with some confidence that the low frequency peaks seen in the frequency domain spectra of signal data from some lumbar EMG tests is caused by ECG contamination. This contamination can be removed, whilst preserving the underlying EMG data, by the Independent Component Analysis algorithm.

6.4.2 EFFECT OF ECG REMOVAL ON LUMBAR EMG OUTCOME SCORES

	Half Width		RMS		RMS Slope		RMS Intercept		MF Slope		MF Intercept	
	Org	**New**	**Org**	**New**	**Org**	**New**	**Org**	**New**	**Org**	**New**	**Org**	**New**
Avg	87.12	75.03	44.98	39.37	0.14	0.15	42.29	36.64	-0.1	0.04	62.15	89.62
SDev	21.45	20.70	16.76	15.10	0.24	0.25	14.36	13.76	0.17	0.48	10.47	14.44
Avg Change	12.10		5.61		0.01		5.56		0.14		27.47	
	13.9%		13%		7.1%		13.4%		N/A		44.2%	
PPMCC T Value	0.82 p< 0.0005		0.96 p< 0.0005		0.86 p = 0.857		0.96 p< 0.0005		-0.75 p = 0.152		0.68 p< 0.0005	

Table 6.7 - Overall Changes in Outcome Measures after removal of ECG artefact

The RMS Slope and MF Slope variable outcomes have not produced useful results. These outcomes are designed to measure how their associated variables (RMS and MF) change from one epoch to the next and, as the ICA algorithm was applied evenly to each epoch, the amount of change was very small. This allows us to state

with some certainty that the magnitude of the ECG contamination did not change over time, as if this were the case one would expect the slope values to change.

Having identified that the actual RMS slope and MF slope values are significantly unchanged, we can now examine whether or not the magnitude of the variables that make up the slope are changed by removing the ECG artefact. Examining the RMS Intercept and the MF Intercept will provide this information as these variables show how high the associated slopes were when they crossed the zero seconds mark. These variables did show a change, which leads us to the conclusion that for fatiguing tests (i.e. where we are looking for change over time) it is more appropriate to use the two Intercept variables to examine any change that has occurred after artefact removal. Both of these variables have recorded a significant change; the RMS Intercept being reduced with a high level of consistency between individuals (PPMCC = 0.96) and the MF Intercept increasing with a slightly lower level of consistency (PPMCC = 0.68).

The overall RMS value for each spectra was reduced with a high level of consistency (PPMCC = 0.96). This value reflects the consistent effect on lowering RMS values when a large peak in the lower frequency areas is removed.

Finally the Half-Width variables were reduced on average by 13%, with a high level of consistency (PPMCC = 0.82). This was to be expected as the low frequency peak caused by the ECG contamination would extend the half-width measurement towards the left hand side of the spectrum (Figure 6.1). It is important to note that the original figures represented EMG spectra that already had some low frequency peak compensation algorithms applied to them. The reduction figures therefore are possibly lower than would be expected.

A 2005 study (Hu et al, 2005) demonstrated that the ICA method could be used to remove ECG contamination in the same manner to the work presented in this

chapter, using artificially generated ECG signals added to clean EMG data rather than purely recorded signals. A second study conducted in 2007, examining the effect of ECG contamination of paraspinal EMG during non-fatiguing exercises (Hu et al, 2007), found similar results to those presented in this chapter, noting a decrease in RMS and an increase in MF after removal of the ECG contamination. No other variables were assessed and EMG signal data was recorded from eight locations. As the EMG data was only recorded in four locations for the work in this chapter, and during a fatiguing test when the ECG spectral characteristics would be expected to change over time, this provided a more stringent test of the ICA algorithm.

6.4.3 OVERALL

Low Frequency Peaks found on lumbar EMG spectra are caused by ECG artefact contamination.

The Independent Component Analysis can be used to remove ECG contamination from the EMG spectra of lumbar fatiguing tests recorded with only four electrodes.

The ECG contamination is constant over time in the 0-20 Hz band so variable slope measurements are unaffected.

Although the angle of the slopes remain unchanged, the height of the slopes does in fact change, the RMS slope becoming lower, and the MF slope becoming higher.

The RMS and Half-Width values are also significantly changed by removing the ECG artefact.

Trunk EMG analysis projects using the Half-Width, RMS, RMS Intercept or MF Intercept values should be aware of the potential for ECG contamination, and use the ICA method to compensate for it (Coxon et al, 2012).

6.5 IMPLEMENTATION

6.5.1 EMG FILES

As described in chapter 5 the EMG test produces two EMG raw data files; one contains volts from the left and right sensors over the thoracic muscles along with subject load information, and the other contains volts from the left and right sensors over the lumbar muscles. These numeric values were tab separated and both files also stored some demographical information on the test subject. The EMG acquisition software and the automated analysis software (chapter 5) used this file format. However, this format had been inherited from previous projects, and was fairly inefficient. A new format was decided upon which would create one data file per test, and comma separate the numerical variables. As the demographic data was repeated in the subject database, this was omitted from the new file types as an added security precaution.

A system was created that would automatically create the new file format from the old file data. The first file from an EMG test was opened and the numeric contents were read into the first 3 columns of a 5 (number of data sets – load pulled, thoracic left/right, lumbar left/right) x 30720 (number of data points – 30 seconds multiplied by a sampling rate of 1024) array. The second file was then opened with the numeric contents being written into the last 2 columns of the same array. After this had been completed this 5 x 30720 array was used to output the numbers to create the new comma separated variable (CSV) file. The numbers were simply outputted to a blank file 5 to a line, with commas being used to separate the individual values. The file naming convention was '(subject number)(test number).csv'. This process was repeated for all of the original test data files.

6.5.2 READ IN FROM EMG FILES

All of the raw data files to be tested (in the new format) were placed in one folder. When the process of removing the ECG component is first started the names and file paths for all of the files in this folder were placed into a database. Once each file had been processed the entry was deleted from the database, allowing the process to proceed from where it had been left should a break be required.

The file at the top of the database list was opened and the contents read directly into a 5 x 30720 array. The file contents were stored in memory during the process for reasons of program speed.

6.5.3 PERFORM FAST FOURIER TRANSFORM

The EMG raw data was transformed into the frequency domain in one second epochs, meaning that 30 frequency domain spectra (one per second of the test) were created per channel. As the sampling rate was 1024 Hz, the frequency spectra would be 512 Hz long (Nyquist) meaning that four arrays containing 30 x 512 elements were created to store the frequency domain data.

A function was created to perform the FFT. This would be passed 1024 data points (corresponding to one second) from the input arrays and would return 512 data points to be stored in the frequency domain data arrays. As 30 iterations were required to completely transform one channel of data, 120 iterations would be needed for each raw data file.

Finally an array was created to hold the composite spectra information. The composite spectra is the averages of the 30 individual FFT epochs and so only one per channel was needed, meaning an array of 4 x 512 elements.

6.5.4 PERFORM INDEPENDENT COMPONENT ANALYSIS

The JADE algorithm (Cardoso & Souloumiac, 1993; Cardoso, 1999) was used to create a “de-mixing” matrix based upon the EMG raw data, of a 4x4 size. If the EMG raw data is considered to be a matrix of 4x30760 rather than four separate arrays of length 30720, it becomes possible to multiply the de-mixing matrix with the EMG raw data matrix. The result of this operation would be in the form of a 4x30760 matrix. Taking each row of this output matrix to be an independent component of the signal (in the time domain) produces the outputs shown in Figure 6.4. An FFT is then performed on these independent components in order to provide the researcher with additional visual information.

The ECG component does not always appear in the same independent component channel. Some work was done on a system that would be able to analyse these independent components to see if an ECG artefact was present and, if so, which channel it was present in. As the complexity of this task grew it quickly moved beyond the scope of this project, and as such it is required that a human observer identify if an ECG artefact is present and in which channel.

The researcher is presented with four sets of information with which to make this decision; time domain and frequency domain spectra of the raw EMG data, and time domain and frequency domain spectra of the EMG data after separation into the independent components. As can be seen from the illustrations in this chapter this was usually a relatively simple task for a trained human observer to accomplish.

Once the appropriate independent component had been identified a high band pass filter was applied to remove the 0-20 Hz signal data from that component. The

researcher was able to check that this had indeed removed the ECG artefact from both the time and the frequency domain spectra. In order to return the independent components to their original states the inverse of the original de-mixing matrix was calculated using the Gauss Elimination method. As multiplying the unaltered independent components by the inverse of the de-mixing matrix would produce the original EMG raw data, performing that operation once the ECG artefact had been removed from the independent components would recreate the initial EMG raw data, but without the ECG artefact.

