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The Use of Surface Electromyography in Muscle Fatigue Assessments–A Review

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Graphical abstract

Reference	$f_{sampling}$ (Hz)	Bandwidth (Hz)
Kalsson *et al.*,[14]	1000	10-800
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Talebinejad *et al.*,[35]	1024	0-500
Subasi *et al.*,[37]	1000	1-500
Tkach *et al.*,[26]	2500	15-450
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Roger *et al.*,[11]	1024	10-500

Abstract

The developments in physiological studies have established the importance of muscle fatigue estimation in various aspects including neurophysiological and medical research, rehabilitation, ergonomics, sports injuries and human-computer interaction. Surface electromyography signals are commonly used in muscle fatigue assessment. Techniques of surface EMG signal processing used to quantify muscle fatigue are not only based on time domain and frequency domain, but also on time–frequency domain. The developments of different signal analysis to extract different indices for muscle fatigue assessments are reviewed in this paper. Several indices in time, frequency, and time-frequency representations for muscle fatigue assessments have been identified. However the sensitivity of those indices needs to be investigated. Minimizing this issue becomes the objective of the recent research in muscle fatigue assessments.

Keywords: Muscle fatigue; surface electromyography; EMG signal processing; muscle fatigue indices

Abstrak

Perkembangan dalam kajian fisiologi telah mewujudkan kepentingan pada kajian keletihan otot dalam pelbagai aspek termasuk penyelidikan neuropfisiologi dan perubatan, pemulihan, ergonomik, kecederaan sukan dan interaksi manusia-komputer. Isyarat permukaan Electromyography biasanya digunakan dalam penilaian keletihan otot. Teknik pemprosesan isyarat permukaan EMG yang digunakan untuk mengukur keletihan otot tidak hanya berdasarkan domain masa dan frekuensi, tetapi juga pada domain masa-frekuensi. Perkembangan pelbagai analisis isyarat yang berbeza dalam mengeluarkan indek yang berbeza bagi menilai keletihan otot telah dikaji dalam artikel ini. Beberapa indek dalam masa, frekuensi dan masa-frekuensi untuk menilai keletihan otot telah dikenal pasti. Walau bagaimanapun kepekaan indek-indek tersebut perlu disiasat. Meminimumkan isu ini menjadi objektif bagi kajian terkini dalam penilaian keletihan otot.

Kata kunci: Keletihan otot; permukaan electromyography; pemprosesan isyarat EMG; indeks keletihan otot

1.0 INTRODUCTION

Muscles that are used intensively showed a progressive decline of performance which largely recovers after a period of rest [1]. This reversible phenomenon is called muscle fatigue. Muscle fatigue can be categorized into three groups: subjective fatigue, which is influenced by psychological factors such as lack of motivation; objective fatigue, which indicates a decline in productivity; and physiological fatigue, which manifests itself by changes in physiological processes [2]. Localized muscle fatigue is an example of physiological fatigue [3], which refers to the inability of a given muscle to produce force or failure to maintain a desired force [4] and it is normally associated with localized pain.

Although fatigue is believed to occur quickly after the onset of a sustained period of exercise [5], muscle fatigue threshold cannot be defined as a simple function of muscle load and timing [6-7]. This is because the muscle capabilities and characteristics are varying from one person to another. Therefore, muscle fatigue indices are commonly used to detect and monitor fatigue development. This information is significant in areas such as sports injuries and performance, clinical analysis of neuromuscular disease, human-computer interactions, ergonomics, as well as rehabilitations.

Many techniques have been used for muscle fatigue assessment. Muscle fatigue is precisely measured by invasive means. However it is unsuitable for some applications such as sports, ergonomics and occupational therapy [2]. For these cases, non-invasive techniques are the option. Generally, non-invasive studies of muscle fatigue acquire signals using techniques such as sonomyography (SMG), near infrared spectroscopy (NIRS), mechanomyography (MMG), and surface electromyography (EMG). These techniques have their own advantages and disadvantages based on their application. In addition, their working principle is also different from each other.

2.0 FUNDAMENTAL OF EMG SIGNAL

Electromyography (EMG) is an easy to use technique and has therefore been used in a vast range of research on muscle physiology. It involves two types of electrode: surface and intramuscular fine wire. Intramuscular fine wire electrode is used to record EMG signal from deep muscle. However, it requires needle insertion into muscle that causes pain to the subject. On the contrary, surface electrode is easy to apply and free from pain [8]. Commonly, surface EMG is used to measure and analyze the electrical activity of specific muscles including the assessment of muscle fatigue in the field of sports science [9] and biomechanics and rehabilitation [10]. The assessment of muscle fatigue based on the surface EMG signal is a prominent area of biomedical research and has been well reported in comprehensive reviews [11].

