CHAPTER 2:
ASSESSMENT OF FATIGUE THROUGH MYOELECTRIC PARAMETERS

2.1 THE MYOELECTRIC SIGNAL

2.1-1 Signal Generation

Voluntary muscular contraction is initiated by stimulation from peripheral nerves controlled by the central nervous system. In particular, electrical impulses are transferred from a motor neuron to associated muscle fibres through the electrochemical transmitter Acetylcholine (Ach). Each motor neuron, together with all of the muscle fibres which it innervates, is a motor unit. As an electrical impulse travels down the muscle fibres of a motor unit, a muscle contraction is elicited.

When an electrical impulse reaches a synapse between a motor nerve axon and a muscle fibre, Ach is released from terminal branches of the axon. Upon contact with the muscle fibre, Ach induces conformational changes within the membrane of the muscle fibre which alter the permeability of the membrane to intracellular and extracellular ions such as potassium (K^+), sodium (Na^+), and chlorine (Cl^-). Before excitation, these ions are balanced by electrical and concentration gradients such that an electrical potential difference of about -90 mV exists across the membrane [4]. Upon excitation, this balance is upset as a net flow inward of Na^+ ions prevails and the magnitude of the potential difference drops. If this magnitude drops to a threshold value (V_{th} , between -70 mV and -50 mV [4]), further conformational changes take place which act as a feed forward mechanism for the influx of Na^+ ions. This causes a rapid local depolarization of the muscle fibre membrane. At a certain potential difference, new conformational changes take place within the membrane which augment an efflux of K^+ ions out of the muscle fibre. This gradually repolarizes the local membrane. The time excursion of this electrical activity is called a membrane action potential (AP) and is depicted in Figure 2-1:

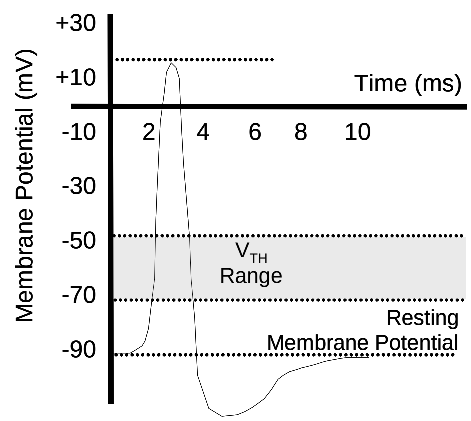

Figure 2-1: Typical Muscle Fibre Action Potential

Although the membrane AP is initiated at the innervation point (IP) of a fibre, it propagates down the length of each fibre (in both directions) because the activity in one part of a fibre stimulates similar activity in adjacent parts. Since APs are dependent upon a threshold voltage (V_{th}), the initiation of one is an ‘all-or-none’ phenomenon; subsequently, its propagation is unattenuated. While propagation speeds vary based on fibre diameter and the metabolite content of surrounding extracellular fluid, the range is between 2 m/s and 6 m/s [4].

Each membrane AP disperses an electromagnetic field through the conducting tissue surrounding the fibre and this field can be detected by surface electrodes placed within the vicinity. However, because the tissue acts as a spatial low pass filter [2, 5], the resulting surface single fibre action potential (SFAP) is dependent on the depth of the muscle fibre. The electrode configuration used to measure the signal, the filtering characteristics of the electrodes, and in the case of configurations with multiple electrodes, the position of the electrodes relative to each other also influence the surface SFAP, along with the propagation velocity of the membrane AP, also known as conduction velocity (CV).

Under normal conditions all muscle fibres associated with a particular motor neuron are stimulated almost simultaneously and surface electrodes are not capable of distinguishing between SFAPs. Instead, they detect the superposition of the surface SFAPs, known as a motor unit action potential (MUAP), as described in Figure 2-2.

