9

sEMG Techniques to Detect and Predict Localised Muscle Fatigue

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1. Introduction

Recent advances in physiological studies have demonstrated the importance of muscle fatigue detection and prediction in various aspects of our lives, including sports, rehabilitation and ergonomics. Automating muscle fatigue detection/prediction in wearable technology has the potential to aid in many applications. However, current research has made little progress towards automating muscle fatigue detection/prediction in computational models. The work presented in this chapter supports the idea that an automated muscle fatigue detection/prediction system can be used to aid sporting performance and to avoid injury. In support of this view, a wearable system that operates based on the detection and classification of three different stages of muscle fatigue (Non-Fatigue, Transition-to-Fatigue and Fatigue) has been developed. Current research focuses on only two muscle fatigue stages (Non-Fatigue and Fatigue); with this limitation in mind, data was analysed with the aim to develop features that best extract muscle fatigue content, using both statistical models and evolutionary computations tools to help find the number of muscle fatigue stages. This enabled the development of an automated muscle fatigue detection system, which provides true prediction capabilities. In doing so, a third stage of fatigue was identified, the so-called Transition-to-Fatigue stage, which occurs before the onset of fatigue. By identifying this transitional fatigue stage, it is possible to predict when fatigue will occur, which provides the foundation of the automated system. To demonstrate the applicability of the Transition-to-Fatigue class, the classification performance of the two class (Non-Fatigue and Fatigue) and three class approaches (Non-Fatigue, Transition-to-Fatigue and Fatigue) were compared. This chapter will include various studies that identify the most suitable methods to apply in the real-time autonomous system. The first section of studies developed various statistical features that best distinguished between the different classes of fatigue, resulting in new combined feature extraction methods called 1D spectro and 1D spectro_std. The second section used evolutionary computation, evolving features and creating pseudo-wavelets improving current state of the art. The various features evolved in this work all produced high classification accuracy from surface electromyography (sEMG) signals emanating from the biceps brachii during both isometric and non-isometric contractions. In the third section, a method to predict the time to fatigue was established using artificial neural network classification based on the three classes of fatigue. This technique was also implemented in the final study that developed a working prototype of the wearable autonomous system. One of the developed feature extraction methods, 1D spectro, was selected for implementation into the wearable autonomous system. This chapter presents preliminary empirical evidence demonstrating that the developed features and methods for fatigue detection/prediction improve the current state of the art. In this chapter, a definition of muscle fatigue is set, then, an overview of the detection of muscle fatigue will be given, followed by a discussion of specific approaches for extracting sEMG features which are related to muscle fatigue. The chapter then concludes with a summary of challenges for the future of this new and exciting technology.

1.1 Muscle fatigue definition

The term 'muscle fatigue' was first introduced by Bills (1943), who categorised it into three groups: subjective fatigue, which is influenced by psychological factors such as a lack of motivation; objective fatigue, which indicates a decline in productivity; and finally, physiological fatigue, which manifests itself by changes in physiological processes. Chaffin (1973) introduced the term 'localised muscle fatigue' as an example of physiological fatigue, which refers to the inability of a given muscle to maintain a desired force and is associated with localised pain.

Studies on localised muscle fatigue have focused mainly on the decline in the force of a muscle contraction during a sustained activity (Barry & Enoka, 2007), which results in a definition of fatigue as the inability of a muscle to continue exerting force or power. Barry & Enoka argue that this definition indicates that fatigue occurs quickly after the onset of a sustained period of exercise, although the subject may be able to sustain the activity. However, the muscle impairment will eventually lead to total fatigue, where it is impossible for the subject to continue performing the task (Bigland-Ritchie & Woods, 1984).

Muscle fatigue is a physiological phenomenon that can only be measured precisely by invasive means, which is clearly unsuitable for most applications, such as in sport science, human-computer interaction, ergonomics and occupational therapy. Therefore, non-invasive techniques have been developed to detect signals that are related to muscle fatigue. Generally, non-invasive clinical studies of muscle fatigue acquire such signals using two main techniques: mechanomyography (MMG) and/or electromyography (EMG). Historically, EMG has been chosen as the most suitable clinical research tool. MMG, on the other hand, is considered to be a mechanical equivalent of surface electromyography (sEMG), that works by recording the low-frequency oscillations that are produced by the muscle fibres when the muscle contracts and expands (Gordon & Holbourn, 1948). Nevertheless, there are other established techniques that are used to detect localised muscle fatigue, such as near infrared spectroscopy (NIRS) and ultrasound, and methods for assessing muscle fatigue, such as the Moore-Garg strain index and the CR Borg scale (Borg, 1970).

It has been known for at least 40 years that the sEMG signal carries information related to muscle fatigue (Edwards, 1981; Lindstrom et al., 1977), making it a suitable method for non-invasive muscle fatigue detection. Furthermore, the sEMG signal provides useful information when measuring and analysing localised muscle fatigue (Hagberg, 1981; Jorgensen et al., 1988; Petrofsky et al., 1982). Myoelectric manifestations of muscle fatigue can be seen in changes in signal frequency and amplitude and in the muscle conduction velocity (CV), while the mechanical factors related to muscle fatigue are manifested in a loss in the force exerted by the muscle (Asghari Oskœi et al., 2008). The myoelectric manifestations are perceived as an objective means by which to analyse muscle fatigue, since they disregard subjective motivators and, compared to mechanical factors, they provide early indicators of fatigue. In addition, sEMG is a very portable, easy to use and fairly inexpensive method.

1.2 How can muscle fatigue be detected ?

There are several techniques for signal detection which are often used in conjunction with each other for the study of muscle fatigue and it may be difficult to determine which to use in a particular application. Most modern research uses one or more of the methods described here in conjunction, such as an accelerometer with sEMG electrodes. Usually, the aim of combining sensors with sEMG or other sensors is validation, labelling or improving the signal to noise ratio.

To date, no consensus has been reached upon the ideal sensor technology to use for MMG recordings (Courteville et al., 1998; Gregori et al., 2003; Watakabe et al., 1998). The literature suggests that accelerometers are more appropriate than condenser microphones due to the effects of background noise. Also, accelerometers are inexpensive and reliable devices whereas condenser microphones are more expensive and have a much larger frequency range (20-2000 Hz) than that needed for accurately recording muscle vibrations (13-35 Hz) (Armstrong, 2010).

Compared to sEMG data collection, accelerometers are physically bulkier, more susceptible to noise from sudden movement and are significantly more expensive than sEMG electrodes. Limitations of NIRS are related to inconsistencies regarding muscle oxygenation during isometric exercise, making it a less reliable method. NIRS sensors are also very sensitive to movement, which makes NIRS an unsuitable candidate technique in sports and other movement-rich scenarios. It is possible to use the goniometer sensor to measure the development of fatigue in a realistic scenario. However, currently available goniometer sensors are expensive, have a short lifetime and must be handled with care. Electronic force gauges are also applicable in measuring fatigue but suffer from fragile construction, high cost and subject encumbrance in most scenarios. The Moore-Garg strain index and the modified Borg Scale can be used for fatigue detection in terms of translating facial/body cues using video processing, but these techniques suffer from privacy issues and can be highly subjective. In addition the Moore-Garg and Borg methods require a second person to measure the subjects' fatigue stages.

1.3 EMG signal pre-processing

Signal filtering is an important process that attenuates unwanted or erroneous electrical signals picked up by sensors and thus allows the experimenter to focus on a narrow energy band of interest. In general, filters attenuate signals within certain frequency ranges (the so-called stopband), thus limiting the frequency spectrum of the recorded signal to that of the so-called passband (De Luca, 1997). Filters can be categorised into four main types: low-pass, high-pass, bandpass and bandstop. Modern technologies have enabled the measurement of EMG signals of low noise and high signal fidelity (i.e., high signal to noise ratio). Filters can also be characterised by the width of their transition zone (De Luca, 1997), with more complex filter designs needed to produce tighter transition ranges. In general, the more complex the filter, the higher is its so-called 'order', i.e., a first order filter is a very simple order filter. The full effective bandwidth of the EMG signal can be measured using differential amplification. Bandpass refers to the range of frequencies from the low frequency to the high frequency limit of a signal. Typical bandpass frequency ranges are from between 10 and 20 Hz (high pass filtering) to between 500 and 1000 Hz (low-pass filtering). Movement artifacts, which are normally comprised of low frequency components (typically < 10 Hz), are removed by high-pass filtering, and signal aliasing is avoided by removing high frequency signal components through the use of low-pass filtering (Gerdle et al., 1999). Merletti (1999) states that the sEMG signals should be between the range of 5-500 Hz due to negligible contribution of the signals power density function outside of this range. Invasive EMG, on the other hand, should have a low-pass cut-off at no less than 1.5 kHz.

