Fatigue Analysis of Triceps Brachii Muscle using sEMG Signals and Recurrence Quantification Technique

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Abstract—Analysis of surface electromyography (sEMG) signals under fatigue conditions in dynamic contraction is gaining clinical relevance in the field of rehabilitation, ergonomics and sports performance. In this work, an attempt is made to analyze the sEMG signals recorded from triceps brachii muscles using Recurrence Quantification Analysis (RQA). The signals are recorded from 21 healthy adults during dynamic contraction involving dumbbell curl exercise. The sEMG signals are pre-processed and segmented into six equal zones along the time scale. The first and sixth zone are considered as nonfatigue and fatigue condition respectively. The signals are then subjected to RQA for further analysis. Two standard RQA features namely determinism (DET) and maximum length of the vertical line (V_{MAX}) are computed for analyzing nonfatigue and fatigue conditions. A new RQA feature known as complexity (CPX) is also introduced for sEMG signal analysis that is derived from determinism. The results of RQA features are statistically verified using ANOVA. All the three RQA features namely, DET, complexity and V_{MAX} are found to be statistically highly significant. In the case of fatigue condition, DET and V_{MAX} increased by 17% and 30% respectively. It appears that RQA method may be a useful technique in differentiating fatigue and nonfatigue conditions under varied dynamic muscle contractions.

Index Terms—muscle fatigue, triceps brachii, surface electromyography, recurrence quantification analysis

I. INTRODUCTION

The triceps brachii is an important skeletal muscle of the upper arm in human body running along the humerus bone and providing stability to shoulder joint during dynamic contraction involving the forearm [1]. Muscles are made up of individual muscle fibers and are further organized into basic units known as Motor Units (MU) [2]. Motor unit is the fundamental unit of muscle consisting of alpha motor neuron and muscle fibers. During the contraction process, the impulse is propagated through peripheral nervous system which in turn excites MU. The muscular force is dependent on many physiological parameters such as firing rate of motor neuron, motor unit recruitment and muscle fiber conduction velocity [3]. Sustained muscle contraction are likely to manifest fatigue [4]. Fatigue is associated with inability of muscle to maintain a desired level of strength during a rigorous exercise or activity [2]. The study of fatigue is gaining importance in the field of sports medicine, rehabilitation, myoelectric and prosthetics control [5], [6].

Surface Electromyography (sEMG) is a noninvasive technique of recording the electrical activity of muscle contractions [7]. In muscle contraction, the change in recruitment and de-recruitment of MU and random firing rate influences the frequency compression during fatigue state [2]. A number of nonlinear techniques have been devised to compute dynamical features of sEMG time series such as information dimension, entropy, dimension spectrum and recurrence [8]. The recurrence plots have been widely explored scientific fields for understanding the dynamics of system. Recurrence quantification analysis (RQA) methods for biological signals such as electroencephalogram [9] and sEMG [10], are useful since it does not require large data and does not depend on statistical nature of signal [11]. It is reported that determinism, calculated from RQA during isometric loading of biceps brachii muscle, is found to be increasing with the progression of muscle fatigue [10].

The aim of this work is to analyze sEMG signals recorded from triceps brachii muscles during dynamic contraction and using recurrence quantification analysis technique. The three RQA features namely, determinism (DET), maximum length of vertical line (V_{MAX}), and a new feature complexity are computed from the sEMG signals using DET feature. The complexity feature is derived from DET and compared with spectral mean power frequency. The 2D and 3D plot are analyzed using RQA features in nonfatigue and fatigue conditions.

II. METHODOLOGY

A. Experimental Protocol and Signal Acquisition

In this study, 21 healthy participants without any history of neuromuscular disorder for performing dumbbell curl exercise with a 6 kg dumbbell [12]. The demographics details are represented in Table I. The experimentation protocol was explained to each
participant before the start of the study and written informed consent form were collected. The subjects were requested to maintain upright body position and hold the dumbbell using their dominant hand for performing curl exercise. Each curl involved flexing the elbow and moving the dumbbell from 0 degrees and to about 140 degrees vertically. This is repeated continuously and the subjects were encouraged to perform as many curls as possible. The curl exercise was performed at a comfortable speed. The signals are acquired continuously till endurance limit is reached and the subject is no longer able to continue. The time for task to failure is recorded for each subject.