Amongst other indices, EMG signal is described by its amplitude, frequency and phase as a function of time. EMG amplitude is normally in the range of 0-10 millivolts (peak-to-peak) or 0-1.5 millivolts (RMS) [12]. The frequency range of an EMG signal is from 0 to 500 Hz whereas the dominant energy of EMG signal is between 50 and 150 Hz [12]. However, most of the surface EMG power spectrum is located between 10 Hz and 250 Hz [13].

EMG signal is a complex and noisy signal. Physiological factors such as skin impedance, subcutaneous tissue thickness, muscle type and location, as well as fiber orientation may affect the EMG signal [14]. Generally, the recorded EMG signal is contaminated with the noise or unwanted signals such as motion artifacts (typically < 10 Hz), electromagnetic radiation (arises from 50 Hz (or 60 Hz) power line interference), cross talk, inherent noise in the electrode, as well as inherent instability of the signal [15-16].

Signal filtering is an important process that attenuates unwanted or erroneous electrical signals picked up by the electrodes. In general, filters limit the frequency spectrum (passband) of the recorded signal or attenuate signals within certain frequency range (stopband) [12]. Movement artifacts, which are normally comprised of low frequency components, are removed by high-pass filtering (cutoff frequency between 10 and 20 Hz). Signal aliasing, on the other hand, is avoided by removing the high frequency signal components through the use of low-pass filtering (cutoff frequency between 500 and 1000 Hz) [17].

Table 1 lists the sampling and bandwidth frequencies used in muscle signal analysis. It can be seen that majority of the researchers used 10 Hz as the low cutoff frequency and 500 Hz as the high cutoff frequency. Most of the studies used sampling frequency between 1000 Hz and 2000 Hz. However, when comparing 3 different sampling frequencies (1024 Hz, 2048 Hz and 4096 Hz), Kilby *et al*. [18] concluded that the sampling frequency of 2048 Hz gives the best visual frequency resolution for the analysis of surface EMG signal.

3.0 MUSCLE CONTRACTION

Surface EMG is used to study muscle function through the analysis of the electrical signals [19] that are generated by muscles during voluntary, involuntary, or stimulated contraction [20]. Nerves are responsible for controlling the contraction of muscles and determining the number, sequence, and force of muscular contraction. Most movements require a force far below what a muscle could in potential generate. However, after performing contractions for a long period of time, the nerve's signal is normally reduced in frequency and the force generated by the contraction diminishes which in turn results in muscle fatigue.

Table 1 The bandwidth and sampling frequencies

Reference	$f_{sampling}$ (Hz)	Bandwidth (Hz)
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Contraction can be divided into dynamic and isometric (static). A dynamic contraction is the most common type of muscle contraction within the body and occurs with general movement [4]. It typically involves the rhythmic and repetitive motion of large muscle groups. This is the type of muscular exertion that is most often used during strength training and cardiovascular exercise. Isometric contractions on the other hand does not involve range of motion, consequently there is less movement interference compared to dynamic contractions [21]. Isometric exercises are generally used in strength training where no visible movement of muscle is involved. Recently, the assessment of muscle fatigue during dynamic tasks is more applicable since daily life activities involve many muscle movements [22]. One potential approach to quantitative measurement of muscle fatigue is surface EMG signal analysis [23].

4.0 SURFACE EMG SIGNAL PROCESSING AND INDICES EXTRACTION

Fatigue is not a physical variable. Therefore its assessment requires the definition of indices based on physical variables that can be measured. Those indices can be extracted from the acquired surface EMG signals. There are several signal processing techniques that have been used in surface EMG analysis to quantify fatigue during isometric and dynamic contraction. In general, surface EMG signals can be processed in three domains: time, frequency, and time-frequency [14]. However, the signals need to be distinguished first whether they are stationary or non-stationary since most practical signals are random. Stationary signal is the signal whose statistical properties do not change in time whereas the signal with statistical properties that constantly change in time is considered non-stationary signal. Similar to other physiological signals, EMG signal is non-stationary.

4.1 Time Domain Indices

Time domain indices are obtained from time representation of the raw signal [6]. Extracting indices in time domain is easy and quick since it involves simple mathematical properties. It has been widely used since the decade of century due to their low computational complexity and low noise environments [25].