EMG signals are filtered by several classical filter types, including the Butterworth filter, Fourier series, the Chebyshev filter, the Elliptic filter and the Thompson or Bessel Filter, and filter equations are frequently recursive, such as in the Butterworth filter (De Luca, 1997). The purpose of the Butterworth filter is to produce a flat as possible frequency response in the passband, resulting in steep rolloffs in higher order filters, making it an ideal filter for conditioning the EMG signal (De Luca, 1997). Additionally its maximum passband gain, the cutoff frequency and the filter order are all clearly specified. In the past, sharp notch filtering was commonly used to remove power-line (A/C) noise components (i.e., either 50 or 60 Hz). However, since there are large signal contributions at these frequencies in EMG experiments, notch filtering results in a loss of information in this setting, and is thus usually avoided (Day, 2010).

Prior to the use of computers in signal processing, signals were mostly filtered by analogue means. Analogue filters usually employ electronic circuits, making use of three fundamental components: resistors, capacitors and inductors, which are arranged in circuits designed to meet particular needs (De Luca, 1997). The performance of an analogue filter is heavily dependent on the quality of the circuit design and the physical components that are used in building the circuit.Hence, digital filtering is often considered to be superior to analogue filtering (Hong & Bartlett, 2008). In the context of this thesis, the versatility of digital filtering makes it particularly suitable for the filtering of sEMG signals, where they are mostly used to remove noise, i.e., a band-pass filter, which combines low and high-pass filters, is used to cut off frequencies from 10-500 Hz. Signals can also be filtered through the application of a low-pass filter, so that slow changes in the signal amplitude are displayed and the signal is thus smoothed. According to Basmajian & De Luca (1985), the RMS signal voltage is the most suited approach to quantify the EMG signal, which is the mathematical equivalent to the standard deviation of the EMG signal.

1.4 Application of EMG in muscle fatigue research

EMG is an easy to use technique and has therefore been used in a vast range of research on muscle physiology. Generally, localised muscle fatigue occurs after a prolonged, relatively strong muscle activity, when a muscle or a group of muscles are fatigued. Due to the variability of inter-person muscle characteristics, there is no simple function of muscle load and timing that defines a precise muscle fatigue threshold. Changes in the EMG signals caused by fatigue are either measured in the time or frequency domain. Integrated EMG (IEMG) usually uses the time domain, and an increase in the signal period, amplitude and power reflect a higher muscle fibre recruitment for a fixed external force. The changes in EMG signal in the frequency domain relate to mean power frequency and median power frequency, which varies due to a shift towards lower frequencies, a small increase in low-frequency signal power, a relative decrease in high-frequency signal power, a decrease in low-frequency spectrum slope and an increase in high-frequency spectrum slope (Eberstein & Beattie, 1985; Gross et al., 1980; Petrofsky et al., 1982; Sato, 1982; Viitasalo & Komi, 1977). There are several reasons for these changes in the EMG signal, such as signal synchronisation, modulation of the recruitment firing rate, grouping and slowing of the CV (De Luca, 1979; Hermens et al., 1986; Viitasalo & Komi, 1977).

Although sEMG has been applied in many studies of localised muscle fatigue, it is not without its limitations, in particular, in studies of dynamic muscle contractions. The use of sEMG requires proper knowledge of the mechanisms of signal generation and propagation. Although signal acquisition *per se* is easy, inaccurate conclusions are easily drawn when inappropriate experimental methods are used (Merletti et al., 2003).

Most research concentrates on isometric contractions to establish typical sEMG readings when conducted in controlled settings. Changes in sEMG amplitude and centre frequency have been studied by Petrofsky et al. (1982), who found a decrease in the centre frequency of the spectrogram for all muscle groups. Research has also shown that a development in muscle fatigue correlates with changes in sEMG signal amplitude and MDF (Hagberg, 1981). Muscle fatigue causes MU recruitment, and the MU firing rate increases as a function of the elapsed time. These changes are not reflected in the EMG changes which occur during fatiguing isometric contraction of the arm flexors at 20-30% MVC (Maton & Gamet, 1989). However, it was recently found that the changes due to fatigue in the sEMG signal (increased amplitude and decreased frequency) suggest that the recruitment of MU firing rates correlates with sEMG amplitude (Calder et al., 2008).

Although CV strongly influences the power spectrum density (PSD) and has the highest inter-person repeatability, it has been argued that fatigue also compresses the frequency content of the sEMG signal in a proportional manner (Linssen et al., 1993). The PSD time-dependency can also be analysed, and is usually estimated from the instantaneous sEMG parameters, although there are shortcomings in the identification of changes in the short-period sEMG signals. A time-varying autoregressive (AR) model was proposed by Zhang et al. (2010), which produced a more stable and accurate instantaneous parameter estimation. Minning et al. (2007) studied differences in the rate of fatigue in the shoulder muscles during voluntary isometric contractions. They discovered day-to-day inconsistencies in the rate of fatigue in the middle deltoid muscle, which also fatigued more rapidly than other muscle groups. However, for the other muscles they found a consistent relationship between trial, day and muscle type. In a study on the relationship between short-time Fourier transform (STFT) and continuous wavelet transforms to analyse EMG signals from the back and hip muscles during fatiguing isometric contractions, it was found that the two methods reveal similar information regarding EMG spectral variables (Coorevits et al., 2008).

Although the success of sEMG is likely to be more prevalent in isometric muscle contractions, more recently EMG has been applied to the study of dynamic contractions (Singh et al., 2007). The analysis of the sEMG spectrum during cycling activities reveals a strong correlation between the onset of fatigue and the reduction of the MDF in dynamic contractions (Singh et al., 2007), and sEMG has been validated using biochemical analysis, indicating that the low-frequency band is a reliable indicator of muscle fatigue in dynamic contractions (Soo et al., 2009). By analysing the quantitative and qualitative changes in EMG patterns, such as IEMG and the frequency of the mean power, it has been argued that in dynamic contractions fatigue is related to qualitative changes in the pattern of MU recruitment, which occurs at a faster rate when the muscle has a higher degree of fast twitch muscles fibres. For the quantitative changes, only a small reduction in the amplitude of the IEMG signal was related to a high percentage of slow twitch muscle fibres (Komi & Tesch, 1979). Masuda et al. (1999) studied changes in sEMG patterns during static and dynamic fatiguing contractions by looking at the muscle fibre CV, MDF and mean amplitude in the vastus lateralis muscle. The muscle fibre CV appeared to be influenced by the metabolic state in the muscle, as it decreased significantly in isometric contractions, while it remained constant during dynamic contractions. This suggests that changes in the MDF cannot be explained wholly by shifts in the muscle fibre CV. Farina (2006) proposed a technique for detection and processing of muscle CV during dynamic contractions, and showed that a decline in CV reflects muscle fatigue. Another method for estimating muscle fatigue during dynamic contraction is to use a source separation technique related to independent component analysis to test whether the firing of MUs becomes more synchronised at the onset of localised muscle fatigue. As argued by Naik et al. (2009), it is widely accepted that lower-frequency sEMG signals indicate muscle fatigue due to MU synchronisation; however, there is little experimental evidence of this theory. Naik et al. concluded that during cycling movements, a global matrix is an applicable measurement for estimating localised muscle fatigue.

