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BICEPS BRACHII MUSCLE FATIGUE PROGRESSION ANALYSIS USING EXTENDED MODIFIED B-DISTRIBUTION BASED TIME-FREQUENCY FEATURES

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INTRODUCTION

The muscle constitutes nearly 40% of total body mass [1]. There are around 640 muscles present in our body which helps in daily activities such as movements, posture maintenance and non-verbal communication. Evaluation of muscle dynamics based on these activities is an important component in the field of biomedical signal processing research. For this purpose, signals are acquired under well defined protocol and are processed to extract useful information that reflects the functional state of neuromuscular system.

Surface electromyography (sEMG) is a noninvasive technique which is used to record the electrical activity of neuromuscular system. The sEMG signal characteristics depends on several physiological parameters such as firing rate, motor unit recruitment pattern, types of motor unit, muscle fiber conduction velocity and low pas filtering effect of volume conductors [2]. These signals are random, nonstationary and multicomponent [3].

Conventional signal processing methods such as time and frequency domain based approaches have been employed for muscle fatigue assessment [2]. However, these methods assume that the signal is stationary. Short time-Fourier transform have been used for the analysis of time varying frequency components of sEMG signals. The assumption of local stationarity and its poor frequency resolution limits STFT application [2]. Cohen class time-frequency distributions (TFD), namely, Wigner-Ville distribution (WVD) and pseudo WVD have been used to characterize the non-stationary behaviour of sEMG signals [7]. TFD features such as instantaneous median frequency (IMDF) and mean frequency have been reported to detect the localized muscle fatigue [8].

Recently, reduced interference TFD's have been developed to remove cross-terms while preserving high time and frequency resolution. B-distribution, modified B-distribution and extended modified B-distribution (EMBD) are belongs to this class. The TFD obtained using these kernels are also known as high resolution quadratic time-frequency distribution [9]. It has been shown that EMBD performs better than BD and MBD in the representation of time-varying frequency components of signals. EMBD time-frequency technique has been used to address the nonstationary and multicomponent property of electroencepelography signals that are associated with neurological conditions such as seizures [10]. Further, it has been used to study the characteristics associated with the fetal movement data and new born EEG signals [11].

In this work, sEMG signals are recorded from biceps brachii muscles during isometric contraction. In addition to the IMDF, spectral features such as instantaneous normalized spectral moment (INSM) of order 2, 3, 4 and 5 are extracted from the EMBD based TFD. These features are used for further analysis.

METHODS

Each submission must be a minimum of 2 pages and a maximum of 4 pages (8.5" x 11"). Submissions may be in French or English. All papers must be submitted electronically in pdf format through the online submission process.

Experimental protocol and Signal Acquisition

Thirty healthy adult volunteers with no history of neuromuscular problems performed the experiment. The subjects are informed about the experiment protocol and consent is obtained from all the subjects. After necessary skin preparation, Ag-AgCl surface electrodes are placed on the belly of biceps brachii muscle. The acquisition of signals is carried out using

Biopac MP36 in bipolar electrode configuration. The sampling rate and gain of the data acquisition system is set at 10 kHz and 1000 respectively. The experimental protocol involved subjects performing a 90° isometric contraction exercise with a 6 kg dumb bell against gravity. The subjects are encouraged to continue the exercise until the subjects drop the hand by an angle of 10°. The drop in angle indicates fatigue. The recorded raw signals are preprocessed using a band pass filter of range 10-500 Hz and a notch filter of 50 Hz.

B-distribution based Time-Frequency Analysis

The general form of quadratic time-frequency distribution is given by [11]

$$\rho_z(t,f) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g(v,\tau)A_z(v,\tau)e^{j2\pi(vt-f\tau)}dvd\tau \quad (1)$$

where $g(v,\tau)$ is a weighting function or kernel in Doppler-lag domain, v is Doppler and τ is time lag.

When $g(v,\tau) = 1$, then the above expression becomes WVD. The mathematical representation of ambiguity domain function can be expressed as

$$A_z(v,\tau) = \int_{-\infty}^{\infty} z(t+0.5\tau)z^*(t-0.5\tau)e^{-j2\pi vt}dt \quad (2)$$

where $z(t)$ is an analytic multicomponent signal, $z(t) = x(t) + iH(x(t))$, $H()$ denotes the Hilbert transform.

When the multicomponent signal is represented in ambiguity domain, the actual frequency components of the signal (auto terms) are present around the origin and the cross terms are located away from the origin. This property helps to design an appropriate kernel filter to attenuate the cross terms with good time frequency resolution. B-distribution is a 2D kernel function. It is centered on the origin of the ambiguity plane and has sharp cut down edges. Thus, this kernel will allow most of the auto terms (signal components) and filter the cross terms. The B-distribution in ambiguity domain is given by [11].

$$g(v,\tau) = |\tau|^{\alpha}\frac{|\Gamma(\alpha+j\pi v)|^2}{2^{1-\alpha}\Gamma(2\alpha)} \quad (3)$$

where, $\Gamma(z) = \int_0^{\infty} t^z e^{-t}dt$, Re(z)>0, α is the kernel smoothing parameter, controls the shape of 2D-filter in ambiguity domain.

