Approximate Entropy in Electromyography during Muscle Fatigue

Payam Wali M. Hussein[1] & Kadir Tufan[2] & Serkan Dursun[3]

[1] Ishik University, Erbil, Iraq
[2] Faculty of Computer Science and IT, Tirana, Albania
[3] Computer Science Department at University of Houston, Houston, TX, USA
Correspondence: Payam Wali M.Hussein, Ishik University, Erbil, Iraq.
Email: payam.wali@ishik.edu.iq

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Abstract: Muscle fatigue (MF) is a phenomenon that involves the decline of one's ability to perform physical action. The early detection of MF is important in the field of ergonomics, sports, occupational work, and human-computer interaction, as MF affects performance and may cause injury. Since MF is not a quantitative value, existing researches in this field are mostly based on different measurable parameters. Electromyography is among the most commonly used signals in analysing MF. The main purpose of this paper is to analyse MF during isometric contractions. For this purpose Discrete Wavelet Transform (DWT) is used to divide each signal to get sub-band frequencies. Approximate Entropy (ApEn) is applied to each sub-band. In the next step, each band is segmented into three sections. Finally, a comparison between the first segment and last segment is performed to evaluate MF.

Keywords: Muscle Fatigue, Electromyography, Discrete Wavelet Transform, Approximate Entropy

1. Introduction

The term Muscle Fatigue (MF) is used to express a decline in the capacity to perform physical action. Previously, MF had been known as a failure point during a contraction when the skeletal muscle cannot generate a required amount of muscle force. Basically, during voluntary muscle contraction if the produced force is decreased then MF happens (Gandevia, 1992). However, various reasons can cause MF, such as metabolic accumulation or generating improper motor commands in the motor cortex.

Researchers try to measure MF for the purpose of early detection due to its importance in the field of ergonomics, sports, occupational work, and human-computer interaction. Since MF affects performance and causes injury, creating a computerised system to anticipate and discover fatigue by warning the person is essential in increasing human performance during daily work, sport, and other manual activities. The system can also be applied in occupational health and ergonomics, especially where there is a risk related to occupation disorders in the muscular system. Localised MF may cause work-related injuries in employees, in particular when the required task needs high stationary muscle activity (Vedsted, 2006).

A Research conducted by the Washington State Department of Labor and Industries, which is also mentioned by *Jones et al.* (2006) in their report, states that above 50% of labourers have faced musculoskeletal abnormalities, mainly during jobs that involve manual handling. *Chaffin et al.'s* (1999) analysis of occupational biomechanics declares that overloading of muscle force is the main cause of MF, and moreover that it causes severe MF, aching in muscles, and strict functional incapacity in muscles and other tissues of the human body. Consequently, it is essential for ergonomists to find an effective method to predict occupational MF.

For the purpose of evaluating MF, it is important to obtain correct information from peoples' muscles. Therefore, an electromyography (EMG) is an essential tool for collecting signals, since it is the study of muscle electrical signals and is a method for assessing and recording the electrical activity produced by contraction and relaxation of muscle tissue. The EMG signal is a complex signal and is controlled by the nervous system. EMG directly looks inside the muscle and records the signals, which helps specialists to analyse these signals and detect muscular performance and medical abnormalities, which depend on structural and physiological properties of the muscles (Raez *et al.*, 2006).

Whilst there are some features to evaluate MF in the extant literature, most primarily concentrate on the clinical aspects and thus the parameters are insufficient to detect MF in its early stages or to evaluate the problem quantitatively. Therefore, in this paper we try to find nonlinear features using Approximate Entropy (ApEn). First of all we divide our original signal using Discrete Wavelet Transform (DWT) for noise elimination and to get a sub-version, and then we compute the ApEn values of each approximation coefficient and detail coefficients. For computing the ApEn, we decided on the suggestions by Pincus in which the embedding dimension (m) is set to 2, and vector comparison distance (r) and time delay (t) set to 0.15 times the standard deviation (Pincus, 1991).