A final FFT was performed on this new EMG data in order to present it in the time and frequency domain to the researcher.

6.5.5 GENERATE RESULTS

The previous process was sufficient to identify that this system can indeed remove an ECG artefact from EMG data, whilst preserving the underlying signal information. The next step would be to see what effect this had on the half-width variables. As it was the automatic analysis system that provided the initial half-width values it would be preferable to use the same system to create the comparison values.

A system was created by which a researcher could create a list of raw data files that needed checking for ECG artefacts. The first file would then be selected and have the relevant FFT and ICA processes performed on it, with the results being displayed to the researcher. The researcher could examine these results to see if an ECG artefact was present and, if so, in which channel. After the channel was selected a filter was used to remove the 0-20 Hz signal component from the relevant signal, and the independent components were recombined to recreate the original signal. Using the output arrays from this process along with the load data

from the original raw data file, an output file was created in the same format as the old EMG raw data file type. This was repeated until all of the raw data files had been assessed.

Finally, the automated analysis software was given these new EMG raw data files and they were analysed in exactly the same manner as were the files that did not have the ECG artefact removed. This permitted an accurate comparison of all of the recorded variables to see if any significant changes had occurred.

CHAPTER 7

COLOUR MAPS

7.1 BACKGROUND

7.1.1 INTERPRETING EMG RESULTS

The EMG analysis methodologies used throughout this thesis begin with a windowed Fast Fourier Transform (FFT) being applied to raw signal data in order to produce a series of frequency spectra. These produced spectra that essentially comprise of a grid of numbers for each channel of EMG of the size 30 (the number of epochs) by 512 (the frequencies up to half the sampling rate of 1024 Hz). In Chapters 5 and 6 these individual epochs were averaged together to create a single composite epoch which could be examined as a graph, see below.

COMPOSITE SPECTRA

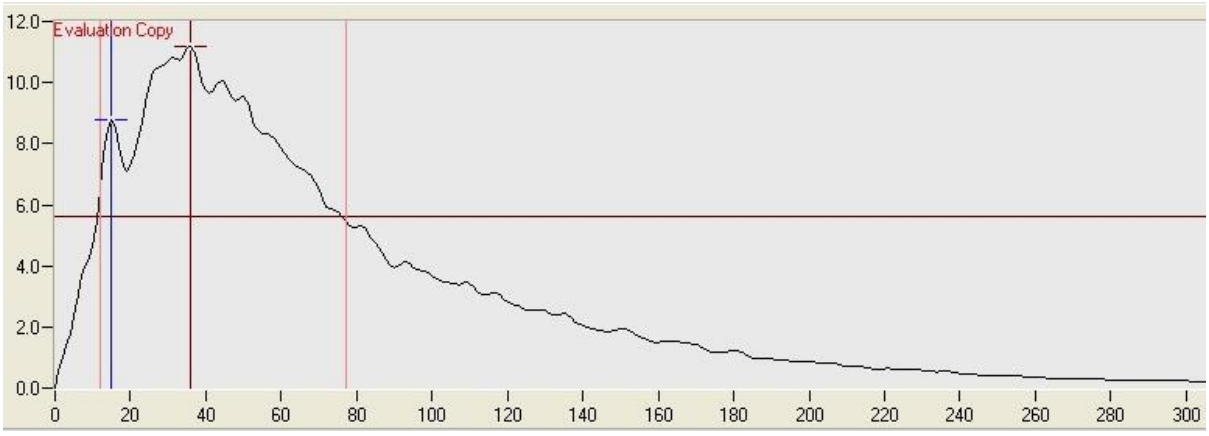


Figure 7.1 - A composite EMG frequency spectrum

This method had the advantage of producing a quick and easy method of viewing the data but some crucial information was lost during the process, specifically

referring to potential temporal aspects of the recorded EMG data. If a certain frequency area became active at a certain point in time only, this artefact would have been essentially smoothed across the other epochs. The composite spectra method does not have the ability to clearly indicate significant changes over time, which would be expected to occur in fatiguing lumbar contractions of sufficient time and intensity. The half-width variable was created in part to counter this failing, i.e. frequency shifts should show up as a wider spectrum, but this remained a less than ideal solution as examination of the half-widths from the one second epochs demonstrated that this was not a sufficiently wide signal window to generate this variable accurately. Using a wavelet based windowing function for this was considered beyond the scope of this project. Efforts were directed towards investigating analysis methodologies that would make more use of the information present in the raw data files.

A second reasoning behind the creation of the half-width variable was that it would provide a simple numerical measure.

3D VIEWER

The logical extension to this method would be to add a third axis to the graph, which would allow the data to be viewed in 3D. The OpenGL toolkit was used to create a system whereby each of the 30 second epochs could be calculated and then placed side by side. To aid clarity the graphic was coloured so that as the height of the signal increased the colour of the graph surface changed from green to red. The gridlines split the graph into sections by epoch and frequency. The researcher had the option of rotating, translating and, zooming the image to facilitate viewing.

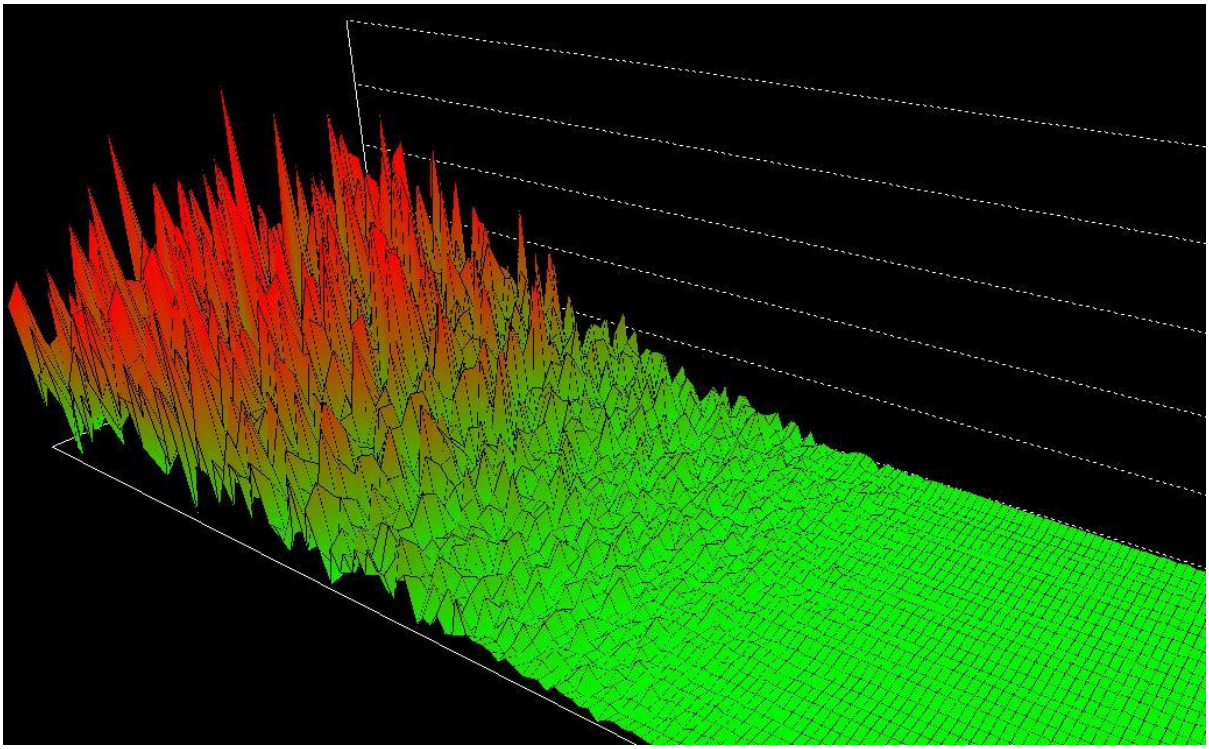


Figure 7.2 - The Individual Epochs 3D Viewer

Whilst this method undoubtedly provided more information to a researcher, it did not possess any obvious facility for easy, quantifiable interpretation. This effect is magnified when it is taken into account that the above image represents one set of data out of the four that comprise each EMG test.

7.1.2 PREVIOUS WORK ON COLOUR MAPS

A compromise between the 2D composite spectra view and the 3D array of individual epochs would be to somehow plot the additional information on a 2D view. One proposed method (Greenough et al, 1998) was to use a spectral colour mapping technique. This method was described in some detail in Chapter 3. Very briefly the information is plotted out so that the researcher is presented with a

viewpoint that suggests they are observing the 3D layout from above. Colour gradients are used to indicate spectral heights at given times/frequencies. In the case of these images, the colours represent low to high frequencies using red through yellow, to green and finally blue respectively.