Table 2 shows indices in time domain that are commonly extracted by researchers. The comparisons among these indices were normally conducted with the objective of obtaining the most robust indices for EMG pattern recognition. Auto Regression (AR) and Cepstrum Coefficient (CC) are considered the most stable indices [25]. However, CC is more robust against noise [26]. Waveform length (WL) is concluded to be better than other indices (MAV, RMS, VAR, ZC, AR and SSC) due to its high rate of accuracy, low discrepancy and stability to changes in segmentation method [28].

Table 2 Common extracted indices in time domain

Indices and definition	Mathematical equation
Integrated EMG (IEMG)	$\sum_{n=1}^{N} \lvert x(n) \rvert$
Root Mean Square (RMS)	$\sqrt{\frac{1}{N}\sum_{n=1}^{N}(x(n)^2)}$
Mean Absolute Value (MAV)	$\frac{1}{N}\sum_{n=1}^{N} \lvert x(n) \rvert$
Zero Crossing (ZC)	$\{x(n) > 0 \; and \; x(n+1) < 0\}$ or $\{x(n) < 0 \; and \; x(n+1) > 0\}$
Waveform Length (WL)	$\sum_{n=1}^{N} \lvert \Delta x(n) \rvert$ $\Delta x(n) = x(n) - x(n-1)$
Willison Amplitude (WAMP)	$\sum_{n=1}^{N} f(\lvert x(n) - x(n+1) \rvert)$ Where f(x)= 1, if x> threshold;0 otherwise
Variance of EMG (VAR)	$\frac{1}{N}\sum_{n=1}^{N}(x(n)-\mu)^2$ µ=mean value
v-Order (vOrder)	$\sqrt[v]{E\{\lvert x(n) \rvert^v\}}$ V=order…1,2,3,
Log-detector	$e^{\frac{1}{N}\sum_{n=1}^{N}\log(\lvert x(n) \rvert)}$
Slope Sign Changes (SSC)	$\sum_{n=1}^{N}\left[f\left[\begin{array}{c}(x(n)-x(n-1))\times \\ (x(n)-x(n+1)\end{array}\right]\right]$ Where f(x)= 1, if x> threshold;0 otherwise
Auto Regression coefficient (AR)	$\sum_{i=1}^{p} a(i)x(n-1) + e(n)$ a(i) – autoregressive coefficient p- autoregressive model order e(n)- residual white noise
Cepstrum Coefficients (CC)	$-a(i) - \sum_{l=1}^{i-1}(1-\frac{l}{i})a(n)c(i-1)$ a(i) – autoregressive coefficient c(i) – cepstrum coefficient i – dimensionality of the model

The latest comparison among indices (37 up-to-date indices) in time and frequency domains was done by [25]. The indices had been grouped into four main types based on their mathematical properties: 1) energy and complexity information methods, 2) frequency information method, 3) prediction model method, 4) time-dependence method. The study concluded that WL has the least computational complexity, AR is robust in prediction model, MAV is better in providing energy information while WAMP is suitable for frequency information.

4.2 Spectrum Indices

In many cases, most distinguished information can be estimated from the frequency representations of the signal [7]. The signal to be analyzed in frequency domain should undergo Fourier transform. The Fourier transform used to represent signal in frequency domain is in the definition of power spectrum:

$$S_x(f) = \frac{1}{T}\left|\int_{-\infty}^{\infty} x(t).e^{-2j\pi f t}dt\right|^2 \qquad (1)$$

where x(t) denotes the signal in time domain. Significant changes in power spectrum indicate muscle fatigue; the power spectral density is increased in low frequency component and decreased in the higher frequency components [7]. Among all indices in frequency domain, mean and median frequencies are usually used by researchers to determine and quantify muscle fatigue [29-31].

Table 3 shows the indices that are normally extracted by researchers in frequency domain. In muscle fatigue research, Shaw and Huang [30] and Bilodeau *et al.* [31] had compared mean and median frequencies. Both studies showed that median frequency is more sensitive than mean frequency. However, study by Thongpanja *et al.* [29] later showed that the mean frequency is better.

