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Characterization of surface electromyography signals of biceps brachii muscle in fatigue using symbolic motif features

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Abstract

Exercise-induced muscle damage is a condition which results in the loss of muscle function due to overexertion. Muscle fatigue is a precursor of this phenomenon. The characterization of muscle fatigue plays a crucial role in preventing muscle damage. In this work, an attempt is made to develop signal processing methods to understand the dynamics of the muscle's electrical properties. Surface electromyography signals are recorded from 50 healthy adult volunteers under dynamic curl exercise. The signals are preprocessed, and the first difference signal is computed. Furthermore, ascending and descending slopes are used to generate a binary sequence. The binary sequence of various motif lengths is analyzed using features such as the average symbolic occurrence, modified Shannon entropy, chi-square value, time irreversibility, maximum probability of pattern and forbidden pattern ratio. The progression of muscle fatigue is assessed using trend analysis techniques. The motif length is optimized to maximize the rho value of features. In addition, the first and the last zones of the signal are compared with standard statistical tests. The results indicate that the recorded signals differ in both frequency and amplitude in both inter- and intra-subjects along the period of the experiment. The binary sequence generated has information related to the complexity of the signal. The presence of more repetitive patterns across the motif lengths in the case of fatigue indicates that the signal has lower complexity. In most cases, larger motif length resulted in better rho values. In a comparison of the first and the last zones, most of the extracted features are statistically significant with $p < 0.05$. It is observed that at the motif length of 13 all the extracted features are significant. This analysis method can be extended to diagnose other neuromuscular conditions.

Keywords

Biceps brachii, muscle fatigue, symbolic transformation, motif analysis

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Introduction

Bouts of high intensity and prolonged muscle activity cause excessive strain on the muscle fibers thereby altering their function and structure. This phenomenon is often referred to as exercise-induced muscle damage (EIMD) and as a consequence leads to reduced force production capabilities, edema, delayed-onset soreness in the exercised muscles and loss in range-of-motion. Reduction in movement economy, elevated levels of perceived exertion, acute and prolonged reductions in VO2 peak have been reported to be observed in the days following EIMD. Muscle fatigue is a precursor to EIMD.[1]

Muscle fatigue is a neuromuscular condition caused due to overexertion of the muscle. It causes a reduction in muscle force production capability. This is a normal phenomenon which is reversible; however, repeated fatigue can result in muscle damage. The gold standard method to access muscle fatigue is by blood test which involves the analysis of the concentration of lactic acid build-up in the muscle.[2] Recently, it has been established that noninvasive techniques such as surface electromyography (sEMG) is a viable tool to access fatigue. sEMG records the electrical activity of the muscle.[3]

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The sEMG signals are nonlinear and nonstationary, so conventional signal processing techniques such as Fourier transform and root mean square value perform poorly.[4] Nonlinear signal processing techniques such as wavelet transform,[5] fractal dimensions[6,7] and multi-scale entropy[8] have been used to quantify fatigue. It is assumed that the fractal dimension of a biological component is constant within the scaling window that can be applied to quantify variations in length, area or volume. The scale-invariant structure of signals from human body reflects its adaptability to underlying physiological process. Measurement of these patterns and scaling properties can indicate healthy or abnormal characteristics.[6,7]

Recently, symbolic transformation techniques have been used to analyze nonlinear time series data such as gas/liquid two-phase flow measurement fluctuation signals,[9] electroencephalogram[10] and other chaotic signals.[11,12] This technique can control noise interference and can improve the efficiency of discovering and quantifying the dynamics of systems.[11]

Symbolic time series analysis is a technique through which features such as the existence of frequent patterns[12,13] or the presence of missing/forbidden patterns[14,15] from stochastic, high-dimensional signals can be extracted.[16,17] The benefit of symbolization is the reduction in sensitivity to noise.

Complexity measures such as sample entropy and permutation entropy have been proposed to characterize the symbolic sequence.[8,18–20] In recent studies on the binary symbolic dynamics reflecting the succession of acceleration and deceleration of the instantaneous heart rate indicate that this technique is capable of discerning the normal from congestive heart failure,[21] and changes in the dynamics related to age.[22]

The presented study is conducted to determine the dynamics of nonfatigue and fatigue state, using symbolic transformation techniques. The sEMG signals are recorded under a well-defined protocol. The preprocessed signals are transformed into symbols, and time series motifs of various sizes are constructed. Features such as the number of missing/forbidden patterns, maximum probability along with Shannon entropy, time reversibility and chi-square value are extracted and are used to quantify the variations in the complexity of the signal toward fatigue.

