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DETERMINATION OF EPOCH LENGTH AND REGRESSION MODEL FOR 15-SECOND SEGMENT OF sEMG SIGNAL USED IN JOINT ANALYSIS OF ELECTROMYOGRAPHY SPECTRUM AND AMPLITUDE

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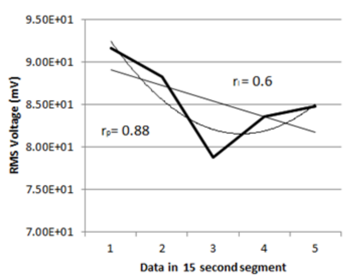
Graphical abstract



Abstract

Regression model is one of the techniques employed in Joint Analysis of Electromyography Spectrum and Amplitude (JASA) to investigate the behaviour of muscle fatigue indices. However, the analysis of the electromyography signal is influenced by the epoch length and regression model used. To meaningfully describe the behaviour of fatigue indices, this study was conducted to determine the appropriate epoch length and regression model for 15-second segment of electromyography signal. Ten subjects participated in this study. With their right forearm and upper arm formed an angle of 90 degree, the subjects were asked to hold a 2-kg dumbbell and stayed in that position for 2 minutes. Surface electromyography (sEMG) was used to record the signal from the biceps brachii muscle. Two fatigue indices were extracted: Root Mean Square (RMS) and Mean Frequency (MNF). The 120-second sEMG signal from each subject was then sliced into 8 segments (15 seconds each). In each segment, the effect of different epoch lengths (1-second, 3-second, and 5-second) was studied. Standard Error Estimate (SEE) was used to decide the suitable epoch length. The 3-second and 5-second epoch lengths were found to fit the regression model better (smaller SEE value). When 3-second and 5-second epoch lengths were applied in different regression models (linear and polynomial), polynomial regression was found to better estimate the behaviour of the fatigue indices (higher correlation coefficient). This study concludes that 3-second and 5-second epoch length can fit the polynomial regression well. However, fatigue behaviour (pattern of changes in fatigue indices) for every 15-second segment of sEMG signal is better described by JASA using polynomial regression with 3-second epoch length.

Keywords: Regression line, sEMG, epoch, muscle activity, isometric contraction, JASA

Abstrak

Model regresi adalah salah satu teknik yang digunakan dalam Analisis Bersama Spektrum dan Amplitud Electromiografi (JASA) untuk menyiasat tingkah laku indeks keletihan otot. Walau bagaimanapun, analisa isyarat electromiografi dipengaruhi oleh panjang epok dan model regresi yang digunakan. Untuk menerangkan tingkah laku indeks keletihan dengan lebih bermakna, kajian ini dilaksanakan dengan tujuan untuk menentukan panjang epok dan model regresi yang sesuai untuk 15-saat segmen isyarat electromyography. Sepuluh subjek telah mengambil bahagian dalam kajian ini. Dengan lengan kanan dan lengan atas membentuk sudut 90 darjah, subjek telah diminta untuk memegang 2-kg dumbel dan berada dalam kedudukan tersebut selama 2 minit. Electromiografi Permukaan (sEMG) telah digunakan untuk merekodkan isyarat otot *brachii* bisep. Dua indeks keletihan diekstrak: Punca-Min-Kuasa-Dua (RMS) dan Frekuensi Min (MNF). Isyarat sEMG selama 120 saat dari setiap subjek kemudian dihiris kepada 8 segmen (15 saat setiap satu). Dalam setiap segmen, kesan panjang epok yang berbeza (1-saat, 3-saat, dan 5-saat) telah dikaji. Aggar Ralat Piawai (SEE) telah digunakan untuk menentukan panjang epok yang sesuai. Panjang epok 3-saat dan 5-saat didapati memadani model regresi dengan lebih baik (nilai SEE yang rendah). Bila panjang epok 3-saat dan 5-saat digunakan dalam model regresi yang berbeza (linear dan polinomial), regresi polinomial didapati lebih baik dalam menganggarkan tingkah laku indeks keletihan (pekali sekaitan yang lebih tinggi). Kajian ini menyimpulkan bahawa panjang epok 3-saat dan 5-saat dapat memadani regresi polinomial dengan baik. Walau bagaimanapun, tingkah laku keletihan (corak perubahan indeks keletihan) untuk setiap segmen 15-saat dari isyarat sEMG boleh digambarkan dengan lebih baik oleh JASA menggunakan regresi polinomial dengan panjang epok 3-saat.

