Auto-Segmentation Analysis of EMG Signal for Lifting Muscle Contraction Activities

E.F. Shair[1,2], A.R. Abdullah[1], T.N.S. Tengku Zawawi[1], S.A. Ahmad[2] , S. Mohamad Saleh[1]
[1]*Faculty of Electrical Engineering, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia.*
[2]*Department of Electrical and Electronics, Faculty of Engineering, Universiti Putra Malaysia, 43400 UPM Serdang, Selangor, Malaysia.*
ezreen@utem.edu.my

***Abstract*—Time-frequency representation of a signal has been widely used in various research areas to analyze non-stationary signals (ie. electromyography (EMG) signals). However, due to the high computational complexity of certain time-frequency distribution techniques, the application of these techniques in the analysis of long duration EMG signals is not suitable. To overcome this problem, muscle contraction segmentation is essential to process the existed EMG signals, since not all of the EMG signal contains valid information to be analyzed. Thus, this paper presents an algorithm to automatically detect and segment the muscle contractions existed in EMG signal during long duration recordings. Surface EMG signals were collected from biceps branchii muscle of ten subjects during manual lifting. Subjects were required to lift a 5 kg load mass with lifting height of 75 cm until experiencing fatigue. The utilization of instantaneous energy of EMG is used to estimate the presence of first muscle contraction, second muscle contraction and until the last muscle contraction. This instantaneous energy is obtained from spectrogram and a threshold value is set to differentiate between muscle contractions and noise. This research shows that the algorithm is able to automatically segment muscle contractions in EMG signal based on the signal instantaneous energy.**

***Index Terms*— Manual Lifting; Spectrogram; Segmentation; Instantaneous Energy; Electromyography.**

I. Introduction

Electromyography (EMG) signal is a measure of the electrical activity in human body produced by skeletal muscles [1]. There are two kinds of EMG signals; surface EMG (sEMG) and intramuscular EMG (imEMG) [2]. For research purposes, sEMG has been the preferred method by past researches due to its non-invasive properties; easy to apply and free from pain [3].

The processing of the signals are essential to analyzed and detect any medical abnormalities, activation level or to analyze the biomechanics of human movement. Common application of EMG signals is in the area of muscle fatigue estimation, where it is define as a progressive decline of the muscles performance during long period of time [4]. Bio-signal processing is a critical part in biomedical engineering in order to classify the time and frequency content of a signal thus represents the muscle condition and helps to detect and monitor fatigue development. One of the problem arises from this research is cause by the high computational complexity of time-frequency distribution (TFD) techniques to analyze the signal especially in dealing with long recordings of EMG signals [5].

To solve this problem, data segmentation is required to segment and separate valid muscle contraction signals from the baseline and noise as in figure 1. This helps to limit and reduce the computational burden and time.

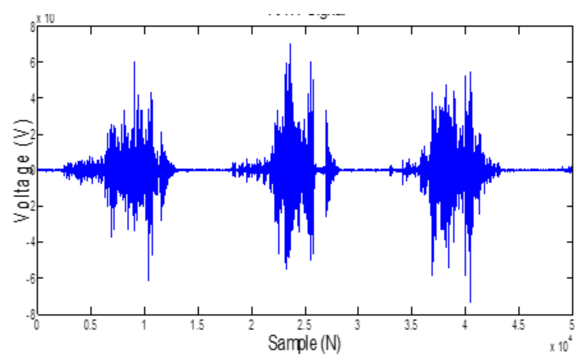

Figure 1: Example of a raw EMG signal

EMG signal consists of two main components, which are muscle activation and baseline. The component with the fatigue information in it is the muscle activation only, and this is the important signal to be analyzed. Some research has been done to segment muscle contraction based on either time or frequency domain [6], [7]. These methods fail to accurately segment the signals due to the nature of the signal itself, where in time domain the statistical properties changes over time and the signal is assumed as a stationary signal, whereas the limitation of spectral analysis is that it cannot provide simultaneous time and frequency localization of the EMG signal.

Since EMG is a non-stationary signal that varies with time, instantaneous energy is proposed to characterize the temporal behavior of the signal. This instantaneous energy is obtained from the time-frequency representation (TFR) produced by spectrogram.