Table 3 Extracted indices in frequency domain

Indices and definition	Mathematical equation
Mean Frequency (MF)	$f_{mean} = \frac{\sum_{k=1}^{N} k.S_x(k)}{\sum_{k=1}^{N} S_x(k)}$
Median Frequency (MDF)	$f_{median} = \frac{1}{2}\sum_{k=1}^{N} S_x(k)$
Peak frequency (PK)	$f_{peak} = (\arg(\max(S_x(k)))$ k=1………N
Mean Power (MP)	$P_{mean} = \frac{\sum_{k=1}^{N} S_x(k)}{M}$
Total Power (TTP)	$P_x = \sum_{k=1}^{N} S_x(k)$
1st, 2nd and 3rd spectral moment	$m_1 = \sum_{k=1}^{N} k.S_x(k)$ $m_2 = \sum_{k=1}^{N} k^2.S_x(k)$ $m_3 = \sum_{k=1}^{N} k^3.S_x(k)$
Frequency Ratio (FR)	$f_{ratio} = \frac{\sum_{k=f_1}^{f_2} S_x(k)}{\sum_{f_1}^{f_2} S_x(k)}$
Variance of central frequency	$f_{var} = \frac{1}{P_x}\sum_{k=1}^{N} S_x(k)(k-f_{mean})^2$
Normalized Spectral Moment (NSM)	$FI_{nsm5} = \frac{\sum_{k=1}^{N} k^{-1}.S_x(k)}{\sum_{k=1}^{N} k^5.S_x(k)}$

Several factors such as electrode position, changes in force, muscle length and the number of active motor units contribute to the non-stationary of the EMG signal during dynamic contractions [14, 21-22, 32-34]. This implies that the commonly used indices such as median and mean frequencies may not accurately reflect muscle fatigue [22] as the indices have relatively low sensitivity [8]. To overcome this issue, Dimitrov normalized spectral moment indices (FInsmk) was developed to detect spectral changes of muscle during fatigue [8]. Compared to median frequency, this new index is claimed to be reliable for both dynamic and isometric contractions.

Gonzalez-Izal *et al*. [22] had compared mean average voltage, median frequency, FInsmk, as well as the extracted indices from time–frequency analysis (instantaneous mean frequency and frequency variance). They found FInsm5 gives the most accurate estimation in detecting muscle fatigue.

In general, frequency analysis is better used to assess muscle fatigue during isometric contraction only. According to Karlsson *et al*. [14], power spectrum estimation is not appropriate method for analyzing surface EMG signals during dynamic contraction. The limitation of frequency analysis using Fourier Transform is also highlighted by Oskoei [28]. On the contrary, Thongpanja *et al*. [36] had highlighted the possibility of analyzing surface EMG signals during dynamic contraction using techniques in time domain and frequency domain. According to the authors, this can be done for window sizes less than 256 samples (250 ms).

4.3 Time-Frequency Indices

Time–frequency representation method provides accurate representation for non-stationary signal by joint representation in time and frequency. Since EMG signals are non-stationary, this method is recommended in recent developments for new EMG indices. Several authors had claimed that EMG indices for dynamic contraction are more reliable when extracted from time-frequency domain as compared to the frequency domain [14, 33]. The commonly used time-frequency analysis methods for EMG signals are: short-time Fourier transform (STFT) [14, 33, 37] wavelet transform (WT) [6, 14, 37-39], Choi William Distribution (CWD) [14, 33], and Wigner-Ville distribution (WVD) [14].

Table 4 shows several mathematical equations of time-frequency analysis method. Research conducted by Karlsson *et al*. [14] had concluded that for dynamic contraction, the estimations provided by the WT have better accuracy and precision on simulated data sets than those obtained with other time–frequency distributions. However, when processing the signal using different quadratic time–frequency distributions (Choi-William distributions, Wigner-Ville distributions and Born Jordan distribution), Bonato *et al.* [33] concluded that the Choi–Williams distribution is the most suitable method to represent the non-stationary signals during dynamic contractions. The indices used are the instantaneous median and instantaneous mean frequencies. The instantaneous median frequency is preferable since it has lower estimation error.

Comparison between STFT and WT were described in Camata *et al*. [38] and Subasi *et al*. [37]. However, Subasi *et al*., [37] also include Wigner Ville Distribution (WVD) in their comparison in order to obtain the best classification of muscle fatigue based on time-frequency analysis. Both studies found that WT shows better performance than STFT methods since the WT enables variable window sizes in analyzing different frequency components within a signal.

Recent study in muscle fatigue estimation during dynamic contraction conducted by Kim *et al.* [43] introduced a new optimized fatigue index (FIhlrOPT) that maximized the correlation with peak power.