Most of the researches that evaluate MF are based on decreasing frequency and increasing amplitude in isometric muscle contractions. Formerly, quantification analyses of MF were performed by using linear methods in which some EMG parameters were used such as Mean Power Frequency (MNF), Median Power Frequency (MDF), Root Mean Square (RMS), and Average Rectified Value (ARV) in which changes in these parameters are recorded by passing time (Soo *et al.*, 2009).

The aim of this paper is to analyse MF during isometric contractions using surface EMG. For this purpose a group of 30 young volunteers (15 females, 15 males) were recruited to our study. They were all healthy subjects without any history of previous injury, metabolic, or muscular disease. The biceps brachii (BB) and triceps brachii (TB) muscles were chosen for the test.

2. Muscle Fatigue In EMG

EMG signals consist of information from the MU, and are good evidence for the identification of physiological and neural changes in the muscular system. The content of the signal is affected by some factors. Thus, it is nothing to do with the raw EMG signals unless suitable procedures and methods for EMG signal analysis are used. (Bogdanis, 2012).

The parameters of MF are increased amplitude in the time domain and declining frequency from high to low in the frequency domain. Nearly a century ago a professor named Piper performed an experiment and observed a certain decrease in the frequency component of surface myoelectric signals during isometric contraction (Tarata, 2003). Cobb and Forbes also perceived an incline in amplitude, which is one sign of MF during an isometric muscle contraction. So, features of MF are increased amplitude in the time domain and transition from high frequency to low frequency in the frequency domain (Enoka *et al.*, 2008).

A signal is obtained and, in some environments, analysed in the time domain where the signal amplitude is denoted as a function of time. Still, for most of the signal analysis techniques, the frequency parameter is widely used, so the signal is evaluated in the frequency domain. For the first time the ability to monitor MF through frequency analysis of myoelectric signals was provided by Kogi and Hakamada, who observed a decline in the frequency of the EMG signal (Kogi *et al.*, 1962). As a result of increasing amplitude and decreasing frequency during MF, some parameters change. Researchers mostly focus on MNF and MDF, which are both frequency domain-related parameters. Hagberg states that if the amplitude of the EMG signal in the time domain inclines as MDF declines, there is definitely MF occurrence (Jonsson, 1988). Al-Zaman *et al*. (2007) depended on this hypothesis and analysed MF at different Maximum Voluntary Contractions (MVC). They concluded that at the end of their study the value of RMS increased, whereas MDF and MNF values decreased. In this study they published quantitative results.

DWT analysis is an alternative method to the time-varying signal analysis tool, in which a signal is decomposed to various components by using wavelet function (Kleissen *et al.*, 1998). Thus, it leads to high frequency resolution in low frequencies and high time resolution in high frequencies. This multi-resolution analysis method is frequently used for the analysis of non-stationary signals due to its ability to obtain transition in both time and frequency domains. DWT is more advantageous than other transformation methods (e.g., Fast Fourier Transform (FFT)) in its ability to identify trends, breakdown points, and impairment in signals. Bartuzi and Roman-Liu show that the wavelet transform parameters might be better at evaluating MF than parameters of FFT for low levels of loads (Janardan *et al.*, 2011). EMG signals are complex in nature and methods of collection data are nonlinear and disordered. Consequently, existing studies have applied various nonlinear tools for evaluating MF. As a result, applied methods afforded extra information about MF (Xie *et al.*, 2010). Webber *et al.* (1995) established that when MF occurs during isometric contraction in the BB muscle, nonlinear methods detect greater changes compared with MDF.

According to the literature, ApEn has been applied in numerous medical fields such as electroencephalography of psychiatric diseases, electrocardiography, respiratory system, and clinical endocrinology (Caldirola *et al.*, 2004). Pincus was the founder of ApEn, which is based on entropy theory (Pincus, 1991). In our literature review there was research of analysing EMG signals in which data are studied before, during, and after isometric muscle contraction. Ahmad and Chapell (2008) found that there was a clear decrease in ApEn value from the starting phase until the end phase.

