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Analysis of Spinal EMG Signal When Swinging an Object

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Abstract

Electromyography (EMG) is bio signal record the electricity generated by muscle, but the signal often influenced by the unwanted noise. In this paper, MVC normalization method is applied to determine the spinal EMG signal on lumbar multifidus muscle when swinging an object. In order to analyse the identical and recognition of spinal EMG signal, three statistical analyses are done. There is one-way ANOVA analysis, RMS analysis and boxplot analysis. The result of MVC test shows that a higher percentage of MVC resulted in higher normalized amplitude. One-way ANOVA analysis shows that the means value among all 15 subjects are different in 100% MVC test. In addition, RMS analysis indicates that the muscle activity is increased when the muscle contraction is increased. In boxplot analysis shows that the increment of percentage MVC resulted in greater median, normalized amplitude and interquartile range. Besides, this paper presents a further investigation on determining the average median and interquartile range different from 0% until 100% MVC test by applied 8^{th} order Gaussian function in curve fitting and exponential weight moving average filter. In boxplot analysis, spinal EMG signal undergoes 8^{th} order Gaussian function in curve fitting has the greatest difference in median when there is an increment on the percentage of MVC test. Lastly, median is the best feature in boxplot analysis to shows the difference in increment of %MVC. Furthermore, 8^{th} order Gaussian function in curve fitting produce more identical data after go through boxplot analysis.

Keywords: Electromyography, MVC normalization, spinal lumbar multifidus, swinging, statistical analyses.

INTRODUCTION

Almost 85% of the caregivers are experienced in lower back pain and survey have been conducted by Isa, Noor Sazarina, et al. [1] to determine the prevalence and risk factors of low back pain among automotive industry worker. From the result, the prevalence of low back pain shows an increment in the point prevalence of 57.9%, 49.5%, and 35.1 % in 12 months, one month, and in 7 days respectively. The spinal cord is important in control the movement of the whole body[2],[3],[4]. Therefore, the EMG is developed in order to help the patient with spinal injuries in physiotherapy [5],[6]. Moreover, with the involvement of EMG in robotic, robot has the ability to mimic human motion which able robotics to be used in rehabilitation, therapy, and medical test[7],[8],[9].

Recently, researcher was focused on the development of an upper limb rehabilitation training system [10] and relation between surface EMG signal and ideal motor muscle [11]. Besides, some of them focus on improving the process speed and response of EMG device [12], [13]. In addition, the investigation on the performance with the implement of two electrode system in electromyogram detection was also done[14]. Due to lack of research that emphasis on the recognition of EMG signal at spinal muscle, robotic or rehabilitation studies faces difficulties in designing the best response to overcome spinal injuries.

Electromyography (EMG) is defined as an evaluation and recording of the myoelectric signal from the skin surface. Myoelectric signal is a signal that generated by muscle's electrical activity [15]. The overall number of humans who had gait disabilities risen together with the needs of appropriate rehabilitation treatment. With EMG, patients with spinal control injury were able to recover their sensory motor function [16]. However, difficulties to achieve high accuracy signal due to noise environment and robustness of EMG pattern recognition faced by researcher [17], [18].

The surface EMG is affected by the noise environment and its feature was not robust. The robust feature of EMG signal determines the noise depend on the strength of the signal. According to Thongpanja et al, the transformation of measure EMG signals into a reduced set of features is normally extracted in time domain and frequency domain [18]. Furthermore, inconsistent due to bodily fatigue affected the capability of the surface EMG pattern recognition. Fatigue inconsistency happened at different times due to different subjects. In addition, environmental issues such as temperature and humidity result in inconsistency fatigue. Thus, the time taken for a resting period between each %MVC test must be taken into consideration. Lastly, the inaccuracy of surface EMG pattern recognition affected the results. The review shows that a lot of researchers having difficulties in getting high accuracy of surface EMG pattern recognition [18]–[20].

The purpose of this report is to analyse the EMG signal produce by spinal muscle using statistical analysis methods. The Maximal Voluntary Contraction (MVC) used to determine the EMG signal on spinal. The experiment is divided into subject, pre-experiment and experiment protocol. The experiment focuses on 0%, 25%, 50%, 75% and 100% MVC when swinging an object. The EMG signals then will be analyse using three methods which are one-way ANOVA analysis, root mean square analysis and boxplot analysis. The one-way ANOVA was made to analyse the mean and variance of EMG signal between each subject. It will justify the EMG signal differences between all subjects. The root mean square analysis (RMS) was done to understand the trend of EMG signal between different levels of muscle contraction. Lastly, the box plot analysis will recognise each %MVC based on three features maximum normalise amplitude, interquartile range, and median.

