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The Best Window Selection of Electromyography Signal during Riding Motorcycle using Spectrogram

Tengku Nor Shuhada Tengku Zawawi [1], Abdul Rahim Abdullah[2], Norhashimah Mohd Saad*[3], Rubita Sudirman [4], Helmi Rashid[5]

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Abstract: Electromyography (EMG) signals are widely used as an important tool which helps to understand human activities. However, EMG signal has the complexity of random signals, highly nonlinear, non-stationary, and multi-frequency properties. Previous researchers have applied the time domain and frequency domain, but it lacks either time or frequency information, thus time-frequency distribution (TFD) such as Spectrogram is suitable and widely used in extracting EMG signals. However, this method using Hanning Window is a fixed window that compromises between time and frequency resolution. Some researchers used time window selection in their research, however, there are no standard guidelines for determining window selection for all EMG signals. Thus, this paper has presented the guidelines for determining the best window size for EMG signal while riding a motorcycle using Spectrogram. There are eight muscles for left and right from four types of muscles group which are Extensor Carpi Radialis, Trapezius, Erector Spinae, and Latissimus Dorsi. Six window sizes of 128, 256, 512, 1024, 2048 and 4096 ms are selected to determine the best size window to be used for the future analysis of the EMG signal. Machine Learning of SVM is used for confirmation performance evaluation for the best window size as the highest accuracy results. The results have proved window size 1024 is the best window size for EMG signal for riding a motorcycle. From this finding, the future analysis of this signal will use this size window when involving Spectrogram method.in the future.

Keywords: *Electromyography (EMG), Time-frequency Distribution (TFD), Spectrogram, Window Selection, Support Vector Machine (SVM)*

1. Introduction

The use of motorcycles is highly relevant in daily activities like transportation, mobility, business, and sports. Compared to drivers of cars, riders on motorcycles are relatively more at risk from a sedentary posture [1]. The constant use of a motorcycle increases the risk of musculoskeletal disorders in riders, including disc dislocation, lower back pain, and spine injury [2]. Due to a variety of factors, such as socioeconomic situations and work-related factors, stress, and exhaustion play a significant role in the cause of motorcycle accidents in developing nations.

Health is becoming a more important topic of discussion, and biosensors for basic health management are becoming more popular. Health monitoring is made more practical by the development of biosensors in wearable forms, which may be used both in hospitals and in normal life. Electromyography (EMG) is one of the most significant and effective methods for assessing the state of muscle activity [3]. EMG signals provide access to the muscular actions. The muscular activity measurement must adhere to the European Standards for (SENIAM). Muscle contractions performed by a rider during riding a motorcycle are non-stationarity and must be considered to assess the functionality of the muscles involved properly [4]. These signals, however, are complicated, multicomponent, and very nonstationary with significant intersubject variability, especially during dynamic contractions.

Many techniques were present by various researchers for features extraction and classifying of biomedical signals. There are some techniques used in analysis of EMG signal which are time domain, frequency domain and time-frequency domain. Fast Fourier Transform (FFT) from frequency domain analysis is the most used methodology in signal processing for signal analysis, although it is limited in its ability to handle non-stationary signals with fluctuating frequency and amplitude, such as EMG data [5]. These properties of EMG signals have made them relatively difficult to extract. It also have the limitation when EMG signal had adjust the muscle force, length and contraction speed with time [6]. To overcome this issue, Dennies Gabor have adjusted Fourier analysis into a small interval called

1PhD Student, Faculty of Electrical Engineering, Universiti Teknikal Malaysia Melaka (UTeM), 71600 Durian Tunggal, Melaka, Malaysia. Email: tgnorshuhadatgzawawi@gmail.com

2Assoc. Professor, Faculty of Electrical Engineering, Universiti Teknikal Malaysia Melaka (UTeM), 71600 Durian Tunggal, Melaka, Malaysia. Email: abdulr@utem.edu.my

3Senior Lecturer, Department of Electronics and Computer Engineering, Faculty of Electrical and Electronic Engineering, Universiti Teknikal Malaysia Melaka, Malaysia. Email: norhashimah@utem.edu.my

4.Professor, Director, Department of Electronics and Computer Engineering (ECE), Faculty of Electrical Engineering, Universiti Teknologi Malaysia, Skudai,Johor, Malaysia. Email: rubita@utm.my

