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Testing of Motor Unit Synchronization Model for Localized Muscle Fatigue

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***Abstract*— Spectral compression of surface electromyogram (sEMG) is associated with onset of localized muscle fatigue. The spectral compression has been explained based on motor unit synchronization theory. According to this theory, motor units are pseudo randomly excited during muscle contraction, and with the onset of muscle fatigue the recruitment pattern changes such that motor unit firings become more synchronized. While this is widely accepted, there is little experimental proof of this phenomenon. This paper has used source dependence measures developed in research related to independent component analysis (ICA) to test this theory.**

I. INTRODUCTION

Muscle fatigue is a condition when the ability of the muscle to contract and produce force is reduced. Localized muscle fatigue is when a muscle or a group of muscles has a reduced ability to contract and produce force despite neural stimulation; generally as a result of prolonged, relatively strong muscle activity. Muscle fatigue threshold cannot be defined as a simple function of muscle load magnitude and timing because muscle characteristics and capabilities vary from person to person. Undetected fatigue can cause injury or pain to the subject.

The cause of local muscle fatigue varies, and depends on the level of muscle activity and the muscle fiber type. During short, high power movement, fatigue may result from the exhaustion of adenosine triphosphate (ATP) or creatine phosphate (CP) reserves, which are required to power movement of the myosin heads which cause contraction.

One explanation for localized muscle fatigue is based on the change in muscle recruitment due to the onset of fatigue. Each skeletal muscle is constructed of multiple motor units (MU) where a motor unit is defined as a motor neuron and all muscle fibers associated with that neuron. Muscle properties associated with force production are time variant. There are number of models that have been developed to explain the motor recruitment strategies. It is widely accepted that when muscles are active, motor units are activated pseudo randomly to ensure smooth generation of force. Muscle activity can be analyzed non-invasively based on the electrical activity from the muscle contraction.

Electromyography (EMG) is a recording of the skeletal muscle activity of the body. It is routinely used by clinicians for analysis of the skeletal muscle activity and diagnosis of diseases of the neuromuscular system. EMG may be recorded invasively by using needle electrodes inserted directly into the muscle through the skin or alternatively may be recorded from the surface of the skin without any invasion of the body. The former is generally referred to as needle EMG while the latter as Surface EMG (sEMG).

Needle EMG recording provides a more exact representation and finer resolution of the electrical activity of muscle fibers than is possible with sEMG. This is because the sEMG signal is a summation of non-synchronous action potentials of a large number of muscle fibers that have been non-linearly attenuated by body tissue between the target muscle and the skin surface, due to the frequency dependent electrical properties of the tissues [1], [2].

As muscle force increases, the number of active motor units increases, referred to motor unit recruitment. Motor unit recruitment is dependent on both the load and the current fatigue status of the muscle, thus introducing a time dependency in the sEMG signal as muscle loading progresses. There is a large variance from subject to subject, due to difference in tissue thickness, electrode location and distribution of the motor unit conduction velocities [3].

Despite the complex nature of the signal, sEMG recordings can be used to extract a useable representation of muscle status. Surface EMG is used to analyze the strength of muscle contraction, to study muscle state and fatigue and to identify possible muscle disorders. Research analysis aimed at extraction of local muscle fatigue information has been frequently based on the observed shift of the power spectral density of the sEMG [2], [4].

The most common EMG features used to assess fatigue are the root mean square (RMS) amplitude [5], the mean or median frequency (MDF) and the power spectral density (PSD) [6]. Fatigue is associated with an increase in the EMG RMS amplitude and a compression of the PSD towards the lower frequencies [7]. However, RMS and MDF methods have shown inconsistent patterns when applied to lower level contractions [8], [9], [10], [11]. In particular, Oberg found that MPF did not change with muscle fatigue at low contraction levels.

Muscle fatigue has been described in terms of motor unit recruitment patterns [12]. It has been explained that recruitment changes and motor units appear to become synchronized with the onset of localized muscle fatigue.

Modeling studies have found that the spectral shift to lower frequencies (and the related drop in median frequency (MPF)) is countered by a reduction in the conduction velocity (CV) [13]. During low-level bicep voluntary contractions, MF also drops, but the CV remains the same. Kleine posits that changes in the firing pattern, particularly synchroniza-

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tion, must be responsible for the spectral shift to lower frequencies not attributable to a conduction velocity change [12]. During fatigue, the motor unit firing patterns become more synchronous (firing at almost the same time) than is expected by chance. In the fatigue state, the central drive to a muscle has to increase, leading to synaptic input that is common to more than one neuron. This leads to increased synchronicity. While widely accepted, there appears to be lack of proof of the synchronization of motor units underpinning the localized muscle fatigue [14]. This paper reports our research that has attempted to test the motor unit recruitment hypothesis.

II. THEORY

To test the hypothesis that there is synchronization of motor units with the onset of muscle fatigue, this paper reports identifying the change in the level of dependence of motor units within a muscle. If there is an increase in the level of dependence of muscle activity recorded from different sites in the same muscle with the onset of muscle fatigue, it would indicate that the activity from these two locations has become synchronized. Electrode pairs that are co-located in the length of the muscle and separated across the spread of the muscle would record activity from multiple motor units, and may have high degree of cross talk.