DATA GATHERING

Data gathering is important in measuring the information on variables and determine the outcome. Fatigue is a feeble symptom and it is always happening after muscle activity. The review showed there is no relation between fatigue awareness on subjects and physiological measures of fatigability [21]. Several variables such as load, task repetition, number of tasks and trials, time to rest and type of task had to be concerned in order to achieve a good prescription in the experiment. The data are collect from the spinal muscle for evaluation. A reference is needed to overcome the problem in real muscle strength comparison since human has different muscle strength [22]. Due to this issue, percentage of maximal voluntary contractions is the best solution to represent different level of muscle contraction.

A. Maximal Voluntary Contractions (MVC)

An amplitude analysis technique applies to EMG signal is known as MVC normalization. The MVC normalization method is widely used in EMG field and it is an act of subject own free will when the muscle contract at the maximum contraction based on muscle status. Besides, recording maximum root means square (RMS) value was used to normalize the series of EMG data [23], [24]. When there is a movement a force is produced and MVC can be used to measure the percentage ratio force applied on maximal voluntary contraction. Normalization based on MVC is useful to increase the consistency in isometric contraction. Maximal voluntary isometric contraction is a common method for extraction of reference amplitude in EMG normalization [22], [25].

Furthermore, maximal voluntary contraction (MVC) method can use to evaluate muscle function and it acts as a treatable indicator of muscle damage [26]. Improper activities result in misjudging. Activity with overload will increase the chance and risk of injury, thus result in inconsistency result.

A normalization method based on MVC is used to measure the relative force at the beginning. Then, each subject is asked to perform a swinging motion with load based on their muscle strength which are 100%, 75%, 50%, 25%, and 0% of their maximum voluntary contraction and the trials is repeated. The normalization is completely done and stops at the moment when the muscle of subject reached maximum and could not swing the load. One minute resting period was given between trials [27].

Figure 1 shows the summary of the MVC normalization method. The solid box shows the process of data gathering by applying MVC while the dash box represents the data analysis process.

DATA ANALYSIS

After all the EMG signal have been gathered, the signal is analysed. The analysis is based on two types of filter which are curve fitting and weight moving average filter.

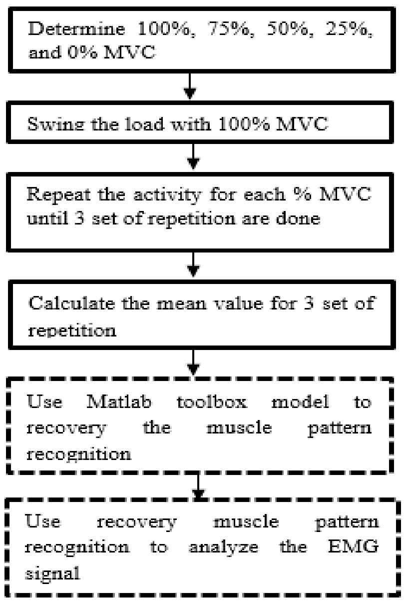

Figure 1: Summarization of MVC normalization method

A. 8^{th} order Gaussian function in Curve Fitting

A curve fitting tool is used to model the pattern of muscle recovery behaviour that obtained from pre experiment protocol to be the truth of normalization method. It performs exploratory data analysis, pre-process data, post-process data and remove outliers. The 8^{th} order Gaussian function is the best examination of all subject data, thus muscle recovery behaviour can be defined in mathematical form as:

$$f(x) = \sum_{i=1}^{n} a_i e^{-(\frac{x-b_i}{c_i})^2} \quad (1)$$

B. Exponential Weight Moving Average Filter

An exponential weight moving average filter is used to smooth the signal and remove unwanted line noise. The exponential weight moving average filter is similar to Gaussian expansion filter and it is applied in order to remove the unwanted noise from the signal. By applying this filter, the observer is able to see the tendency in the signal.

STATISTICAL ANALYSIS

This section discusses about the data and signal analysis of the EMG signal. Data obtained from actions and activity which the electromyograms (EMG) were recorded by using the EMG sensors. The statistical analysis methods had been applied to analyse muscle activation and they are good in indicate muscular activities.