Kata kunci: Garisan regresi, sEMG epok, aktiviti otot, pengecutan isometri, JASA

1.0 INTRODUCTION

Muscle fatigue is known as a feeling of weakness or muscle pain or a reduction in muscle performance [1]. It describes the gradual decrease in muscle's ability to generate force, perform voluntary movements, or perform repetitive actions [2]. The reduction in muscle force can be monitored by analysing changes in electromyography activities. An electromyography (EMG) is a measurement of the electrical activity in muscles as a by-product of contraction. Fatigue is known to be reflected in the EMG signal as an increase of its amplitude and a decrease of its spectral characteristics [3].

Human muscles start experiencing fatigue during submaximal voluntary contraction [4]. The stimulation of motor neurons during muscle contraction induces the production of action potential [5]. The intensification of muscle contraction leads to the increase in action potential; thus, it increases the amplitude of the EMG signal [4]. However, once the muscle reaches the maximal voluntary contraction, the action potential declines and so as the amplitude of the EMG signal [4]. In frequency domain, changes in spectral parameters are related to the variation of velocity produced by the muscle fibre [2]. During submaximal voluntary contraction, muscle fibre conduction velocities tend to decrease; thus, causes the spectral parameters to shift to lower frequency [4].

The changes in both time and frequency domains had been used by Luttman *et al.* [6] to decide either the muscle had experienced fatigue or force changes. The method is called Joint Analysis of Electromyography Spectrum and Amplitude (JASA). In general, JASA method divides muscle activity into 4 regions: fatigue, overcome fatigue, force increase and force decrease [7], as summarized in Table 1.

It can be seen in Table 1 that muscle fatigue can be distinguished from muscle force based on the behaviour (changing pattern) of fatigue indices shown in the two domains: time-domain and frequency-domain.

Table 1 Regions of muscle activity based on JASA

Region	Trend of fatigue indices	
	Time Domain	**Frequency Domain**
Fatigue	Increase	Decrease
Overcome Fatigue	Decrease	Increase
Force Increase	Increase	Increase
Force Decrease	Decrease	Decrease

The muscle is considered as experiencing fatigue when fatigue indices in time domain show opposite trend (increasing or decreasing) to the fatigue indices in frequency domain. On the contrary, when fatigue indices in time-domain and frequency-domain show same trend, the muscle is classified as experiencing force changes.

The commonly extracted fatigue indices in time-domain as well as frequency-domain are listed in Table 2. Root Mean Square (RMS) and Average Rectified Values (ARV) are the commonly used amplitude-based fatigue indices in studying EMG signal inconsistency [6]. To describe the changes in frequency, Mean Frequency (MNF) and Median Frequency (MDF) are normally used. The reduction of muscle fibre velocity explains the decrement of MNF and MDF that are normally observed during fatigue condition [8, 9].

Regression model is one of the widely used techniques in trend analysis. In fatigue analysis, the goal is to discern whether the fatigue indicator has increased or decreased over time [10]. In regression analysis, the length of epoch influences the scattering of data which in turn affects the accuracy of the trend analysis [7, 11]. Epoch length used in muscle fatigue study ranges from 0.5 seconds to 5 seconds. Mesin *et al.* [1] used 0.5-second epoch length to determine the index value of muscle fatigue on peripheral muscle and muscle central. On

the other hand, Hendrix [12] used 5-second epoch length to determine muscle fatigue threshold.
To describe the behaviour of the fatigue indicators, linear and polynomial regression models are commonly used. Oliveira and Gonçalves [13] used linear regression model to determine the onset of muscle fatigue (fatigue threshold). In contrast, Potvin and Bent [14] applied polynomial regression model to observe the trend of the fatigue indicators during dynamic contraction.