Several studies have identified the state of peripheral fatigue (Dimitrov et al., 2006; Gonzalez-Izal, Malanda, Navarro-Amezqueta, Gorostiaga, Mallor, Ibanez & Izquierdo, 2010). In a recent study, Gonzalez-Izal, Malanda, Navarro-Amezqueta, Gorostiaga, Mallor, Ibanez & Izquierdo (2010) compared several EMG parameters to assess peripheral fatigue during dynamic contractions. In that study, new spectral indices (FInsmX) developed by Dimitrov et al. (2006) were based on discrete wavelet transforms (DWT) and were compared to spectral parameters, such as mean average voltage, median spectral frequency and ratios between different scales obtained by DWT. Results showed the newly proposed spectral indices to be the best for assessing peripheral fatigue, both in correlation with the power output changes and in their regression. These new spectral indices have also been shown to be a useful tool in detecting changes in muscle power output in fatiguing dynamic contractions, and they can be used as predictors of changes in muscle power output (Gonzalez-Izal, Rodriguez-Carreno, Malanda, Mallor-Gimenez, Navarro-Amezqueta, Gorostiaga & Izquierdo, 2010).

Detecting muscle fatigue in an automated system requires a real-time measurement of changes in localised muscle fatigue. Stulen & De Luca (1982) developed a muscle fatigue monitor, which was a non-invasive device measuring localised muscle fatigue by spectral compression calculating median frequencies and two other parameters of the spectrum. This study used the MDF, which the author states is a more reliable analysis feature than other traditional parameters, e.g. mean or mode frequencies. Kramer et al. (1987) proposed a robust and relatively reliable parameter of fatigue that could be calculated off-line from computed, real-time sEMG data obtained from a simple analogue device. Wavelet coefficients can be used in non-stationary and time-varying signal processing, hence they have been applied in the assessment of localised muscle fatigue for both static and dynamic contractions using sEMG signals. The amplitude of approximation coefficients coincide with muscle fatigue development. Moshou et al. (2005) proposed a method for automating the detection of muscle fatigue by using NNs, where a two-dimensional self-organising map visualises the approximation of wavelet coefficients, enabling the visualisation of the onset of fatigue over time, and thus separating the EMG signal from fresh and fatigued muscles. Tepavac & Schwirtlich (1997) developed a technique which utilises the processed sEMG signal as an activation signal that changes the pattern to control a functional electrical stimulation (FES) system. Their technique is able to notify the user that a rapid drop in the muscle force is approaching, providing the capability of a simple on-off fatigue detection in FES applications. In the development of this technique the authors used seven different sEMG parameters, however the best relationship was established between the MDF and force changes, which were the parameters used to determine the prediction of the onset of fatigue and detection of fatigue. This is an interesting technique although it is not performed in autonomous, real-time system.

1.5 sEMG signal analysis and feature characterisation

Feature extraction is used in pattern recognition, being a form of dimensionality reduction (Samet, 2006). This method is used for transforming input data to a certain set of features which will extract the relevant information from that data. sEMG signals can be analysed to detect muscle fatigue by examining the changes in EMG measurements. Studies on sEMG show that an increase in EMG signal amplitude or shifts in the spectrogram are indicators of muscle fatigue in static contractions (Chaffin, 1973; De Luca, 1997; Duchene & Goubel, 1993; Kadefors et al., 1968; Lindstrom et al., 1977; Marras, 1990). Hagberg (1981) established that significant changes in the sEMG signal indicate muscle fatigue. Studies on muscle fatigue during isometric contraction have established typical sEMG readings when conducted in controlled settings. Changes in sEMG amplitude and centre frequency were studied by Petrofsky et al. (1982), who found a decrease in the centre frequency of the spectrogram for all muscle groups. It has also been shown that a development in muscle fatigue correlates with changes in amplitude and MDF (Hagberg, 1981). A variety of parameters have been used to investigate sEMG signals to determine muscle fatigue; however it is common to study the signal in terms of its frequency at a certain time, in both the time and time-frequency domains. Table 1 categorized the papers according to the feature extraction methods used by authors.

Feature extraction method	Refrence ID
RMS	(Basmajian & De Luca, 1985; Kumar & Mital, 1996)
STFT	(Merletti & Parker, 2004)
Total Band Power	(Welch, 1967)
New spectral parameter FI 1 to FI 5	(Dimitrov et al., 2006)
PSD	(Ortengren et al., 1975)
MDF	(Kumar & Mital, 1996)
IMDF	(Asghari Oskœi et al., 2008; Roy et al., 1998)
Cohen class transformations	(Cohen, 1995; Raez et al., 2006; Ricamato et al., 1992)
Gabor Transform	(Gabor, 1946)
Wavelet analysis	(Kumar et al., 2003; Laterza & Olmo, 1997)
Autogression analysis	(Graupe & Cline, 1975; Kim et al., 2005; Tohru, 1992)
Entropy	(Jaynes, 1957; Sung et al., 2008)
Recurrence Quantification Analysis	(Filligoi et al., 2010; Morana et al., 2009)
HOS	(Hussain et al., 2008; Kanosue et al., 1979)
Composite Features	(Boostani & Moradi, 2003; Hudgins et al., 1993; Phinyomark et al., 2009)

Table 1. Signal analysis and feature characteristics

1.5.1 Time domain and frequency domain analysis

A signal is acquired, and in some circumstances, analysed, in the time domain where the signal amplitude/voltage is represented as a function of time. However, for many analysis techniques, it is the frequency of the signal that is of greater value, and consequently the signal should be analysed in the frequency-domain, whereby the signal undergoes a Fourier transform so that it is represented as a function of frequency, rather than time.

Both the average rectified value, which measures the average of the absolute signal value, and the RMS, which is a measure of the signal power (Kumar & Mital, 1996), are used in the analysis of the raw EMG signal in the time domain. The RMS of the EMG signal calculates the square root of the average power of the raw EMG signal over a specific time period (Basmajian & De Luca, 1985). De Luca's group acknowledged both the average rectified value and RMS as appropriate analysis methods, however, several authors prefer the RMS (De Luca, 1997;

Merletti et al., 2003), since it can be used to obtain a moving average (Basmajian & De Luca, 1985). The moving average approach is used for processing raw EMG signals from dynamic contractions, as it identifies the rapid changes in the muscle activity during such contractions by using short duration sampling windows (Payton & Bartlett, 2008). Merletti et al. (2003) suggested that EMG analysis of dynamic contractions can make use of another processing method, the 'linear envelope', which uses a low pass filter to smooth the rectified EMG.

When a signal crosses the zero amplitude line, it is said to have made a 'zero-crossing'. When applied to sEMG data, the general idea is that an active muscle will produce more AP, and hence generate more zero crossings. However, at the onset of fatigue, the zero crossing rate drops dramatically due to the reduced conduction of electrical current in the muscle. Therefore zero-crossings are counted using geometric calculations to give an indication of the muscle status.

The total band power (TBP) of the sEMG signal can be estimated using the method by Welch (1967). This method has been used previously in several sEMG fatigue analyses (Cifrek et al., 2009; Helal et al., 1992) and has proved to be useful in quantifying the power of the EMG signals.

The frequency content of a signal can be determined by performing a Fourier transform to reveal its individual frequency components. The fast Fourier transform (FFT), a method for calculating the discrete Fourier transform, is suitable for use in stationary signals. EMG signals, which are non-stationary, should be represented in both the time and frequency domains. Therefore, the STFT, which analyses a small temporal section of the signal, can be used to determine the frequency and phase evolution of the EMG signal over time.

The time and frequency resolution depend upon the sampling rate and the temporal length of the signal section. Due to the inverse relationship between time and frequency in the Fourier transform, it follows that the higher the time resolution the lower the frequency resolution will be and *vice versa* (Merletti & Parker, 2004). The spectogram of the signal is the squared magnitude of the STFT.

Dimitrov et al. (2006) proposed a new spectral parameter with higher sensitivity than traditional indices for both dynamic and isometric contractions, which is a valid and reliable tool for the assessment of muscle fatigue. The parameter used the FFT to calculate ratios between different spectral moments measured over the power spectral density.

Following an FFT, this parameter represents the ratio between the low- and high-order spectral moments of the EMG power spectrum. Gonzalez-Izal, Malanda, Navarro-Amezqueta, Gorostiaga, Mallor, Ibanez & Izquierdo (2010) used this index to measure the changes in muscle power during a high-intensity dynamic protocol, and compared it to other frequency and amplitude parameters. It was found that the logarithm of this index detects the changes most accurately by assessing peripheral impairments.