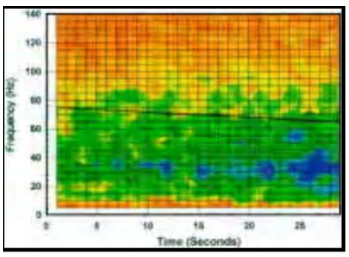


Figure 7.3 - A Spectral Colour Map with frequency on the Y-axis and time on the X-axis. Colours from red through to blue represent low to high signal amplitudes respectively

The advantage this method has over the previous two is that one can clearly see how the individual frequency spectra epochs change across the 30 second test period. The authors of this study examined the efficacy of this method of displaying EMG data with regards to discriminating between different categories of back pain subjects. Some example results are shown below.

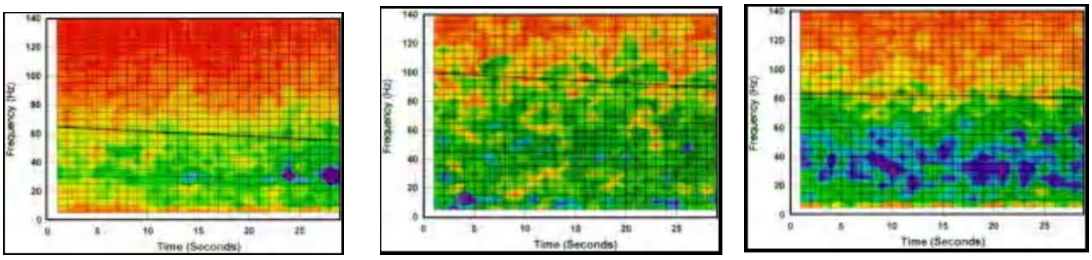


Figure 7.4 - Spectral Colour Maps for subjects with no pain ever, acute pain and chronic pain from left to right respectively

As can be seen, some differences did exist in the colour maps between groups, which would not have been so obvious using either the 3D viewer or the composite spectrum.

7.1.3 SUGGESTED IMPROVEMENTS

The colour map research project did identify a number of areas for improvement. The first area was that the test was carried out by highly trained medical professionals on a subject population who were all in full time hospital employment. It would be of some benefit to see whether or not the same results could be obtained if the tests were carried out by less well medically trained research staff on a more heterogeneous subject population.

The original colour map project did not identify a quantifiable measure that could be used to discriminate between groups. The method used was an examination of the width of the green band, assessed by eye. This was a clearly effective, but somewhat objective measurement.

The manual production of the spectral colour maps was a long and drawn out process. Not only does this method preclude a large scale batch production of spectral colour maps, but it has implications for the re-test accuracy of any data. A system that would create a spectral colour map from a given raw EMG data file with no other user input would save on research time and be entirely consistent.

Finally the subject population was quite limited in size and were only seen on the one occasion. If a large population was assessed over a number of years, perhaps the technique could be examined for its use as a predictor for low back pain.

7.2 METHODOLOGIES

7.2.1 SUBJECTS

One hundred and ninety two subjects were tested. Subjects were recruited from members of the general public. They were each tested on three occasions; initial contact, after 12 months and finally after 24 months. In addition to the EMG test, subjects completed questionnaires designed to enable calculation of their LBOS, ZUNG and MSPQ scores at each visit. After drop-outs, a total of 444 data sets were acquired.

The height and weight of all the subjects were recorded. Percentage body fat was estimated with a skin fold calliper and from this the lean body mass was calculated.

7.2.2 ISOMETRIC LUMBAR TESTING

With the subject standing, a pelvic rest was set 6 cm below the anterior superior iliac spines. The subject was positioned with a trunk angle of 30^{o} using a goniometer. Loading was performed by the subject pulling upwards with straight arms on a bar attached to a load cell fixed to the floor. The target load was to be 70% of the subject's lean body mass. The subject exerted this force on the bar for 30 s while surface EMG was recorded.

7.2.3 EMG RECORDING

EMG recording sites were carefully prepared in order to ensure a constant inter-subject level of impedance. Surface electrodes were placed bilaterally over the erector spinae muscles at the L4/L5 and T5/T6 levels, with the inter-electrode distance being 10 cm. The lumbar recordings would be used to create the half-width variables, whilst the thoracic recordings were taken to provide additional input signals for the ICA method.

A Medelec 2ME EMG system was used to amplify and filer the EMG signal (band pass 3-300 Hz). The analogue output of the EMG system was digitized on a laptop computer using a National Instruments DAQ-Card-700 PCMCIA analogue to digital converter. Four channels of EMG and the output of the load cell were sampled at 1024 Hz using a continuous double-buffered process, while the acquisition software maintained a real-time bar graph display of load centred at 70% of the subject's lean body mass. This clear display helped the subjects maintain a steady and accurate force for the 30 s duration of the test.

The EMG testing was performed by non-medically trained individuals. This was a deliberate choice so as to be able to assess the robustness of this data collection technique.

7.2.4 EMG ANALYSIS

The 30 s EMG recordings were divided into 30 epochs containing 1024 voltage samples. A Fast Fourier Transform was applied to each epoch to obtain a power spectrum, each of which were stored individually. The frequency for each epoch where the signal intensity was equal above and below that frequency was

calculated and saved as the median frequency. Examining these median frequencies together enabled the creation of a median frequency slope.

7.2.5 CREATING THE COLOUR MAPS

The 30 individual epochs were saved into a 30 x 512 element array which was then made available to the part of the software that created the colour maps. This software used the OpenGL (Open Graphics Library) Application Programming Interface (API) to create the body maps. OpenGL is a standard specification defining a cross-platform, cross-language API for writing applications that produce 2D and 3D graphics (OpenGL 4.0 Specification).

The colour maps were created as a series of flat, 2D polygons. To create a polygon in OpenGL, the procedure is to list the co-ordinates of the polygon, in Cartesian format, in order. As each epoch contains only a single line of data, each polygon is comprised of data from two separate epochs. This layout is illustrated below.

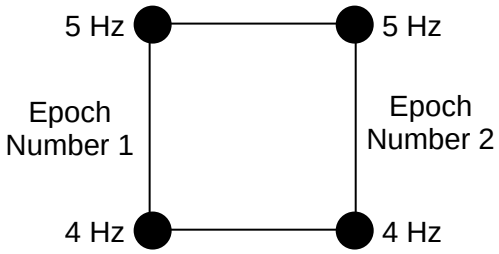


Figure 7.5 - A sample polygon from the OpenGL based colour maps

As in the previous work, colour is used to illustrate the height of the spectrum at each point. The same method of using 12 distinct colour bands that the previous study implemented was reused in this project. OpenGL uses RGB (red/green/blue)

values ranging from 0 to 1 to represent colour, so (0,0,0) is black, (1,1,1) is white and (1,0,0) would be red. The first stage of the colour band allocation process would be to normalise all of the ECG epoch values so that they fall between 0 and 1. All of the spectral values in the epoch array are investigated to record the highest number present; the number 1 is then divided by this number to produce a ratio value. The ratio value is then multiplied against each individual spectral component to produce a second epoch array, this time containing normalised values.

Twelve colours were selected, ranging from shades of green, through to yellow and finally onto red, each being used to represent increasing spectral heights. These bands were assigned equal sections of the 0 to 1 range, and a lookup table was used to assign each point in the normalised epoch array to the appropriate colour band.

To produce the colour maps, the polygons were drawn in a grid fashion and each vertex (the points on the corners in Fig 7.5) assigned a colour according to the band that particular point is in. The OpenGL API then interpolates colour across the polygon, so that (using Fig 7.5 as an example) if points 4 and 5 on epoch 1 were in a red band and points 4 and 5 on epoch 2 were in a green band, the square would transition smoothly from red to green along the horizontal axis.

7.2.6 CREATING THE LINE OF BEST FIT MEDIAN FREQUENCY SLOPE

As previous studies (Humphrey et al, 2005) have indicated that the median frequency slope has some facility in discriminating between LBP and non-LBP subjects it was decided to include this on the colour map. The viewer could choose

to see a coloured dot on each epoch line representing the median frequency for that epoch, a line of best fit representing all of the dots across the 30 epochs, or both.

To create the line of best fit, the least squares method was used. This method gives the start and end Cartesian co-ordinates of a line that represents the line of best fit for a given data set.