### TABLE I. DEMOGRAPHIC DETAILS OF SUBJECTS

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Unit</th>
<th>Mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>Years</td>
<td>21.07 (0.91)</td>
</tr>
<tr>
<td>Weight</td>
<td>Kgs</td>
<td>68.08 (13.37)</td>
</tr>
<tr>
<td>Height</td>
<td>cm</td>
<td>170.6 (5.79)</td>
</tr>
</tbody>
</table>

Ag/AgCl electrodes (1cm diameter; 3 cm inter-electrode distance) are used to record the sEMG signals from muscle in a bipolar configuration. The skin was abraded and cleaned before placing electrodes. The signals are amplified (Gain=1000) and sampled at 10000 Hz with Biopac MP36 system (24-bit data acquisition; CMMR 110 db) [11]. The signals are preprocessed (10Hz-400 Hz) and filtered using a notch filter (50 Hz), and down sampled to 1000 samples per second for RQA analysis.

### B. Recurrence Quantification Analysis

RQA is a method of non-linear data analysis for investigating dynamic systems [13]. The qualitative information in the recurrence plot is a representation of correlations between the states of the time series over all available time scales. The time series are projected into phase space consisting of higher dimension. Since phase space of more than two dimensions can be visualized by a projection, it is difficult to investigate the recurrence of state space. In the Recurrence Plot (RP), any recurrence state is represented as a Boolean matrix.

\[
RP(i, j) = \Theta(\epsilon - || X(i) - X(j) ||), j = 1, 2, 3...N
\]  

\(X(i)\) and \(X(j)\) are embedded vectors, \(i\) and \(j\) are time indices, \(N\) is the number of measured points, \(\epsilon\) is threshold radius and \(\Theta\) is Heaviside step function [14], [15]. The Heaviside step function is a discontinuous function whose value is zero for negative argument and one for positive argument. If \(x(i)\) is the sEMG sequences, then the phase space vector \(X(i)\) can be represented as

\[
X(i) = (x(i), x(i + \tau), x(i + 2\tau), .... x(i + (m-1)\tau)
\]  

where \(\tau\) is the time delay and \(m\) is the embedding dimension. The dynamic characteristics of the series are hidden in form of structures such as single dots, vertical lines and diagonal lines in the RP [16]. The features and parameters derived from RQA technique are based on these structures.

The RQA features are analyzed in this study are determinism (DET), maximum length of the vertical line \((V_{\text{MAX}})\) and complexity (CPX).

DET is the percentage of recurrence points that form diagonal structures to all recurrence points in the recurrence plot (R) reflecting deterministic or predictable characteristics in dynamical systems [17]. The line segments are parallel to the main diagonal. Higher value of DET means higher periodicity. The vector point \((i, j)\) in the recurrence plot is considered as recurrent if the distance between the vectors \(y(i)\) and \(y(j)\) is less than the threshold. The value of DET is given as below.

\[
DET = \frac{\sum_{i,j=1}^{N} D_{i,j}}{\sum_{i,j=1}^{N} R_{i,j}}
\]  

The DET is usually expressed as a percentage. In this analysis, the DET value is taken between 0 and 1 for representation.

\(V_{\text{MAX}}\) is the longest line segment that is vertical in the recurrence plot. It is a measure of complexity that gives information on periodic-chaos state and transition of chaos-chaos regions [18].

Complexity feature is derived from the RQA measure determinism. This feature is previously reported for analyzing EEG signals and found to be useful [19]. Higher value of CPX indicates origin of signal from highly irregular or chaotic system. This may be due to presence of random series and may be due to higher nonlinearity. It is represented as

\[
CPX = -20 \log_{10}(DET)
\]  

The workflow details for the RQA analysis using sEMG signals in nonfatigue and fatigue conditions is shown in Figure 1.