II. Experimental Setup

A. Subjects

Ten volunteers (5 men and 5 women) in healthy condition were used as subjects in the study. The subjects aged were between 21 to 25 years (mean ± S.D.: 23 ± 1.633) and all were right handed, with no history of musculoskeletal injuries. Table 1 shows the complete demographic data of the subjects.

Table 1
The subjects' demographic data

Criteria	Minimum	Mean	Maximum
Age (year)	21	23	25
Body mass (kg)	48	61.5	75
Body height (cm)	156	163	170

B. Data Acquisition

This study focuses on the right biceps branchii muscle and the subjects were required to do manual lifting task with different lifting height. sEMG signals are sampled at 1500 Hz and filtered by a low pass filter with the range of 0-500 Hz using surface EMG (TeleMyo 2400T G2, Noraxon, USA) and MyoResearch XP Master Software (Noraxon, USA). The procedure for surface electrode placement follows the Non-Invasive Assessment of Muscle (SENIAM) guideline to obtain maximum pickup area of the EMG signals and to ensure signals obtained from each subject is stable [8]. Figure 2 is the surface EMG electrodes attached at the biceps branchii label as input (A) and reference electrode location (B).

Figure 2: Surface EMG electrode's placement at the right biceps.

The muscle area was prepared by cleansing the skin surface using BD Alcohol Swabs of 70% Isorophyl Alcohol, and leave to dry before rubbing with the Signa Gel, 250g tube which is highly conductive before attaching Ag/AgCl electrodes (diameter 10mm).

C. Lifting Tasks

sEMG data were then recorded during manual lifting task with 5 kg load mass and 75 cm of lifting height. The starting standing position of the subjects are 0° in front of the shelf. They were required to lift the load onto the shelf repetitively until experiencing fatigue muscle. This is when the simulation time stopped. Each lifting produced muscle contractions, and each contraction signal was divided into four phases as in the Figure 3. Details for the phases are shown as follows:

Phase 1: Subject takes the load
Phase 2: Traveling the load onto the shelf
Phase 3: Place the load onto the shelf
Phase 4: Release the load

Figure 3: Four phases involved in each lifting for 75cm lifting height

III. Segmentation Analysis Technique

Raw data of the EMG signals are post-processed using a new algorithm to produce time-frequency representation (TFR) and instantaneous energy using spectrogram. Hanning window of 1024 is used to analyze the EMG signal since it produces the best result in terms of resolution. The work carried out to determine the best window size has been reported in [9] and will not be further discussed.

The instantaneous energy are basically used to provide auto-segmentation of the muscle contraction in the EMG signal before proceeding to the next part of the research which is fatigue muscle identification based on instantaneous RMS voltage, Vrms(t). This part is already explained in [10].

A. Spectrogram

Spectrogram is one of the TFR that represents the three dimensional of the signal with respect to time and frequency in magnitude. The FFT have the limitation, which is not able to cater non-stationary signal whose spectral characteristic changes in time and frequency. It is the result of calculating the frequency spectrum of window frames of compound signal and provides high frequency resolution [9], [11], [12]. Spectrogram is the squared magnitude of the short time Fourier transform (STFT) and can be expressed as Equation (1) below:

$$S_x(t,f) = \left| \int_{-\infty}^{\infty} x(\tau) w(\tau - t) e^{-2\pi f \tau} \right|^2 d\tau \qquad (1)$$

where $x(\tau)$ is the input and $w(t)$ is the observation window. Hanning window is used because it has lower peak side slope suitable for this task.

B. Instantaneous Energy

Instantaneous energy has been used in various disciplines of research particularly for non-linear dynamic signals such as bio signals. The used of instantaneous energy in analyzing bio signals specifically electrocardiogram (ECG) signal has been studied by [13]. Instantaneous energy is estimated from the TFR to identify the characteristics of EMG signal. Formula for instantaneous energy can be defined as the integration of TFR from $f = 0$ to maximum frequency as shown in Equation (2).

$$E(t) = \int_{f=0}^{f_{max}} S_x(t,f)df \qquad (2)$$

where $S_x(t,f)$ is the TFR of the signal and f_{max} is the maximum frequency.

C. Thresholding

Since segmentation involves separating a signal into regions corresponding to the signal properties, the difference in the signal instantaneous energy holds a good measure to distinguish between the object of interest (muscle activation) and the rest (baseline and noise). This latter group is also referred to as the background. A simple way to segment such regions is through thresholding technique, the separation between muscle activation and the baseline plus noise.