3. Procedure of Recording EMG Signals

The purpose of this paper is to analyse MF during isometric contractions using surface EMG. For this aim, a group of 30 young volunteers (15 females, 15 males) participated in our study. They were all healthy people without any history of previous injury, metabolic, or muscular disorders. The BB and TB muscles were chosen for the test. These muscles are antagonists to each other, so they move in opposite directions. For instance, during the flexion movement done by the arm, while the BB muscle contracts the TB as the antagonist extends. Similarly, when the BB extends, the TB contracts (Mader *et al.*, 2005).

In literature there are some features to evaluate MF, such as increasing amplitude in the time domain and transition from high frequency to low frequency in the frequency domain. MF was evaluated with these features that can be computed from EMG signals. But these parameters might not be enough to detect MF in its early stages and to evaluate quantitatively. Therefore, in our research we try to find nonlinear features using ApEn. First of all we divide our original signal using DWT for noise elimination and to get a sub-version, and then we compute the ApEn values of each approximation coefficient and detail coefficients. Finally, in order to evaluate the results scientifically a statistical analysis is done.

EMG signals were obtained from the 30 healthy subjects' BB and TB muscles in an isometric constant force experiment. The female participants were asked to hold a 2.5 kg dumbbell and male participants to hold a 5 kg dumbbell. During the isometric contractions, EMG signals were recorded instantaneously from the BB and TB muscles (Okkesim *et al.*, 2014). The specific information about recording channels and experimental details are given in Table 3.2.

Table 3: Data channels

Channel	Data
1	Biceps Brachii EMG
2	Triceps Brachii EMG

Table 3: Specifications of EMG and volunteers.

Name	Value
Muscle Type	Biceps brachii and triceps brachii
Frequency	1000 Hz
Type of Contraction	Isometric
Dumbbell Weight	Female (2,5 kg) - Male (5kg)
Number of participants	30 (15 females and 15 males)
Age	Female = 25.5 ± 1.96, Male = 23.86 ± 3.5
Weight	Female = 62.8 ± 9.94 kg, Male = 75.9 ± 11.26 kg
Height	Female = 1.66 ± 0.06 m, Male = 1.76 ± 0.06 m

In our experiments isometric contractions were analyzed. During the isometric muscle contraction, the length of the muscle remains stable but the muscle tone is changed.

At the beginning of the test, the exercise and its purposes were expressed clearly to the volunteers. Excluding during the arm exercise, the volunteers were asked to keep their body as stable as possible as was wanted. Initially the related regions were cleansed with medical supplies in order to remove sediment and the dead layer of skin. Then EMG electrodes were placed on the muscle bundles. Silver-surface, bipolar, 4 mm-radius surface electrodes were placed on the bundles of muscles that were located by testing manually. For the isometric contraction experiment, female volunteers were asked to hold a 2.5 kg dumbbell while their arm was open at a 90° angle for three minutes, and male volunteers were asked to hold a 5 kg dumbbell with their non-dominant arm.

3.1 Discrete Wavelet Transform

DWT analysis simultaneously shows information in discrete - time and frequency domain of a signal. Thus, it leads to high frequency resolution and low time resolution in low frequencies, and high time resolution and low time resolution in high frequencies. This analysis method is frequently used for the analysis of non-stationary signals. DWT is more advantageous than other transformation methods (e.g., FFT) to identify trends, breakdown points, and impairment in signals (Janardan *et al.*, 2011).

Mallat states that decomposing a discrete signal of $\chi\,[n]$ is possible (Ocak, 2009). So, DWT of a signal $\chi[n]$ is calculated by passing through a series of low pass (LP) and high pass (HP) filters. As a result we get the first Approximation Coefficients and Detail Coefficients from LP and HP filters, respectively, as shown in Figure 3.4. The approximation is a high frequency component whereas detail is a low frequency component of the signal. Then the first level of approximation and detail coefficients pass through the same steps to get second coefficients. This procedure continues for all levels, and in each of them frequency resolution is doubled and time resolution is halved.