Naik et al [15], [16] have demonstrated that the dependence of multiple sources can be determined using independent component analysis (ICA). Their work has demonstrated that the determinant of the global matrix is an indicator of the dependence of the sources. If the sources are independent, the determinant value is close to unity while when there is dependence between the sources, this value becomes close to zero. Based on this principle, it is hypothesized that when the muscle is not fatigued, the determinant of the global matrix generated by ICA would be close to unity, and when the muscle is fatigued, this would reduce and should become close to zero.

A. ICA theory

ICA is an iterative technique used to estimate statistically independent source signals s = $[s_1, s_2, ..., s_n]^T$ from a given set of their linear mixtures x = $[x_1, x_2, ..., x_n]$. If the mixing process is assumed to be linear, it can be expressed as:

$$x(t) = As(t) \tag{1}$$

A is the $N \times M$ scalar matrix representing the unknown mixing coefficients and it is called transfer or mixing matrix. The goal of ICA is to find a linear transformation W of the dependent sensor signals $x(t)$ that makes the outputs as independent as possible:

$$\hat{s}(t) = Wx(t) \tag{2}$$

where $\hat{s}(t)$ is an estimate of the sources. The sources are exactly recovered when W is the inverse of A up to a permutation and scale change. Since both the sources and the mixing coefficients are unknown, it is impossible either to determine the variances or the order of the independent components.

G is the global matrix and is the product of the mixing matrix with the estimated unmixing matrix. After sorting the order ambiguity between the mixing and unmixing matrix, under ideal conditions, this matrix should be a unity matrix and the determinant should be unity [15], [16]. If the recordings are not all independent, the determinant of this matrix is no longer unity and is close to zero. This can be used as an indicator of the dependence of the input to the system.

One shortcoming of this is that it requires prior knowledge of the mixing matrix, which in real situations is not possible. To estimate G, one option is to use the sub-band ICA.

B. Sub-band ICA

Sub-band ICA, an extension of ICA. It assumes that each source is represented as the sum of some independent subcomponents and dependent subcomponents, which have different frequency bands. Wide-band source signals are a linear decomposition of several narrow-band sub components $s(t) = s_1(t) + s_2(t) + s_3(t), \ldots, s_n(t)$. Such decomposition can be modeled in the time, frequency or time frequency domains using any suitable linear transform. We obtain a set of un-mixing or separating matrices: W_1,W_2,W_3,$\ldots$,W_n where W_1 is the un-mixing matrix for sensor data $x_1(t)$ and W_n is the un-mixing matrix for sensor data $x_n(t)$. If the specific sub-components of interest are mutually independent for at least two sub-bands, or more generally two subsets of multi-band, say for the sub band "p" and sub band "q" then the global matrix

$$G_{pq} = W_p \times W_q^{-1} \tag{3}$$

will be a sparse generalized permutation matrix P with special structure with only one non-zero (or strongly dominating) element in each row and each column [17].

III. METHODOLOGY

A. Recording Equipment

Surface Electromyography was recorded using BIOPAC 100 (California, USA), a proprietary sEMG acquisition system. Prior to placing the electrodes the participants' skin was cleaned using mild soap. The following parameters were used during the recording:

- Preamplifier Gain: 2000
- Low Pass Filter: 500Hz
- High Pass Filter: 10Hz
- Notch Filter: 50dB at 50Hz
- Sampling frequency: 1500

Two-channel SEMG were recorded from biceps muscles using surface electrodes during isometric contractions. The placement of electrodes is shown in Figure 1.

Fig. 1. Placement of electrodes for the experiments

B. Experimental protocol

Four healthy volunteer subjects participated in the trial. The experimental protocol was approved by the Human Ethics Committee of RMIT University. One pair of electrodes was placed on either side of the biceps muscle to acquire a two-channel recording of sEMG. The subject performed isometric contraction using fixed standard load. The load was chosen to be about 75% maximum voluntary contraction. The sEMG was recorded throughout the experiment until the subject complained of muscle fatigue. The typical time period of each recording was 180 seconds.

C. Data Analysis

The sEMG signals recorded during the period were analyzed using ICA techniques to detect localized muscle fatigue. Initially the FastICA MATLAB software was used to separate the sources. This is a known application of ICA, used to reduce crosstalk prior to calculating the amplitude features (RMS). The determinant of global matrix generated using ICA was then used as an indicator for identifying the number of active sources and localized muscle fatigue.

TABLE I

MEDIAN FREQUENCY OF RECORDED SURFACE ELECTROMYOGRAM OF THE TWO SEMG CHANNELS, BEFORE AND AFTER FATIGUE

	Before fatigue		After Fatigue	
Subject	Channel		Channel	
	1	2	1	2
1	55	67.7	71.2	59.2
2	56.8	59.2	47.1	50.1
3	57.4	57.4	48.7	48.9
4	80.9	67.1	80.1	69.4
Mean	62.53	62.85	61.78	56.9

IV. RESULTS AND OBSERVATIONS

The results are tabulated in Tables I, II and III. Table I shows the calculated median frequency of sEMG (2 channels) during initial (prior to fatigue) and final (following fatigue) data segments. Table II shows the RMS values of sEMG (2 channels) for initial and final segments of the isometric contraction after source separation using ICA. Table III shows the value of the determinant of the global matrix, calculated to determine the dependency properties using ICA. From Table I, it is evident that the median frequency of neither channel reveals clear information regarding the synchronization and dependency properties of the muscle during fatigue.