On the whole, many studies conclude that WT show better performance in extracting indices in time-frequency domain. However, in the case where supplementary information about spectra is not available from WT, S transform method can be considered [44]. In general, S transform provides multi resolution analysis while retaining the absolute phase of each component of the signal. Awkwardly, S transform has not much been explored in physiological signals even though it has been successfully implemented in areas such as power quality disturbance [40-41] and Geophysic [42]. Only few published literatures report the use of S transform in biomedical field; electrophysiology (EEG) [45] and electrocardiography (ECG) [46].

Table 4 Time-frequency processing method

Methods	Mathematical equation
STFT	$STFT(t,f) = \int_{-\infty}^{\infty} x(\tau)w(\tau - t)\, e^{(-2\pi f\tau)}\, d\tau$ where w(t) – window function
CWT	$CWT(t,a) = \int_{-\infty}^{\infty} x(\tau)\frac{1}{\sqrt{\lvert a\rvert}}\Psi^*\left(\frac{\tau - t}{a}\right) d\tau$ t- translation a-scale parameter Ψ-mother wavelet
WVD	$WVD_x(t,f) = \frac{1}{2\pi}\int x(t+\frac{\tau}{2})x^*(t-\frac{\tau}{2})e^{-2\pi f t}d\tau$
CWD	$CWD_x(t,f) = \iint \frac{1}{\sqrt{\frac{4\pi\tau^2}{\sigma}}}\exp(-\frac{(\mu-t)}{\frac{4\tau^2}{\sigma}})$ $x\left(\mu+\frac{\tau}{2}\right)x^*(\mu-\frac{\tau}{2})e^{-2\pi f t}d\mu d\tau$
ST	$S(t,f) = \int_{-\infty}^{\infty} x(\tau)\frac{\lvert f\rvert}{\sqrt{2\pi}}e^{-\frac{(\tau-t)^2\tau^2}{2}}e^{-j2\pi f\tau}d\tau$

5.0 EMG CLASSIFICATION

Classification normally refers to supervised learning where individuals are classified based on their characteristics. Literatures have reported various methods for EMG signal classification such as Artificial Neural Network (ANN) [47], Linear Discriminant Analysis (LDA) [7], Fuzzy System [47-48] and Support Vector Machine (SVM) [28, 49-50]. Since the extracted indices from EMG signal are used as the input to a classifier, the high accuracy of the classification depends on the used indices extraction method. It is important to note that the non-stationary nature of the signals makes classification more complicated [17].

Dimension reduction methods play an important part in selecting the best indices to be input to the classifier. These methods decrease the computational time and the burden to the classifier [16]. There are many familiar dimension reduction methods such as PCA (Principle Component Analysis) [49] and ICA (Independent Component Analysis) [37]. The used of PCA to provide data compression for both training and testing data sets has been combined with Multilayer Perceptron Neural Network (MLPNN) and Support Vector Machine (SVM) for the diagnosis of muscular disorder [49]. Furthermore, the combination of PCA and SVM provides better classification than the combination of PCA and MLP. In other study, the combination of ICA and MLPNN has been applied in the

Levenberg Marquadht (LM) algorithms and the Gradient Descent Algorithm (GDA) to detect muscle fatigue [37].

Recently, support vector machine (SVM) has become the most popular machine learning methods for the classification, since it shows better accuracy than other methods (see Table 5). Moreover, SVM has advantages due to their simplicity, short duration of training time and stability in the training phase [49]. The comparison of the SVM kernels, namely linear, polynomial, and radial basis function (RBF), were observed to the selected muscle fatigue indices based on the PCA methods [50]. The study reported the classification accuracy of 97%, 96% and 88% for the linear, RBF and polynomial kernels, respectively.

Table 5 Comparison of classification methods

Reference	Identification	Classification methods	Results (%)
Guler *et al*., 2005 [49]	Diagnosis muscular disorder	MLPNN SVM	84.16 85.42
Oskoei *et al*., 2008 [28]	Six upper limb motion	SVM LDA MLPNN	95.5 94.5 88.5
Al-Mulla *et al*., 2011 [4]	Transition to fatigue Fatigue	LDA	90.37
Al-Mulla *et al*., 2009 [47]	Nonfatigue Transition to fatigue Fatigue	Fuzzy ANN AR GP	85 84 99 83.17
George *et al*., 2012 [48]	Rest Slow contraction Fast contraction	Fuzzy PNN	97.3 93.6
Subasi *et al*., 2013 [37]	Myopathic Neorogenic Normal	kNN SVM RBFN PSOSVM	95.17 96.75 94.08 97.41
Patidar *et al*., 2013 [51]	Myopathic Normal	BPNN	96.76
Zhang *et al*., 2014 [50]	Muscle fatigue detection	SVM	96.0

Note: SVM-Support Vector Machine; LDA-Linear Discriminant Analysis,; MLPNN-Multilayer Perceptron Neural Network; ANN-Artificial Neural Network; AR- Coefficient Autoregression; GP-Genetic Programming; PNNC- Probabilistic Neural Network; kNN-k-Nearest Neighbor; RBFN-Radial Basis Function Networks; PSOSVM-Particle Swarm Optimization Support vector Machine; BPNN- Back Propagation Neural Network.