5Senior Lecturer, School of Mechanical Engineering, Faculty of Engineering, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia. Email: helmi_rashid@uitm.edu.my

** Corresponding Author Email: norhashimah@utem.edu.my*

Short-time Fourier Transform (STFT) from linear time-frequency distribution (TFD) before produced Spectrogram analysis which is more obtain the power distribution and energy distribution of the signal along the frequency direction at a given time [7]. However, the window size used is fixed for all frequency and is compromising between time and frequency resolution [8]. This window selection is very important to provide the higher accuracy result for EMG signal analysis. There are some researhers have presented window selection for their research, however, this window selection don't have the standard criteria for determining the best window size [9]. Thus, it is important for this reseach for find the best window size for riding motorcycle for the future analysis in this reseach.

From the previous study of EMG signal analysis for during riding motorcycle, most of the researchers used statistical analysis involving ergonomics [1], [10], and it is not very detail in EMG signal processing [11].

2. Research Method

In the research method, there are some parts of framework for the data collection and analysis of EMG Signal. It is start with the collaboration between Advanced Digital Signal Processing (ADSP) Laboratory Faculty of Electrical Engineering, UTeM, Melaka and Motorcycle Engineering Technology Laboratory (METAL) at the Faculty of Mechanical Engineering, Universiti Teknologi MARA (UiTM) Shah Alam, Selangor. Prior to this study, an ethics approval application was submitted to the Research Ethics Committee of the Research Management Institute (RMI), Universiti Teknologi MARA on August 20, 2013 with the project entitled 'Motorcyclist Muscle Fatigue Index Awareness and Prevention Analysis Support System in Prolonged Riding'[12].

2.1. Flow of the Research

Spectrogram is one of the linear TFD approaches that can extract features more accurately during the analysis process. Figure 1 shows the overall results of spectrogram analysis to pattern and recognition of types of muscular fatigue utilising muscle fatigue features indicator. From this figure, there are some processes that should be performed to pattern and recognise the features to differentiate the types of muscle fatigue which are window selection to find the best window size to the fixed Hanning Window of spectrogram method. Then some time-frequency representation of muscle fatigue indicator's features is measures, from this measurement. This feature is indicated for muscle fatigue onset. Time to muscle is measured. However, this paper is focused on window selection parts.

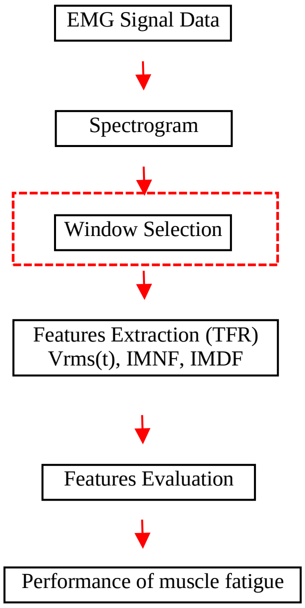

Fig. 1. Flow diagram of the Research

2.2. Sources of Data Collection

The data used in this study is the secondary data obtain from METAL Laboratory. Initially named as the Motorcycle

Ergonomics Test Lab, the research scope was broadened beyond Postura MotergoTM motorcycle simulator facility including the Myon 320 wireless sEMG system and several other monitoring devices as Figure 2.

(a) (b)

Fig. 2. Experiment (a) Collecting data and (b) Simulator riding motorcycle

2.3. Respondents

Specific inclusion criteria, such as information on rider deaths based on literature, gender, age, riding experience, license possession, 6-month accident-free record, and a healthy body with a normal (BMI), were used to select a group of motorcyclist responses. Due to the gender and age requirements, only male motorcyclists between the ages of 23 and 25 were included in the study.

According to the study, motorbike fatalities are most common in this group. The participants also required a minimum B2 motorcycle license and one year of riding experience to be qualified for the evaluation. The criteria for a healthy body with a normal BMI and a six-month accident-free history was implemented to make sure that the motorcyclist's crucial muscle groups weren't harmed or scarred, as this could affect surface electromyography (sEMG) outcomes during evaluations.