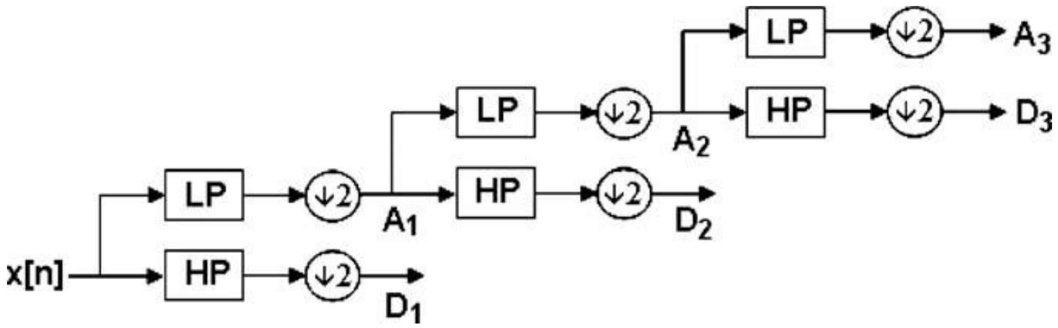

Figure 1: Wavelet Tree Decomposition Structure (Chu *et al.*, 2007)

Thus, mathematically DWT is calculated by this equation;

$$\mathrm{DWT}(j,k) = \frac{1}{\sqrt{|2^j|}} \int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-2^j k}{2^j}\right) dt \qquad (3.1)$$

In this study we used the DWT method since it has been successful in analysing non-stationary signals, such as EMG (Yang *et al.,* 2004). Proper selection of the number of decomposition levels and suitable wavelet function are important for EMG signal analysis. We used Daubechies' wavelet decomposition with order 3, since many studies mention the performance of other levels of wavelet decompositions and level 3 is not common in the existing research (Buranachai *et al.*, 2009).

3.2 Approximate Entropy

ApEn is a non-linear measurement tool that was initially proposed by Pincus to fulfil requirements of signal complexity. It is based on a logarithmic likelihood that calculates repetitions of patterns of length m that are close within a defined r that will remain close to patterns of length $(m + 1)$. ApEn takes into account the temporal order, which makes it more suitable to represent the points of time series and therefore is a preferred measure of regularity. The development of ApEn overcame the drawbacks of previously used tools in quantifying signal complexity such as having a measure to handle noise successfully and being applicable for small data samples and other model constraints (Nieminen *et al.*, 1996).

The main parameters of ApEn are data length (N), embedded dimension (m), time delay (t), and tolerance width (r).

In practice, we implement the following formula for ApEn for fixed m, r, and τ:

$$\mathrm{ApEn}(\mathrm{m}, \mathrm{r}, \tau, \mathrm{N}) = \Phi^{\mathrm{m}}(\mathrm{r}) - \Phi^{\mathrm{m}+1}(\mathrm{r}) \quad (3.2)$$

3.3 Student T-Test

The t-test is used to compare two arrays of measurable data when samples are collected differently from one another. The t test can be implemented having the mean

value, standard deviation, and size of the array. The impact of the student's t-test is to realise that if there is a significant difference between the two arrays then the test can support a hypothesis (James, 1997).

4. Results and Discussion

In this study, raw EMG signals were analysed using DWT, in which Daubechies' wavelet was used at the third level. As such, one approximation coefficient at the third level (A3) and three detail coefficients (D3, D2, D1) were computed. As a result, for one EMG signal we get four subparts: A3, D3, D2, and D1. For all coefficients we received different results as shown in the plot diagram in Figure 2.