Methods

Experimental protocol

Fifty healthy subjects of age 26.12 (3.12) years, weight 69.4 (11.56) kg and height 1.63 (0.28) m with no previous history of neuromuscular condition participated in the study. Prior to the experiment, the participants are briefed about the protocol. It is ensured that all the participants are well rested. The protocol involved dynamic contraction exercise to activate the biceps brachii muscle. The participants held a 6-kg-force dumbbell in the supine position; continuous flexion and extension exercise is performed. The experiment is continued until they are unable to lift the load. The participants reported their first discomfort time, and the time to fatigue is also noted.[4] The study is approved by the Institute's ethics committee (IEC/2017/04/SR-2/02), and informed consent is obtained from the participant as per the Helsinki declaration.

Signal acquisition

sEMG signals are recorded from the biceps brachii muscle as per the guidelines of Surface EMG for Non-Invasive Assessment of Muscles (SENIAM) standards. After skin preparation with abrasive and alcohol, Ag–AgCl electrodes are placed on the belly of the biceps brachii muscle. A bipolar configuration is used with an inter-electrode distance of 2 cm. Furthermore, the ground electrode is placed on the elbow. Biopac MP36 a biomedical amplifier with a 24-bit analog-to-digital converter and a sampling rate of 10,000 Hz are used to acquire the signals. The signal-to-noise ratio and common mode rejection ratio of this system are 89 and 110 dB, respectively. The experiment was conducted in an electrically isolated environment with precautions to prevent electric shocks.[8,23]

The signal is downsampled to 1000 Hz, as it reduces the computational complexity. The motion artifacts, power line interference and high-frequency noise are removed using bandpass filter (10–400 Hz) and notch filter (50 Hz).[4] The signal is segmented into 10 equal zones, and the symbolic time series analysis is carried out.

Symbolic transformation

First difference partition method is a dynamic transformation technique which involves computation of the arithmetic difference of adjacent data points. This results in a first difference signal which is relatively resistant to noise and spikes in the data. A positive value is assigned a symbol "1", and a negative value has a symbol of "0"[9,21]

$$y(n) = x(n+1) - x(n), \quad n = 1, 2, 3, \ldots, N-1 \tag{1}$$

$$z(n) = \begin{cases} 1, & if\, y(n) \geqslant 0 \\ 0, & Otherwise \end{cases} \tag{2}$$

The transformed symbolic sequence is analyzed by choosing a standard motif length L. Motifs or words are formed by defining a standard window length to group consecutive symbols, and the window is shifted along the symbol series. Each motif is converted into its decimal equivalent to form a code series. The relative frequency of each motif is calculated. Here, a motif length of 2–13 is used.[9]

Symbolic sequence statistics

Given a sequence of words, the following measures are used to analyze the sequence.

Word probability is the ratio of the count of the occurrence of each pattern to the total number of patterns in the time series. For a binary sequence of motif size 2, there are four patterns, namely, "00," "01," "10" and "11."[9] For a motif of size n, a total of 2^n patterns are generated

$$Wpr = \frac{Count\ of\ the\ occurance\ of\ each\ pattern}{Total\ number\ of\ patterns\ in\ Time\ series} \tag{3}$$

The maximum probability value indicates how often a pattern occurs and can be considered as a factor of self-similarity. It is computed as follows

$$Max\_prob = Max(p_i) \tag{4}$$

The feature representing the forbidden pattern ratio (FPR) is calculated as the ratio of the number of patterns with 0 probabilities to the total number of possible patterns

$$FPR = \frac{\#\ of\ patterns\ p_i = \ = 0}{\#\ of\ possible\ patterns} \tag{5}$$

The definition of modified Shannon entropy is given below

$$H_s = -\frac{1}{\log N_{obs}} \sum_i p_i \log p_i \tag{6}$$

where p_i is the probability of the ith symbol sequence, the standard definition of Shannon entropy is that if the regularity of the system is lost then the entropy is large.