Table 1. Summary of the Demographic Data of the Respondents

Number of Respondents	24
Age	23-25 years old
Gender	24 males
Height (mean)	171.38 cm
Weight (mean)	70.6 kg
Body mass index (BMI) (mean)	23.76
Body mass index (BMI)	
Underweight - <18.5	
Normal Weight -18.5 - 24.9	17 respondents
Overweight - 25.0 - 29.9	7 respondents
Obese - > 30.0	

2.4. Electrode Placement

There are four types of muscle groups used in riding motorcycle which are Extensor Carpi Radialis, Trapezius, Erector Spinae and Latissimus Dorsi for the left and right to become eight types of muscles. Figure 3 shows the position of electrodes placement to participated in riding motorcycle's experiments.

Fig. 3. A Motorcyclist Respondent being fixed with sEMG Electrodes and Transmitter [12]

2.5. Interfacing EMG Signal and Software

The software used to record muscle activities of the motorcyclist respondents for the prolonged motorcycle riding simulations was the same one used in the earlier pilot on-road motorcycle riding experiment. Hence the software setup was saved and reused in subsequent assessments but with prior test carried out on the signals' synchronization between the Myon sEMG transmitters and the receiver as shown in Figure 4. The test served to identify malfunctioning transmitters which may be due to weak battery or problems with electrode connection. Faulty transmitters were replaced. Since there were 16 transmitters in total, only eight were used for the four bilateral muscle groups in the simulation session.

Fig. 4. Interfacing process between EMG sensor and Myon sEMG software [12]

2.6. Analysis Method Spectrogram

In this article, the time-frequency distribution (TFR), a three-dimensional representation of the signal energy with respect to time and frequency derived from the linear TFD, is used. Compared to FFT, it provides clearer information. Electromyography (EMG) signals are one type of signal that can have features extracted for further analysis using an appropriate frequency [13].

This method illustrates frequency content changes over time in general terms. Greater time resolution is produced when the window size is smaller, but frequency resolution is decreased. Window effect is to reason for this. Since the window width was kept constant, all frequencies have fixed frequency and time resolution. [14]. The algorithm of spectrogram is as follow:

$$S_x(t,f) = \left|\int_{-\infty}^{\infty} h(\tau) w(\tau - t) e^{-j2\pi f\tau} d\tau\right|^2 \qquad (1)$$

where h(τ) is the input and w(t) are the observation window. As a result of its decreased peak side slope, the Hanning window is used in this research method.

2.6.1. Window Selection

The horizontal axis (y-axis) displays the frequency resolution, while the vertical axis (x-axis) displays the time resolution. In this study, the size window values of 128, 256, 512, 1024, 2048, and 4096 are used to test the linear TFD approach. The optimum value of good time-frequency resolution is tested to choose the best window size to use for the analysis of EMG signal. The equation from (2) to (5) is used to calculate the frequency resolution (Fr) and time resolution (Tr) of the time-frequency resolution (TFR).

$$F_r = \frac{F_s}{N_w} \qquad (2)$$

$$T_r = \frac{1}{F_r} \qquad (3)$$

where N_w is the window length, and F_s is the sampling frequency.

The relation between F_r and T_r is based on the certain criteria to fulfill as the best window size recognition as (2) and (3)

$$F_r \leq f_{min} \quad (4)$$

where f_{min} and T_r must be smaller than 1s to recognise the flow each time interval. Based on (5), the window sizes that were chosen for the window selection process were 128, 256, 512, 1024, 2048, and 4096. The time resolution and frequency resolution will have a direct impact on each window's size as in (2) through (4).

$$N_w = 2^n \quad (5)$$

where N_w is for size window and ^{n} is any real number based on Nyquist Theorem.

Instantaneous RMS Voltage is a parameter that computes the value of RMS voltage at a specific moment of time as shown in (6):

$$\mathrm{Vrms(t)} = \sqrt{\int_0^{\mathrm{fmax}} \mathrm{S(t,f)dt}} \quad (6)$$

where $S(t,f)$ is the time-frequency distribution and f_{max} is the maximum frequency of interest. This parameter is used to choose the most suitable window size for the best EMG signal flow to prevent either too general or too much ripple for signal characteristics that make the signal interpretation more challenging to understand. Support Vector Machine (SVM) is used for performance evaluation of window size with measure the accuracy of classification process for each size window. The highest is chosen.

3. Result and Discussion

To obtain parametric characteristics from TFR with high performance of assessment and to improve the analysis of the EMG signal, a spectrogram is used to determine the optimal size window length to be used in the following analysis. The best size window for EMG data from prolonged motorcycle riding must be chosen for this technique to obtain the best analysis results [15]. For each of the time intervals T1 to T24, there are 300 seconds (600,000 samples). To reach 2 hours (120 minutes) of motorcycle riding, which is regarded as prolonged riding for 'kapcai' motorcycles, it took 5 minutes out of each time interval.