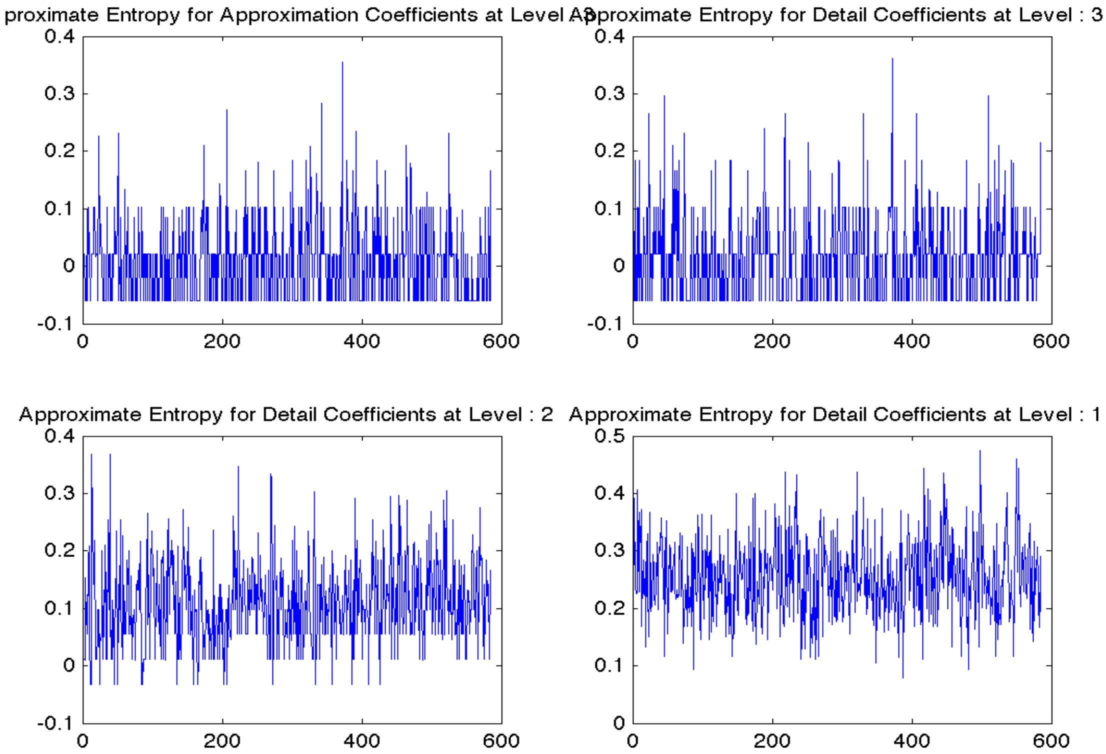

Figure 2: Decomposition of EMG with db3.

DWT has been used by different researchers and with different mother wavelets, such as Daubechies' db2, db3, Sym 4, and Sym5. Because of its advantages over FFT, as managing stronger non-stationarities which were observed in the EMG signals from an isotonic muscle contraction. Among the wavelets we chose Daubechies' db3 because in the literature there are a lot of successful researches for analysing EMG with db3 (Pah *et al.*, 2014).

A clear and generally accepted description of fatigue is essential to ensure that researchers get comparable results; however, up to the present time, most research has only identified the non-fatigue and fatigue phases of muscles. Other characteristics of MF research are central and peripheral mechanisms of fatigue, recommending that fatigue is not a particular state, but relatively contains different components that lead to fatigue. Hence, Al-Mulla *et al.* (2011) has classified another phase of fatigue, called Transition-to-Fatigue, which is in between non-fatigue and complete fatigue. Based on Al-Mulla *et al.*'s work, we computed each coefficient's ApEn values in which each ApEn array contained a sample size of 1,125. We divided the arrays into three segments, and mean and standard deviation values of each segment were calculated. Then, we applied the t-test in order to find any statistical significance. In the literature of analysing EMG during and after isometric muscle contraction, Ahmad and Chapell found that there was a clear decrease in ApEn value from the starting phase until the end phase (Ahmad *et al.*, 2008). However, in our results ApEn values increased from the first segment until the third segment.