Figure 1. Workflow details for the RQA analysis using sEMG signals in nonfatigue and fatigue conditions.
The workflow details are explained in the flow chart shown in Fig. 1. The raw signals are preprocessed and divided into six segments on time scale. There are several means to normalize the sEMG signal. The time scale normalization of six segments is based on the previous work [20], [21]. The first and the last segment are considered as nonfatigue and fatigue condition in this study. The nonfatigue and fatigue segments are divided into smaller epochs of 500 ms and the window is moved with a 250 ms overlap. The RQA toolbox is configured with the window settings and the DET and $V_{\text{MAX}}$ are derived. The CPX feature is computed using DET. The RQA features computed for both the nonfatigue and fatigue zones at each epoch level were further subjected to statistical test. The features are compared using ANOVA and Tukey test. The differences were considered highly significant at $p < 0.01$.

![Figure 2. Representative sEMG signal with six zones.](image)

III. RESULTS AND DISCUSSION

The representative sEMG signal recorded from triceps brachii muscle during dynamic contraction is shown in Fig. 2. The sEMG signals are found to be complex with varying amplitude and peaks. There are distinct burst of spikes throughout the duration of sEMG signal representing the flexion and extension activity. The number of bursts and duration of whole signal varied across participants depending on their physiological characteristics and individual endurance limit. The subjects in this study performed curl exercise ranging from 27 seconds to a high of 103 seconds. This may be due to varied anthropometry data, endurance and motivation of individuals. The sEMG signals can be normalized using several methods such as amplitude, maximum voluntary contraction and time scale methods. In this study, the sEMG signals are normalized by dividing the time scale into six equal zones [22]. The first zone (Z1) and sixth zone (Z6) are considered as nonfatigue and fatigue condition respectively. Higher amplitudes are observed in the fatigue zone ($\pm 1.5$mv) in each burst cycle as compared to the nonfatigue zone ($\pm 0.5$mv) for the representative signal.

![Figure 3. Comparison of DET values in nonfatigue (blue) and fatigue (red) epochs regions for the representative sEMG signal.](image)

The RQA features are computed for nonfatigue and fatigue segment by creating a small overlapping epochs. The DET for fatigue and nonfatigue conditions are represented in Fig. 3. The values of DET in fatigue conditions (red) are found to be higher than in nonfatigue conditions (blue). The DET feature is the measure of determinism and periodicity in time series. The lower DET is an indication of higher randomness and lower predictability. In the initial stages of contraction when the signals are in nonfatigue condition, the sEMG signals are highly random and nonstationary in nature. This may be due to higher firing rates of motor units and increased recruitment of motor units for force generation. Thus, the DET value may be observed to be in lower range (0.2 to 0.4) during the nonfatigue conditions. However, in sixth zone which is the fatigue state, the DET value appeared to increase steadily to higher values. There may be an increase in motor unit synchronization and reduction of conduction velocity leading to higher regularity of sEMG signals. The results of DET matched with previous work and found to be statistically significant [23], [24]. The $V_{\text{MAX}}$ feature was found to be higher in fatigue condition and reduced in nonfatigue condition. The normalized $V_{\text{MAX}}$ was found to be low in during nonfatigue and progressively increased in fatigue regions. The lower value of $V_{\text{MAX}}$ implies that the system is of high complexity in dynamical system. This also means that the system stays for a short time in a state similar to previous state during nonfatigue condition. However, in the fatigue condition, the system stays in the same state for a relatively longer time which may due to slower motor unit conduction velocity and reduction of firing rate.

The complexity feature is found to be progressively decreasing during fatigue state. Higher complexity means that the signal is random and highly nonstationary. Lower values of complexity are an indication of repetitive regular structures and hence considered to be predictable. There is an increase of synergies of motor unit action potential during fatigue stages and thereby the signals may be more predictable. In the nonfatigue conditions, the increased randomness of motor units causes an increase in complexity of the signal. The mean
complexity in nonfatigue and fatigue condition is found to be around 7.5 and 4.9 respectively. The box plot for the mean complexity feature, in nonfatigue and fatigue conditions are represented in Fig. 4. This trend of reduction of complexity with fatigue is comparable with mean power frequency taken in the same epoch. This may be an indication of higher nonstationary components and possibly regions of muscle discomfort before complete fatigue state is set. The statistical analysis is carried out using RQA features for nonfatigue and fatigue conditions. The mean and standard deviations of all the RQA features are tabulated in Table II. It is observed that all the three features are highly statistically significant in fatigue conditions. The 3-D plot with $V_{\text{MAX}}$, DET and Complexity gave a better visual method of sEMG signal analysis indicating lower disorderliness and higher complexity in nonfatigue and fatigue condition respectively. The data for all the subjects in this study are plotted in 3-D graph and represented in Fig. 5. There is a clear demarcation observed for nonfatigue and fatigue regions in most of the subjects.