Statistical analysis consists of three methods and these methods are showing good results in previous work done. The statistical methods are one-way ANOVA analysis, boxplot analysis and root mean square (RMS) analysis.

A. 4.1 One-way ANOVA Analysis

One-way ANOVA method is used to analyse and determine the effect of the EMG signal on the classification performance of lumbar multifidus muscles [28]. Besides, it used to test the feature in order to observe the characteristic of each feature between different classes [29]. One-way ANOVA analysis integrated normalized EMG activities of lumbar multifidus muscle for each respective phase [16]. Some assumptions are making and taking into consideration. An assumption state that:

Null hypothesis, H_o: $\mu_1 = \mu_2 = \mu_3 = \cdots = \mu_k$

In this work, one-way ANOVA analysis was used to compare the means and variance between 15 subjects in MVC normalization method. A signal that achieves a common mean of $p > 0.05$ and it means there are no significant differences between all subjects. On the other hand, when the significant level $p < 0.05$, the means value for 15 subjects are not all the same. Therefore, the tests are known as significant when the variance of tests is small as compared to the variance between subjects [22], [30].

B. 4.2 Root Mean Square Analysis

In order to identify the performance of EMG signal pattern recognition, the analysis on the root mean square value (RMS) for the % MVC test is done. When swinging an object, the RMS value of the EMG signal is used to obtain the data of percentage of maximal voluntary contraction (% MVC). Generally, the parameter of RMS is mostly applied in the scientific fields. RMS value shows a better response in the levels of muscle activity during muscle contraction.

C. Boxplot Analysis

Boxplot shows the graphical layout and it consist the basic of five values which are the minimum value and maximum value in the dataset, lower hinge (first quartile), upper hinge (third quartile) and median. Boxplot used in illustration of small data sets. Besides, boxplot further enable summarization of outliers and determination of trimmed mean value. An extreme observation can significantly affect the data measured in a larger data set [31] The objective of boxplot is to investigate the distribution of data. The red line that divided the box into two parts represents the middle quartile (median) which illustrates the value of midpoint for normalized amplitude of EMG signal.

EXPERIMENT

The experiment is divided into subject, pre-experiment and experiment protocol.

A. Subject

The experiment consists of 15 male subjects and they were between 20 to 30 years old. All 15 subjects are in healthy condition and have no history of accident on their spine.

B. Pre-experiment

Pre-experiment is the preparation session before start the experiment. There are two preparation session, the first session is briefing session while the second session is skin preparation. Skin preparation is a process of removing the hair and shave alcohol on the skin of subjects.

C. Experiment Protocol

Total five sets of experiments had been conducted. There are 0%, 25%, 50%, 75% and 100% MVC test and each test is repeated for 3 times. The experiment is using the MVC normalization method to determine and evaluate the presence of an inconsistent issue in the experiment. After all the preparation is done, the motion lab EMG sensor and electrode is placed on the lumbar multifidus muscle. The position of the sensor and electrode are shown in Figure 2, positive electrodes are connected to the muscle, while negative electrode is connected to the bone.

Lumbar multifidus muscle is selected because it is a small and powerful muscle, which related to upper limb movement and provide support to the spine [32]. After putting the electrode on the lumbar multifidus muscle, the procedure followed by a connection phase.

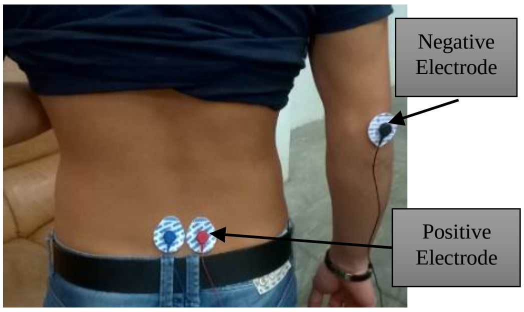

Figure 2: Location of electrodes on lumbar multifidus muscle

A device named as model GDS 3254 digital oscilloscope is used. The motion lab EMG sensor is connected to the muscle sensor V3 kit. This sensor is used to estimate the filtered and rectified electrical activity of a muscle. Then, it connected to the digital oscilloscope for data acquisition. The myoelectric signal is collected by electrode from muscle. After obtaining the data, the data is integrated and analysed. Figure 3 shows the process flow of the experiment.