The window size selection will affect the appearance of the signal in terms of frequency resolution (F_r) and time resolution (T_r). The higher F_r, the lower the T_r. Sampling frequency (F_s) used is 2000 Hz. In, it stated that frequency used is in the range of 10-400 Hz. It means that the minimum frequency used is 10 Hz and the maximum frequency is 400 Hz. The frequency component below 10 Hz and more than 400 Hz is usually corrupted by the movement artifact and non-stability of electrodes interfaces. The best window size have to be measure for Spectrogram to offer better accuracy [7], [9], [16], [17] . The window selection is tested with six different sizes of windows which are 128, 256, 512, 1024, 2048 and 4096.

Table 1. TFR of Spectrogram method and Vrms(t)

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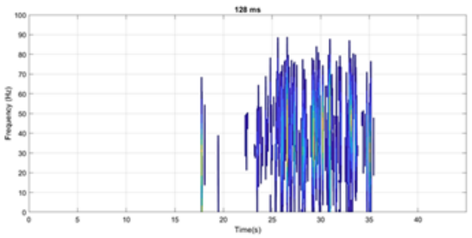
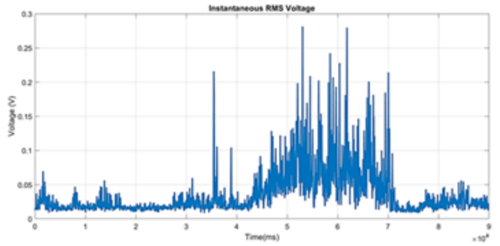
<tr><td>128</td><td>
</td><td>
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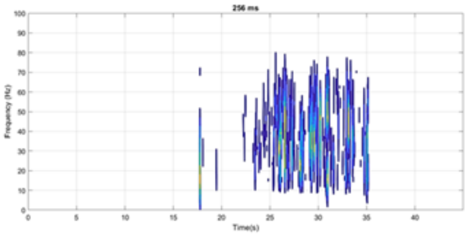
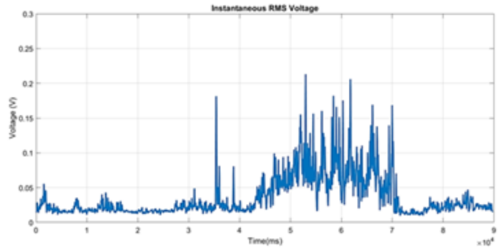
<tr><td>256</td><td>
</td><td>
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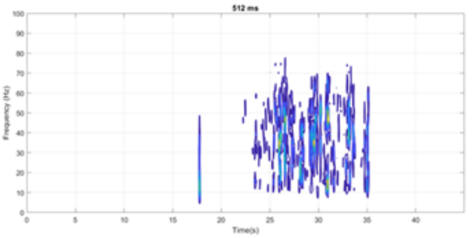
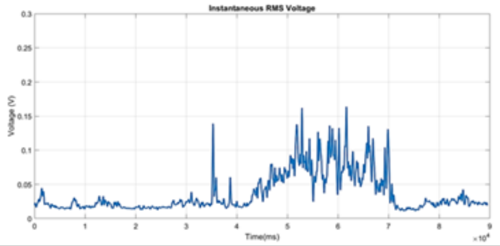
<tr><td>512</td><td>
</td><td>
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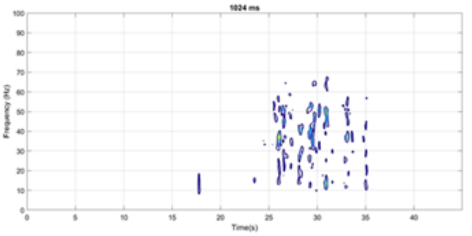
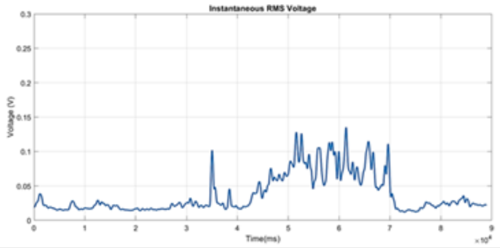
<tr><td>1024</td><td>
</td><td>
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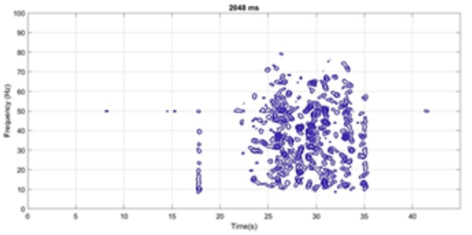
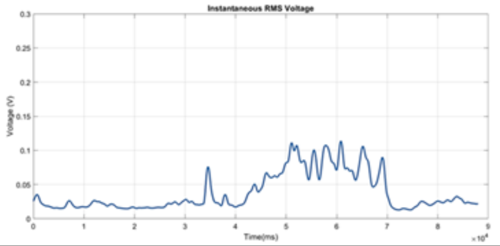
<tr><td>2048</td><td>
</td><td>
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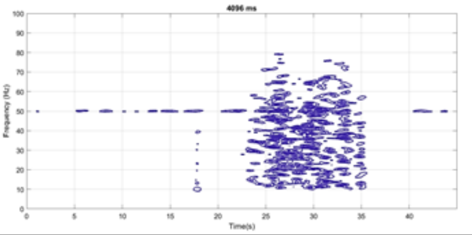
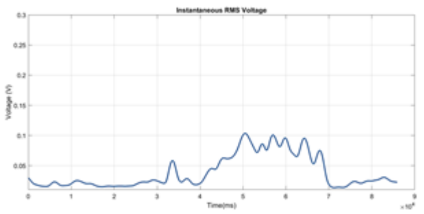
<tr><td>4096</td><td>
</td><td>
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Table 2. Comparison of window size performance with time resolution 2000ms and time interval 300s