For the line of best fit $Y = mX + b$;

$$\boldsymbol{m} = \frac{\sum xy - \frac{(\sum x)(\sum y)}{n}}{\sum x^2 - \frac{(\sum x)^2}{n}}$$

$$\boldsymbol{b} = \overline{y} - m\overline{x}$$

Where;

n = Number of points

$\overline{x}$ = The mean of all of the X co-ordinates

$\overline{y}$ = The mean of all of the Y co-ordinates

7.2.7 AN EXAMPLE COLOUR MAP

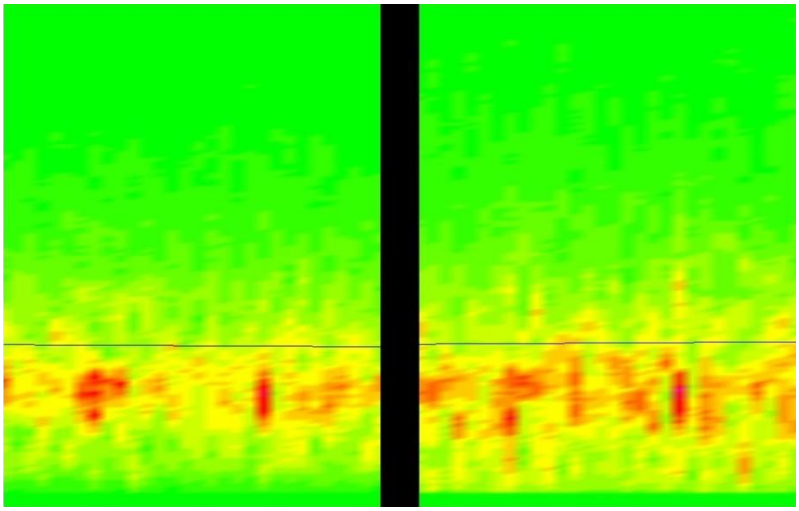


Figure 7.6 - An example colour map

This is an example of a spectral colour map produced using the previously described method. It shows two images, relating to readings from the left and right sides of the test subject's back muscles. The x axis represents time (0 to 30 seconds) and the y axis represents frequency (0 to 200 Hz). The 200 Hz cut-off was chosen as little to no relevant signal information is present above this level and showing a limited area increases the level of detail of the relevant information. Green indicates a low amount of signal data at a given frequency/epoch, yellow a medium amount and finally red indicates the highest amount of signal information was present at that frequency/epoch. Each colour has four different levels, giving a total of 12 colour bands.

The horizontal black line is the median frequency slope. It is a line of best fit for the individual median frequency values. If the slope is level then the median frequency is unchanged for the duration of the test. A sloped line indicates that the median frequency has increased or decreased during the test. A change in median frequency over the test could indicate fatigue, and asymmetry between sides for this variable could indicate some instability in the lumbar musculature.

7.3 RESULTS

7.3.1 FIRST STAGE

SUBJECTS

An initial experiment was carried out to see if the colour maps could be used to discriminate between subjects with LBP and subjects without LBP. As part of the EMG testing process the subject filled out a questionnaire, one of the questions being a visual analogue scale (VAS) rated from 0-10 asking how much back pain they experienced on a typical day. If they answered 3 or above to this question, they were categorised as having back pain at that time and categorised accordingly. A test population of 40 was randomly selected, 20 from the LBP group, 20 from the non-LBP group. Faulty EMG recordings had been removed from the potential test subject group before selection commenced. The test population size was chosen as a compromise, small enough so that assessor fatigue would not have an effect on the discrimination outcomes, and large enough to give reasonable meaningful results.

ASSESSORS

Four staff members from James Cook Hospital were selected, three of whom were specialist nurses and the third was a computer student on placement from the University of Teesside. None of these individuals had any previous experience with EMG testing and they were given a short five minute talk about how to interpret the colour maps with respect to discriminating between LBP and non-LBP groups.

The information conveyed in this talk was that a narrow band of red and yellow colour, with a flat median frequency line, was a good indication that a colour map represented a subject that did not suffer from LBP. Also, the point that a more

symmetrical set of colour maps indicates a subject without LBP was raised. Conversely, a colour map having a wide or growing red and yellow band, a sloped median frequency line or a lack of symmetry between left and right sides would suggest less than optimal lumbar muscle recruitment and therefore a good likelihood that the colour map represented a subject suffering from LBP. They were also shown two example images, as seen below;

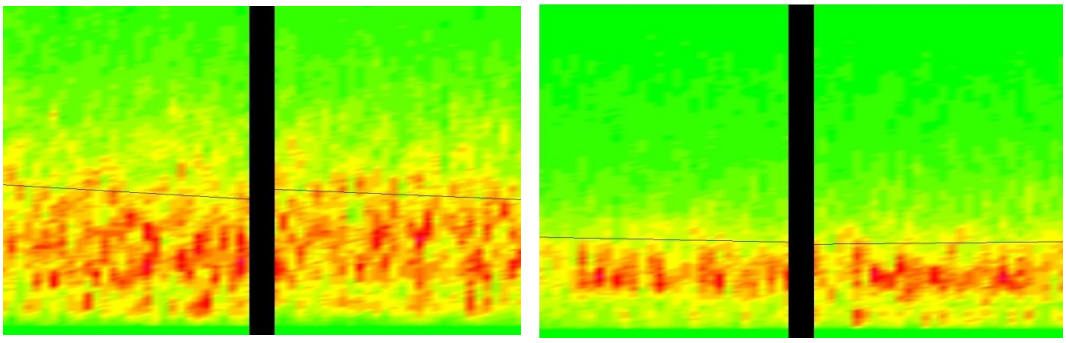


Figure 7.7 - Colour Maps showing subject with (left) and without (right) LBP.

After this talk they were presented with the 40 colour maps, in a random order. They were asked to progress through the images as quickly as they felt comfortable doing and indicate if they felt the image represented a subject with or without LBP.

RESULTS

The results were fairly disappointing. Only one assessor recorded results significantly greater than what one would expect to get from simple chance. The figures are detailed below.

	Assessor 1	Assessor 2	Assessor 3	Assessor 4
Accuracy	58%	55%	40%	73%
Sensitivity	48%	77%	56%	62%
Specificity	53%	17%	46%	18%

Table 7.1 - Results from the first stage of the colour map analysis

In all but one case the sensitivity figures are higher than the specificity figures. This would suggest that the assessors in this stage were better at identifying which colour maps represented subjects with LBP than subjects without LBP. The assessors had a tendency to over diagnose LBP, indicating that colour maps from subjects without LBP suggested they did have LBP. This information led to stage two of the tests.

7.3.2 SECOND STAGE

If, as has been shown in many papers, EMG variables can discriminate between LBP and non-LBP, would this discriminatory effect be in place on a subject who is about to experience LBP?

SUBJECTS

The same variable was used to discriminate between LBP and non-LBP subjects as before, that is did they answer above three on the VAS based question "How much back pain do you experience on a typical day?" The modification from the last study however was that the subject score at the next time they were tested was also taken into account. There were now three subject groups. The first had no back pain at the time of the EMG test and no back pain one year later, the second had back pain at the time of the EMG test and still had back pain one year later, and the third

group had no back pain at the time of the test, but went on to develop low back pain during the course of the next year.

This method of grouping test subjects obviously reduced the total number available as a subjects final EMG test could not be used, they would have no data regarding their back pain after one year as they would not have been seen again after their final EMG test. Sufficient numbers remained however to select 20 subjects from each of the three groups, making a total of 60 colour maps to be assessed.

ASSESSORS

A different assessor team was chosen than from the first set of results. The assessors who worked on the first stage would have more experience at this point and so using them again would not provide a fair comparison. To keep the assessment personnel as homogenous as possible, two specialist nurses and computer placement student were selected to act as assessors. They were given the same instruction on interpreting the colour maps, and shown the same pictures. Despite the additional subject group, assessors were still asked to split the subjects into two groups; those thought to have LBP, and those not thought to have LBP. This was to identify which group the colour maps of the subjects who had no LBP at the time of the test but then went on to develop LBP, would belong to. Subjects from this group being identified as subjects with LBP could mean that EMG variables relating to LBP are visible before the actual onset of pain.

RESULTS

The low specificity scores in the first stage of results were caused by a high number of false positives, that is colour maps that appeared to indicate LBP whilst the subject said they did not actually have LBP.

If higher specificity scores are seen in this batch of results it would seem to indicate that a source of inaccuracy with the first data set had been removed. Results are shown below.