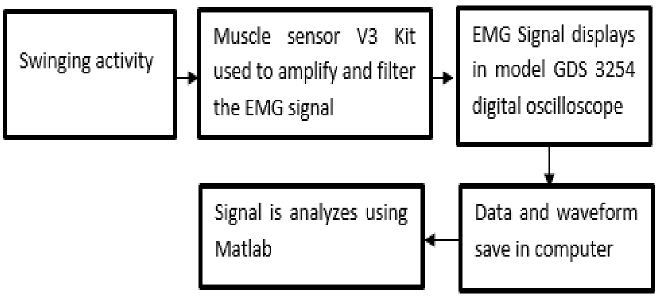

Figure 3: Process flow of the experiment

The experiment started with the MVC normalization method. This procedure is followed the experiment procedure done by Sabri [22]. All the experiment setup, task and activity must be the same in order to reduce the inconsistency issue. All the experiments are done in the laboratory.

Firstly, the MVC normalization method is tested on the muscle of subjects and the data are recorded. The initial of hand position were set at 90 degree and the subject is asked to swing the load from a position of 90 degrees to 180 degrees as shown in Figure 4. Then, all subjects were asked to swing the load starting from the 100% of the maximal voluntary contraction (MVC) value with standing position. Two minutes resting period was given between each %MVC Test and 30 second resting period was given between each repetition.

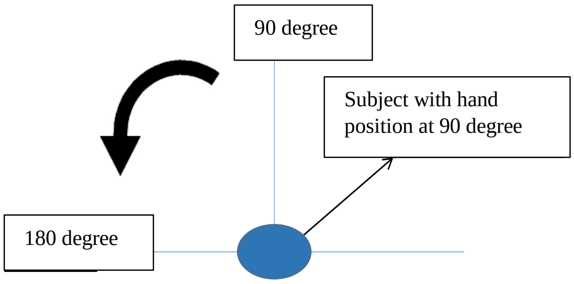

Figure 4: Movement of subject in swinging object

RESULT AND DISCUSSION

Figure 5 shows the average result of 0%, 25%, 50%, 75% and 100% of MVC test among 15 subjects which had been filtere d by muscle sensor V3 kit. The higher percentage of MVC resulted in greater normalized amplitude. It means the greater the load, the greater the myoelectric generated by the muscle. At 0% MVC, the normalized amplitude is falling below 0V. This is due to the greater distance between positive and negative electrodes. However, this setup was consistently used for others %MVC where it will not affect the recognition process.

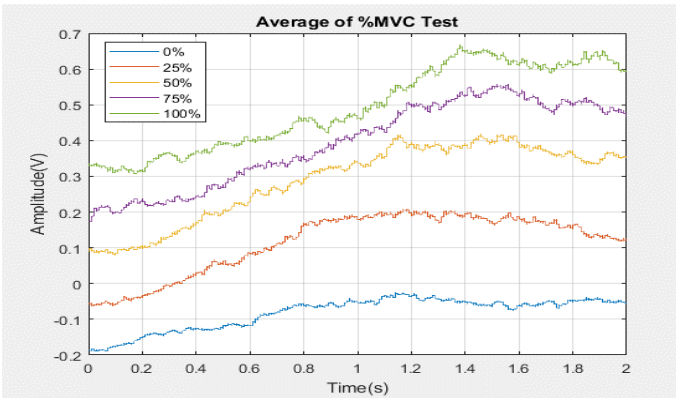

Figure 5: Average of %MVC Test

A. One-way ANOVA Analysis

In One-way ANOVA analysis, the significant level set $p < 0.05$ for all the data and allocate variance to different trials. The one-way ANOVA analysis for 100% MVC is shown in table 1, the p value is 2.79721e-254 which is less than 0.05. The results are same for another 0%, 25%, 50%, and 75% MVC, the p-values are less than 0.05. It shows that the differences between mean and variance are statistically significant. In addition, it states that the mean and variance value from all the 15 subjects are not all same. The null hypothesis state in the method section is rejected and the difference between the means are great enough for the researcher to exclude sampling error explanation. This difference was due to subject body condition that difficult to

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control. From this analysis, it shows that direct recognition was not possible due to each subject produce different EMG signal at same %MVC.