The accuracy and strength of the trend analysis are normally described using Standard Error Estimate (SEE) and Correlation Coefficient (r) respectively [15,16]. These values (SEE and r) are used to reflect the influence of the data distribution and types of regression model in describing the behaviour of fatigue indices. The lower the SEE value, the nearer the distributed data to the regression line. Meanwhile, the closer the r-value to 1, the stronger the relationship between the fatigue index and the independent data.

The effect of epoch length and type of regression model on muscle fatigue study lead this research to determine the appropriate:

i. epoch length (1 second, 3 second or 5 second) for good distribution of surface EMG data in JASA
ii. regression model (linear or polynomial) to describe the behaviour of the fatigue indices.

2.0 METHODOLOGY

2.1 Participants

Ten college students (male = 5; female = 5) from Universiti Teknologi Malaysia (UTM) participated in this study. None of them have had muscle stiffness complaints. Their mean (± standard deviation) age, body mass, and height were 23.5 (± 1.3) years, 59.9 (± 8.3) kg, and 161.6 (± 7.68) cm, respectively.

2.2 Data Acquisition

The subjects were first told about the flow of the experiment. They were also asked to minimize their movement during the experiment to reduce noise.

Isometric contraction was the main task in this study. By locking the elbow in 90-degree position, the subjects were required to hold a 2-kg dumbbell for 2 minutes. Surface EMG (Neuro Prax System) was chosen to record the electrical signal of biceps brachii muscle activity. Surface EMG involves non-invasive process and is suitable to be applied on the subject's body [17]. Disposable electrodes which were affixed to the subject's skin were used in this study to capture the sEMG signal. The frequency of muscle signal ranges up to 500 Hz; thus, 1 kHz sampling frequency was applied in this study.

The captured raw signal required further processing. Off-line analysis was performed in laptop using Matlab software. At this stage, the unwanted signal (noise) was removed and the fatigue indices of interest were extracted.

2.3 Data Analysis

To produce a clean muscle signal, band-pass filter (cut-off frequencies of 30 Hz and 500Hz) was used to filter the noise and band-stop filter was applied to remove the 50 Hz line noise. Although the bandwidth of 30-300 Hz and 20-500 Hz were used by Danion [18] and Thongpanja [19] respectively, this study used 30 Hz low cut-off frequency to reduce the ECG interference [20] and 500 Hz high cut-off frequency to avoid the anti-aliasing within sampling [21]. Fatigue indices in both time and frequency domains were then extracted from the filtered signal.

RMS was the chosen fatigue index. To extract this time-domain parameter, the computation of the filtered signal's linear envelope was required. The Linear Envelope function processes the full wave rectified EMG signal with a low pass filter. Full wave rectification is the process used to convert the negative signal to positive value [21]. The rectification step is essential for getting the shape or "envelope" of the EMG signal. Then, the rectified signal was low-pass filtered by applying digital smoothing algorithms (suppressed high frequency components of the EMG signal by taking the mean value in a window) [21]. This results in an "envelope" representation of the data in the time domain which emulates the force development over time in the muscle. The application of this function was described in RMS equation as presented in Table 2.

To study the changing pattern in power spectrum of muscle signal, MNF was chosen as the fatigue index. MNF value was extracted from power spectrum density (PSD) using the periodgram in Welch's method and its criteria are summarized in Table 3. MNF in equation form is presented in Table 2.

During fatiguing contraction, the muscle response tends to decrease. Meanwhile, the blood flow would be occluded and recovered within 15 seconds [2]. Due to that reason, 15-second segment (eight slices) was selected in this study to analyze the muscle activity (fatigue or force changes) during the 120-second isometric contraction. The effect of three different epoch lengths (1-second, 3-second, and 5-second) was studied in each segment. Different epoch length produced different number of data for each studied fatigue index.