■6.0 CONCLUSION

The use of surface EMG to assess muscle fatigue was reviewed. The purpose of this paper is to give detailed information about the use of surface Electromyography in muscle fatigue assessment, emphasizing on the methodologies used for detecting, processing and classifying EMG signals. When analyzing the surface EMG signals, indices extraction is an important process which affects the developed application. Traditionally, a range of indices in time, frequency, and time-frequency domains have been extracted for the analysis of surface EMG signals relating to localized muscle fatigue.

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References

[1] D. G. Allen, G. D. Lamb and H. Westerblad, 2008. Skeletal Muscle Fatigue: Cellular Mechanisms. *Physiological Reviews*. 88: 287–332.

[2] M. R. Al-Mulla, F. Sepulveda, and M. Colley. 2012. sEMG Techniques to Detect and Predict Localised Muscle Fatigue, EMG Methods for Evaluating Muscle and Nerve Function, Mr. Mark Schwartz (Ed.). InTech.

[3] D. B. Chaffin, 1973. Localized Muscle Fatigue–Definition and Measurement. *Journal of Occupational and Environmental Medicine*. 15: 346–354.

[4] M. Gonzalez-Izal, A. Malanda, E. Gorostiaga, and M. Izquierdo, 2012. Electromyographic Models to Assess Muscle Fatigue. *Journal of Electromyography and Kinesiology*. 22(4): 501–512.

[5] B. K. Barry, and R. M. Enoka. 2007. The Neurobiology of Muscle Fatigue: 15 Years Later. *Integrative and Comparative Biology*. 47(4): 465–473.

[6] M. Hussain, and M. Mamun, 2012. Effectiveness of the Wavelet Transform on the Surface EMG to Understand the Muscle Fatigue During Walk. *Measurement Science Review*. 12(1): 28–33.

[7] M. R. Al-Mulla, F. Sepulveda, and M. Colley. 2011. A Review of Non-Invasive Techniques to Detect and Predict Localised Muscle Fatigue. *Sensors*. 11(4): 3545–3594.

[8] G. V. Dimitrov, T. I. Arabadzhiev, K. N. Mileva, J. L. Bowtell, N. Crichton, and N. A. Dimitrova. 2006. Muscle Fatigue During Dynamic Contractions Assessed by New Spectral Indices. *Medicine and Science in Sports and Exercise*. 38(11): 1971–1979.

[9] C. E. Milner. 2008. *Functional Anatomy for Sport and Exercise: Quick Reference*. New York, USA: Routledge.

[10] S. Naider-Steinhart, and M. Katz-Leurer. 2007. Analysis of Proximal and Distal Muscle Activity During Handwriting Tasks. *American Journal of Occupational Therapist*. 61(4): 392–398.

[11] D. R. Rogers, and D. T. MacIsaac. 2013. A Comparison of EMG-Based Muscle Fatigue Assessments During Dynamic Contractions. *Journal of Electromyography and Kinesiology*. 23(5): 1004–1011.

[12] C. J. De Luca, 1997. The Use of Surface Electromyography in Biomechanics. *Journal of Applied Biomechanics*. 13: 135–163.

[13] P. Konrad, 2005. The ABC of EMG. A Practical Introduction to Kinesiological Electromyography. Noraxon INC. USA.

[14] S. Karlsson, J. Yu, and M. Akay, 2000. Time-Frequency Analysis of Myoelectric Signals During Dynamic Contractions: A Comparative Study. *IEEE Transactions on Biomedical Engineering*. 47(2): 228–238.

[15] M. B. I. Reaz, M. S. Hussain, and F. Mohd-Yasin. 2006. Techniques of EMG Signal Analysis: Detection, Processing, Classification and Applications. *Biological Procedures Online*. 8(1): 11–35.

[16] R. H. Chowdhury, M. B. Reaz, M. A. B. M. Ali, A. A. Bakar, K. Chellappan, and T. G. Chang, 2013. Surface Electromyography Signal Processing and Classification Techniques. *Sensors*. 13(9): 12431–12466.