EMG signals can be analysed in the time-domain using the PSD to describe how the power of a signal is distributed among its frequency components. Significant changes in the power spectrum indicate muscle fatigue (Ortengren et al., 1975), such that after fatigue onset the PSD is increased in the low frequency components and decreased in the higher frequency components.

Two of the most common frequency-dependent features in sEMG analysis are the MF and MDF. The MF is "the average frequency of the power spectrum and is defined as its first-order moment" (Asghari Oskœi et al., 2008), while the MDF is an index used in studies of spectral shifts and can be defined as "the frequency which divides the power spectrum in two parts with equal areas" (Kumar & Mital, 1996, p. 170). The power spectrum represents the MDF of the power, based on a continuous spectrum distribution. Hagberg (1981) stated that if the MDF decreases along with as the sEMG signal amplitude increases, which is a strong indication of fatigue.

The spectral frequency can be redefined to represent the non-stationary nature of the signal, or the instantaneous frequency, of the frequency content of the signal (Karlsson et al., 1999). The instantaneous median frequency (IMDF) was introduced by Roy et al. (1998). Studies by Asghari Oskœi et al. (2008) concluded that a significant decline in the IMDF of the signal is a significant manifestation of fatigue occurrence. In addition, Georgakis et al. (2003) demonstrated that the average instantaneous frequency is superior to the mean and median frequencies for the analysis of muscle fatigue during sustained contractions.

Some analysis methodologies use both the time and frequency domains to analyse the EMG signal. For example, the Cohen class transformation, a time-frequency representation applied in biomedical signal processing, is well-suited for analysis of signals from dynamic contractions. It is a distribution function introduced by Cohen (1995) using bilinear transformations, giving clearer results than the STFT. However, due to its use of bilinear transformations, the Cohen class is affected by cross-term contamination in its analysis of several functions, which can be avoided using window functions. The Wigner-Ville distribution function (WVD), proposed by Wigner in 1936 (Raez et al., 2006), was first used for corrections to classical statistical mechanics, however, it is also applicable as a transform in time-frequency analysis. This transform has higher clarity than the STFT and has more properties than most other time-frequency transforms, using all available information in the EMG signal. In 1948 Ville revised this function into a quadratic representation of the local time-frequency energy of a signal (Raez et al., 2006). It was discovered by Ricamato et al. (1992) that the WVD would detect the frequency ranges of the MUs, displaying recruitment patterns as muscles contract. However, Davies & Reisman (1994) found that the WVD joint density spectrum is noisy although its localisation properties are excellent and "generally concentrated around the instantaneous frequency of the signal". Another member of the Cohen's class functions is the Choi-Williams distribution (Davies & Reisman, 1994), which makes use of kernels to reduce the interference, something the Cohen's class distribution suffers from, although it is only possible for the kernel function to filter out the cross-term contamination.

The Gabor transform (named after Dennis Gabor) is a discrete Fourier transform utilising Gaussian windows, which is used in time-frequency analysis (Gabor, 1946). The transform determines the sinusoidal frequency and phase content of specific sections of a signal that changes over time, which is an advantage when representing local features. By using Gaussian windows, this function gives more weight to the signals near the time being analysed. Although this method is more precise than other methods, giving few errors, there are some major problems. The Gabor transform gives imaginary numbers with no physical meaning and it requires a lot of resources for full computation. Nevertheless, this transform guarantees energy conservation of the signal.

There are many time-frequency functions which can be used to analyse sEMG signals during localised muscle fatigue. Davies & Reisman (1994) showed that STFT can most precisely represent spectrum compression during muscle fatigue. Due to the cross-term contamination in the WVD, it is not possible to display the changes in the frequency components with muscle fatigue accurately. In a comparison between the STFT, the WVD, the continuous wavelet transform and the Choi-Williams distribution, Karlsson et al. (2000) found that the continuous wavelet transform resulted in a more precise estimation of EMG signals when applying various time-scale methods to analyse sEMG signals.

1.5.2 Wavelet analysis

By using a wavelet function (WF), the wavelet transform (WT) decomposes a signal into numerous multi-resolution components (Kleissen et al., 1998; Laterza & Olmo, 1997). It is used to detect and characterise the short time component within a non-stationary signal, providing information regarding the signal's time-frequency. The WF, being both dilated and translated in time and a linear function which does not suffer from cross-terms, undertakes a two-dimensional cross correlation with the time domain sEMG signal, making it an excellent alternative to other time-frequency parameters (Laterza & Olmo, 1997).

There are a number of so-called 'mother wavelets' that can be used for signal decomposition, including Symm-let, Coiflet, Haar, Morlet, Daubechies and Mexican Hat (Kumar et al., 2003). To select the most appropriate mother wavelet for a specific application and signal type, the properties of the WF and the characteristic of the signal should to be analysed and matched. Certain wavelets have somewhat established guidelines for their use, e.g., Db4 is said to be suited for signals using feature extractions and linear approximation with more than four samples, while Db6 is suited for signals that are approximated by a quadratic function over the support of six and finally coiflet6 is better suited for data compression results (Walker, 2000).

Guglielminotti & Merletti (1992) hypothesised that if the wavelet analysis is selected to fit with the shape of the MUAP, the WT would give the best energy location in a time-scale. Kumar et al. (2003) stated that the STFT does not give an optimal time or frequency resolution for the non-stationary signal, although the relatively short time windows may trace spectral variations with time. The WT, comprised of numerous WFs, can be used to decompose the sEMG signal. The output of the power transform domain is calculated and thus functions as a deciding parameter in selecting the most appropriate WF to give the highest contrast between sEMG cases. It has been shown that it is possible to detect muscle fatigue status by determining the Sym4 or Sym5 WFs and decomposing the signal at levels 8 and 9 (out of 10 levels). Kumar et al. (2003) discussed the effectiveness of decomposing the sEMG signal to measure its power in order to identify muscle fatigue as an automated process.

1.5.3 Autoregression analysis

Regression statistics is used to determine the relationship between an independent variable or variables and a dependent variable. An autoregressive (AR) model is a random process used in statistics and signal processing to model and predict natural phenomena. Graupe & Cline (1975) developed the AR moving average (ARMA) model to represent EMG signals, where the signals were split into short time intervals and the signal was considered to be stationary. However, Sherif (1980) replaced this model by a model using the AR integrated moving average (ARIMA) model, to be used on the non-stationary EMG signals. Hefftner et al. (1988) exploited the computational speed of the AR model for EMG feature discrimination.

Kim et al. (2005) measured fatigue in the trunk muscle using the first AR model, and concluded that the model was capable of assessing fatigue in static exercises, being sufficiently sensitive to detect fatigue at low force levels. Several authors have revised the AR parameters, adding a non-linear element (ARMA) (Bernatos et al., 1986) and a non-stationary identifier (Moser & Graupe, 1989). However, the ARIMA model is complex with a high computational cost and Tohru (1992) argued that more accurate models (ARMA and ARIMA) are not needed for studies on dynamic contractions.

1.5.4 Entropy

Entropy is a function that can be used in various fields, such as thermodynamics, communication and computer science. In physics, entropy is a statistical measure of disorder in a system, representing the probability that a certain outcome exists, while in information theory the basis of entropy relates to the randomness in a signal or in a random event (Jaynes, 1957). This is also applicable to a general probability distribution, rather than a discrete-valued event. Sung et al. (2008) argue that entropic measures reveal part of the sEMG signals that are not included in the power spectrum, and can be a useful tool in detecting muscle fatigue in gender differences.

1.5.5 Recurrence quantification analysis

Recurrence quantification analysis, a method of nonlinear data analysis which is used for the investigation of dynamical systems, is highly effective in detecting changes in the sEMG signal and is almost equivalent to the frequency domain analysis of the signal in non-isometric contractions (Filligoi et al., 2010). Morana et al. (2009) recently used recurrence quantification analysis in a study of muscle fatigue and stated that this method can be used to detect peripheral muscle fatigue.