### Table II. ANOVA Analysis for RQA Features

<table>
<thead>
<tr>
<th>RQA Features</th>
<th>Nonfatigue</th>
<th>Fatigue</th>
<th>p Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>DET *</td>
<td>0.43 (0.088)</td>
<td>0.57 (0.087)</td>
<td>5.15E-6</td>
</tr>
<tr>
<td>Normalized $V_{\text{MAX}}$ *</td>
<td>0.65 (0.23)</td>
<td>0.94 (0.11)</td>
<td>4.79E-6</td>
</tr>
<tr>
<td>Complexity *</td>
<td>7.53 (1.88)</td>
<td>4.99 (1.36)</td>
<td>7.47E-6</td>
</tr>
</tbody>
</table>

* Statistically Highly Significant at p=0.001

**Figure 4.** Box plot representation of complexity feature in nonfatigue and fatigue condition.

**Figure 5.** 3-D plot representation of complexity, determinism and $V_{\text{MAX}}$ feature in nonfatigue (blue) and fatigue condition (red).

### IV. Conclusions

EMG signal is a complex physiological signal and its complexity increases during intense dynamic contractions. In this work, sEMG signals are recorded from triceps brachii muscles of 21 participants. The experiment is conducted in a controlled environment using standard experimentation protocol. The subjects are selected in similar age group to minimize the variance in sEMG recording. The sEMG signal are pre-processed - filtered in the range of 10Hz to 500 Hz and used for further analysis. The signals are divided into six segments for normalizing on time axis. The first and sixth segments are considered as nonfatigue and fatigue zones. The zones are subjected to RQA methods and three features such as determinism, complexity and maximum length of vertical line are computed in fatigue and nonfatigue zone. The complexity for sEMG signals is a new feature derived from determinism and it is a representation of chaotic behavior of signal. The higher complexity is measure of randomness. The results of determinism indicate that the signals have more synergies in fatigue condition and this may be due to motor unit synchronization and reduction of conduction velocity. The value of DET feature increased from nonfatigue to fatigue condition by 17%.

The signals are found to be highly complex in nonfatigue stage and there is a reduction in complexity during fatigue conditions. The result of reducing complexity in fatigue conditions concurs with previous work reported on biceps brachii muscles [25]. The 3-D visual plots are generated with DET, $V_{\text{MAX}}$ and complexity features for representing the nonfatigue and fatigue trends. This plot appears to be a good visualization tool and can further be used for classifying muscle fatigue for different age groups and contraction levels. The ANOVA results show high statistical significance for all three RQA features. The new feature complexity is found to be most highly significant feature ($p = 7.47E^{-6}$). Complexity and DET measures of RQA method appears to be useful technique for analyzing sEMG signals during dynamic contraction and can be further deployed as a signal biomarker for determining the onset of fatigue.

### References


Ramakrishnan Swaminathan received his Ph.D degree in Biomedical Engineering, Department of Applied Mechanics from IIT Madras in 1997. He was a DAAD fellow at RTWH, Aachen, Germany, before joining as faculty at Anna University. Currently, he is a Professor and Head of Biomedical Group in Department of Applied Mechanics, IIT Madras. Dr. Ramakrishnan has over 21 years of research and teaching experience, and his current research focus is on Biomedical Image and Signal processing, Biomedical Instrumentation and Measurements, enhancing diagnostic relevance of medical equipment and regulatory services. Dr. Ramakrishnan has published over 220 papers in peer-reviewed journals and conferences, and supervised over 20 Ph.D/MS research scholars.

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