[17] R. G. Mello, L. F. Oliveira. 2007. Digital Butterworth Filter for Subtracting Noise from Low Magnitude Surface Electromyogram. *Computer Methods and programs in Biomedicine*. 87(1): 28–35.

[18] J. Kilby, and K. Prasad, 2013. Analysis of Surface Electromyography Signals using Discrete Fourier Transform Sliding Window Technique. *International Journal of Computer Theory and Engineering*. 5(2): 321–325.

[19] G. T. Kim, M. A. Ahad, M. Ferdjallah, and G. F. Harris. 2007. Correlation of Muscle Fatigue Indices between Intramuscular and Surface EMG Signals. Conference Procedings-IEEE Southeastcon, 378–382.

[20] A. O. Andrade. 2005. Decomposition and Analysis of Electromyographic Signals. PhD Thesis, University of Reading, UK.

[21] D. Farina, M. Gazzoni, and R. Merletti, 2003. Assessment of Low Back Muscle Fatigue by Surface EMG Signal Analysis: Methodological Aspects. *Journal of Electromyography and Kinesiology*. 13(4): 319–332.

[22] M. Gonzalez-Izal, A. Malanda, I. Navarro-Amezqueta, E. M. Gorostiaga, F. Mallor, J. Ibanez, and M. Izquierdo, 2010. EMG Spectral Indices and Muscle Power Fatigue during Dynamic Contractions. *Journal of Electromyography and Kinesiology*. 20(2): 233–240.

[23] R. A. Marson, 2011. Study of Muscular Fatigue by EMG Analysis during Isometric Exercise. Proceedings of the IEEE Biosignals and Biorobotics Conference (BRC). 1–4.

[24] M. T. Tarata, 2003. Mechanomyography versus Electromyography, In Monitoring the Muscular Fatigue. *Biomedical Engineering Online*. 2(3).

[25] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, 2012. Feature Reduction and Selection for EMG Signal Classification. *Expert Systems with Applications*. 39(8): 7420–7431.

[26] D. Tkach, H. Huang, and T. A. Kuiken. 2010. Research Study of Stability of Time-Domain Features for Electromyographic Pattern Recognition. *Journal NeuroEngineering and Rehabilitation*. 7: 21.

[27] R. Boostani, and M. H. Moradi, 2003. Evaluation of the Forearm EMG Signal Features for the Control of a Prosthetic Hand. *Physiological Measurement*. 24(2): 309.

[28] M. A. Oskoei, and H. Hu, 2008. Support Vector Machine-Based Classification Scheme for Myoelectric Control Applied to Upper Limb. *IEEE Transactions on Biomedical Engineering.* 55(8): 1956–1965.

[29] S. Thongpanja, A. Phinyomark, P. Phukpattaranont, and C. Limsakul, 2012. A Feasibility Study of Fatigue and Muscle Contraction Indices Based on EMG Time-Dependent Spectral Analysis. *Procedia Engineering*. 32: 239–245.

[30] D. Shaw, and C. R. Huang, 2010. Assessing Muscle Fatigue by Measuring the EMG of Biceps Brachii. 3rd International Conference on Biomedical Engineering and Informatics (BMEI). 773–777.

[31] M. Bilodeau, S. Schindler-Ivens, D. M. Williams, R. Chandran, and S. S. Sharma. 2003. EMG Frequency Content Changes with Increasing Force and during Fatigue in the Quadriceps Femoris Muscle of Men and Women. *Journal of Electromyography and Kinesiology*. 13(1): 83–92.

[32] M. Jordanic, and R. Magjarevic, 2012. Estimation of Muscle Fatigue During Dynamic Contractions Based on Surface Electromyography and Accelerometry. In *MIPRO*, 2012 Proceedings of the 35th International Convention. 201–205.

[33] P. Bonato, S. H. Roy, M. Knaflitz, and C. J. De Luca, 2001. Time-Frequency Parameters of the Surface Myoelectric Signal for Assessing Muscle Fatigue during Cyclic Dynamic Contractions. *IEEE Transactions on Biomedical Engineering*. 48(7): 745–753.

[34] K. Y. Lee, S. Lee, 2011. Endurance Time Prediction of Biceps Brachii Muscle using Dimitrov Spectral Index of Surface Electromyogram during Isotonic Contractions. *International Journal of Precision Engineering and Manufacturing*. 12(4): 711–717.

[35] M. Talebinejad, A. D. C. Chan and A. Miri, 2010. Fatigue Estimation using a Novel Multi-Fractal Detrended Fluctuation Analysis-Based Approach. *Journal of Electromyography and Kinesiology*. 20: 433–439.