Window size (N_w)	*Frequency Resolution (F_r)(Hz)*	*Time Resolution (T_r) (s)*	*Frequency resolution (F_r) versus minimum EMG frequency (10Hz)*	*Time Resolution (T_r) to detect time interval*	*Discussion*
128	15.625	0.064	**F_r < 10Hz** Fr must be equal or less than minimum frequency 10 Hz of EMG signal – **accepted** The rate of Tr over 1 cycle is 0.6/1	**Tr < 0.1s** Tr should be less than 0.1s for measurement 1 cycle of EMG Signal – **accepted** Able to detect with detail for time interval	Able to detect minimum frequency of EMG signal 10Hz Good in time resolution but poor frequency resolution - time and frequency with very high ripples (high noise) **Rejected**
256	7.812	0.128	**Fr < 10Hz** Fr must be equal or less than minimum frequency 10 Hz of EMG signal – **accepted** The rate of Tr over 1 cycle is 1.3/1	**Tr < 0.1s** Tr should be greater than 0.1s for measurement 1 cycle of EMG Signal – **accepted** Able to detect with detail for time interval	Able to detect minimum frequency of EMG signal 10Hz Good in time resolution but poor frequency resolution - time and frequency with high ripples (high noise) **Rejected**
512	3.906	0.256	**Fr < 10Hz** • Fr must be equal or less than minimum frequency 10 Hz of EMG signal – **accepted** The rate of Tr over 1 cycle is 2.5/1	**Tr < 0.1s** Tr should be greater than 0.1s for measurement 1 cycle of EMG Signal – **accepted** Able to detect with detail for time interval.	Able to detect minimum frequency of EMG signal 10Hz Good in time resolution but poor frequency resolution - time and frequency with still high ripples (still high noise) **Rejected**
1024	1.953	0.512	**Fr < 10Hz** Fr must be equal or less than 1/2 frequency minimum 10 Hz of EMG signal – **accepted.** The rate of Tr over 1 cycle is 5.1/1 Good frequency resolution and able to detect the minimum frequency – **accepted.**	**Tr < 0.1s** Tr min should be less than 1/10 Hz @ 0.1s for measurement 1 cycle of EMG Signal – **accepted.** Able to detect with detail for time interval.	Able to detect minimum frequency of EMG signal 10Hz Good in time and frequency resolution - time and frequency with low ripples (minimum noise) **Accepted**
2048	0.977	1.024	**Fr < 10Hz** Fr must be equal or less than minimum frequency 10 Hz of EMG signal – **accepted** The rate of Tr over 1 cycle is 10.2/1	**Tr < 0.1s** Tr should be less than 0.1s for measurement 1 cycle of EMG Signal – **rejected** Thus, cannot detect with detail for time interval	Unable to detect minimum frequency of EMG signal 10Hz Poor in time resolution but high frequency resolution - time and frequency with low ripples (minimum noise) Have some loss of information due to the higher Tr than 0.1s **Rejected**
			Fr < 10Hz Fr must be equal or less than minimum frequency 10 Hz	**Tr < 0.1s** Tr should be less than 0.1s for measurement 1 cycle of	Unable to detect minimum frequency of EMG signal 10Hz Poor in time resolution but high