1.5.6 Higher-order statistics

Higher-order statistics (HOS), a technique based on probability theory, characterises and analyses the nature of a random process, making it appropriate for use in the random time series produced by EMG signals. Due to the nature of the EMG signals, in particular when fatigue components are present in the signal, HOS will give more insight in terms of analysing the complexity of the EMG signal. In muscle fatigue HOS is used due to the increasing complexity of the EMG signal, the second order HOS (and higher orders) are used to detect non-gussian/non-linear properties of the signal. This is particularly useful method in muscle fatigue studies, which is an alternative of using the Gaussian/linear processes, such as the power spectrum of a signal giving the distribution of power among signal frequency. Moments and cumulants define the HOS of a signal. When analysing deterministic signals, moments are of great importance, while cumulants are useful for stochastic type signals (Gündoğdu et al., 2006). It has been used in sEMG studies to estimate the amplitude and the number of new MUAPs, as proposed by Kanosue et al. (1979). Several authors have studied HOS in sEMG signal processing, in particular testing it for Gaussianity and linearity, coherence and coupling of the signal. Their findings showed that during contractions at low- and high-force activity, HOS features are non Gaussian, while during the mid-level force the distribution is maximally Gaussian (Hussain et al., 2008; Raez et al., 2006; Shahid, 2007). HOS is also used to suppress Gaussian white noise in the sEMG signal (Hussain et al., 2008).

1.5.7 Composite features

The term ‘composite features’ relates to the use of a combination of common features to develop a new feature that aids in the analysis of sEMG signals. MacIsaac et al. (2006) presented a mapping function that maps segments of multiple myoelectrical signals for fatigue estimation of dynamic contractions, where the inputs are time domain features. This function is tuned by ANNs and is capable of use in real-time applications. Results show

that this function better maps the sEMG signals than either the MF or the IMDF for different conditions.
Although combining features is a fairly new approach in the field of localised muscle fatigue research, there has already been work on multiple features utilised for myoelectric control of prosthetics. The concept of multiple features was introduced to overcome the stochastic nature of the the EMG signal, which makes it difficult for only one parameter to reflect the uniqueness of the EMG signal to a motion command. Hence various features are used for extraction at different times of the signal. Hudgins et al. (1993) used this method first for time domain features, such as mean absolute value, mean absolute value slope, wavelength form, zero crossings and slope sign changes, which were then classified using an ANN. This new method of control increased the number of prosthetic functions which can be controlled by a single channel of myoelectric signal without the amputee having to increase his/her effort. Other researchers have also applied this multiple function technique. Phinyomark et al. (2009) calculated two novel features by modifying the mean and median frequencies. Instead of calculating the power spectrum, they calculated the mean and median of the amplitude spectrum (MMNF). Then they used a combination of the MMNF, a histogram of EMG and Willison amplitude as a feature vector in a classification task, giving a better classification recognition result of the EMG in noisy environment than other features. Boostani & Moradi (2003) aimed at selecting the best features which would give a high rate of motion classification for controlling an artificial hand. Nineteen EMG signal features were taken into account, including combining the WT with other signal processing techniques. The results of this study showed that the best features for motion classification were wavelet coefficients of EMG signals in nine scales, and the cepstrum coefficients. Although the above-mentioned studies do not investigate muscle fatigue *per se*, they all use a combination of features of the EMG signal to improve the classification outcome.

2. Feature selection

Feature selection is an important process that ensures that the selected features contain class related information, since most features do not hold such information. In machine learning and statistics, as well as pattern recognition and data mining, feature selection is a technique whereby a subset of relevant features is selected from the data, which is then applied in a learning algorithm (Sewell, 2010). Feature selection typically creates a model that facilitates the generalisation of the unseen dimensions and may substantially enhance the comprehension of the classifier model which is produced (Kim & Street, 2010). In supervised learning, which has been thoroughly investigated, the aim is to select a feature subset which produces high classification accuracy (Kim & Street, 2010). However, for unsupervised learning the goal is to identify an optimal subset that produces high quality clusters for a set number of clusters. There are two main types of feature selection: the wrapper approach and the filter approach.

2.1 The wrapper approach

The wrapper approach uses a classification method to evaluate the most optimal feature or feature sub-set. This model, often used in machine learning, is excellent for improving the performance of the classifier due to using the same bias for both the feature selection and the learning of the classifier (Kohavi & John, 1997). The wrapper method searches for the optimal feature subset or a near-optimal subset that will best suit a certain algorithm and a domain, and it differs from other approaches as the measure of relevance is defined as the accuracy obtained by nonlinear regression (Kohavi & John, 1997). The wrapper approach goes through two phases (Liu & Motoda, 1998). In the first phase, which is the feature sub-set selection, the best sub-set is selected based on the classifier's accuracy. It is only the optimal features with highest accuracy which is kept for use in the second phase. Learning and testing is the second phase, where a classifier learns and trains from the optimal sub-set and then tests it on the test data to obtain its predictive accuracy. Cross-validation is then used to estimate the accuracy as the accuracy of the training data may not ensure accuracy in the testing data. Although cross-validation may help in the difficult task of estimating the true accuracy, it will lengthen the process of feature selection. Other disadvantages of the wrapper approach is linked to being unable to handle great sizes of data and to the limitation in choice of classifiers (Liu & Motoda, 1998). As the classifier is rebuilt for each feature sub-set in the first phase it eliminates the use of classifiers which requires great computational resources.

2.2 The filter approach

The filtering approach has been linked to data mining, when a classifier cannot be directly linked with the data set and where the aim is data reduction (Liu & Motoda, 1998). In this model the relevance measure is defined independently from the learning algorithm. In the filtering approach the subset selection procedure is like a preprocessing step (Kojadinovic & Wottka, 2000). Even this model consists of two phases. Firstly, the feature selection uses separation index or other measures such as distance, dependency, consistency and information to get the best feature sub-set. Secondly, the classifiers learns from the training data set and tests it on the testing data set. This model can handle huge data sets due to the feature selection process in phase one, which is a less complex and time consuming method. The filter approach also tend to be much faster and cheaper than the wrapper approach, however, the disadvantage is that the best subset of variables may not be independent of the representational biases of the algorithm used in the learning phase (Kojadinovic & Wottka, 2000).

In research on localised muscle fatigue, feature selection is used to facilitate the pattern recognition and classification of the features analysing the sEMG signals (Tamil et al., 2008; Yan et al., 2008). Various methods have been applied in this process, however, the DBI for measuring clustering selection is commonly used for EMG pattern recognition (Huang & Chen, 1999; Petrofsky, 1981; Wang et al., 2004)

Clustering is generally considered as an unsupervised algorithm for grouping a heterogeneous population into a set of homogeneous classes. However, this strategy does not always ensure grouping similar classes together.

2.2.1 Davies-Bouldin index

Cluster validity is an important measurement of how well clusters are related to other clusters generated by clustering algorithms. In most applications the clustering result needs validation. The number of clusters is determined as a user parameter in the majority of clustering algorithms. There are many methods of finding the best number of clusters, however Davies & Bouldin (1979) developed the Davies-Bouldin index (DBI), which measures the ratio of the sum of within-cluster scatter to between-cluster separation, so that it uses both the clusters and their sample means. The DBI evaluates the cluster quality by utilising the average error of each class, serving as a measure of cluster quality by calculating the distance of the cluster members to the cluster centroids and the distances between the cluster centroids. In the DBI small values indicate that clusters are compact with their centres far apart. Hence, the optimal number of clusters is considered as the number that minimises the DBI. The formulation of the modified DBI proposed by Sepulveda et al. (2004) can be used to measure cluster quality. For data based on real numbers, the DBI always yields a real value ≥ 0. The DBI is a measure of the standard deviation of the signal. A small DBI indicates well separated and grouped clusters, which means that the lower the DBI the more separable are the classes. There are several methods to measure cluster quality, but the DBI has been applied in research on muscle fatigue (Boostani & Moradi, 2003). The DBI is related to the performance of the linear Fisher discriminant classifier to pairwise clusters.

3. Classification methods

Classification methods, used in statistics and computational problem solving, are supervised machine learning procedures where individuals are grouped according to their characteristics, which can also be called traits, variables, characters, etc. This method bases its training set on previously labelled individuals. There are many ways of classifying a signal. Signal classification methods can be in continuous time or discrete time, analog or digital, periodic or aperiodic, finite or infinite, and deterministic or random. Discrete/continuous classification is determined by whether the signal is countable (discrete) or continuous.