TABLE II

RMS OF RECORDED SURFACE ELECTROMYOGRAM FOR THE TWO CHANNELS

	Before fatigue		After Fatigue	
Subject	Channel		Channel	
	1	2	1	2
1	1.1113	1.0031	1.5246	2.6763
2	1.0051	1.0476	1.9573	1.1848
3	1.0112	1.0005	2.4577	1.9825
4	1.1002	1.0455	1.9573	2.2843
Mean	1.057	1.0242	1.9742	2.032

Preliminary analysis of the RMS values calculated from the separated sources (Table II) shows a general trend of increasing amplitude after fatigue for both channels. However, the RMS value alone does not reveal much about the synchronicity of the motor units, only that the work required to produce the same force is increasing as the muscle becomes fatigued.

It is posited here that the model of motor unit synchronicity during fatigue can be tested by determining the dependence of the recorded signals. In order to confirm the dependant properties of sources as explained in theory, a Global matrix was computed. The determinant of the global matrix is an indicator of the dependence of the sources. If the sources are independent, the determinant value is close to unity, whereas when there is dependence between the sources, this value becomes close to zero [18].

The example of global matrix is shown below:

- ***Isometric contraction (Before fatigue)***

$$GlobalMatrix(G) = \begin{pmatrix} 0.8345 & -0.3456 \\ 0.4560 & 0.7241 \end{pmatrix}$$

det(G) = 0.7619 (Independent)

- ***Isometric contraction (After fatigue)***

$$GlobalMatrix(G) = \begin{pmatrix} 0.0083 & 0.0100 \\ -0.0023 & 0.1773 \end{pmatrix}$$

det(G) = 0.0015 (Dependent)

From Table III, it is observed that the determinant of the global matrix for all subjects is close to unity before fatigue and this moves closer to zero once the subject becomes fatigued. This shows that when the muscle is not fatigued, the motor units are firing independently and when the muscle is fatigued, the motor units are dependant and therefore more synchronized.

TABLE III
VALUE OF THE DETERMINANT OF THE GLOBAL MATRIX

Subject	Before fatigue	After Fatigue
1	0.7619	0.0015
2	0.7684	0.0012
3	0.7856	0.0013
4	0.7731	0.0016
Mean	0.7723	0.0014

V. DISCUSSION AND CONCLUSION

Many research groups have reported a link between sEMG spectrum (or median frequency) and fatigue. Fatigue has been associated with a spectral shift towards lower frequencies. However, it has been reported that that MPF does not change with muscle fatigue at low contraction levels [11]. Modeling studies have shown during low-level bicep voluntary contractions, the motor unit conduction velocity does not reduce, as is generally observed during high level contractions. In the fatigue state, the central drive to a muscle has to increase, leading to synaptic input that is common to more than one neuron. This has been explained in literature based on increased synchronicity in the motor unit firing patterns.

The work presented here has attempted to prove the motor unit synchronization model by associating synchronicity with dependence. In a non-fatigued state, the motor units in a contracting muscle will fire almost randomly in order to ensure smooth movement. Surface EMG taken from two channels should therefore reveal independence from each other. The determinants calculated using the global matrix has confirmed that the sEMGs taken in the non-fatigued state are independent from each other.

Alternatively, the determinant calculated using the global matrix on the fatigued sEMGs shows dependence. These results support the contention that motor unit synchronicity increases in the fatigued state.

To compare results with earlier work, the RMS and MPF before and after fatigue were also calculated. The MPF result supports the spectral compression of the signal after the onset of muscle fatigue. The RMS results indicate an increase in the RMS with the onset of muscle fatigue.

Based on literature, the human bicep muscle recruits additional muscle fibers as force increases, up to around 88% MVC. Above 88% MVC, the frequency of motor unit firing increases to allow muscle force output to modulate up to the maximal contraction force [19]. However, both an increase in motor unit firing rate and an increase in the number of active motor units can increase the signal amplitude (represented by RMS). As these experiments were conducted at 75% MVC it is not clear which of these factors the increase in RMS is related to. However, during fatigue, it is acknowledged that increased effort is required to sustain the same force level; a point which is reflected in the uniform RMS increases calculated here. Although a confirmation of known results, this RMS increase does not contribute to the practical knowledge regarding motor unit synchronization.

Of the three features studied here; RMS, MPF and independence, independence offers the most information about motor unit synchronization. As the global matrix showed a clear independence before fatigue and dependence following fatigue, it can be concluded that this practical study goes some way to confirming the theories proposed in the motor unit synchronization model. It may also be a useful indicator of muscle fatigue, although easy implementation of this would need to be considered for real time applications.

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