Time irreversibility is the Euclidean norm with the word's probability. Time irreversibility aims to count words, especially is suitable for multi-dimensional space

$$T_{fb} = \sqrt{\sum \left(P_{f,i} - P_{b,i}\right)^2} \tag{7}$$

The other factors, namely, the chi-squared χ^2_{fb} calculates the forward symbolic sequence and backward symbolic sequence statistics and closely resembles time irreversibility

$$\chi^2_{fb} = \sum_i \frac{\left(P_{f,i} - P_{b,i}\right)^2}{\left(P_{f,i} + P_{b,i}\right)} \tag{8}$$

where $P_{f,i}$ and $P_{b,i}$ are the forward and backward sequence word probabilities.

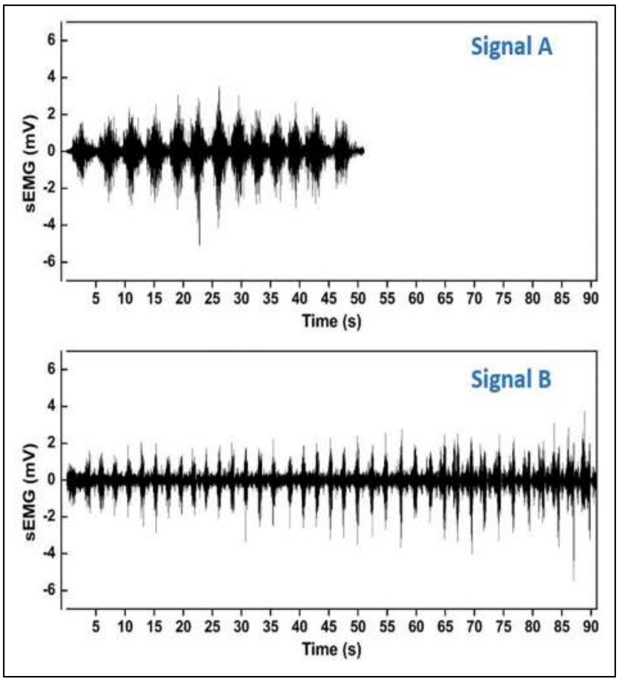

Figure 1. Representative sEMG signals from two age-matched subjects.

Statistical tests

First, to study the variation of the features with respect to time, a Spearman rho rank correlation is computed. The R-value and the p-values are computed to test the significance of the trend. Second, to compare the first and the last zone, the normality of the data is studied using Anderson–Darling test (adtest) to access the features in the zones. Furthermore, the normally distributed data are tested using paired t-test and the other features are compared using Wilcoxon signed rank test.

Results and discussion

The signals recorded from age-matched subjects have different signal amplitude and frequency. The signal from the same subject has different patterns with fatigue. This makes the processing of these signals to be non-trivial, hence the use of nonlinear signal processing techniques is required. The representative sEMG signals recorded from biceps brachii muscles of two age-matched subjects are shown in Figure 1. The amplitude of the sEMG signal varied in the range of millivolt (mV). For the representative signals, the amplitude varied between ±4.0 mV for subject A and ±3.0 mV for subject B. The peak positive and negative amplitude of these signals in the study ranged from 0.32 to 8.21 mV and −0.29 to −7.39 mV, respectively.

The burst patterns occurred during each curl (flexion–extension action) and corresponding to concentric (shortening of the muscle) and eccentric (elongation of the muscle). These variations in amplitude of sEMG signals may be attributed to factors such as variations

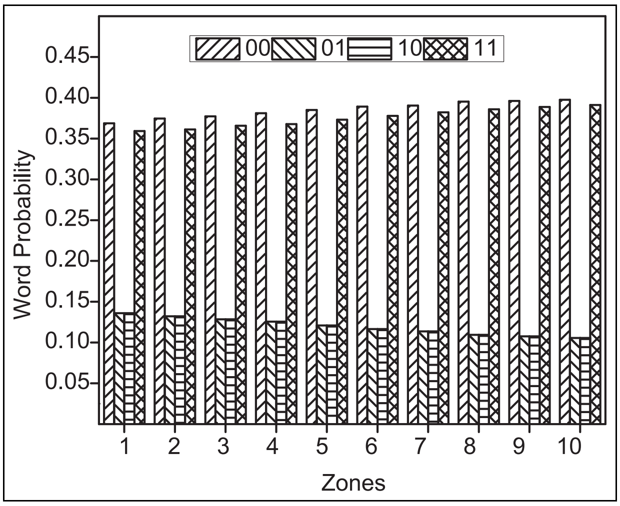

Figure 2. The bar chart on variation in word probability of a size 2 motif word with respect to zones. The mean value of 50 subjects is showcased here.