An important consideration for window size is how well it balances time resolution and frequency resolution. It is implied that a longer window offers greater frequency discrimination but less localisation in time [18]. Thus, Spectrogram with six different window sizes is investigated to obtain the optimal time-frequency information.

As can be seen from Table 1, the window sizes of 128, 256, and 512 offer very accurate time resolution (Tr) but have low frequency resolution and make it challenging to identify the signal's maximum amplitude to obtain time and frequency information. For TFR, the contour showed the highest peak amplitude in yellow and the lowest amplitude in blue at 0.2 to 1.0 seconds.

Table 2 shows the details on how the window size is investigated and selected as the best window length. The selection is based on the guidelines that have mentioned in equation in (2) to (5) on the criteria must be fulfilled to become the best size window. This table demonstrates in detail the determining the best window length for window selection process. The information provided and guidelines given is clear to decide the best size window to be use for spectrogram analysis to analyse detail features for future analysis of muscle fatigue conditions during riding the motorcycle. By using Spectrogram with the best window size can provide good time and frequency resolutions and the analysis will be accurate and reliable with good temporal resolution.

Figure 5 represent example taken from respondent motorcyclist 4 with at the highest peak amplitude of time interval 18 which 1 hour and 30 minutes of riding motorcycle for most activated muscles from the outcome time and frequency domain analysis which is Extensor Carpi Radialis.

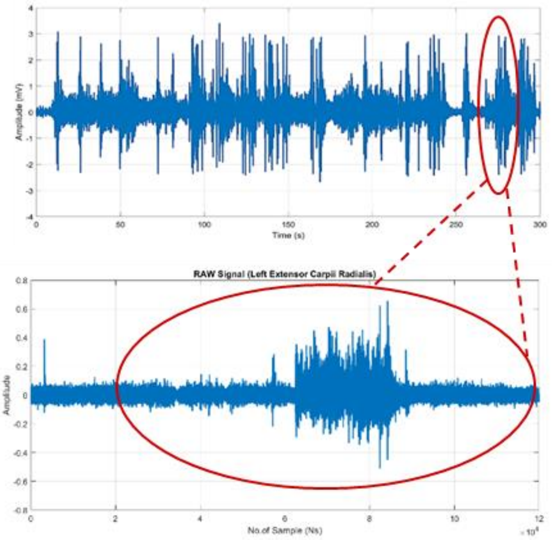

Fig. 5. The example raw data signal for window selection testing

The sampling frequency used during the experiment setup by METAL Lab is 2000 Hz with bandpass-filter 10-400 Hz. Thus, to provide good frequency resolution frequency, it should be lower than the minimum the cut off 10 Hz. There are 600,000 data collected, 300s of time interval, however each 1s in consider as important information in measuring time to fatigue in the further analysis to make sure no information loss between all-time intervals.

For Respondent 12 to analyse the accuracy performance for each time segment processed, Table 3 shows the mean accuracy classification method for five different window sizes (128 ms, 256 ms, 512 ms, 1024 ms, 2048 ms, and 4096 ms). Support Vector Machine (SVM) is the type of classifier that is used in machine learning to test the accuracy of the classification process since it is one of the best classifiers for EMG signal. Previous researchers have also used this size window.