[36] S. Thongpanja, A. Phinyomark, F. Quaine, Y. Laurillau, B. Wongkittisuksa, C. Limsakul, and P. Phukpattaranont, Effects of Window Size and Contraction Types on the Stationarity of Biceps Brachii Muscle EMG Signals. Proceedings of the 7th International Convention on Rehabilitation Engineering and Assistive Technology Article no. 44.

[37] A. Subasi, and M. K. Kiymik, 2010. Muscle Fatigue Detection in EMG using Time–Frequency Methods, ICA and Neural Networks. *Journal of Medical Systems*. 34(4): 777–785.

[38] T. V. Camata, J. L. Dantas, T. Abrão, M. A. Brunetto, A. C. Moraes, and L. R. Altimari, 2010. Fourier and Wavelet Spectral Analysis of EMG Signals in Supramaximal Constant Load Dynamic Exercise. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. 1364–1367.

[39] N. M. Sobahi, 2011. Denoising of EMG Signals Based on Wavelet Transform. *Asian Transactions on Engineering*. 1(5): 17–23.

[40] S. Mishra, C. N. Bhende, and K. B. Panigrahi. 2008. Detection and Classification of Power Quality Disturbances using S-Transform and Probabilistic Neural Network. *Power Delivery, IEEE Transactions on*. 23(1): 280–287.

[41] P. K. Dash, K. B. Panigrahi, D. K. Sahoo, and G. Panda. 2003. Power Quality Disturbance Data Compression, Detection, and Classification using Integrated Spline Wavelet and S-Transform. *IEEE Transactions on Power Delivery*. 18(2): 595–600.

[42] C. R. Pinnegar, and L. Mansinha, 2003. The S-Transform with Windows of Arbitrary and Varying Shape. *Geophysics*. 68(1): 381–385.

[43] J. Kim, S. Kim, S. Park, S. Ahn, Y. Lee, and Y. Kim. 2013. Bandwidth Optimization of the Fatigue Index to Estimate Muscle Fatigue during Dynamic Contractions. *International Journal of Precision Engineering and Manufacturing*. 14(7): 1185–1191.

[44] R. G. Stockwell, L. Mansinha, and R. P. Lowe. 1996. Localization of the Complex Spectrum: the S Transform. *IEEE Transactions on Signal Processing.* 44(4): 998–1001.

[45] S. Assous, and B. Boashash, 2012. Evaluation of the Modified S-Transform for Time-Frequency Synchrony Analysis and Source Localisation. *EURASIP Journal on Advances in Signal Processing*. 49.

[46] P. Rakovic, E. Sejdic, L. J. Stankovic, and J. Jiang, 2006. Time-Frequency Signal Processing Approaches with Applications to Heart Sound Analysis. *Computers in Cardiology*. 33: 197–200.

[47] M. R. Al-Mulla, F. Sepulveda, M. Colley, and A. Kattan, 2009. Classification of Localized Muscle Fatigue with Genetic Programming on SEMG during Isometric Contraction. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. 2633–2638.

[48] K. Shalu George, K. S. Sivanandan, and K. P. Mohandas, 2012. Fuzzy Logic and Probabilistic Neural Network for EMG Classification–A Comparitive Study. *International Journal of Engineering Research and Technology*. 1(5).

[49] N. F. Guler, and S. Koçer, 2005. Classification of EMG Signals using PCA and FFT. *Journal of Medical Systems*. 29(3): 241–250.

[50] J. Zhang, T. E. Lockhart, and R. Soangra, 2014. Classifying Lower Extremity Muscle Fatigue during Walking using Machine Learning and Inertial Sensors. *Annals of Biomedical Engineering*. 42(3): 600–612.

[51] M. Patidar, N. Jain, and A. Parikh, 2013. Classification of Normal and Myopathy EMG Signals using BP Neural Network. *International Journal of Computer Applications*. 69(8): 12–16.

[52] D. Roman-Liu, T. Tokarski, and K. Wojcik, 2004. Quantitative Assessment of Upper Limb Muscle Fatigue Depending on the Conditions of Repetitive Task Load, *Journal of Electromygraphy and Kinesiology.* 14: 671–682.

[53] S. Solnik, and P. DeVita, 2010. EMG Frequency during Isometric, Submaximal Activity: A Statistical Model for Biceps Brachii. *Acta Bioengineering and Biomechanics*. 12(3): 21–28.