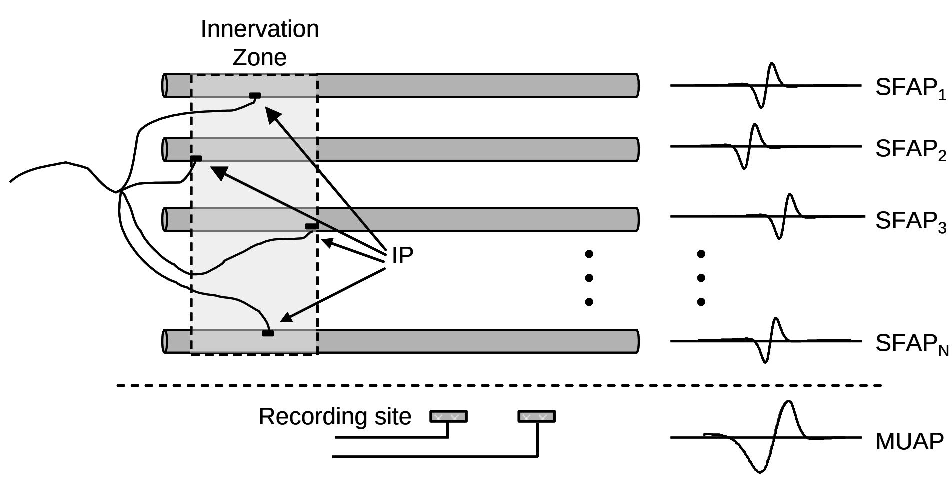

Figure 2-2: Schematic Representation of the Generation of a MUAP

Also indicated in this figure is the innervation zone (IZ) of the motor unit. This is the region within which all fiber IPs reside. The location and size of IZs vary widely from muscle to muscle and some muscles have been shown to have more than one; two IZs, 4-6 mm wide, for instance, have been observed in the brachial biceps [3, 5, 6].

While a single MUAP elicits a twitch from a muscle, to sustain a full contraction a series of MUAPs is required. A time series of nervous impulses generates a series of MUAPs capable of sustaining a contraction. This series can be modeled as a MUAP train (MUAPt) characterized by the shape of the MUAP together with the properties of the time series.

Because the MUAP is a summation of SFAPs, its shape is determined by the parameters which define each SFAP. However, the MUAP is defined not only by the shape of its contributing SFAPs but also by their spatial proximities. Thus, the MUAP is also dependent on the relative positions of the fibres and their IPs, with respect to each other and the recording electrodes.

The time series, which defines the firing statistics of a motor unit, can be modeled as a random point process which has been characterized by an interpulse interval (IPI) with a Poisson [7] or Wiebel [8] distribution based on empirical evidence, although other distributions have also been observed. For instance, Buchthal et al. [9], Clamman [10], and Pan et al. [11] all observed a Gaussian-like IPI distribution for data obtained from the brachial biceps.

Unless the contraction is very weak, more than one motor unit is active at the same time. In this case, the summation of all of the MUAPts within the detectable range of electrodes is measured. If the number of MUAPts increases significantly, the resulting random signal can be characterized by a Gaussian distribution as a result of the central limit theorem [1, 12, 13]. The signal measured by the electrodes is known as a myoelectric signal (MES) and its associated recording is an electromyogram (EMG). While the MES varies widely from muscle to muscle and is further dependent on muscle force and joint angle, when measured with surface electrodes in bipolar configuration, its amplitude generally ranges from 1-5 $\mu V_{p\text{-}p}$ to 1-5 $mV_{p\text{-}p}$ and its bandwidth generally spans DC to 500 Hz [14].

2.1-2 Signal Stationarity

Any random process with a time invariant statistical characterization is said to be strictly stationary [15]. Accordingly, the autocovariance function of a stationary process is time invariant and the mean and variance are indeed constant. While these conditions are not sufficient to define stationarity in a strict sense, they are generally accepted to define a random process which is wide sense stationary, and any process which is not wide sense stationary is clearly not strictly stationary [16].

The concept of stationarity can also be applied to a sample function of a random process. Stationary sample functions, often referred to as self-stationary, are characterized by time-average statistics which do not change significantly from segment to segment [16]. Also, sample functions which may not be entirely stationary but can be sectioned into stationary segments of sufficient length are described as pseudo-stationary or quasi-stationary [17]. The MES is a sample function of a random process which is characterized by a number of statistical parameters. If any of these parameters change with time, the resulting MES will be non-stationary.

A static muscle contraction is a contraction during which muscle force and joint angle remain relatively constant; thus the statistical parameters of an MES produced from static contractions are centrally motivated to remain invariable and non-fatiguing static contractions yield relatively stationary signals. Furthermore, since fatigue progresses relatively slowly through the duration of a sustained contraction, fatiguing static contractions are generally pseudo-stationary.

Conversely, a dynamic contraction is a contraction during which muscle force and/or joint angle (hereon in collectively termed 'dynamic factors') change as the contraction progresses. The neuromuscular system uses a combination of temporal and spatial summation to accommodate changes in muscle force. Temporal summation involves increasing the firing rate of already active motor units whereas spatial summation involves the recruitment of more motor units into the active state [4].