To save the processing time, overlap technique is normally avoided in any analysis that involved large segment of signal [3]; such as the one that was analysed in this study (15 seconds).

Table 2 Fatigue indices in time and frequency domains

Domain	Description	Index	Equation	Ref.
Time	Indices were extracted from raw EMG time series.	RMS	$RMS = \sqrt{\frac{1}{T}\int_0^T EMG(t)^2 dt}$	5, 8, 22
		ARV	$ARV = \frac{1}{T}\sum_{t=1}^{T} \lvert EMG(t)\rvert$	5, 8, 22
		IEMG	$IEMG = \sum_{t=1}^{T} \lvert EMG(t)\rvert$	22
Frequency	Indices were extracted based on the transformation of Power Spectrum Density (PSD)	MNF	$MNF = \frac{\int_0^{\frac{fs}{2}} f.PSD(f)df}{\int_0^{fs/2} PSD(f)df}$	5, 9,22
		MDF	$\int_0^{MDF} PSD(f)df = \int_{MDF}^{fs/2} PSD(f)df$	5, 9, 22

Suitable epoch lengths were selected based on the SEE value of each segment. Statistical t-test was also performed to evaluate the significance of the studied epoch lengths.

Table 3 The criteria for Welch's Method

Criteria	Description
Window	Hamming
Window Length	256
Overlap	25%

The suitable epoch lengths were then used to determine the appropriate regression model: linear or polynomial (2nd order was used as it is commonly used in the nonlinear study of the fatigue indices [23]). The value of correlation coefficient, r, was used to decide the appropriate regression model that best fit the distributed data in each 15-second segment. Table 4 summarizes the analysis performed in this study.

Table 4 Summary of the performed analysis

Objective	Variable	Evaluation Test	Statistical Test
Epoch Length	1-second (15 data) 3-second (5 data) 5-second (3 data)	SEE	t-test
Regression Model	Linear 2nd Order Polynomial	Correlation Coefficient	t-test

3.0 RESULTS AND DISCUSSION

3.1 Epoch Length

Figure 1(a) and (b) show SEE values of each 15-second segment that were produced from the filtered sEMG signal for one subject and Figure 1 (c and d) show the average of SEE values for each subject. It can be seen that in each segment, the SEE values were highest in 1-second epoch length followed by 3-second and 5-second epoch lengths. In general, the lower the SEE value the better the data would fit in the regression model.

SEE values are dependent on the number of data. In this study, for each 15-second segment, the three studied epoch length produced different number of data. According to Burning and Kintz [24], the number of data during the plotting process affects the accuracy of regression analysis. Generally, higher number of data produces larger error when estimating the regression model.

When performing t-test, SEE values for 1-second epoch length were found to be significantly different ($p < 0.05$) from the 3-second and 5-second epoch lengths. However, less than 50% of SEE values between the 3-second and 5-second epoch lengths (30% for RMS; 40% for MNF) were observed to differ significantly.

3.2 Type of Regression Model

The strength of the observed trend is described by the correlation coefficient (r) value; the closer the r-value to 1, the better. Figure 2 shows a sample of r-values obtained from linear and polynomial regression models.

The comparison of the r values between linear and polynomial models for one subject is tabulated in Table 5. Table 6 compares the average of r-values between the two regression models for all subjects. The fluctuations of data in each fatigue index obviously affect the selection of regression model. Both tables indicate that the polynomial model was more suitable to be applied on fluctuating data compared to linear model; r-values are closer to 1. The r-values for polynomial model were also found to be significantly different ($p < 0.05$) from the r-values for linear model. This finding indicates that the data for the muscle fatigue indices were not normally distributed [14] with respect to time.