The equation 3 becomes null when $\tau = 0$. In this case, the kernel may attenuate most of the auto-terms. In order to overcome this, MBD kernel is introduced and its mathe matical representation is given by [11]

$$g(v,\tau) = \frac{|\Gamma(\beta+j\pi v)|^2}{\Gamma^2(\beta)} \quad (4)$$

Where, β is a kernel parameter.

It is observed that the equation 4 is one dimensional filter in Doppler domain. In order to remove the null kernel function where most of the auto-terms are concentrated and to achieve smoothing in two dimensions, namely, Doppler and lag directions, an extended version of modified B-distribution is developed and is given by [11]

$$g(v,\tau) = \frac{|\Gamma(\alpha+j\pi\tau)|^2}{\Gamma^2(\alpha)}\frac{|\Gamma(\beta+j\pi v)|^2}{\Gamma^2(\beta)} \quad (5)$$

Where α and β are kernel parameters. For this analysis, the values of these parameters are chosen from [11].

Time-Frequency Features

Time-frequency based features such as instantaneous median frequency and instantaneous normalized spectrum moment of order 2, 3, 4 and 5 are extracted and used for further analysis.

Instantaneous Median Frequency (IMDF)

Median frequency is defined as the frequency at which the total power is divided in to two equal halves. The IMDF is calculated from the time frequency spectrum by extracting the median frequency at each instant of time. The mathematical expression for IMDF is given in [5, 9].

Instantaneous Normalized Spectral Moment (INSM):

Normalized spectral moment is a ratio between the spectral moment of order -1 and order 2 or higher. It is extracted from the power spectrum of the signal. The instantaneous variation of normalized spectral moment is computed by replacing the power spectrum with time-frequency spectrum. INSM is given by

$$INSM(t)_k = \frac{\int_0^{f_{max}} f^{-1}P_z(t,f)\,df}{\int_0^{f_{max}} f^k P_z(t,f)\,df} \quad (6)$$

$$\log INSM_k = log_{10} INSM_k$$

where $k = 2,3,4$ or 5 and it indicates the order of INSM. Log $INSM_2$ denotes logarithmic of

instantaneous normalized spectral moment of order 2.

RESULTS AND DISCUSSION

The sEMG signal recorded during isometric contraction is shown in Fig. 1. The amplitude of the signal is higher during the final stage of the exercise. The endurance time of this subject is found to be around 78 seconds. The amplitude and anthropometric parameters such as body mass, standing height, body mass index, biceps circumference and hand length, etc.

The variation of IMDF is shown in Fig. 2. It is found that the IMDF reduces with the progression of muscle fatigue. Negative slope is resulted in linear regression technique and it is found to be -0.28. These spectral shifts towards lower frequency regions may be attributed to the inability of muscular system to generate the required force. It may be due to the reduction in the muscle fiber conduction velocity and motor unit synchronization in muscle fatiguing contractions.

Figs. 3 and 4 show the instantaneous variations of log INSM of order 2 and 5 respectively. It is found that this feature increases with the progression of muscle fatigue and results in positive slopes. in the duration of intracellular action potentials and the reduction in the action potential propagation velocity with fatiguing contractions.Further, the higher value of log INSM at the time instance of task failure may also be attributed to the effect of increased negative after potentials that are responsible for low and ultra-low frequencies of sEMG spectrum. Similar trends have also been observed in the case of log INSM3 and INSM4. Large variations are seen in log INSM5 in comparison with log INSM2. The correlation coefficient is found to higher for log INSM5.

The mean and standarad deviation (Std) of time-frequency features are tabulated in Table 1. IMDF is found to have negative slope in all the subjects. The mean and Std of IMDF is -0.28±0.2. The mean slope of log INSM5 is found to 21% and 51% greater than log INSM3 and log INSM2 respectively. It is observed to be similar for log INSM5 and log INSM4. Further, it is found that log INSM5 have higher correlation. From these results, it is observed that among all other INSM's, the order 5 is more sensitive for the detection of muscle fatigue progression.