Table 1: One-way ANOVA analysis

ANOVA Table

Source	SS	df	MS	F	Prob>F
Columns	162.14	14	11.5814	276.26	2.79721e-254
Error	25.782	615	0.0419		
Total	187.921	629			

B. Root Mean Square Analysis

The results with calculation of RMS value are tabulated in table 2. The RMS is calculated to provide the most insight on the amplitude of the EMG signal. Table 2 shows that the higher the %MVC, the higher the RMS value. As the results, RMS value of % MVC indicates that the muscle activity is increased when the muscle contraction, or indirectly the load is increased.

Table 2

RMS value for average %MVC

%MVC	0%	25%	50%	75%	100%
RMS	0.0936	0.1428	0.3072	0.4104	0.5057

C. Boxplot Analysis

The 8^{th} order Gaussian function in curve fitting and exponential weight moving average filter are done for the comparison of data in boxplot analysis. Figure 6 shows the boxplot analysis for different %MVC test. Interquartile range (IQR) is the difference between first quartile and third quartile of the box. The average median different from 0% until 100% MVC is 0.13272075 while the average IQR different from 0% until 100% MVC is 0.0385925. At 0% MVC, IQR is the smallest among %MVC so it has the highest consistency. The maximum amplitude in boxplot analysis is 0.66702. The value for each features was state in table 3.

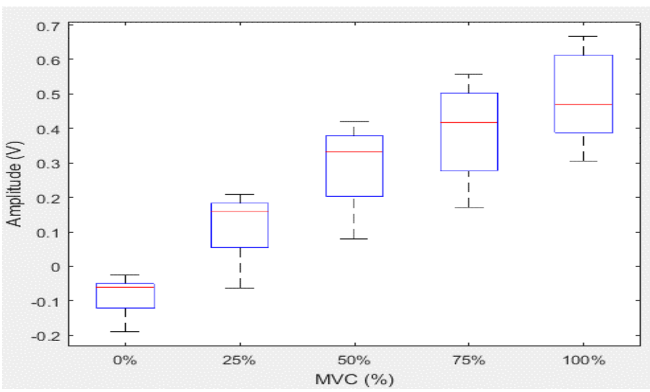

Figure 6: Boxplot

Table 3: Result of boxplot

%MVC	Median	IQR	Maximum Amplitude
0%	- 0.060953	0.07103	-0.025753
25%	0.15791	0.128025	0.20882
50%	0.33142	0.17526	0.41929
75%	0.41703	0.22567	0.55691
100%	0.46993	0.22594	0.66702

Figure 7 shows the boxplot analysis after applying the curve fitting with the 8^{th} order Gaussian function for different %MVC test. The average median different from 0% until 100% MVC is 0.13320475 while the average IQR different from 0% until 100% MVC is 0.037645. The maximum amplitude in boxplot analysis is 0.6536. The value for each features was state in table 4.

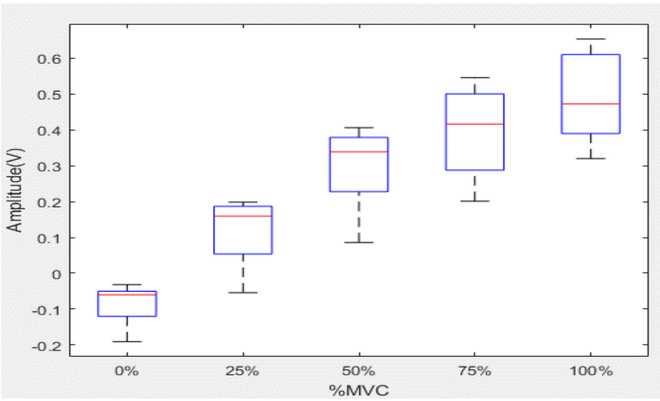

Figure 7: Boxplot (8^{th}order Gaussian function in Curve fitting)

Table 4: Result of boxplot (8^{th} order Gaussian function in Curve fitting)

%MVC	Median	IQR	Maximum Amplitude
0%	- 0.060069	0.06978	-0.031941
25%	0.15928	0.133187	0.19816
50%	0.33864	0.15135	0.40618
75%	0.41609	0.21306	0.54601
100%	0.47275	0.22036	0.6536

Figure 8 shows the boxplot analysis after applying the exponential weight average filter for different %MVC test. The average median different from 0% until 100% MVC is 0.124118475 while the average IQR different from 0% until 100% MVC is 0.04021425. The maximum amplitude in boxplot analysis is 0.74379. The value for each features was state in table 5.