in the firing rate, volume conductor effects and non-linear recruitment pattern of the motor units. Furthermore, the endurance time for the subjects varied with 55 s for subject A and 91 s for subject B. This variation in the endurance time is greatly influenced by the anthropometric factors and the fiber distribution.[8,23]

In Figure 2, the mean word probability of the binary pattern, namely, "00," "01," "10" and "11" for the signal zones 1–10 is shown. It is seen that the "00" pattern has the highest probability in all zones. It is followed by "11" pattern. An increasing trend is observed in these patterns as the signal progresses to fatigue. Accordingly, a decrease in the occurrence of "01" and "10" pattern is observed. It is to be noted that in an equiprobable distribution of a size 2 motif the word probability is 0.25. Based on this, it can be shown that the EMG signal is quasi-stochastic and there is an underlying pattern. Furthermore, the structure becomes more predictable with the progression of fatigue.

In Figure 3(a), the variation of the mean maximum probability with the progression of fatigue at various motif sizes is shown. It is seen that the highest values are seen in the size 2 motif. This is due to the lower number of possible words. As the motif length increases, the maximum probability reduces. However, it is to be noted that compared to an equiprobable distribution, the motif size of 13 has the maximum distinction. An increasing trend is observed with the progression of fatigue. It might be due to the synchronization of motor units that results in more repetitive patterns with fatigue.

Figure 3(b) shows the variation in the mean forbidden pattern for multiple motif sizes with respect to the zones of fatigue. It is seen that there is an increase in the number of forbidden pattern with fatigue. Furthermore, the highest value is observed in the size 13 motif. This is due to the fact that there are close to 2^{13} patterns and only a few patterns repeat. It is to be noted that this feature compliments the maximum probability value as an increase in the probability of one pattern will result in loss in another pattern.