	Assessor 1	**Assessor 2**	**Assessor 3**
Accuracy	88%	78%	90%
Sensitivity	64%	60%	63%
Specificity	86%	92%	100%

Table 7.2 - Results from the second stage of the colour map analysis

As can be seen, roughly similar levels of sensitivity were obtained as compared to the first batch of results. The specificity scores however were much improved, presenting resultant accuracy figures that were well above what would be expected from pure chance alone.

7.4 DISCUSSION

7.4.1 COLOUR MAP PRODUCTION

The initial part of this project was to assess the suitability of a technique to automatically create accurate EMG colour maps. The technique presented here was successful in creating colour maps from raw EMG test data files in a consistent and speedy manner. Should future EMG analysis projects require such functionality, the method is also easily adjustable so that the number and colour of the bands can be changed. The option also exists for displaying other outcome variables, such as the spectral half-width, on the colour maps.

The whole of the creation process; reading the signal data from the raw EMG files, performing the FFTs, calculating the various outcome variables, populating the individual epoch arrays, calculating and displaying the median frequency line of best fit, and producing the actual colour maps, takes less than one second on a moderately powerful computer. This means that there is no need to create a repository of pre-processed EMG colour maps, they can simply be created and displayed as and when they are needed.

These two points combined suggest that a method for quickly, reliably and consistently creating EMG colour maps has been created.

7.4.2 LBP DISCRIMINATION RESULTS

The interpretation of the colour maps is a continuation of the hypothesis that mechanical low back pain is essentially an instability issue. If, as discussed in Chapter 2, the majority of the lumbar stability effect originates from the spinal musculature, rather than skeletal or neurological sources, an assessment of the

suitability of these spinal muscles for a given task should be able to discriminate between LBP and non-LBP subjects. In a fatiguing test it would be expected that there would be some alteration in the spectral characteristics of the EMG signals recorded from the paraspinal musculature, and this amount of alteration across the whole of the test should be different in a subject with a high rate of spinal musculature fatigability from a subject with a low rate of fatigability. Therefore, again connecting lumbar fatigability rates to mechanical low back pain, this rate of change should be able to discriminate between LBP and non-LBP subjects.

The first round of testing suggested that non-expert assessors, with only a minimum of training, were able to use the colour maps to identify which subjects did have LBP. The high levels of false-positives recorded indicate that the reverse was not true. Whilst a positive colour map meant that a subject could accurately be allocated to the LBP group, a negative colour map did not provide confidence that a subject could be allocated to the non-LBP group.

The second round of testing took advantage of that fact that as the subjects were continually assessed over two years, information about their back pain levels the year after a given test date was available. This meant that a subject could be classified as being in the LBP group if they either had LBP at the time of the test, or if they went on to develop it within the next year. Altering the subject group in this manner preserved the sensitivity levels achieved in the first round, whilst increasing the specificity. This indicates that the second method was better able to identify people without LBP who did not also develop LBP 12 months later.

This suggests that future lumbar EMG studies looking to use various outcome measures to discriminate between LBP and non-LBP subjects should attempt to take into account the subject's LBP levels some time after the actual date of the test. It is possible that lumbar EMG tests could be used to identify the underlying

conditions that cause mechanical LBP before the onset of symptoms (Coxon et al, 2010).

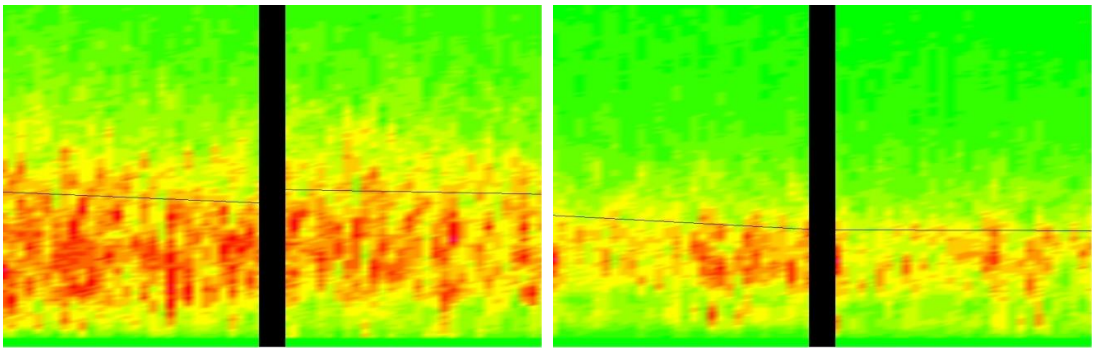


Figure 7.8 - Colour Maps from the non-LBP group.

With the above images, both sets are of subjects from the non-LBP group. The test subject on the left had developed LBP when seen the following year.

7.4.3 LIMITATIONS

COLOUR MAP INTERPRETATION

Using the “eyeball” method of interpreting the colour maps is certainly not an ideal solution, and is one that is open to varying degrees of interpretation by the assessor. It would be preferable to have an interpretation method that returned, for example, a single number which could be used to assign a subject to either the LBP or non-LBP group. That is not to say that the eyeball method is inappropriate. The original colour map research used a similar method, and the same method has been used in other studies when dealing with complex visual information (Murphy et al, 2009; Greenough et al, 1998). In addition to this there exists a large body of

evidence that confirms the efficacy of human pattern recognition that goes beyond the scope of this work.

Regardless of this however, an objective and repeatable method of interpreting EMG colour maps should be sought. The high specificity figures demonstrated that subjects without LBP, and who would not go on to develop LBP, could be discriminated from the rest of the test subject population. The fact that a human brain can interpret the colour maps sufficiently well to discriminate between these groups suggests that the information is present in the colour map, and new research should be directed towards extracting it.

PREDICTIVE EFFECT

This work identified nothing more specific regarding any potential predictive effect, than noting that a subject's future LBP categorisation may have an effect on current EMG outcome measures. It would be of some benefit if a study specifically designed to examine this aspect were commissioned. Questions such as how far into the future would a predictive effect carry and is there any change in outcome measures as the onset of actual symptoms approaches would provide valuable insight into quantifying these predictive effects.

7.5 IMPLEMENTATION

7.5.1 PROCESS RAW DATA

The raw EMG data were taken from previously recorded EMG tests. The data were stored in the newer EMG file format, comprising of file headers containing some subject demographical data followed by five columns of comma separated values containing load achieved (in kg), and lumbar left/right and thoracic left/right surface

EMG measurements (in μV). As only test data that had been previously manually identified as being free from errors was used, there was no need to include any of the previously described error checking and correction algorithms.

The raw data was read into an array comprising of 4 (number of electrode locations) by 30270 (number of samples - 30 times 1024 samples per second) elements. A fast Fourier transform was carried out on each of the four rows on a second by second basis and the resultant frequency spectra stored in a different data array, comprising of 4 (number of electrode locations) by 30 (the number of test epochs - 1 per second of the test) by 512 (frequency values - sampling rate of 1024 Hz divided by 2) elements. There was no need to calculate a composite spectrum for this analysis method.

7.5.2 MEDIAN FREQUENCY CALCULATION

Once the necessary frequency spectra calculations had been completed, each electrode location had provided 30 individual frequency spectra. Each of these needed to be assessed and the median frequency calculated. The median frequency is a measurement of the point in a frequency spectrum where the spectral intensity is equally bisected on both sides. For example, if a signal was sampled at 200 Hz and then transformed into the frequency domain, and each resulting frequency component (200 / 2 gives 100 components) had identical spectral intensity levels (for the purpose of the example), the median frequency would be 50 Hz.

To algorithmically calculate the median frequency for a given spectrum, the first step is to calculate the total spectral intensity present. Specifically this step consists of totalling the values stored in each element of the array containing the frequency

spectrum values. This total is then divided by two and stored. Next, starting from the beginning of the array, the individual elements are added together. After each addition, the current total is checked against the half-spectral intensity value calculated previously. Once the current total exceeds this value the median frequency has been reached, and corresponds to the element number the algorithm halts at.

7.5.3 SMOOTH DATA FOR GRAPH

As described in the previous colour map study (Greenough et al, 1998), after the various outcome variables were calculated, the frequency spectra were smoothed in order to create a more even colour map. This was achieved by the use of a Moving Average Filter.