There are numerous ways to classify the sEMG signals, although the non-stationary nature of the signals make classification more complicated (Khezri & Jahed, 2007). A number of classification methods used for sEMG fatigue related signals are described below.

One common method for sEMG classification is to measure the Euclidean distance between the waveform of an MUAP; where a shimmer is generated in the representation of time-triggered and non-overlapping MUAPs (Raez et al., 2006). The shimmer is influenced by external factors, such as background noise and noise from offsets. In addition, the shimmer of the MUAP is affected by the variance within a class as well as the distance between the classes.

Christodoulou & Pattichis (1995) suggested using an ANN as a classification method, which can be implemented in three phases. The first phase is unsupervised learning, which is built on competitive learning and on a one-dimensional self-organising feature map. In the second phase the learning vector is quantified, which is a self-supervised learning method which aids classification performance. Finally, the third phase is that of classification. The fuzzy approach has been compared with the ANN method on four subjects, and very similar classification results were obtained. It is superior to the latter in at least three points: slightly higher recognition rate, insensitivity to over-training and consistent outputs demonstrating higher reliability (Chan et al., 2000). Table 2 categorized some papers according to the classification methods used by authors.

Classification method	Refrence ID
GP	(Holland, 1975; Koza, 1994; Poli et al., 2008)
GA	(Koza, 1994; Michalewicz, 1996; Raikova & Aladjov, 2002; Wang, Yan, Hu, Xie & Wang, 2006)
ANN	(Bishop, 1995; Xie et al., 2010; 2009)
Fuzzy systems	(Chan et al., 2000; Kiryu & Yamashita, 2007; Takagi & Sugeno, 1985)
LDA	(Balakrishnama & Ganapathiraju, 2010; Fisher, 1936)
Support Vector Machine	(Gunn, 1998; Hsu et al., 2003)
One Clause at a Time	(Torvik et al., 1999)
Cross validation	(Kohavi, 1995; McLachlan et al., 2004)
Confusion matrix	(Kohavi & Provost, 1998)

Table 2. Classification Methods

3.1 Evolutionary computation

Genetic programming (GP), which implements a learning engine based on Darwin's theory of the natural selection of the fittest, was founded by Koza (1994). GP is based on the concept of evolutionary algorithms introduced in 1954 by Nils Aall Barricelli, who applied it to evolutionary simulations. GP optimises a computer program in order to solve tasks and creates computer programs as part of the solution (Holland, 1975). The optimal program (fittest) is selected from three standard genetic operators (crossover, mutation and reproduction), which modify the GP's structure and create new (and often improved) offspring (generations) (Michalewicz, 1996). GP is closely related to genetic algorithms (GAs) (Holland, 1975), however, GP actually creates computer programs as part of the solution. GP uses a tree structure to represent the computer programs it produces and reproduces when a genetic program is run (Koza, 1994). The tree structures represent the population and the new generations which are created and is similar in construction (and appearance) to what is commonly known as a family tree. Setting a maximum tree depth avoids excessive growth of (tree-based) individuals during the evolutionary process (Koza, 1994). GAs and GPs also work according to the strategy of the survival of the fittest, this time searching the solution space of a function. GAs have proved to be a useful means to solve linear and nonlinear problems, where the areas of the state space are explored through mutation, crossover and selection operations applied to individuals in the population (Michalewicz, 1996). GAs and GP use the determination of six fundamental components: solution representation, selection function, genetic operators, initialisation, termination and a fitness function. This will be explained in the following sub-sections.

3.1.1 Solution representation

In order to describe each individual in the population of interest, GAs us a chromosome (or individual) representation in which each individual is made up of a sequence of genes. This scheme decides which genetic operators it should use, in addition to determining the structure of the problem (Houck et al., 1996). Each individual consists of a sequence of genes from a specific alphabet. Binary digits, floating point numbers, integers, symbols etc. can make up the alphabet. In this thesis, GAs are utilised that use an alphabet consisting of floating point numbers. Research shows that better solutions are produced with a more natural problem representation, and it is also more efficient (Michalewicz, 1996). Hence, bounded floating point numbers are a useful representation of individuals for function optimisation.

3.1.2 Selection function

In a GA, individuals are selected to produce successive generations. The selection is based upon the fitness of an individual, where the fittest individuals have an increased probability of being selected and any individual can be selected more than once (Nordin & Banzhaf, 1996).

3.1.3 Genetic operator

Genetic operators are the basis for the search mechanism of GAs. Based on present solutions in the population, the operators are utilised to establish new solutions. The two main operators are crossover and mutation. Crossover uses two of the existing individuals to reproduce two new individuals, while mutation randomly changes the genes in one individual to get a single new solution (Michalewicz, 1996). A reproduction operator selects a parent based on its fitness and creates identical copies of that parent in the next generation (Koza, 1994). There are several options for applying genetic operators to a multi-tree representation. It is possible to apply a particular operator that is selected to all trees within an individual. Another possibility is to iterate over the trees in an individual and select a potentially different operator for each. Finally it is possible to constrain crossover to occur only between trees at the same position in the two parents or it was possible to let evolution freely crossover different trees within the representation.

3.1.4 GA Initialisation and GA termination

An initial population must be provided for the GA and it is common for it to be randomly generated. Since GAs have the ability to produce exciting solutions, the initial population may sometimes be seeded with specifically chosen individuals amongst the otherwise randomly generated individuals. To obtain a termination the GA goes from generation to generation to select parents and reproduce offspring, which then go on to become the next generation of parents (Houck et al., 1996). One possible termination strategy is to use the population convergence criteria, where most of the whole population is forced to converge to a single solution. However, the most popular termination strategy is to decide on a specified maximum number of generations.

3.1.5 Fitness function

The fitness function is an important concept of GAs as this is the indicator for how well a generated solution solves a specific problem; it evaluates the quality of the individuals and guides the evolution to uncover progressively improved solutions during a system run, while the fitness measure specifies what needs to be done (Koza, 1994). In order to select the best suited individuals, a fitness measure is determined by the user and the program will measure the fitness based on a fitness function. The fitness function is objective and quantifies the optimality in solutions. There are two main classes of fitness functions: one where the fitness function can mutate and one where it cannot. In order to calculate the fitness the program may need to run several times with a variety of parameters so that the output can be evaluated (Garner, 2010); this is termed 'training'. One common way to represent the fitness is to measure the difference between the theoretical or ideal value and the actual value, which means that a low fitness value indicates less error.

3.2 Artificial neural networks

An artificial neural network (ANN), also called neural network (NN), is an information processing model inspired by how biological neural networks process information (Bishop, 1995). The key element of ANN is its structure, consisting of interconnected groups of artificial neurons that processes information by a connectionist approach to computation, solving a specific problem. It is called an artificial neural 'network' as the network describes the basis of the system with inter-connected neurons in various layers. ANNs are adaptable systems where the structure is changeable depending on internal and external information flowing through the network in the learning phase, and are capable of modelling complex relationships. ANNs are used in classification, in particular for pattern recognition, but also in data processing (e.g. filtering, clustering, blind source separation and compression) as well as for robotics, and regression analysis.

One of the advantages of ANNs is their ability to find meaning in complicated data (Bishop, 1995). In pattern recognition, where trends are complex and cannot be derived by humans or linear computer models, they act as an expert analysing the problem. In addition, ANNs have other capabilities such as creating their own organisation of information given in the training phase and learning tasks simply by training experience. ANNs are also a useful method in real-time operations, where computations are executed in parallel, hence special hardware devices can be used in order to take advantage of this capability.