As a measure of entropy, ApEn can be computed using short and noisy experimental data sets, irrespective of the presence of any nonlinear properties. In this study, we found statistically significant changes in ApEn during the different stages of MF in healthy subjects, with lowest values during the last segment and highest values during the first segment.

Among our four data sets Approximate Entropy for Approximation Entropy Coefficients at level 3, Approximate Entropy for Detail Coefficients at level 3, Approximate Entropy for Detail Coefficients at level 2, Approximate Entropy for Detail Coefficients at level 1, that referrers to AA3, AD3, AD2 and AD1 in the tables respectively.

AA3 showed the best statistical difference for male volunteers that is 0.0088 and 0.0214 for female volunteers.

Table 4: Results of the statistical analysis of the AA3 for segment comparison

FirstSegment- LastSegment	p = 0.0088

According to the results of mean values and t-test as shown in tables 4.2, 4.3, and table 4.4 respectively, p value showed a larger result than 0.05, so detail coefficients at each level are not statistically significant.

Table 5: Statistical analysis of the AD3 for segment comparison of BB in males

FirstSegment- LastSegment	p=0.9684

Table 6 Statistical analysis of the AD2 for segment comparison of BB in males

FirstSegment- LastSegment P - Value	0.4991

Table 7: Statistical analysis of the AD1 for segment comparison of BB in males

FirstSegment- LastSegment	p=0.2120

Table 8: Statistical analysis of the AA3 for segment comparison of BB in females

First Segment - Last Segment	p=0.0214

When we did the calculations for female data also we got the same results as male volunteers data. According to the results of mean value and t-test as shown in tables 4.6, 4.7, and 6.8 p value showed a larger result than 0.05, so detail coefficients at each level are not statistically significant.

Table 9: Statistical analysis of the AD3 for segment comparison of BB in females

First Segment - Last Segment	p=0.1189

Table 10: Statistical analysis of the AD2 for segment comparison of BB in females

First Segment - Last Segment	p=0.7529

Table 11: Statistical analysis of the AD1 for segment comparison of BB in females

First Segment - Last Segment	p=0.5202

The same operations are repeated for female isometric data of TB muscle. However, different results are obtained. When we look at tables 4.9, 4.10, 4.11, and 4.12 we see that unlike BB muscle data the p value of TB in each coefficient is higher than 0.05 this means there are not any significant difference.

Table 12: Statistical analysis of the AA3 for segment comparison of TB in females

First Segment - Last Segmet	p= 0.8380

Table 13: Statistical analysis of the AD3 for segment comparison of TB in females

First Segment - Last Segment	p= 0.5401

Table 14: Statistical analysis of the AD2 for segment comparison of TB in females

First Segment - Last Segment	p= 0.8642

Table 15: Statistical analysis of the AD1 for segment comparison of TB in females

First Segment - Last Segment	p= 0.3245

Finally we can say literature is poor on application of DWT and ApEn for evaluation of MF. Therefore the performance of the proposed method is not compared to previous studies since we could not classify similar studies but came up with a new try of methods for evaluation of MF in isometric muscle contractions.

5. Conclusion

The result shows that fatigue happens during isometric contractions. Among our four data sets, only AA3 showed the best statistical difference in which the p value is 0.0088 for male BB muscle signals and 0.0214 for female BB muscle signals. However, the results of the TB muscle signals are not statistically significant since the p value of all coefficients is greater than 0.05.

In the present work, the proposed ApEn was only applied to an EMG signal during isometric contractions. ApEn measurements in EMG might be clinically useful in the evaluation of fatigue stages and to calculate muscle activity. However, the fatigue analysis of the EMG signals noticed during isotonic contractions has been useful in a number of applications of daily activities such as sports medicine ergonomics and rehabilitation, so it is important to consider isotonic contractions. Also, it is vital to analyse longer fatigue situations in order to get applicable results since our study is for short-term fatigue. Further study is needed to explain the usefulness of the ApEn in relation to the automatic diagnosis of MF.

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