The MAF is one of the most common filters used in the Digital Signal Processing field due to its simplicity of construction and use, and the good results it achieves.

$$y[i] = \frac{1}{m} \sum_{j=-(M-1)/2}^{(M-1)/2} x[i+j]$$

Figure 7.9 - The Moving Average Filter

In the above example, x[ ] is the input signal and y[ ] is the output signal. The number of points the algorithm uses for the smoothing process is denoted by M. For example to work out point 60 of an output signal for a three point MAF the equation is;

$$y[60] = \frac{x[59] + x[60] + x[61]}{3}$$

Figure 7.8 - Implementation of one point of the Moving Average Filter

The MAF is used primarily to remove random background noise from recorded signals in the time domain. As the algorithm possesses very little ability to resolve one set of frequencies from another it is wholly unsuited for this task when considering signals in the frequency domain. The MAF algorithm has a second use however, which is that of a general smoothing algorithm. This usage is suitable for use within both the time and frequency domains, and it is this use that is utilised here.

A three point MAF was applied to the colour map grid in both longitudinal and latitudinal directions. Each individual epoch had a MAF applied to its whole length and then the filter was applied across the epochs. This provided the desired evening out effect.

7.5.4 CALCULATE COLOUR BANDS

The spectral height in the colour maps is to be represented by one of 12 colours. This necessitates the use of a normalisation algorithm to fit the signal intensity values on one of these 12 bands. An iterative process was used to check each value in the epochs array to identify which was the largest. This number was then divided by 12 to create a normalisation value. Dividing each of the signal intensity values by this normalisation value would create a new epoch array where the values ranged between zero and 12. If a given normalised spectral height fell between zero and one then it was assigned to the first colour band, if it fell between one and two it was assigned to the second colour band, and so on.

Band	OpenGL Colour (R,G,B)
1	(0.0,1.0,0.0)
2	(0.2,1.0,0.0)
3	(0.4,1.0,0.0)
4	(0.8,1.0,0.0)
5	(1.0,1.0,0.0)
6	(1.0,0.8,0.0)
7	(1.0,0.6,0.0)
8	(1.0,0.4,0.0)
9	(1.0,0.2,0.0)
10	(1.0,0.0,0.0)
11	(1.0,0.0,0.2)
12	(1,0.0.0,0.4)

Table 7.3 - OpenGL Colour Bands

7.5.5 DISPLAY COLOUR MAPS

IMPLEMENT OPENGL WINDOW

The first stage in creating an OpenGL application is to define a window, the structure used to actually display the graphical output. When using a 3D application, this window is used as a projection surface where a 2D representation of a 3D display is represented. The term projection in this case is used to describe the process whereby this 3D collection of objects is converted to a flat, 2D picture suitable for viewing on a 2D computer screen. In the case of this project, the data is already in a 2D format, as colour is used to represent the third dimension. This means that using a 2D orthographic perspective window allows direct viewing of the signal data without using the projection algorithms.

The orthographic projection window was sized so that the X co-ordinates ran from 0 to 65 (2 times 30 epochs – left and right – with a 5 unit gap between them) and the Y co-ordinates ran from 0 to 200 (these figures correspond to Hz values, there is typically very little signal information present above 200 Hz so only showing this component allows for greater clarity of the lower end of the spectrum).

DRAW COLOUR MAPS

To draw shapes using OpenGL, the first step is to define the type of shape that is to be drawn with a begin statement, and then encapsulating the required shape properties within this structure. The structure is completed with an end statement. In this case the required shape is a Quad, which is a four sided polygon, filled with a specific colour. The shape is spatially defined by the co-ordinates of its four corners, or vertices. The order in which these co-ordinates are presented (known as the winding direction) is important as the Quad is only visible from the one side. If the winding direction was reversed the shape would be invisible as it would be presenting its underside to the projection window. In addition to the spatial location of each individual vertex, they also have a colour property. If this colour property is the same for each vertex the resultant polygon will be of a uniform colour, if different colour values are used for each vertex, the resultant polygon colour will be the result of an interpolation of the colour values between the vertices.

An example of the code used to draw a Quad, and the resultant shape, is presented below;

```
glBegin(GL_QUADS)
        glColour3f(1.0,0.0,0.0)
        glvertex2i(0,0)

        glColour3f(0.0,1.0,0.0)
        glvertex2i(1,0)

        glColour3f(1.0,0.0,0.0)
        glvertex2i(0,1)

        glColour3f(0.0,1.0,0.0)
        glvertex2i(1,1)
    glEnd()
```

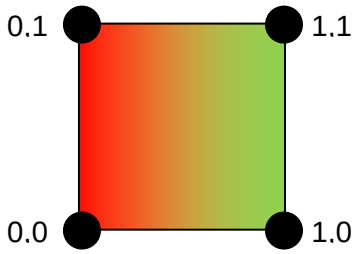


Figure 7.10 - Source code to create a Quad and the resultant shape

The glBegin statement defines the shape that is to be drawn. This is followed by the four sets of instructions that represent each vertex.

The first line from each set (e.g. glColour3f(1.0,0.0,0.0)) defines the colour that will be assigned to each point. The "3f" part of the instruction means that the arguments (the numbers in the brackets) will be three floating point numbers, floating point meaning that decimal places will be allowed. The colours represent the amount of red, green and blue that will be present in the overall colour, so (1.0,0.0,0.0) is red,

(0.0,1.0,0.0) is green, and (1.0,0.0,1.0) would be yellow. If desired, fractions can be used so that (0.5,0.5,0.5) would be grey.

The second line from each set (e.g. glvertex2i(0,0)) defines the X and Y co-ordinates that denote where the vertex is to be placed on the 2D drawing window. The "2i" part of the instruction means that the arguments will consist of two integer values, decimal places are not allowed.

Finally, calling glEnd states that all four vertices have been defined and all of the necessary information is present to draw the shape. This process is repeated until the entire signal dataset has been displayed on the colour map.

7.5.6 DISPLAY MEDIAN FREQUENCY SLOPE

As previously discussed, the line of best fit for a given dataset can be calculated using the least squares method, as described below;

For the line of best fit $Y = mX + b$;

$$\boldsymbol{m} = \frac{\sum xy - \frac{(\sum x)(\sum y)}{n}}{\sum x^2 - \frac{(\sum x)^2}{n}}$$

$$\boldsymbol{b} = \overline{y} - m\overline{x}$$

Figure 7.11 - Least Squares method to calculate points of line of best fit.

Where;

n = Number of points

$\overline{x}$ = The mean of all of the X co-ordinates

$\overline{y}$ = The mean of all of the Y co-ordinates

To algorithmically perform this calculation, 5 initial numbers must be calculated;

n = Number of points

Sx = The SUM of all of the X co-ordinates

Sy = The SUM of all of the Y co-ordinates

Sxy = The SUM of all (x * y)

$Sx2$ = The Sum of all (x * x)

These numbers are then used to perform the following calculations;

$m = (n * Sxy - Sx * Sy) - (n * Sx2 - Sx * Sx)$

$b = (Sy - M * Sx)/n$

Finally, the two sets of X and Y co-ordinates that denote the start and end point of the line of best fit can be calculated using the equation $Y = mX + b$.

CHAPTER 8

CONCLUSIONS

8.1 BACKGROUND

8.1.1 BACK PAIN

The aetiology of Mechanical Low Back Pain (LBP), that is back pain presenting with no obvious pathology, remains controversial. There is a growing consensus that the source of this pain stems from an instability issue; that is as the spinal discs age they experience a decrease in hydrostatic pressure, leading to an increase in the potential for movement along the lateral and posterior and anterior axes. It is suggested that an increase in motion provokes irritation in the spinal ligaments, leading to the onset LBP.

Studies have shown that the vast majority of the stability of the spinal column is provided by the spinal musculature. The actual structure of the spine contributes little to the overall stability, and this contribution only occurs at the extreme ranges of motion. Decreased hydrostatic pressure in a spinal disc would mean the spinal structures would contribute even less to the overall spinal stability, putting more of the task onto the spinal musculature. Methods of assessing the spinal musculature may prove useful in assessing a subjects susceptibility to LBP.

8.1.2 ELECTROMYOGRAPHY

Electromyography (EMG) is an effective method for assessing muscles by way of the electrical leakage from the innervation points of said muscles. Currently, conducting an EMG test is not a simple procedure. Firstly an appropriate testing location must be selected, one without unshielded electronics or fluorescent lighting. Any local strong magnetic fields should also be avoided. The test itself needs

careful preparation if it is to be successful. The electrode locations must be identified carefully and the skin sites prepared to ensure an appropriate level of impedance, and the test subject must be willing and able to complete the required actions on their part. As the human body can be considered an electrically conductive medium, signals from muscles other than those of interest to the EMG test can be detected at an electrode site. This is known as crosstalk and can be difficult to detect and remove as these signals will naturally possess similar characteristics to the actual signals of interest. ECG contamination falls into this broad category. Finally the raw EMG data must be processed in order to produce the required outcome measures, which will need to be interpreted by trained personnel.

