Analysis of Surface EMG Signals during Dynamic contraction using Lempel-Ziv Complexity

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Analysis of Surface EMG Signals during Dynamic Contraction using Lempel-Ziv Complexity

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Abstract—**In this work, an attempt has been made to analyze progression of muscle fatigue in surface electromyography (sEMG) signals by estimating the complexity. The sEMG signals are acquired from biceps brachii of 50 healthy volunteers during dynamic contraction. The pre-processed signals are segmented into non-overlapping epochs of various sizes (500ms, 750ms and 1000ms) and Lempel-Ziv Complexity (LZC) is computed for each epoch. The linear regression technique is used to track the slope variations of LZC. The values of LZC show a decreasing trend during the progression of muscle fatigue. The magnitude of negative trend remained nearly constant irrespective of epoch size. Further, inter-subject variability of LZC measure is found to be minimum. The results shows that this method is useful in analyzing progression of muscle fatigue during dynamic contractions.**

Keywords—Surface EMG; Lempel-Ziv Complexity; Biceps brachii; Muscle fatigue.

I. INTRODUCTION

Surface Electromyography (sEMG) is a non-invasive technique for recording the electrical activity of skeletal muscles during its contraction. sEMG has been extensively used for fatigue studies [1]. Muscle fatigue is the reduction in the ability of the muscle to contract and exert required force [2]. It can occur due to prolonged or intense muscle activity.

The sEMG signals during dynamic contractions are highly nonlinear and non-stationary. Nonlinear analysis can provide more information on the dynamics of the physiological process as compared to classical linear time series analysis or spectral analysis [3]. Nonlinear techniques such as Lyapunov exponent, correlation dimension, Kolmogorov complexity and Lempel-Ziv complexity (LZC) are used for analyzing physiological signals. LZC measures number of distinct patterns and avoids the confounding effects of number of patterns in the time series [4]. LZC measure has been used to study complexity of sEMG signals in isometric contractions at various levels of maximum voluntary contraction [5].

In this work, sEMG signals are recorded from biceps brachii muscle during dynamic contraction. LZC measure is estimated from the preprocessed signal and is used for further analysis.

II. MATERIAL AND METHODS

A. Signal Acquisition and Protocol

The study involved 50 healthy subjects with average age of 27.12 yrs, average height 1.67 m and average weight 70.20 kg. The subjects are asked to perform dumbbell curl exercise with 6 kg load in their dominant hand until they are unable to lift load further [2]. A written informed consent was obtained from volunteers. Signals are recorded for entire duration with Biopac MP36 bio-amplifier system at a sampling rate of 10 kHz. Ag-AgCl surface electrodes (3cm inter-electrode distance) with bipolar configuration is employed. The raw signals are preprocessed offline using Butterworth filter (10-400Hz) and notch filter (50Hz).

B. Lempel-Ziv Complexity

The LZC measure is based on coarse gaining of measurement sequences [6]. It is an indication of number of distinct patterns and rate of their recurrence along the sequence. For computing the LZC measure, the sEMG signal should be transformed into symbolic sequences. In this study we used a binary sequence conversion. The original signal samples are converted into 0-1 sequence [P = s(1), s(2),...,s(n)] in comparison with threshold T_d. s(i) is defined as 0 if $x(i) < T_d$ and 1 if $x(i) \geq T_d$. The threshold Td is estimated as the median value of signal as it is more robust to outliers.

Further, sequence P is scanned from left to right and complexity count is increased by one unit every time a new pattern is encountered. A detailed description of this algorithm is reported in [7]. For obtaining complexity measurement independent of sequence length, c(n) is normalized. If length of sequence is n and number of different symbols is α, then

$$LZC = c(n)[\log_{\alpha}\{c(n)\}+1]/n \qquad (1)$$

where, α is 2 for binary conversion. The normalized LZC reflects the arising rate of new patterns from the sequence. The pre-processed signals are segmented into 500ms epochs and the LZC measure is computed. The complexity was also computed at 750ms and 1000ms to study effect of epoch size. A linear regression technique is used to track the slope variations.

III. RESULTS AND DISCUSSION

The representative recorded sEMG signal is shown in Fig. 1a. where subject performed task for 67 seconds. The time required for task failure is found to be subject dependent. It is observed that signals varied among different subjects. This random nature of the signal may be due to varied firing rate, volume conductor effects, and random recruitment pattern of the motor units. It is also observed that the amplitude and frequency component of the signals varied with subjects.