While both of these alterations may contribute to the non-stationary nature of dynamic MES, their influence is not always apparent in descriptive MES parameters, especially power spectral parameters. Ample evidence suggests that firing statistics have little impact on global frequency parameters [11,18,19] because their impact is limited to frequency components under 20 Hz [20]. Also, recruitment has been shown to be a factor only when considerably different motor units are recruited [21, 22].

Changes in joint angle rearrange the geometry of muscle fibres with respect to each other and the recording electrodes. Because the location of muscle fibres with respect to electrodes affects SFAP shape through tissue filtering, and because the locations of muscle fibres with respect to each other affect MUAP shape through summation, geometric changes can have profound influence on the non-stationary nature of dynamic MES and subsequent descriptive parameters.

The degree of stationarity in the MES is a critical consideration when using descriptive MES parameters to infer the state of a muscle. In this regard, the state of a muscle may refer to a muscle's activity level, force level or associated joint angle, as well as a muscle's state of fatigue. If the MES is not sufficiently pseudo-stationary, assessment of the muscle is problematic for two reasons. First estimation error may become unmanageable in descriptive parameters for which averaging is necessary, because averaging techniques may result in uncontrolled biases as a result of the non-stationarities. Second, it may become difficult to differentiate between the factors which may be contributing to the variation in parameters. Thus, when characterizing MES with descriptive parameters, signal stationarity must be taken into account.

2.1-3 Signal Characterization

Signal generation parameters such as firing statistics, the number of fibres in a motor unit and the number of active motor units contributing to a contraction all yield information regarding the state of a muscle. However, such parameters are not easily extracted from surface MES measurements, and in some cases are impossible to ascertain. Nevertheless, there are descriptive parameters in the MES which do provide information regarding the state of a muscle and have been used to classify MES from different contractions, to estimate force levels of contractions and/or to assess fatigue.

2.1-3a Typical Time Domain Descriptive Parameters

In 1993 Hudgins [23] proposed an MES feature set which enabled a neural network to differentiate between MES derived from different classes of contractions. This group of parameters has since then been shown to be a relatively rich characterization of the MES [24], though other more complex feature sets are capable of outperforming this simple set in classification tasks. Nevertheless, the simplicity of Hudgins' feature set makes it an appealing set of descriptive MES parameters. The set is made up of the parameters listed in

Table 2-1, described in discrete terms where x_k represents the k^{th} sample of MES segment p made up of K samples [24]:

Name	Description	Mathematical Representation	
Mean Absolute Value (MAV)	The mean of the absolute value of a segment of MES.	$\bar{x}^{(p)} = \frac{1}{K}\sum_{k=1}^{K}\lvert x_k\rvert$	(2-1)
Mean Absolute Value Slope (MAVS)	The difference between MAV estimates from adjacent MES segments.	$\Delta\bar{x}^{(p)} = \bar{x}^{(p+1)} - \bar{x}^{(p)}$	(2-2)
Zero Crossings (ZC)	The number of times in the segment that the MES crosses zero. To reduce overestimation due to noise, a threshold criteria 'ε' is implemented.	n_{ZC} is incremented if: $[\{x_k > 0 \text{ and } x_{k+1} < 0\}$ or $\{x_k < 0 \text{ and } x_{k+1} > 0\}]$ while $\lvert x_k - x_{k+1}\rvert \geq \varepsilon$	(2-3)
Slope Sign Changes (SSC)	The number of times in the segment that the slope of the MES changes sign. To reduce overestimation due to noise, a threshold criteria 'ε' is implemented.	n_{SSC} is incremented if: $[\{x_k > x_{k-1} \text{ and } x_k < x_{k+1}\}$ or $\{x_k < x_{k-1} \text{ and } x_k > x_{k+1}\}]$ while $\lvert x_k - x_{k+1}\rvert \geq \varepsilon$	(2-4)
Waveform Length (WL)	The cumulative length of the waveform over the MES segment.	$l = \sum_{k=1}^{K}\lvert x_k - x_{k-1}\rvert$	(2-5)

Table 2-1: Time Domain Parameters Describing MES

Along with MAV, a number of other amplitude parameters have been advanced. Among them are the root mean square (RMS) and integrated amplitude (IEMG) defined in Equations , 2-6 and 2-7, respectively [5].