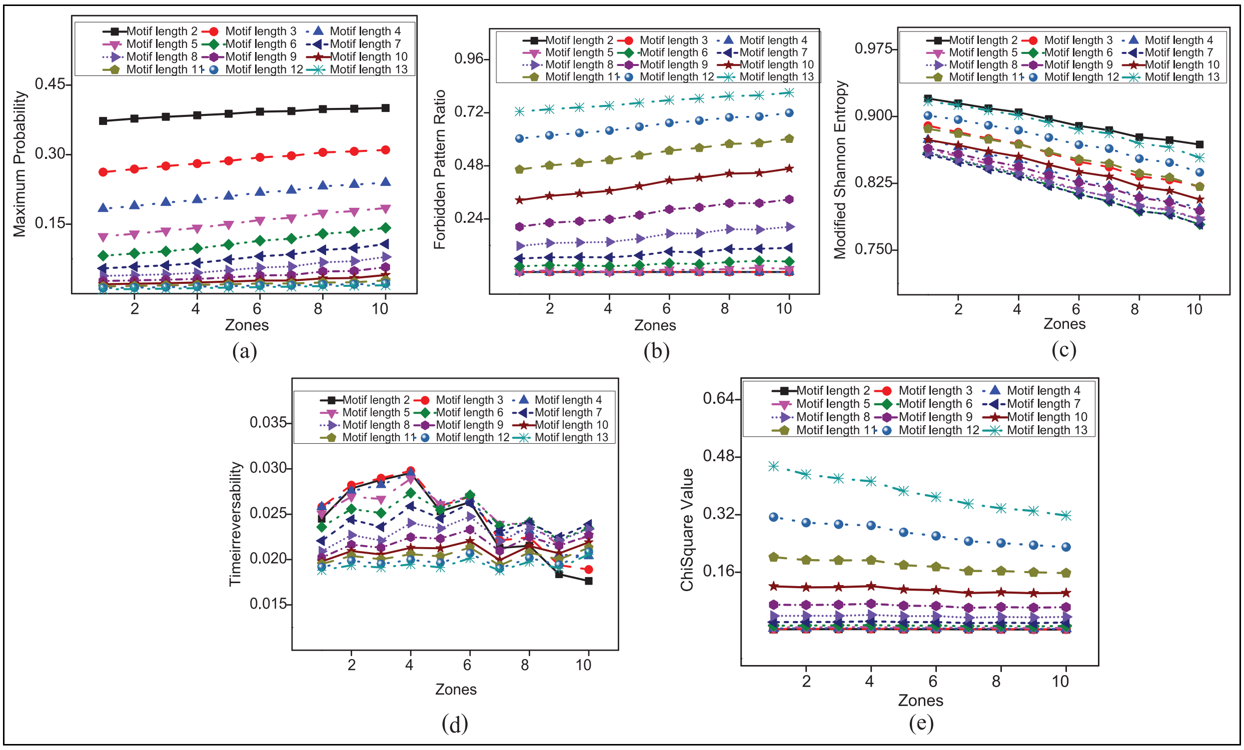

Figure 3. Influence of motif size on the analysis of progression of muscle fatigue using features, namely: (a) maximum probability, (b) forbidden pattern ratio, (c) modified Shannon entropy, (d) time irreversibility and (e) chi-square value.

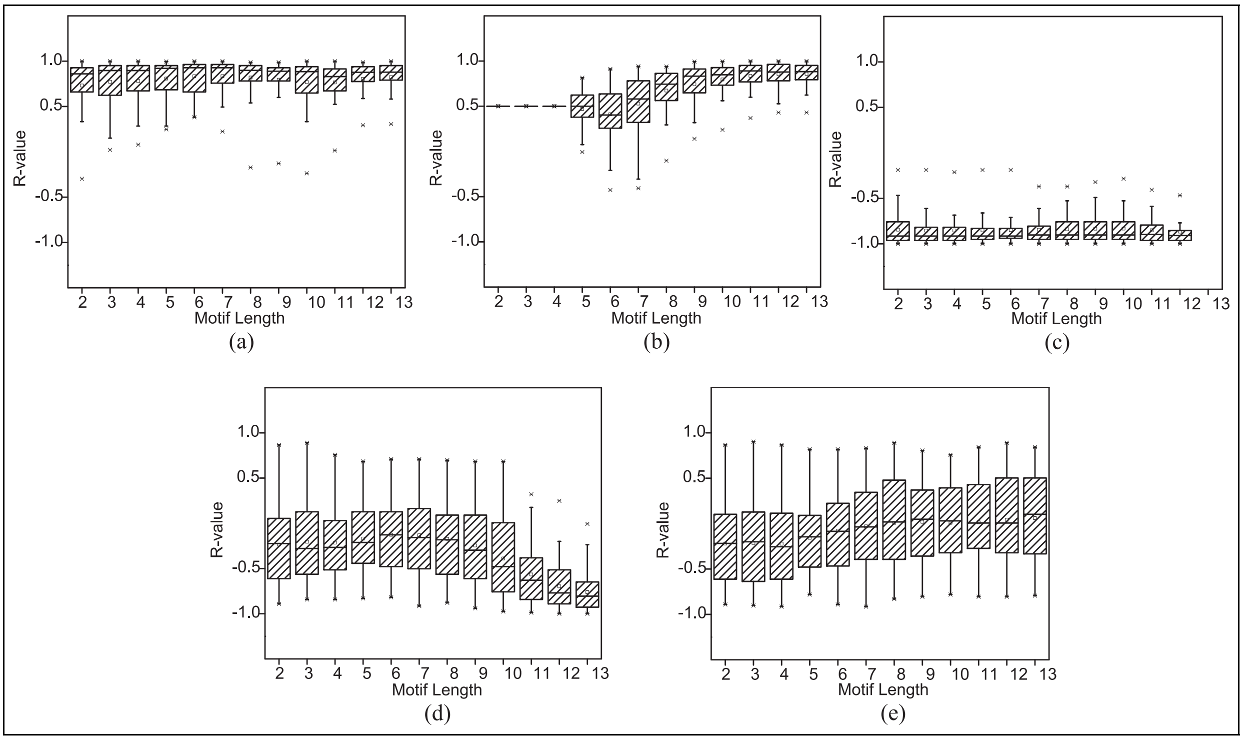

Figure 4. The Spearman rho correlation values for features, namely: (a) maximum probability, (b) forbidden pattern ratio, (c) modified Shannon entropy, (d) time irreversibility and (e) chi-square value.