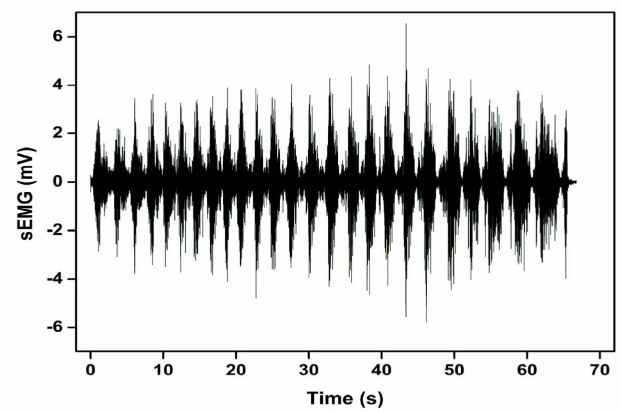

Fig. 1a. Representative pre-processed sEMG signal

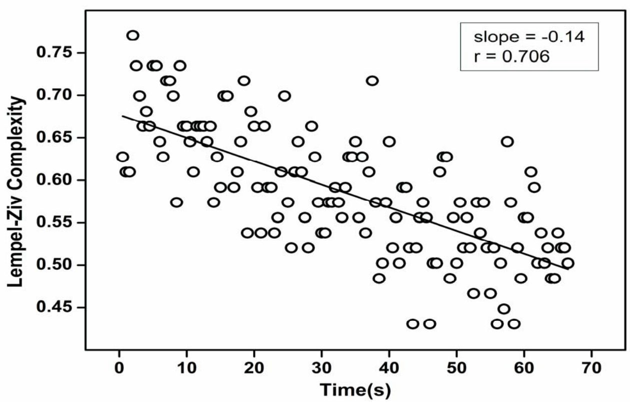

Fig. 1b. Normalized LZC for representative sEMG signal

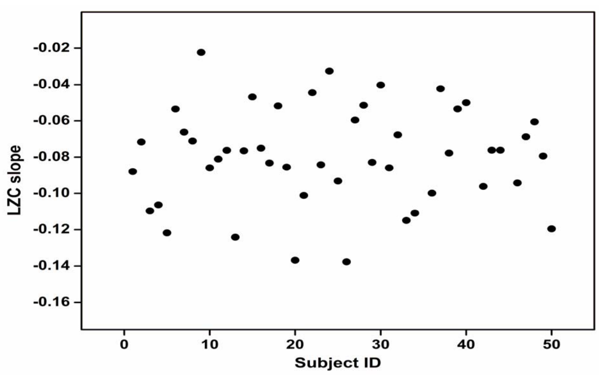

Fig. 2. Variation of slope of LZC for 50 subjects

Fig. 1b. shows variation of normalized LZC measure for the 134 epochs (500ms) of the representative signal. It is observed that LZC values are higher in the initial conditions and decreases with progression of fatigue. This indicates decreased complexity of the sEMG signals in fatigue conditions. A linear correlation coefficient of 0.706 is obtained for LZC measure and slope. The LZC measure is also found to be computationally inexpensive.

Values of LZC close to one indicates a large number of random patterns and higher rate of their occurrence in the signal. This suggests higher rate of creation of different motor unit action potential sequences in sEMG signal. This might be due to higher firing rate of motor units in initial conditions, followed by decreasing trend with progression of fatigue. The number of unique patterns within each epoch is also computed. Thus the decreasing randomness indicated by LZC measure in fatigue period could be due to higher degree of determinism in motor unit action potential trains of the sEMG signal. This also indicates an increase in synchronization between firing motor units.

Table 1. Mean slope of LZC for different epochs

Epoch size	Mean LZC slope
500 ms	-0.123 (0.041)
750 ms	-0.121 (0.039)
1000 ms	-0.120 (0.038)

Fig. 2. shows the slope of the LZC across 50 subjects and it is seen that the values are negative for all the subjects. The inter-subject variability of the complexity is also found to be minimum. The varying rate of decrease in complexity indicates rate of progression of muscle fatigue is different for each subject. It is also observed from the Table 1 that irrespective of the epoch size the trend is always decreasing and a maximum slope is obtained with 500ms epoch.

IV. Conclusion

The sEMG signals are random and exhibit high degree of nonstationarity behavior during dynamic contractions. In this work, variations in the complexity of sEMG signals using LZC measure is studied. The results show distinct variation of LZC with progression of fatigue. Further, negative slope for linear regression fit is observed for all subjects and its variation with epoch size is minimal. It appears that degree of nonlinearity and nonstationarity at end of the experiment is reduced due to lower complexity values. This is in agreement with existing results in literature. Thus, this study is useful in analyzing the progression of muscle fatigue and it can be extended to other neuromuscular conditions.

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