$$\bar{x}_{RMS}^{(p)} = \sqrt{\frac{1}{K}\sum_{k=1}^{K}{x_k}^2} \qquad (2\text{-}6)$$

$$\breve{x}_{IEMG}^{(p)} = \sum_{k=1}^{K} |x_k| \tag{2-7}$$

2.1-3b Typical Frequency Domain Descriptive Parameters

While parameters such as ZC and SSC can be used to infer the frequency content of MES, direct estimation of power spectral parameters is also common practice. Typically the power spectrum is estimated by taking the Fourier transform of the time-averaged autocorrelation function [15]:

$$\Phi(f) = F[R_{xx}(\tau)] = F\left[\frac{1}{2T} \int_{-T}^{T} x(t) \cdot x(t+\tau) \cdot dt \right] \tag{2-8}$$

where, $\Phi(f)$ represents the power spectrum, and $R_{xx}(\tau)$ represents the autocorrelation function of $x(t)$, an MES segment of duration 'T'. This is equivalent to obtaining the periodogram of the MES, which is defined according to [15]:

$$\Phi(f) = \frac{1}{2T} \cdot |X(f)|^2 \tag{2-9}$$

where $|X(f)|^2$ represents the Fourier Transform of the signal $x(t)$. Recognizing that the power spectrum represents the frequency distribution of power in a given signal, typical parameters used to characterize the power spectrum once it has been estimated are the bandwidth, mean frequency and median frequency as defined in discrete terms in Table 2-2:

Name	Description	Mathematical Representation	
Bandwidth (BW)	The frequency, ' f_{BW} ' below which a specified high percentage ' ρ ' of the energy of the signal exists	$f_{BW} = f_{N_{BW}}$ where $\rho = \sum_{i=1}^{N_{BW}} \Phi(f_i)$	(2-10)
Normalized Mean Frequency (MF)	The normalized mean frequency ' f_m ' of the frequency distribution.	$f_m = \frac{\sum_{i=1}^{N_{\max}} f_i \cdot \Phi(f_i)}{\sum_{i=1}^{N_{\max}} \Phi(f_i)}$	(2-11)
Median Frequency (F_{MED})	The median frequency ' f_{med} ' of the frequency distribution (the frequency below which 50% of the energy of the signal exists).	$f_{med} = f_{N_{BW}}$ where $\sum_{i=1}^{N_{BW}} \Phi(f_i) = \sum_{i=N_{BW}}^{N_{\max}} \Phi(f_i)$	(2-12)

Table 2-2: Frequency Domain Parameters Describing MES

Any power spectral estimate derived from a record of data is plagued with both bias and variance. The record can be represented by the product of the signal in question and a square window with duration ' T ' equal to the record duration. The bias is therefore caused by spectral leakage resulting from the convolution with the window in the frequency domain. This can be reduced by shaping the window and increasing the window duration [25]. An increased window duration also increases the frequency resolution of the estimated spectrum ($\Delta f = \frac{1}{T}$), an equally appealing outcome.

The variance of the power spectral estimate is more problematic. As verified by Oppenhiem and Schafer [**Error! Reference source not found.**], the variance of the periodogram does not improve with increasing record duration. Thus, to obtain a smooth power spectral estimate for a given signal record, some form of averaging must be implemented. The Bartlett and Welsh Methods are both common smoothing methods based on averaging [25, **Error! Reference source not found.**]. Using these techniques, a data record is divided into epochs from which periodogram estimates are obtained and the power spectral estimate for the record is obtained by averaging the periodograms across windowed epochs. Bartlett's method employs non-overlapping rectangular windows. Welsh's method employs overlapping shaped windows, commonly the Hanning window.

Increasing 'E', the number of epochs averaged per record, decreases the variability 'σ_R^2' of a record's power spectral estimation according to:

$$\sigma_R^2 = \frac{1}{E} \cdot \sigma_e^2 \qquad (2\text{-}13)$$

where σ_e^2 represents the variance across epoch (assuming that the epochs are uncorrelated). However, a trade-off must be established between reducing the bias of each periodogram and reducing the variability. For a given record duration 'T', to increase E, the duration of each epoch must be reduced; thus to reduce variability, bias and resolution must be compromised. Since Welsh's method utilizes shaped and overlapping windows, an acceptable compromise can usually be obtained using this averaging technique [25].