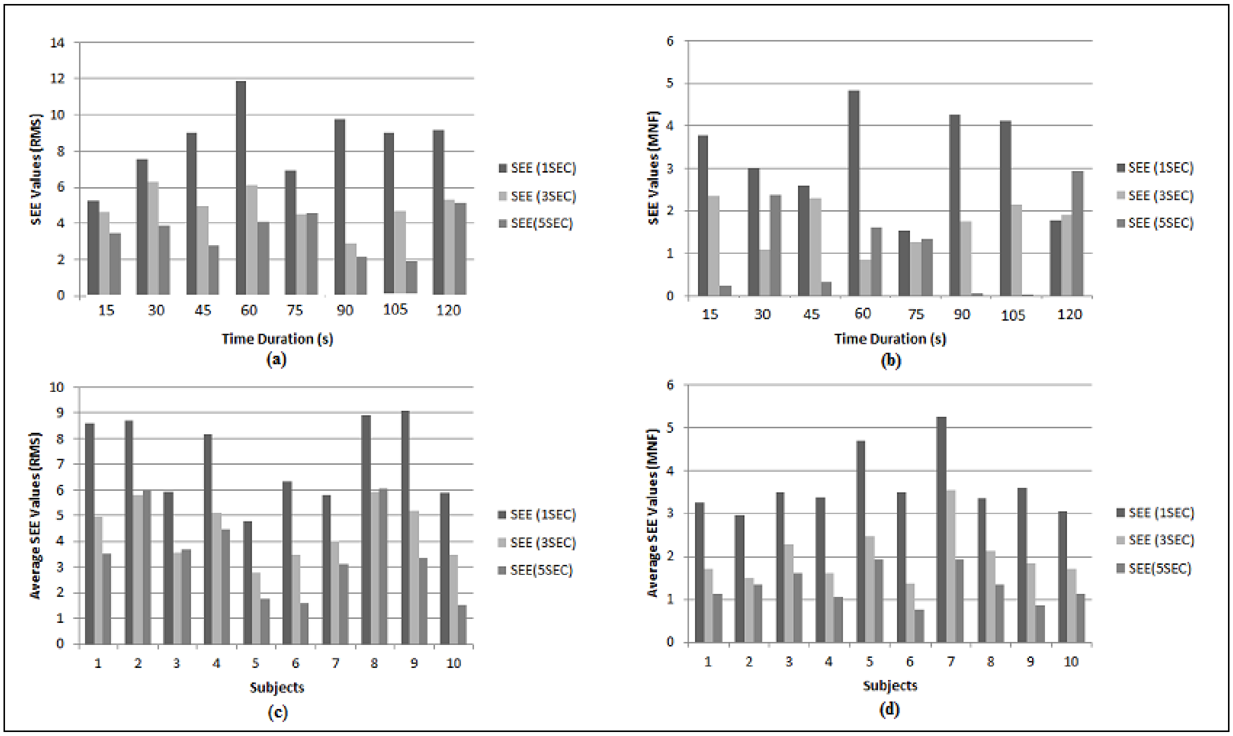


Figure 1 (a) SEE value for RMS (one subject), (b) SEE value for MNF (one subject), (c) Average SEE values for RMS (all subjects), (d) Average SEE values for MNF (all subjects)

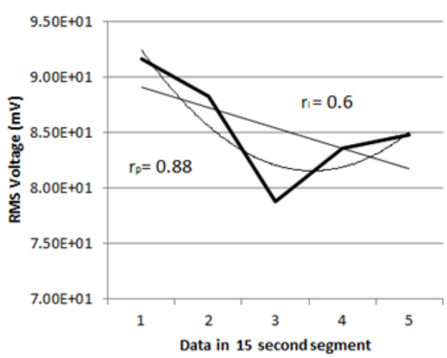


Figure 2 The graph of RMS value using linear and polynomial regression models

The relationships between muscle force-time, muscle length-tension, and muscle load-velocity have been manifested in non-linear distribution [23]. This explains why the linear model was not appropriate to be applied when analysing the muscle performance.