This level of complexity means that errors can occur in numerous parts of the test. Errors in the testing location tend to manifest themselves as a specific frequency spike (for example a 50 Hz spike from exposure to UK mains electricity) or a more Gaussian noise distribution from background radio signals. Signs that errors occurred during the testing process take the form of ‘dead’, or obviously aberrant electrode traces. Another source of error that occurs during the testing process is current induced by the wires used to connect the electrodes to the amplifier swaying, which provides motion relative to the Earth’s magnetic field. The presence of this error is indicated by the same Gaussian form that the background radio signals present. Insufficient participation on the part of the subject may not show up on the actual EMG data and must be assessed from other sources, for example monitoring and recording load cell values.

The analysis process can also be a source of errors. Often the raw data, which would be based in the time domain, would need to be shifted into the frequency domain, by the use of a Fourier Transform or Wavelets. These are complicated operations and care needs to be taken that they are carried out correctly. The

spectra resulting from EMG tests (either in the time or frequency domain) need to be assessed in order to create which ever outcome measures are being examined for that particular research project. Again this can be a complex operation and often a time consuming one. If the time consumption effect becomes large enough, this can have an effect on sample sizes as the analysis process simply takes too much time.

It would clearly be of some benefit if systems could be created that would reduce the incidence and scope of these potential errors. This would clear the way for larger, more robust EMG studies.

8.2 AUTOMATIC ANALYSIS/ERROR DETECTION

8.2.1 BACKGROUND

This project was designed to investigate if the analysis component of an EMG test could be automated with a view to reducing the time taken to process a large dataset, and to improve the accuracy of the produced outcome measures. In addition to this the facility to alert a researcher to the presence of a test error on pre-recorded EMG data would be assessed.

The rule base was constructed based upon interviews with the staff responsible for the manual analysis. This provided the required analysis techniques and the indications they used to identify the presence of test errors.

8.2.2 TESTING PROCESS

A dataset that had already undergone manual analysis and assessment was selected. The same dataset was provided to the automated system, which was used to perform the same analysis and produce the same outcome variables as the manual analysis. The end result was two databases, hopefully containing similar values.

8.2.3 RESULTS

The results generated by the automated system correlated closely with the manual system. The automated system also proved to be proficient at identifying errant

traces using the rules provided by the researchers who had used the manual system.

The automated system showed proficiency at analysing and assessing raw EMG files at least to the same degree as the research staff. The manual analysis of the dataset used in this project took two researchers just over two weeks to complete, whilst the automated system took just under 10 minutes. This indicated that the required goal that the automated system be faster than the manual system was met. Whilst an objective assessment was not carried out, it seems fair to assume that the new automated system would be at least as consistent as the original manual one.

Further to these stated goals, there was an additional benefit to using the automated system. Now that the analysis time was so short, additional assessments of a dataset whilst changing the analysis methods or outcome measures became an almost trivial operation.

8.2.4 FUTURE WORK

The automated system presented here was quite specifically tailored to the research project being undertaken. A more flexible system would have the advantage of being adaptable to different EMG analysis methodologies.

8.3 ECG CONTAMINATION REMOVAL

8.3.1 EMG CONTAMINATION

ECG contamination is a known issue when dealing with EMG recordings of the paraspinal region. It is a non-trivial operation to compensate for this errant signal information as the ECG frequency spectrum overlaps an area of interest in the EMG spectrum. In addition to this, the ECG signal would be expected to alter significantly during the course of a 30 s fatiguing test which provides additional challenges to template subtraction methods.

The Independent Component Analysis (ICA) method overcomes these difficulties by comparing all electrode locations at once, and creating output traces based upon the mutual statistical independence of the input signals.

8.3.2 INDEPENDENT COMPONENT ANALYSIS

The four inputs (one per EMG channel) have the ICA method applied to them and a single output trace is created for each channel. These outputs are separated by the statistical independence of the information in them, rather than electrode location. Performing a 20Hz high band pass filter on the output trace that contained the ECG contamination would remove it from the system, whilst the 0-20 Hz signal information in the other three output traces was preserved. These could then be re-integrated in order to recreate the original input signals, minus the ECG contamination.

8.3.3 RESULTS

Applying the ICA method to EMG test data files with known ECG contamination showed that this method was indeed suitable for removing this contamination, whilst preserving underlying EMG signal data. Generating the de-mixing matrix, performing the filter operation on the contaminated output trace, calculating the inverse of the de-mixing matrix, and then using this to reintegrate the output traces takes less than one second on a moderately powerful computer, so this method adds little to any analysis times.

The effect that removing this contamination had on various outcome measures was also examined, these were the lumbar half-width, the RMS, the RMS slope, the RMS intercept, the median frequency slope and the median frequency intercept. Significant changes were noted in the half-width, RMS, RMS intercept, and the median frequency slope. Any studies utilising these outcome measures should take note of the effect that ECG contamination would be having on their results.

8.3.4 FUTURE WORK

Little attention was paid to the de-mixing matrices. One matrix was created per EMG test and this was used to un-mix the input traces. Investigations into if the removal strategy could be improved by performing the ICA method on each one second epoch, rather than the whole 30 second test, were not carried out. Carrying out the ICA method on each epoch and then examining the consistency of these matrices over time could also provide valuable information. If the matrices remain the same during the course of the test, it may be possible to implement an "on the fly" system whereby the contamination could be removed during the data acquisition process, using a set matrix as a de-mixing lens.

8.4 COLOUR MAPS

8.4.1 INTERPRETING COMPLEX DATASETS

One of the issues with assessing EMG test data is the large quantity of information that is presented to the researchers. A way of getting around this is by using various outcome measures in an attempt to quantify various spectral characteristics. This has the advantage of providing quick and easy to interpret scores that can be compared against certain benchmarks, but it can sometimes hide important information that is not taken into account when creating the outcome measures.

8.4.2 COLOUR MAPS

Out of the various methods examined, the method of producing a colour map showing frequency spectra representing multiple one second epochs, with epoch number (i.e. time) on the x axis, frequency on the y axis, and spectral height being represented by colour, proved to be the most effective method of displaying the complex signal data. Creating these maps however was a non-trivial operation and as such methods were investigated whereby the maps could be created quickly and consistently. Successful completion of this task would mean this method of viewing EMG data could become a useful diagnostic tool and so investigations could take place to assess the facility of this method for discriminating between LBP and non-LBP subjects.

8.4.3 RESULTS

Utilising the OpenGL Libraries proved an excellent method of producing the various colours needed to denote the various colour bands on the maps. The method was fast and consistent, which negated the need for batch processing and storing resultant image files. The colour maps could simply be created as and when they were needed, using raw EMG test data files.

When minimally trained, non-EMG research staff were asked to use the maps to discriminate between LBP and non-LBP subjects, disappointing results were obtained. The sensitivity values were around 60%, and the specificity values around 50%, meaning that these tests proved little better than simple chance.

This led to a second round of testing with a change in subject selection, this time future back pain status was taken into account. If a subject was in the non-LBP group when the test was conducted and remained in the non-LBP group one year later, they were placed in the non-LBP group. If a subject had LBP at the time of the test, or if the subject did not have LBP at the time of the test but went on to develop it one year later, they were placed in the LBP group. Using this method of subject separation provided far more positive test results. The colour maps indicating that a subject would not have LBP became far more accurate (specificity average of 93% from 38%), whilst the positive colour maps achieved only slightly improved levels (sensitivity average of 62% from 60%).

This would suggest that EMG data shows some evidence of the underlying causes of LBP existing within the spinal musculature of a test subject before the subject experiences the actual symptoms.

8.4.4 FUTURE WORK

If a human observer can use these spectral colour maps to identify non-LBP subjects, there must exist in the dataset used to create these maps the information to produce a suitably quantifiable outcome measure. It would be of some interest to see if a system, based on genetic algorithms and provided with a suitably large dataset of LBP and non-LBP subjects, could be used to computationally generate such an outcome measure.

8.5 FUTURE RESEARCH DIRECTIONS

8.5.1 DATA ACQUISITION

Test errors are still unfortunately a large part of EMG testing. This effect is compounded when it is considered that often the actual analysis of the raw EMG data takes place after the subject has left, meaning a wasted test opportunity. There clearly exists a need for a system to be created that can assess the current test configuration, and alert operators to the presence of test errors before data collection actually commences.

This would require careful analysis of EMG testing and the quantification of the various error types and their detection algorithms. It would also be preferable if some method of reliably causing the various error types could be devised for testing purposes.