REFERENCES

1. CJ De Luca, MA Sabbahi, FB Stulen, G Bilotto, "Some properties of the median frequency of the myoelectric signal during localized muscle fatigue", Biochemistry of Exercise, HK Knuttgen, JA Vogel, J Poortmans, Eds. 13, pp. 175-183 1983.

2. CJ De Luca, "Myoelectrical manifestations of localized muscular fatigue in humans", CRC Critical Reviews in Biomedical Engineering, 11(4), pp. 251-279, 1984.

3. M Naeije, H Zorn, "Relation between EMG power spectrum shifts and muscle fibre action potential conduction velocity changes during local muscular fatigue in man", European Journal of Applied Physiology, 50, pp. 23 - 33, 1982.

4. AC Guyton, ***Human Physiology and Mechanisms of Disease***, 5th Ed, WB Saunders Company, Philadelphia, 1992.

5. V Basmajian, CJ De Luca, 1985.***Muscles Alive: Their Functions Revealed by Electromyography***, 5th Ed., Williams & Wilkins, Baltimore, USA, 1985.

6. T Masuda, H Miyano, T Sadoyama, "The position of innervation zones in the bicpeps brachhii investigated by surface electromyography," IEEE Transactions on Biomedical Engineering, 32(1), pp. 36-42, 1985.

7. P Lago, NB Jones, "Effect of motor unit firing time statistics on EMG spectra", Medical and Biological Engineering and Computing, 15, p. 648-655, 1977.

8. CJ De Luca, "A model for a motor unit train recorded during constant force isometric contractions," Biological Cybernetics, 19, pp. 159-167, 1975.

9. F Buchthal, P Pinelli, P Rosenfalk, "Action potential parameters in normal human muscles and their physiological determinants", Acta. Physiologica Scandinavica, 32, pp. 219-229, 1954.

10. HP Clamman, "Statistical analysis of motor unit firing patterns in human skeletal muscle," Journal of Physiology, 9, pp. 1233-1251, 1969.

11. ZS Pan, Y Zhang, P Parker, "Motor unit power spectrum and firing rate" Medical and Biological engineering and Computing, 27(1), pp. 14-18, 1989.

12. Parker et al, IEEE Proceedings, 1975.

13. P Gatev, T Ivanova, GN Gantchev, “Changes in the firing pattern of high-threshold motor units due to fatigue”, Electromyography and Clinical Neurophysiology, 26(2), p. 83-93, 1986.

14. CJ De Luca, M Knaflitz, ***Surface Electromyography: What’s New?***, CLUT, Torino, Italy, 1992.

15. S Haykin, ***Communication Systems***, John Wiley & Sons, Inc., New York, 1994.

16. JS Bendat, AG Piersol, ***Measurement and Analysis of Random Data***, John Wiley & Sons Inc., New York, 1968.

17. P Bonato, G Gagliati, M Knaflitz, “Analysis of surface myoelectric signals recorded during dynamic contractions”, IEEE Engineering in Medicine and Biology, 15, pp. 102-111, 1996.

18. MG Hagg, “Interpretation of EMG spectral alterations and alteration indexes at sustained contractions,” Journal of Applied Physiology, 73(4), pp. 1211-1217, 1992.

19. HJ Hermens, TAM van Bruggen, CTM Baten, WLC Rutten, HBK Boom, “The median frequency of the surface EMG power spectrum in relation to motor unit firing and action potential properties,” Journal of Electromyography and Kinesiology, 2(1), pp. 15-25, 1992.

20. CJ De Luca, “The use of surface electromyography in biomechanics,” Journal of Applied Biomechanics, 73(4), pp. 1211-1217, 1992.

21. AD Cechetto, PA Parker, RN Scott, “The effects of four time-varying factors on the mean frequency of a myoelectric signal,” Journal of Electromyography and Kinesiology, 11(5), pp. 347-354, 2001.

22. D MacIsaac, PA Parker, RN Scott, “Non-stationary myoelectric signals and muscle fatigue,” Methods of Information in Medicine, 39, pp. 125-129, 2000.

23. B Hudgins, PA Parker, RN Scott, “A new strategy for multifunction myoelectric control,” IEEE Transactions on Biomedical Engineering, 40(1), pp. 82-94, 1993.

24. KB Englehart, “Signal representation for classification of the transient myoelectric signal,” PhD Dissertation, University of New Brunswick, Fredericton, Canada, 1998.

25. RE Chalis, RI Kitney, “Biomedical signal processing part 3: The power spectrum and coherence function,” Medical and Biological Engineering and Computing, 29, pp. 225-241, 1991.