Thresholding creates binary number by turning all values below a certain threshold to zero and all values above the threshold to one.

If $M(t)$ is the thresholded version of $IE(t)$ at some global threshold E_{thres},

$$M(t) = \begin{cases} 1 & if\ E(t) \geq E_{thres} \\ 0 & otherwise \end{cases} \qquad (3)$$

where $E(t)$ is the instantaneous energy.

From the thresholded instantaneous energy, the segmented raw signal can be obtain as:

$$x_s(t) = x(t) \cdot M(t) \qquad (4)$$

where $x_s(t)$ is the segmented raw signal.

An important thing when deals with thresholding, to set the threshold value, parallel diagram of the raw signal and the instantaneous energy are referred to see if two or more distinct modes can be identified. Different threshold values may result in losing too much of the muscle activation signal or sometimes getting too many extraneous signals (baseline and noise).

IV. Results And Discussion

The algorithm is applied to the raw EMG signal in figure 6(a). It consists of 36 lifting repetitions before experiencing muscle fatigue. The raw data is in time domain and spectrogram is used to obtain the time-frequency representation (TFR) of the signal (Figure 6(b)). The instantaneous energy in figure 6(c) are calculated based on the overall TFR. Instantaneous energy is due to the energy transfer from the body during the contraction of muscle activity. The maximum instantaneous energy produced is 6.42×10^{-5} J and the minimum is 1.59×10^{-5} J. A threshold value of 0.5×10^{-7} is set to the instantaneous energy to produce the activation intervals for each muscle contraction (Figure 6(d)). Values above the threshold are represented as 1, while values below the threshold are represented as 0. The red dotted lines in figure 6 is to show that the instantaneous energy parameter able to accurately identify the muscle contraction and separates it from the baseline.

From the RAW signal, segmented data are analyze one by one to transform the data from time to frequency domain through FFT and then analyzed by using spectrogram before represents it in instantaneous RMS voltage, $V_{rms}(t)$ to obtain the information of fatigue muscle and pattern of the signal.

However, the calculation and analysis of the $V_{rms}(t)$ is not included in this paper as it already been discussed in [10]. Figure 4(a) shows the overall raw EMG signal for the whole 36 lifting repetitions that spread from 0 sample through 5.5×10^5 samples. The result of the auto-segmentation process leads to the signal in Figure 4(b), which shows the graphical view of the first muscle contraction (0 to 10800 samples).

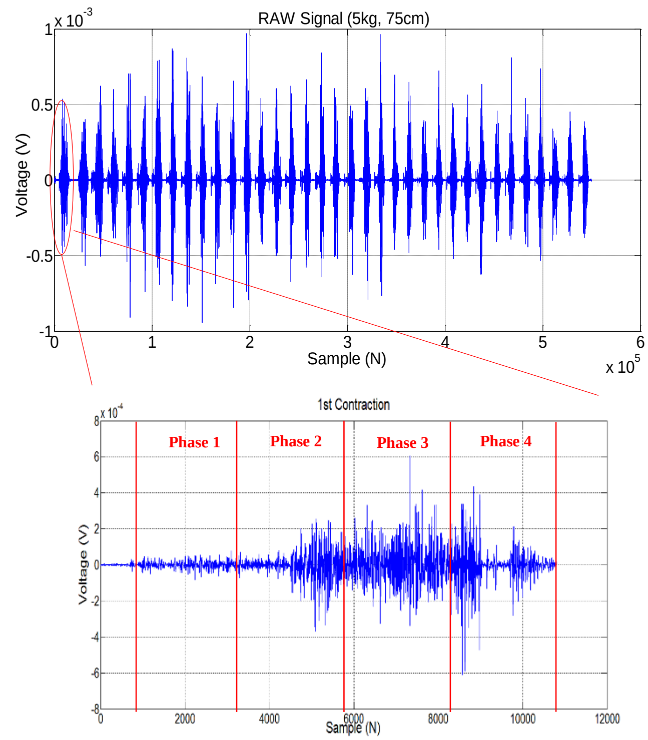

Figure 4: (a) Overall raw EMG signal. (b) Raw EMG signal of the first muscle contraction

It can be seen that each muscle contraction can be retrieve without losing any of the important information. The first muscle contraction represents all of the four lifting phases for the first repetition.