In Figure 3(c), the line plot of the mean of the modified Shannon entropy is shown. A decrease in the entropy values is observed with progression of fatigue indicating a more repetitive pattern. It is seen that the maximum value is observed in motif sizes 2 with a value of 0.92 in the first zone. This is closely followed by the motif size of 13. The slope in the case of 13 is higher than that of the motif size of 2.

Figure 3(d) shows the variation in the time irreversibility with the progression of fatigue. The features are highly overlapping. The highest values in zone 1 are observed in the motif of sizes 3 and 4. Motifs 6 and 7 have a constant slope.

In Figure 3(e), the variation of the chi-square value at various motif sizes is shown. The first six motif sizes have a decreasing trend. In the following motif, there is no trend observed. The largest slope is observed in motif size of 13. A maximum value of 0.45 is seen in the first zone at motif size 13.

To quantify the trend across 50 subjects, Spearman rho statistics is used. The *R*-values of the various features are described below.

In Figure 4(a), the distribution of the Spearman rank correlation coefficients for 50 subjects for the maximum probability feature is shown. All the motif sizes have an increasing trend; most of them have *R*-value greater than 0.5. The least variance is seen in motif length of 13. In Figure 4(b), the *R*-value of the forbidden pattern is shown. It is seen that for the lower motif sizes, namely, 2–4, an *R*-value of 0.5 is observed. At higher scales, the variance decreases, and the mean value is observed to increase.

In Figure 4(c), the variation in *R*-value with respect to motif length for the modified Shannon entropy feature is shown. The *R*-values are negative in all motif lengths. The last two motif lengths have the least variance. In Figure 4(d), the Spearman rho correlation coefficient of time irreversibility for the analysis of the progression of fatigue at various motif lengths is shown. It is seen that at the initial few motif lengths, the mean *R*-values are closer to 0 indicating that there is no clear trend. At higher scales, the variance is low and the mean value is less than 0.5.

In Figure 4(e), the *R*-values of the chi-square feature are shown and it is seen that at all motif lengths, the values are closer to 0. Furthermore, at lower lengths, the features have a negative correlation. This makes this feature inappropriate for analyzing the progression of fatigue.

Table 1 shows the comparison of various features in the first and last zone of the sEMG signal. The variation in the mean and standard deviation of the Shannon entropy is shown. Zone 1 has higher values in all motif sizes. It is seen that in zone 1, the maximum value is observed in motif length of 2. It is seen that lower and higher motif sizes have large values and the intermediate motif sizes have lower values. This might be because the extremities are not normally distributed. In addition, a lower standard deviation is observed in zone 1 in all motif lengths.

Table 1. The statistical significance of various features in differentiating the first and the last zones.

	Motif length	Zone 1		Zone 10		*P*-value	Normal
		Mean	SD	Mean	SD		
Shannon entropy	2	0.920	0.021	0.869	0.037	0.005	No
	3	0.890	0.027	0.821	0.045	0.005	No
	4	0.874	0.030	0.797	0.049	0.005	Yes
	5	0.863	0.031	0.784	0.051	0.005	Yes
	6	0.859	0.032	0.779	0.053	0.005	Yes
	7	0.857	0.031	0.779	0.053	0.005	Yes
	8	0.859	0.031	0.784	0.052	0.005	Yes
	9	0.864	0.030	0.794	0.051	0.005	Yes
	10	0.874	0.028	0.807	0.049	0.005	Yes
	11	0.886	0.027	0.821	0.046	0.005	No
	12	0.901	0.025	0.837	0.044	0.005	No
	13	0.917	0.024	0.854	0.042	0.005	No
Max_prob	2	0.373	0.018	0.401	0.018	0.005	No
	3	0.262	0.029	0.310	0.029	0.005	No
	4	0.183	0.031	0.239	0.031	0.005	No
	5	0.124	0.030	0.185	0.030	0.005	No
	6	0.082	0.025	0.142	0.025	0.005	Yes
	7	0.055	0.018	0.107	0.018	0.005	Yes
	8	0.038	0.011	0.079	0.011	0.005	Yes
	9	0.027	0.008	0.057	0.008	0.005	No
	10	0.020	0.006	0.040	0.006	0.005	No
	11	0.016	0.005	0.029	0.005	0.005	No
	12	0.012	0.004	0.022	0.004	0.005	No
	13	0.009	0.004	0.018	0.004	0.005	Yes
FPR	2	0	0	0	0	–	Yes
	3	0	0	0	0	–	Yes
	4	0	0	0	0	–	Yes
	5	0.001	0.010	0.014	0.020	0.005	Yes
	6	0.025	0.017	0.047	0.031	0.005	Yes
	7	0.060	0.027	0.109	0.045	0.005	Yes
	8	0.117	0.040	0.205	0.066	0.005	No
	9	0.204	0.058	0.328	0.080	0.005	No
	10	0.324	0.073	0.467	0.083	0.005	No
	11	0.463	0.078	0.603	0.076	0.005	No
	12	0.603	0.071	0.720	0.063	0.005	No
	13	0.725	0.057	0.811	0.047	0.005	No