3.3 Fuzzy systems

Fuzzy logic, a form of logic that is tolerant to contradictory data, is used in biomedical signal processing and classification to overcome problems where signals are stochastic and therefore may be contradictory in nature (Chan et al., 2000). Fuzzy systems can be trained to identify patterns which are not identifiable by other methods. Fuzzy systems determine fuzzy operators, which may be unknown, on fuzzy sets, requiring the use of 'IF-THEN' rules. Fuzzy systems are used to model or classify problems with variables and rules that can be analysed by a human user. A fuzzy classifier is an algorithm that labels objects by class, and it is argued that the classifier can predict the class label. Kucheva et al. (2000) argued that any classifier that uses fuzzy logic in its training set can be considered to be a fuzzy classifier. A fuzzy system has a vector that contains the values of the features for a specific task, and the system runs a training algorithm and a training data set. Once the system is trained it can be applied to unseen objects. There are several models of fuzzy classifiers, and the simplest method is a rule-based approach that works as an 'IF-THEN' rule system, where the class label is the consequent part of the rule. If the consequent part of the rule contains linguistic values the output will be a soft label with values from the discriminant function. Takagi & Sugeno (1985) identified a fuzzy classifier where the function is the consequent. This method also works according to the IF-THEN rule, however, the rule is a regressor over the feature data space.

3.4 Linear discriminant analysis

Linear discriminant analysis, (LDA), also related to Fisher's linear discriminant, is a technique applied in statistics, pattern recognition and machine learning which finds a linear combination of features for the characterisation or separation of two or more classes. The result can be used as a linear classifier or for dimensionality reduction in later classification. This model is closely related to other techniques, e.g. regression analysis, analysis of variance and principal component analysis, however, in LDA the variance is categorical. LDA can easily execute cases with unequal within-class frequencies, whose performance is examined on randomly produced test data (Balakrishnama & Ganapathiraju, 2010). In this method the ratio of between-class variance to the within-class variance is maximised in any data set, which ensures optimal separability.

There are two different approaches for the transformation of data sets and classification of test vectors in the transformed space: class-dependent transformation and class-independent transformation (Balakrishnama & Ganapathiraju, 2010; Fisher, 1936). The class-dependent transformation involves maximising the ratio of between-class variance to within-class variance. The main aim is high class separability, which is obtained by maximising this ratio. The data sets are transformed independently by the use of two optimising criteria. The class-independent transformation maximises the ratio of overall variance to within-class variance. In this method, only one optimising criterion is used to transform the data sets, which means that data points are transformed regardless of their class identity. In this approach, each class is considered as a separate class against all other classes. LDA is often used for the characterisation of two classes. Here the sample set is considered to be a training set which will find a good predictor for the second class. The following linear transformation describes the classification where the LDA maps the data (feature vector) x:

$$y = w^t x + w_0, \tag{1}$$

where w and w_0 are determined by maximising the ratio of between-class variance to within-class variance to guarantee maximal separability. The LDA uses two classes that are classified at one time:

$$X \in \begin{cases} Class\ 1, & \text{if } y > 0\,, \\ Class\ 2, & \text{if } y < 0\,. \end{cases} \tag{2}$$

3.5 Support vector machine

A support vector machine (SVM) is essentially a supervised learning method which can be used in classification and regression. By undergoing training, the SVM uses an algorithm to develop a model that will predict which category the examples in the training set belongs to. SVMs are a useful technique of data classification (Gunn, 1998; Hsu et al., 2003).

3.6 One clause at a time

One clause at a time (OCAT) is a classification function developed by Torvik et al. (1999), where the aim was to create a flexible, but simple prediction function. In their study on predicting if a muscle is fatigued or rested by investigating the peaks and characteristics fractile frequencies in the EMG signals, they found, in their comparison with other classification methods, that OCAT achieved the highest accuracy. Although ANNs also showed great accuracy they need subjective fine tuning and are complex in their interpretation. Nevertheless, they acknowledged that the more classical methods might be more powerful as long as valid assumptions are made, which is why they stated that more research is needed. This is an interesting but fairly dated approach that attempts to predict localised muscle fatigue.

3.7 Research on classification of EMG signals

There are several approaches to signal classification, but for EMG signal processing, NNs, described in section 3.2, have often been suggested. More specifically, the dynamic recurrent NN, which has two different adaptive parameters using fully interconnected neuron-like units and which maps the relationship between arm movement and EMG muscle activity, was proposed by Cheron et al. (1996). Del Boca & Park (1994) suggested ANNs as a suitable technique for real-time applications of EMG. Their method can precisely identify the features of the EMG signals, and the EMG features are extracted by Fourier analysis, using a fuzzy algorithm for clustering. The operations are undertaken in real-time by an FFT performed by the multipliers in a digital signal processor. The use of fuzzy systems, as described in section 3.3, is also a classification method that has been used in muscle fatigue research as a fatigue index, showing better results than conventional fatigue indices (Kiryu & Yamashita, 2007). Xie et al. used a fuzzy approximate entropy analysis of sEMG signals (Xie et al., 2009) and a cross-fuzzy entropy (Xie et al., 2010) as means by which to assess muscle fatigue.

As mentioned in section 3.1, GP, a specialisation within the field of GAs (Holland, 1975) and based on Darwin's theory of evolution, finds the best suited computer program to perform a set task. Whereas GAs search the space of a function to find an optimum solution, GP creates computer programs as part of the solution. Raikova & Aladjov (2002) used hierarchical

genetic algorithms (HGAs) to investigate the motor control for muscle forces during dynamic conditions. The HGA used genetic operators to find the moments of neural stimulation of all the MUs, which are the variables in genetic terms, so that the sum of MU twitches fulfills the set goals. Results showed that HGAs are a well suited method to examine motor control.
Wang, Yan, Hu, Xie & Wang (2006) have carried out several studies on classification of EMG signals using the wavelet packet method. One such study developed a classification method for sEMG signals based on discrete harmonic wavelet packet transform (DHWPT). Firstly, the relative energy of sEMG signals in each frequency band was extracted using DHWPT, and, secondly, a GA selected appropriate features that reduced the feature dimensionality. An NN would classify four types of prosthetic movement, utilising the selected features as the input vectors. This method produced high classification accuracy, in addition to saving computational time due to the fast algorithm in the DHWPT. In a similar study, Wang, Wang, Chen & Zhuang (2006) improved this sEMG signal classification method by using an optimal wavelet packet (OWP) method based on the DBI. Principle component analysis was applied for a reduction of the feature dimensionality of the outputs of the OWP decomposition. By using a neural network classifier to discriminate between the classes, the mean classification accuracy was 93.75%, outperforming the previous method developed by Wang, Yan, Hu, Xie & Wang (2006). Despite the fact that these two methods are based on EMG classification used for prosthetic movement, the classification methodologies are inventive and are of interest if they are applicable to sEMG signal classification of localised muscle fatigue.

3.8 Validation of classification

A statistical method for validation is cross validation, which evaluates how the classification results are applicable to an independent data set (Kohavi, 1995). Cross validation is based on an evaluation on the learning algorithm used for the applied classification technique. In cross validation the data is divided into two parts, out of which one is used for the training set and the other for the testing set (to validate the applied technique). There are several cross validation methods, such as repeated random sub-sampling validation, K-fold cross-validation, k x 2 cross-validation and leave-one-out cross-validation (Kohavi, 1995). Repeated random sub-sampling validation involves a random separation of the dataset into training and validation data. In every separation, the model fits the training set and predicts the outcomes for the data in the testing set (which is unseen). This strengths of this method are that it does not take long to compute compared to the other models and the proportion of the data set separation is not dependent upon the iterations (folds), however, some of the data may never be selected in the validation sub-sample while other data may be selected several times (Refaeilzadeh et al., 2008). K-fold cross validation partitions the original data set in for K sub-samples, out of which one subset is used for the validation process and the rest is used for the training set. This process is repeated K-times (iterations), ensuring that each of the K sub-samples are only used once in the validation and all of the observations are used for both training and validation (McLachlan et al., 2004). This is an advantage of this method, while the disadvantage is that the training algorithm needs to re-run several times, which means it requires a lot of time before it can make an evaluation. $K \times 2$ cross validation is a variant of K-field validation, and this method is useful for large data sets, where the user randomly assign the data into two equal sets. Leave-one-out cross validation involves using a single observation from the original sample as the validation data, and the remaining observations as the training data. This is repeated such that each observation in the sample is used once as the validation data. This is the same as a K-fold cross-validation with K being equal to the number of observations in the original sample. Leave-one-out cross validation is also a method similar to K-fold classification, however, the number of iterations are equal to the number of data points in the sets, and each observation is used once as the validation data. This is an expensive method due to the number of times the training process is rerun.