3.3 The Combination of Epoch Length and Regression Model

The appropriate selection of epoch length and type of regression model are essential in JASA. Therefore, the effects of 3-second and 5-second epoch length on polynomial model was compared (Table 7). The 3-second epoch length produced variations of r-values as compared to the 5-second epoch length that only produced unity r. Similar pattern was observed in r-values for MNF. Even though r = 1 indicates the best estimate of trend, the quantity of data in 5-second epoch length restricts the description on the behaviour of the fatigue indicators; only three data in a segment. Since SEE values between 3-second and 5-second epoch length were not significantly different, 3-second epoch length was decided to be more appropriate to be paired with the 2nd order polynomial regression to describe the behaviour of fatigue indices in 15-second segment of sEMG signal.

Table 5 The r-values for RMS and MNF (1 subject)

Fatigue Index	Regression Model	Segment							
		1	2	3	4	5	6	7	8
RMS	Simple	0.37	0.85	0.73	0.30	0.60	0.65	0.09	0.35
	Polynomial	0.84	0.85	0.84	0.69	0.88	0.65	0.62	0.49
MNF	Simple	0.32	0.89	0.35	0.33	0.01	0.81	0.03	0.37
	Polynomial	0.32	0.94	0.41	0.40	0.10	0.92	0.20	0.56

Table 6 The average of r-values for RMS and MNF (10 subjects)

Fatigue Index	Regression Model	Subject									
		1	2	3	4	5	6	7	8	9	10
RMS	Simple	0.49	0.55	0.55	0.37	0.63	0.55	0.40	0.51	0.41	0.35
	Polynomial	0.73	0.79	0.79	0.72	0.76	0.75	0.78	0.75	0.53	0.66
MNF	Simple	0.39	0.53	0.37	0.49	0.51	0.52	0.31	0.39	0.37	0.37
	Polynomial	0.48	0.69	0.58	0.73	0.67	0.63	0.63	0.62	0.55	0.73

Table 7 The r-values (polynomial regression) for all subjects and segments (RMS parameters)

Subject		1		2		3		4		5		6		7		8		9		10	
Epoch Length (second)		3	5	3	5	3	5	3	5	3	5	3	5	3	5	3	5	3	5	3	5
15-second SEGMENT	1	0.84	1	0.90	1	0.97	1	0.76	1	0.41	1	0.66	1	0.88	1	0.93	1	0.96	1	0.57	1
	2	0.85	1	0.95	1	0.87	1	0.84	1	0.82	1	0.76	1	0.99	1	0.84	1	0.88	1	0.91	1
	3	0.84	1	0.95	1	0.75	1	0.69	1	0.52	1	0.82	1	0.26	1	0.61	1	0.50	1	0.66	1
	4	0.69	1	0.94	1	0.30	1	0.79	1	0.96	1	0.79	1	0.39	1	0.39	1	0.58	1	0.86	1
	5	0.88	1	0.73	1	0.85	1	0.88	1	0.86	1	0.89	1	0.22	1	0.56	1	0.89	1	0.73	1
	6	0.65	1	0.69	1	0.79	1	0.69	1	0.89	1	0.66	1	0.22	1	0.86	1	0.70	1	0.64	1
	7	0.62	1	0.96	1	0.98	1	0.10	1	0.96	1	0.44	1	0.88	1	0.91	1	0.79	1	0.69	1
	8	0.49	1	0.22	1	0.84	1	0.99	1	0.62	1	0.30	1	0.35	1	0.91	1	0.91	1	0.91	1

4.0 CONCLUSION

The appropriate use of epoch length and regression model in JASA is important. The application of 3-second and 5-second epoch lengths produces better accuracy in regression analysis than the 1-second epoch length. The polynomial regression model describes the behaviour of the fatigue indicators better than the linear model. However, due to the higher number of data, behaviour of fatigue indicator in every 15-second segment of sEMG signal is better described by JASA using polynomial regression with 3-second epoch length.

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