Another method of error elimination that is worth further attention is blind source separation, of which the ICA method is a subset. If a sufficient number of electrodes are used to gather test data then it is entirely possible that test errors could simply be removed in a similar manner to the ECG removal method described in Chapter 6.

8.5.2 DATA ANALYSIS

The high levels of specificity demonstrated by the colour map technique of presenting spectral frequency information were possible due to the large amount of data presented. More formally, as a computer screen is a two dimensional entity,

whilst the component spectra and the colour map actually contain the same amount of data the colour map contains more information. It can be said to have more entropy per data unit. As the human brain is a potent pattern recognition machine, projects that develop display techniques that follow this principle should be favoured.

The fact that future LBP classification seems to have an effect on lumbar EMG variables has implications for research examining this field. These relationships need more research to identify the scale and the scope of any potential effects. It would also be recommended that, wherever possible, research subjects are followed up after a certain period of time to ascertain their back pain levels. This would allow subject grouping as described in the second round of testing in Chapter 7, that is that subjects without LBP at time of test but who go on to develop LBP (within a certain amount of time) should be categorised as being in the LBP group at time of test.

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APPENDIX A

CONFERENCE ABSTRACTS

A.1 AUTOMATION OF PARASPINAL EMG ANALYSIS

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INTRODUCTION:

It has previously been reported that EMG variables recorded from the lumbar spinal muscles may be recorded reproducibly, are able to discriminate low back pain subjects from normal volunteers and are predictive of future back pain. At present, however, an experienced operator is required to acquire the signals and to determine the value of some variables. This has hindered the transfer of the technique from the laboratory to the clinical setting.

METHODS:

The EMG signal is subjected to a Fast Fourier Transform and a power spectrum is produced. An Expert System has been developed to examine this power spectrum. In accordance to a rule base several variables are generated including the half width. The error analysis can detect a number of possible errors of recording that can affect test results and unusual traces are flagged for further consideration. In some defined cases a correction is automatically applied.

RESULTS:

The Standard error between the manually generated half width and the automatically calculated value is 30%. Using the automated system 5% of subjects were found to change classification from normal to at risk. The sensitivity and specificity of detecting recording errors was 0.5 and 0.4 respectively. Work is ongoing.

CONCLUSIONS:

The new system has reduced data set analysis from days to minutes, thus many different methods of analysis can be compared and contrasted readily. The automatic calculation of half width and other variables has brought clinical usage one step closer, and allow EMG analysis to provide a useful tool for monitoring treatment and measuring outcome.

A.2 USE OF COLOUR MAPS AS A DISCRIMINATOR BETWEEN LBP AND NO LBP PATIENTS

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BACKGROUND

Previous work[1] has suggested that Spectral Colour Mapping (SCM) may have potential as an objective measurement tool for analysing Electromyography (EMG) data from spinal muscles, but the production and analysis of these maps is a complex undertaking. It would be beneficial for a system to create these maps and be useable with a minimum of training.

STUDY DESIGN

Subjects were recruited from the general population. Lumbar and Thoracic EMG data were gathered during a 30 second isometric contraction at a load of 70% of the subject's lean body mass. The subjects completed questionnaires on the same day, which allowed categorisation into LBP and No-LBP groups.

METHODS

EMD data were recorded from 192 subjects across two years (initial contact, 12 months and 24 months). The data were analysed and SCMs produced, with those that suggested faulty EMG recordings being eliminated. From the remaining subject population, 60 recording were selected. Of these 60, 20 reported LBP at the time, 20 reported no LBP at the time, and 20 reported no LBP at the time but reported LBP 12 months later.

COLOUR MAPS

The 30 second test data was split into 30, one second epochs. Colour values were scaled to the individual data set maximum and divided into 12 bands. The colour of a particular point on the map represents the spectrum height at that particular frequency in a particular epoch. Median Frequency values were calculated for each epoch and a ling of best fit added to the colour map to further aid the diagnostic process.

READING COLOUR MAPS

The colour map images are split vertically to show left and right sides. The X-Axis shows time (0-30 seconds, left to right) and the Y-Axis shows frequency (0-200 Hz, bottom to top). The green colour bands indicate areas of lowest frequency intensity levels, the yellow colour bands indicate areas of medium frequency intensity levels, and the red colour bands indicate areas of highest frequency intensity levels.

INTERPRETING COLOUR MAPS

Observers were given a timed five minute instruction session regarding interpreting EMG SCMs. Each observer was then presented with the 60 maps in a random order. They were allowed to examine the maps and then reported whether they thought the map indicated a subject with or without LBP. They were not told that some of the test subjects had no LBP at the time but had gone on to develop it; they only had to categorise into two groups.

An answer was correct if a negative colour map reading was linked to a subject who had no LBP, and if a positive reading was linked to a subject who had, or went on to develop, LBP.

RESULTS

	Accuracy	Specificity	Sensitivity
Observer 1	90%	100%	63%
Observer 2	88%	86%	64%
Observer 3	78%	64%	60%

CONCLUSIONS

These results showed that SCMs can now be created quickly and reliably. They also show that observers with a minimum of training can use EMG SCMs as a discriminator between LBP and no LBP groups. In addition, this measurement can be used to identify possible future onset of LBP in otherwise asymptomatic subjects.

The results were closely correlated to the experience level of each observer. This would seem to indicate that improving and extending the instruction period would improve these scores.

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A.3 METHOD FOR REMOVING ECG CONTAMINATION FROM LUMBAR EMG SIGNALS

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INTRODUCTION:

It has previously been reported(1,2,3) that EMG signals from the lumbar spine are highly prone to contamination by ECG artefacts. As the ECG spectrum overlaps an area of interest in the EMG spectrum this has obvious implications for the accurate analysis of EMG data.

METHODS:

EMG data was recorded from 192 subjects across two years (initial contact, 12 months and 24 months). When a moving average filter was applied to this raw data an obvious ECG trace could be observed in the case of a large proportion of the tests. The application of a Fast Fourier Transform on this raw data demonstrated a large low frequency spike, with little known correlation to lumbar muscle spectral characteristics, but highly indicative of an ECG signal.

As multiple source signals were recorded per test, the Independent Component Analysis technique was able to be used to split the EMG raw signal into statistically independent components. This technique is designed to take the multiple signal inputs, and convert them into multiple outputs, where the inputs are distinguishable by electrode location; the outputs are distinguishable by signal biological origin.

RESULTS:

Upon extraction, one of the signal traces showed a clear ECG trace. The Fourier Transform of this trace showed the low frequency spike, with no other signal components present. The Fourier Transform of the EMG trace showed the original EMG graph, with no low frequency peak. Specific spatial information has been exchanged for a much cleaner signal.

A.4 DOES ECG CONTAMINATION OF LUMBAR EMG HAVE A MEASUREABLE EFFECT ON OUTCOME MEASURES?

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INTRODUCTION

ECG contamination of paraspinal EMG measurements is a known issue [1,2], with several proposed methods of correction[3,4]. In addition to this some question remains to how much of an effect this contamination actually has on the EMG recordings.

METHODS

From a population of 455 previously recorded EMG datasets, 33 severely contaminated sets of data were selected. These 33 datasets were analysed to produce the Half-Width, RMS, RMS Slope, RMS Intercept, MF Slope, and MF Intercept variables.

The Independent Component Analysis method was used to separate the EMG data into a series of additive subcomponents which allowed the removal of ECG contamination whilst preserving underlying EMG. The subcomponents were then reintegrated to produce the original EMG signal, minus the contamination.

The resultant signal data were analysed to produce the same outcome variables so a comparison could be made.

RESULTS

	Half Width		RMS		RMS Slope		RMS Intercept		MF Slope		MF Intercept	
	Org	New	Org	New	Org	New	Org	New	Org	New	Org	New
Avg	87.12	75.03	44.98	33.37	0.14	0.15	42.29	36.64	-0.1	0.04	62.15	89.62
SDev	21.45	20.70	16.76	15.10	0.24	0.25	14.36	13.76	0.17	0.48	10.47	14.44
Avg Change	12.10	13%	5.61	13%	-0.004	-33%	5.56	14%	-0.16	21%	-27.47	-45%
PPMCC	0.82		0.96		0.86		0.96		-0.75		0.68	
T Value	p< 0.0005		p< 0.0005		p = 0.857		p< 0.0005		p = 0.152		p< 0.0005	

Significant differences exist in the Half-Width, RMS, RMS Intercept and MF Intercept variables between pre and post ECG removal.

Any Paraspinal EMG study planning on making use of these variables should be aware of the ECG contamination issue and the ICA removal method described here.

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