4. Approaches in labeling the sEMG

In labelling the sEMG signal, only the kinematic data (the elbow angle and its standard deviation) were considered as they are reliable indicators in healthy individuals when assessing muscle fatigue onset (Barry, 1992; Guo et al., 2008; Herberts et al., 1980; James et al., 1995; Jarić et al., 1997; Taimela et al., 1999; Tho et al., 1997; Vedsted et al., 2006). The use of the kinematic variables defines the boundaries (Non-Fatigue, Transition-to-Fatigue and Fatigue) of the sEMG signal, providing the basis for training the sEMG classifier.
As the onset of muscle fatigue is diffuse, the use of fuzzy-logic classification is appropriate for setting the boundaries when labelling the sEMG. This study used both a fuzzy classifier to automate the labelling and human experts to verify the outcome of the fuzzy classifier. The two main criteria in labelling the sEMG signal are described below using fuzzy logic terms. The fuzzy classifier had two inputs (elbow angle and its standard deviation) and a single output. The labelling by the fuzzy classifier was verified by a human expert using Table 3 as a guide. The changes in the elbow angle and their indication of fatigue is based on a study by Van Roy et al. (2005). This study claims that changes in the elbow angle of 1.8 +/- 2.9 degrees in men indicates fatigue.

- Figure 1 indicates the fuzzy set input for the elbow angle provided by the goniometer (0 to 180°): Angles of 89° and above indicate Non-Fatigue, while angles below 86.5° indicate Fatigue. The figure also has a superimposed illustration of a single goniometer trial signal giving an example of how the fuzzy classifier identifies the boundaries to enable the labelling of the sEMG signal.
- Figure 2 indicates the fuzzy set input for the arm oscillations (Hristovski et al., 2010) (i.e., the standard deviation of the elbow angle), which was also provided by the goniometer: An increase in the standard deviation of the goniometer signals indicates either low angular oscillation or high angular oscillation. Calculation of the standard deviation was performed using a four-second non-overlapping window of the goniometer signal, then re-sampled to match the original signal size. Further examination of Figure 2, with the superimposed standard deviation signal, reveals that for this particular signal, at around 110 seconds, which resides at 0.6 standard deviations, the subject underwent the transition from the class of Non-Fatigue to that of Transition-to-Fatigue and at around 200 seconds indicates a Fatigue state at 1.0 standard deviations.

As with all fuzzy classifiers, only a single label was chosen as the final output (Slezak et al., 2005). Table 3 defines the rule base; the rule with the greatest firing strength was selected. The above fuzzy classifier inputs (elbow angle and amplitude of arm oscillation), when used in conjunction, were found to assist in finding the boundaries of the classes. Both inputs were used to define a 6 rule type-1 fuzzy classifier, using both triangular and trapezoidal antecedents and product inference.
Preliminary tests showed that the average sEMG signal in this data set was comprised of the muscle fatigue classes in the following estimated proportions: Non-Fatigue 54.5 %; Transition-to-Fatigue 43.18 % and Fatigue 2.32 %. These proportions varied between participants, with the only common feature being that the relative sizes and order of each

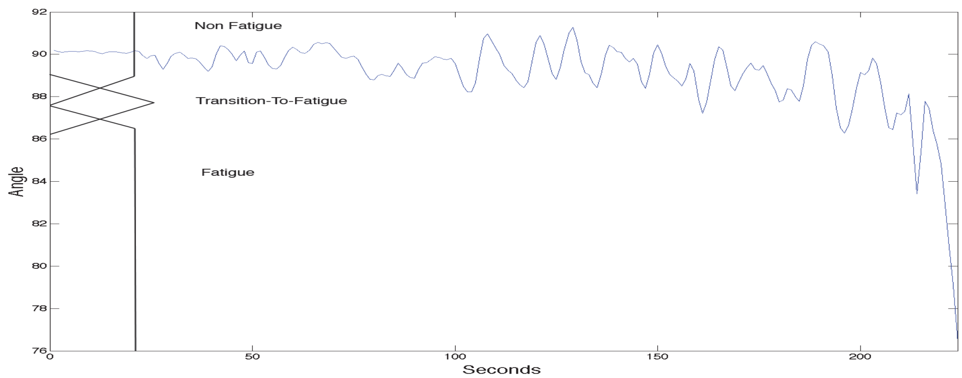

Fig. 1. The fuzzy set input for the angular position of the elbow.

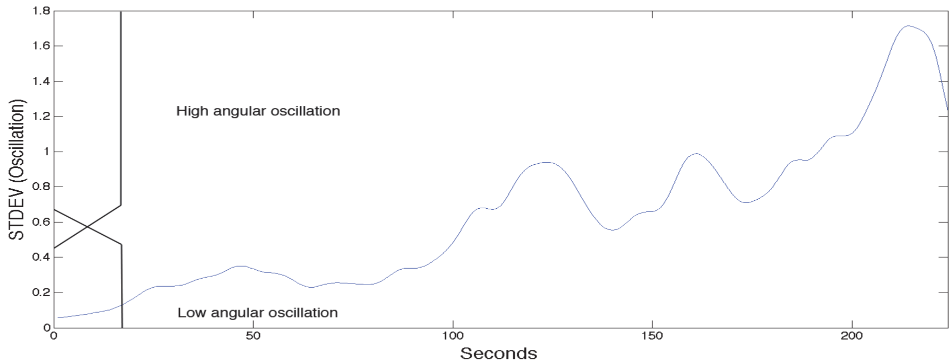

Fig. 2. The fuzzy set input for the angular oscillation (i.e., elbow angle standard deviation).

Rule	IF Input 1 (Elbow angle)	Input 2 (Oscillation)	THEN Output
1	Non-Fatigue	Low	Non-Fatigue
2	Non-Fatigue	High	Transition-to-Fatigue
3	Transition-to-Fatigue	Low	Transition-to-Fatigue
4	Transition-to-Fatigue	High	Transition-to-Fatigue
5	Fatigue	Low	Fatigue
6	Fatigue	High	Fatigue

Table 3. Rule base for signal labelling.

signal component were always the same: Non-Fatigue component > Fatigue component > Transition-to-Fatigue component. For illustration purposes, Figure 3 shows an outcome of the labelling process for a single trial.

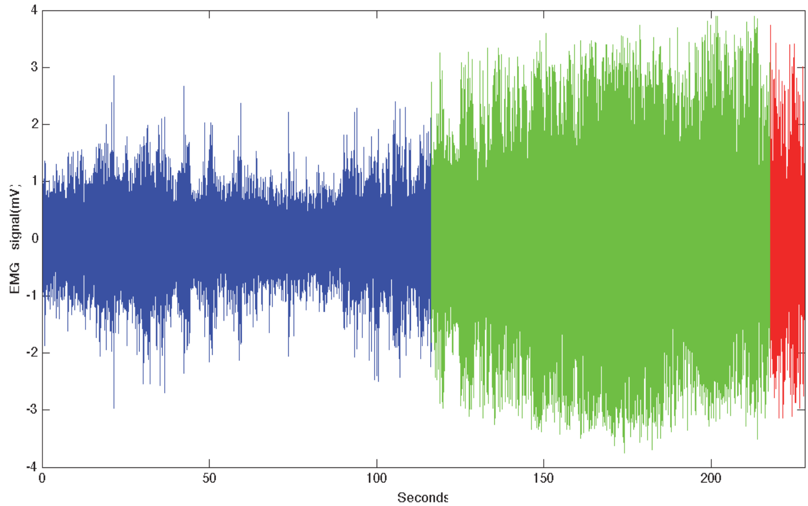

Fig. 3. An illustration of the sEMG signal after labelling (Blue=Non-Fatigue, Green=Transition-to-Fatigue and Red=Fatigue).

5. Conclusion

The defintion of localised muscle fatigue in the current litrutre has diffrent schools of thought, this chapter brought forward these definition to the reader. The chapter also looked at current state of the art in detecting, processing and calssification of sEMG for localized muscle fatigue. The novel concept of a three-phase approach to muscle fatigue(non-fatigue, transition-to-fatigue, and fatigue) was presented in this chapter.

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