Table 3. Classification accuracy of five different window sizes of Spectrogram

	Classification Accuracy (%)					
Time Segments	128 ms	256 ms	512 ms	**1024 ms**	2048 ms	4096 ms
T1	85.00	85.42	97.06	97.60	92.50	88.24
T2	82.92	89.17	91.18	91.18	92.08	89.58
T3	85.42	86.67	98.00	91.18	92.92	78.24
T4	86.67	88.33	88.24	97.06	75.83	97.24
T5	87.08	88.33	88.24	91.20	92.92	97.06
T6	87.92	87.50	82.35	91.28	93.75	73.53
T7	85.00	88.33	94.35	85.14	88.14	85.00
T8	82.92	87.50	97.01	88.23	92.08	82.92
T9	85.42	90.00	89.58	94.30	93.72	85.32
T10	86.67	89.58	92.08	97.30	83.53	85.67
T11	87.08	82.50	90.42	98.67	91.52	84.08
T12	87.92	92.08	89.58	93.64	92.75	87.22
T13	73.53	92.92	90.83	92.08	91.08	85.42
T14	82.45	95.83	90.42	90.42	92.92	89.17
T15	79.80	92.92	93.72	89.58	92.83	86.67
T16	88.96	93.75	94.33	90.83	92.92	88.33
T17	85.42	76.67	87.08	90.42	93.75	88.33
T18	90.00	79.58	82.50	92.08	88.33	87.50
T19	89.58	92.08	90.42	92.92	86.67	92.50
T20	92.08	92.08	96.25	95.83	80.42	92.08
T21	88.75	90.42	93.75	92.92	90.08	89.58
T22	86.25	89.58	93.75	93.75	87.50	95.83
T23	90.42	90.83	95.42	97.06	91.83	92.92
T24	89.67	90.42	95.83	91.18	85.00	87.50
Mean	86.12	88.85	91.77	**92.74**	89.79	87.91
STD	3.9229	4.3941	4.2064	**3.2701**	4.6409	5.4105

As can be seen, the Spectrogram with size window 1024 measured the highest accuracy of 92.74% of accuracy compared to the other size windows. It is followed 512, 2048, 256, 4096 and 128. 4096 ms results in the second lowest performance compared to the other window size, with a mean classification accuracy of 87.91%. The table shows that the larger window size resulted in a decrease in time resolution, which would result in poor classification performance. However, a spectrogram with a 128 ms resolution achieved a mean classification accuracy of 86.12%, which is a lower result and suggests that the frequency accuracy is poor due to the inadequate frequency resolution.

From Figure 6, indicates the performance of mean classification accuracy for five window sizes (128 ms, 256 ms, 512 ms, 1024 ms, 2048 ms and 4096 ms) for operational signal transformation process in classifying process. It is shown that 1024 ms size window gains the highest accuracy followed by 512 ms, 2048 ms, 256 ms, 4096 ms and 128 ms.

Spectrogram with 1024 ms yielded the best classification performance for EMG signal in this study. On the one hand, classification performance showed degradation for 512 ms and 2048 ms. This is because Hanning Window does reveal balance in time and frequency resolution, thus leading to poor time and frequency information in the process of signal transformation process [16].

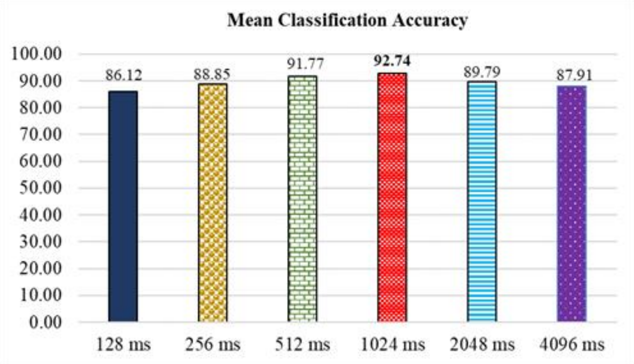

Fig. 6. The example raw data signal for window selection testing

From all the analysis for window selection process, it is proven window size 1024 ms is the best window length to provide accurate data analysis from extraction EMG Signal in this research.

4. Conclusion

As the conclusion, results presented in this paper have shown that the determining the best window size for Spectrogram is acceptable to be use for the analysis of EMG signal for riding motorcycle. The best window size of spectrogram has provided good time and frequency resolution that is very crucial for providing accurate results. The sampling frequency is 2000 Hz with bandpass-filter 10-400 Hz. Thus, to provide good frequency resolution, it should be equal or lower than the minimum the cut off 10 Hz. Time resolution should be less than 0.1s for measurement 1 cycle of EMG signal dan able to detect detail for each time interval. Size window 1024 has proven as the best window size by tested as the highest accuracy result for the performance of classification process by SVM.

4.1. Acknowledgement

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