SD: Standard deviation; FPR: forbidden pattern ratio.

The maximum probability features have higher values in the case of fatigue at all motif lengths. At all motif lengths, the fatigue has a value greater than the equiprobable distribution. At most motif lengths, the distribution of the data is nonnormally distributed. The difference between the two cases is double in the case of motif length of 13.

FPR is the absence of certain motifs. It is seen that the number of forbidden patterns increase with motif length as expected. The FPR is higher in the case of fatigue condition at motif lengths greater than 4. At lower motif lengths, there are no forbidden patterns in both nonfatigue and fatigue conditions. At lower motif lengths, the data distribution is normal. The distinction between the patterns is the highest at motif length of 13.

The time irreversibility characteristics of zone 1 and zone 10, shown in the table indicate that the mean varies between 0.018 and 0.026. A higher value is observed in nonfatigue conditions in motif sizes 2–6. It is higher in fatigue for motif lengths 7–13. The standard deviation is high in the initial few motif lengths. As motif length increases, the standard deviation decreases. It is seen that the data are distributed normally at all motif lengths.

An increasing trend with respect to motif length in the chi-square values is observed in both nonfatigue and fatigue conditions. A clear distinction is observed in higher scales of chi-square value. The value is higher in the case of nonfatigue condition. Furthermore, the data are normally distributed at all motif lengths.

The statistical test such as paired *t*-test and Wilcoxon signed rank test are performed based on the normality of the data. It is found that at motif size of 13 all features are significant in differentiating the zones 1 and 10, that is, nonfatigue and fatigue condition. Furthermore, the Shannon entropy feature and the maximum probability features are significant at all motif sizes. The FPR feature is significant at motif sizes greater than 4.

The motifs of shorter lengths identify large fluctuations (instantaneous change in state) present in the signal, and the larger motif lengths represent the presence of smaller fluctuations (slow change in state). These features quantify the degree of regularity across various scales of data. The presence of more number of regular patterns indicates variation in the physiological process of muscle control. This might be due to the synchronization of motor units which leads to presence of more regular patterns.

Conclusion

The muscles are the crucial part of the human body that supports us in our movement. Muscle fatigue is a condition in which the muscles are unable to provide the required force. The characterization of muscle fatigue plays a crucial role in preventing muscle damage. In this work, an attempt is made to develop features that can discern the dynamics of the muscle's electrical properties. The sEMG signals are recorded from healthy adult volunteers under dynamic curl exercise. The signals are preprocessed, and the first difference signal is computed. Furthermore, thresholding techniques are used to generate a binary sequence. The binary sequence is windowed and the resultant patterns are analyzed using features such as the average symbolic occurrence, modified Shannon entropy, chi-square value, time irreversibility, maximum probability of pattern and FPR. The results indicate that the recorded signals differ in both frequency and amplitude in both inter- and intra-subjects. The binary sequence generated has information related to the complexity of the signal. The extracted features from the sequence are distinct. The Spearman rho correlation coefficient extracted from the features indicates that the maximum R-value which is significant is observed in modified Shannon entropy and maximum probability at motif length of 7; in the case of FPR. it is maximum at motif length of 13. Most of the extracted features are statistically significant with $p < 0.05$. It is observed that at the motif length of 13 all the extracted features are significant. In addition, it is observed that repeated patterns are present in the case of fatigue and is in coherence with our previous research where an increase in multifractality is observed with fatigue in these signals.[7] These techniques can be extended to analyze other neuromuscular conditions.

Declaration of conflicting interests

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