TFR of the first muscle contraction is shown in figure 5. Since the amplitudes of the signal are represented in colours (blue –low amplitude, red – high amplitude), the peak of the signal can be easily distinguished. From the TFR, $V_{rms}(t)$ is then calculated for each contraction and the average $V_{rms}(t)$ represents as a reliable fatigue indices. Detailed explanations of this fatigue indices can be referred from the previous paper, as this study only focuses on the development of an auto-segmentation algorithm.

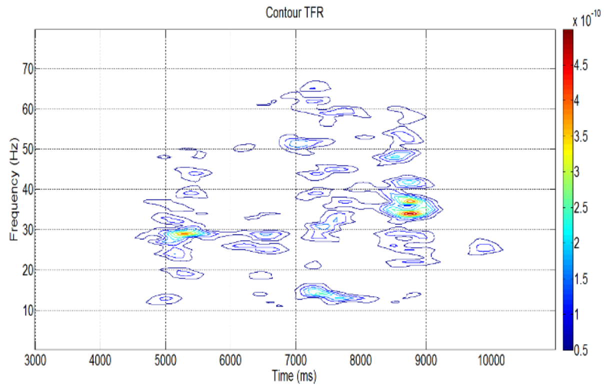

Figure 5: TFR of the first muscle contraction by using spectrogram

A. *Performance measurement*

In order to assess accuracy of the simulation results, mean absolute percentage error (MAPE) was used as index. Smaller value of MAPE offers more accurate results. It can be define as:

$$MAPE = \frac{1}{N}\sum_{n-1}^{N}\left|\frac{x_i(n) - x_m(n)}{x_i(n)}\right| x100\% \qquad (5)$$

where $x_i(n)$ is actual value, $x_m(n)$ is measured value and N is number of data.

The duration for the actual muscle contraction from n = 1 until n = 36 are measured and compared with the duration of the segmented muscle contraction. The MAPE of the analysis is important to determine the performance of the segmentation process, thus provide an important measure when compared with others segmentation techniques. The performance measures based on MAPE can be classified into 4 types as follows:

Table 2
MAPE performance measures [14]

MAPE values	Performance Measures
< 10%	Excellent
10 – 20%	Good
20 – 50%	Acceptable
> 50%	Unacceptable

Table 3 shows the comparison between the actual signal and segmented signal. From the analysis, MAPE obtained is 1.404% which is considered as excellent performance based on Table 2.

V. Conclusions

Instantaneous energy is proposed as a new technique to automatically segment EMG signal. Investigation of the biceps branchii muscle from 10 subjects shows that instantaneous energy has a distinct pattern to differentiate between muscle activation and baseline. This important finding is expected to help reduce the computational burden in the analysis of TFD for long duration of EMG signal recordings.

Table 3
Comparison performances between actual signal and segmented signal

No. of muscle contraction	Actual Duration (seconds)	Segmented signal duration (seconds)	Absolute percent error (%)
1	7.032	7.197	2.346
2	6.842	6.970	1.871
3	6.853	6.950	1.415
4	5.065	5.176	2.192
5	5.301	5.317	0.302
6	5.322	5.359	0.695
7	5.458	5.569	2.034
8	5.691	5.781	1.581
9	5.394	5.425	0.575
10	4.451	4.477	0.584
11	4.570	4.658	1.926
12	5.350	5.478	2.393
13	5.832	5.990	2.709
14	4.586	4.604	0.392
15	5.260	5.279	0.361
16	5.650	5.767	2.071
17	5.101	5.117	0.314
18	5.150	5.188	0.738
19	5.296	5.393	1.832
20	5.692	5.727	0.615
21	5.780	5.827	0.813
22	5.820	5.849	0.498
23	5.503	5.639	2.471
24	5.430	5.487	1.050
25	7.032	7.156	1.763
26	5.380	5.443	1.171
27	5.614	5.649	0.623
28	5.680	5.795	2.025
29	6.060	6.192	2.178
30	4.889	4.975	1.759
31	4.870	4.885	0.308
32	5.190	5.361	3.295
33	4.620	4.695	1.623
34	4.370	4.497	2.906
35	6.010	6.009	0.017
36	6.182	6.249	1.084