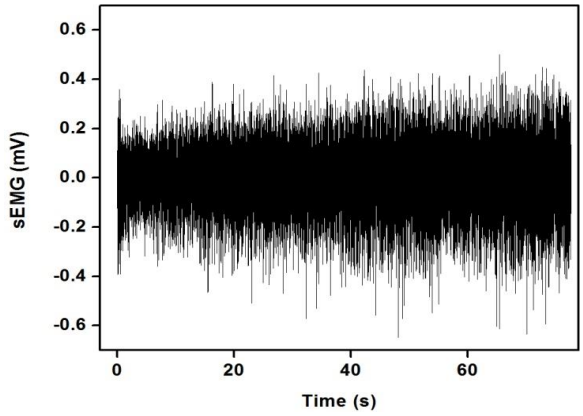

Fig. 1. Representative recorded sEMG signal

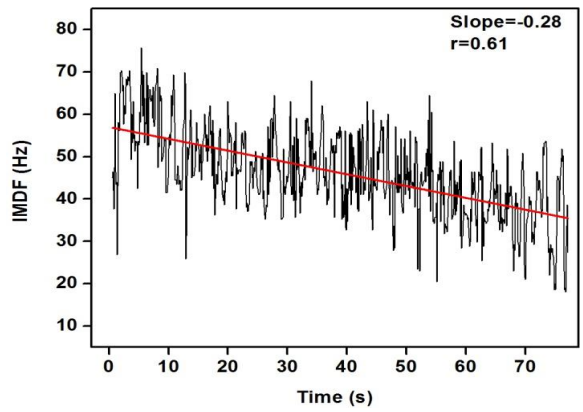

Fig. 2. Instantaneous median frequency of representative signal

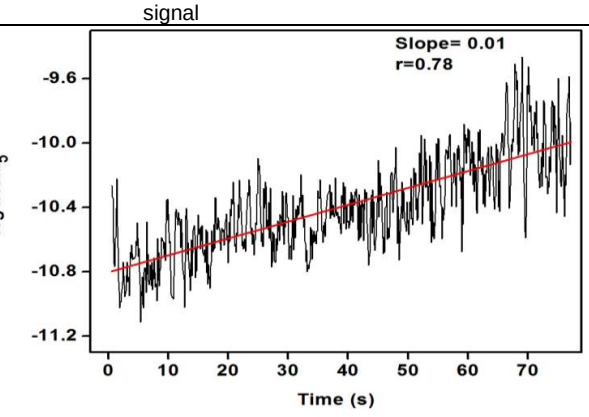

Fig. 3. Instantaneous variations of logarithmic $INSM_2$

These instantaneous changes in the spectral parameters demonstrate the nonstationary property of sEMG signals. These variations may be attributed to the influence of frequency content related physiological parameters such as changes in firing rate and motor unit recruitment pattern, anisotropic and isotropic nature of volume conductors [2].

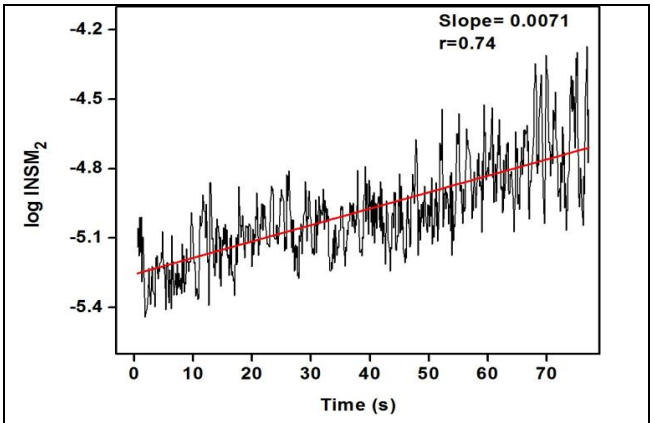

Fig. 4. Time course of logarithmic $INSM_2$

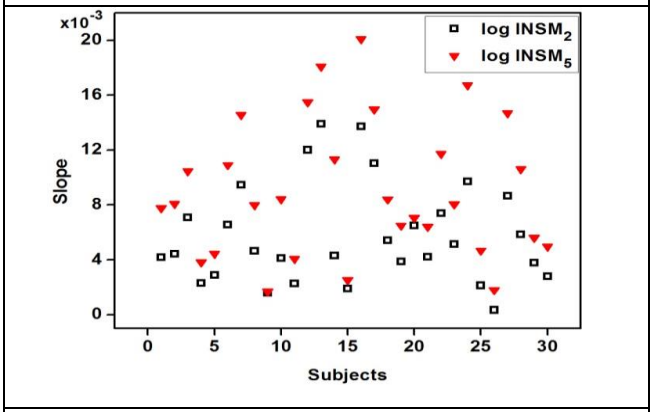

Fig. 5. Slope of log $INSM_2$ and log $INSM_5$ for all subjects

Table 1: Statistical parameters of IMDF and INSM of order 2,3,4 and 5

Time-frequency Features	Slope	Correlation coefficient
	Mean (Std)	Mean (Std)
IMDF	-0.28(0.2)	0.47(0.16)
log $INSM_2$	6.6E-3(5E-3)	0.60(0.18)
log $INSM_3$	8.2E-3(6E-3)	0.62(0.15)
log $INSM_4$	9.4E-3(7E-3)	0.63(0.16)
log $INSM_5$	10E-3(8E-3)	0.67(0.15)

CONCLUSION

In this study, the instantaneous variation of time-frequency features associated with the progression of muscle fatigue is analyzed. sEMG signals are recorded from the biceps brachii muscle during isometric contractions. The time-frequency spectrum is computed using EMBD kernel. The results show that EMBD based TFD is able to represent the nonstationary variations of sEMG signals. It is found that IMDF decreases and INSM increases with isometric muscle fatiguing contractions. Further, it is observed that the log INSM5 exhibits higher slope and is more sensitive for the analysis of muscle fatigue progression. Thus, it appears that this method could be useful to identify the onset of muscle fatigue in clinical conditions and myoelectric control.

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