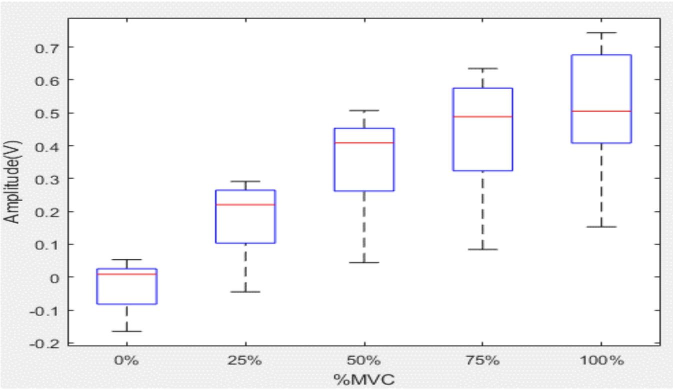

Figure 8: Boxplot (Exponential weight moving average filter)

Table 5: Result of boxplot (Exponential weight moving average filter)

%MVC	Median	IQR	Maximum Amplitude
0%	0.0085461	0.107693	0.053292
25%	0.22051	0.16121	0.29118
50%	0.40855	0.1907	0.50696
75%	0.48815	0.2518	0.63475
100%	0.50502	0.26855	0.74379

Table 6 shows the standard deviation for median and IQR difference from 0% until 100% MVC in boxplot analysis. Standard deviation is used to quantify the amount of variation of a set of data values in statistical analysis. Based on the result, median and IQR difference show a low standard deviation. Moreover, IQR difference shows the lowest standard deviation. The results indicate the median and IQR difference illustrate high concentrated of data since the data point are close to the mean.

Table 6: Result of standard deviation

SD / Boxplot	σ (median difference)	σ (IQR difference)
Original	0.066474	0.022712
8^{th} order Gaussian function in Curve fitting	0.068042	0.025215
Exponential weight moving average filter	0.079509	0.017880

From the boxplot analysis, the median did not lie at half of the first quartile and third quartile. Therefore, the distribution is not symmetrical. IQR is a more appropriate measure of variability than standard deviation if the data is not symmetrical [33]. Higher %MVC results in greater median and IQR. The larger the IQR, the data set is more variable while the smaller the IQR, the data have higher consistency.

For the average IQR different from 0% until 100%, the EMG signal undergo 8^{th} order Gaussian function in curve fitting is the smallest, 0.037645 while the signal undergo exponential weight moving average filter is the highest, 0.04021425. It shows that the EMG signal undergo 8^{th} order Gaussian function in curve fitting has a higher consistency of data.

EMG signal undergoes undergo exponential weight moving average filter has the greatest maximum amplitude, 0.74379 among three different boxplot analysis. It shows that by applying the exponential weight average filter, the maximum value of amplitude is increased. Besides, EMG signal undergo 8^{th} order Gaussian function in curve fitting has the greatest average median difference from 0% until 100% MVC which is 0.13320475. Median shows the greatest increment from 0% until 100% MVC as compare to IQR. Thus, median is the best feature in boxplot analysis to shows the difference in increment of %MVC. Furthermore, 8^{th} order Gaussian function in curve fitting produce more identical data after go through boxplot analysis.

Lastly, the increment of the median and IQR for each percentage of MVC is getting smaller from 0% to 100% MVC in the boxplot analysis. Based on the standard deviation of the median and IQR difference, it shows that in order to determine an accurate percentage of MVC when swinging an object, multiple reference is needed.

CONCLUSION AND RECOMMENDATION

The results show that the increment of the percentage of MVC increases the normalized amplitude when swing an object. The one-way ANOVA analysis shows that the mean and variance from the 15 subjects are not the same, thus the MVC normalization method is considered as a good method to use. RMS analysis indicated that the muscle activity is increased when the muscle contraction is increased. The boxplot analysis for original signal, signal undergo the 8^{th} order Gaussian function in curve fitting and signal undergo Exponential weight average filter show that the higher the percentage of MVC, the greater the maximum amplitude, IQR and median. EMG signal undergoes 8^{th} order Gaussian function in curve fitting shows the greatest average median difference from 0% until 100% MVC. The results show that the median is the best feature to use as recognition for each %MVC. Future works will focus on the implementation of this recognise signal to identify unknown spinal EMG signal when performing the swinging motion. Percentage of accuracy will be measure to identify the performance before further implementation made. Lastly, the combination of recognition, identification, will be implemented for the development of rehabilitation and assistive robotics.

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