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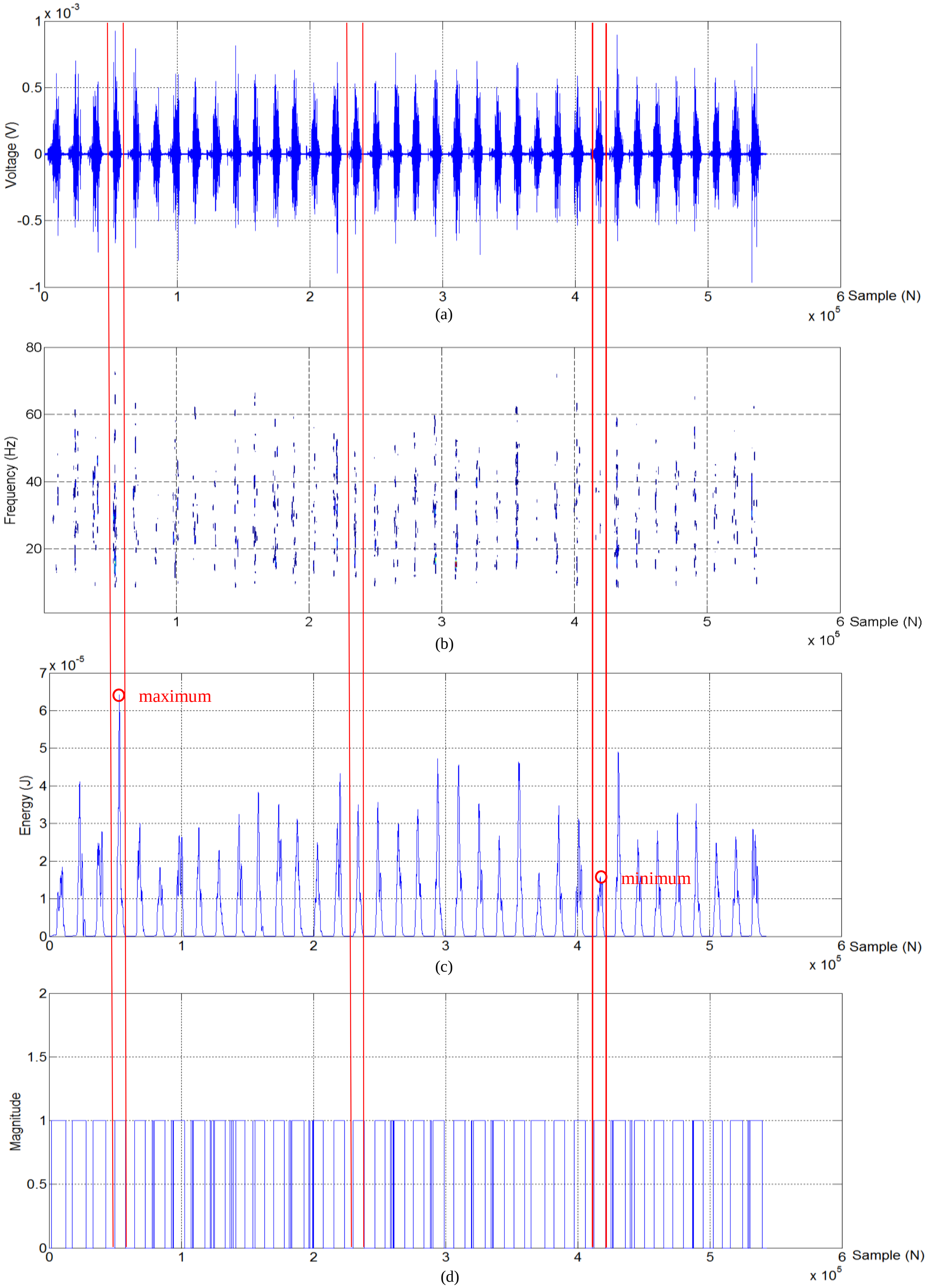

Figure 6: (a) The raw sEMG signal obtained from biceps branchii during manual lifting. (b) The time-frequency representation of the overall signal. (c) The instantaneous energy for each muscle contraction. (d) Activation intervals for each muscle contraction obtained using the threshold calculation.

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