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Research paper

Analysis of Spinal Electromyography Signal When Lifting an Object

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Abstract

Lifting and swinging are daily activities that human do using the spine. Furthermore, spine provides support during standing and walking. Therefore, it is very important in everyday activities and it will be inconvenient when it is injured. Technology has provided ways to machine and human integration in helping or supporting people in their daily tasks. To make this integration successful, machines or robots need to understand the human muscle activity. To do so, electromyography (EMG) a bio signal record the electricity generated by muscle was implemented. However, the signal often influenced by the unwanted noise. In this paper, the MVC normalization method is applied to determine the spinal EMG signal on lumbar multifidus muscle when lifting an object. In order to analyze the identity of spinal EMG signal, two statistical analyses are done; 1) ANOVA analysis and 2) Boxplot analysis. The signal will go through 8th order Gaussian function or Exponential Weight Moving Average Filter before being analysed. Results show that Exponential Weight Moving Average Filter gives more consistent value compared to 8th order Gaussian function which is 0.0428V RMSE based on linear fitting done from the maximum amplitude gather from the boxplot analysis done.

Keywords: *lifting; spine; EMG; ANOVA; RMSE.*

1. Introduction

Mobility and strength of a human supported by lower spine or lumbar spine that connects the upper body to lower body. This connection allows movements such as turning, bending or twisting while strength provide support during standing, walking and lifting posture [1]. Nearly 85% of the caregivers are experience in lower back pain and survey conducted by [2] have determine the prevalence and risk factors of low back pain among automotive industry workers. The result 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. Due to the importance and sensitivity of spinal, the EMG was used in order to help the patient with spinal injuries in physiotherapy [3, 4]. 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 [5-7].

Recently, researchers emphases on the upper limb rehabilitation training system development [8] and studying the relation between the surface EMG signal and ideal motor muscle [9]. Besides, some of them focus to improve the process speed and response of EMG device [10, 11]. Furthermore, implementation of two electrode systems in electromyogram detection was investigated [12]. Due to lack of research that stress on the recognition of EMG signal at spinal muscle, robotic or rehabilitation studies faces difficulties in designing the best response to overcome spinal injuries.

The EMG signal can be depending by several external factors altering its shape and characteristics, from the muscle membrane up to the electrodes [13]. The factors that affect EMG signal and force falls into three basic groups: causative, intermediate and deterministic factors [14]. According to [15], the transformation of measure EMG signals into a reduced set of features is normally extracted in time domain and frequency domain. In addition, in [13] describes that a significant amount of EMG that is detected by the local electrode site may be produced by neighboring muscles. Lastly, the inaccuracy of the surface EMG pattern recognition affected the results. The review shows that a lot of researchers having difficulties in getting high accuracy of the surface EMG pattern recognition [15-17].

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 lifting an object. The EMG signals then will be analysed using two methods which are one-way ANOVA 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. Lastly, the box plot analysis will recognise each %MVC based on three features maximum normalise amplitude, interquartile range and median. The method and methodology were plan same as [18] to ensure the comparison between the signals gather here can be directly compared with the swinging motion.

2. Proposed Method

Explanation on the research method was divided into three which are the data gathering process, data analysis and statistical analysis. MVC normalization method is shown in Fig. 1. The dash box represents the data analysis process while the solid box shows the process of data gathering by applying MVC shows how the data was gather.

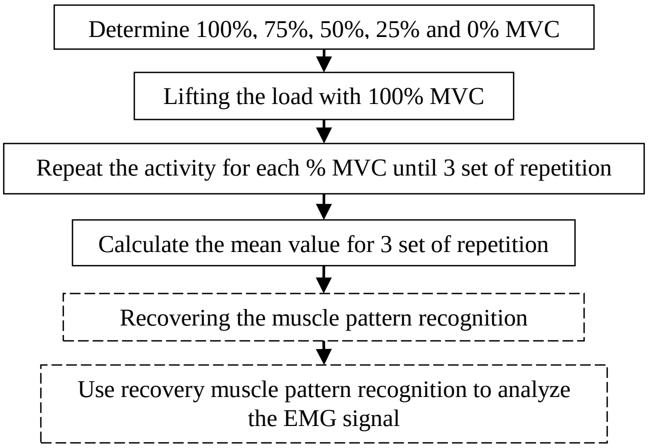


Fig. 1: Summarization of MVC normalization method

2.1. Data Gathering

Maximal voluntary contractions (MVC) were implemented to represent different level of muscle contraction. The method used due to fatigue, which is the 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 [19]. 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. A reference is needed to overcome the problem in real muscle strength comparison since a human has different muscle strength.

MVC normalization is an amplitude analysis technique applies to EMG signals. 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, the series of EMG data was normalized using the maximum root means square (RMS) [20]. 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. In EMG normalization. Maximal voluntary isometric contraction is a common method for extraction of reference amplitude [21].

A normalization method based on MVC is used to measure the relative force at the beginning. Then, each subject is asked to perform a lifting motion with a load based on their muscle strength which is 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 the subject reached maximum and could not lift the load. One minute resting period was given between trials [20].

2.2. Data Analysis

After gathering all the EMG data, it will go through data analysis. The analysis included two types of filter, which is curve fitting and weight moving average filter.

The curve fitting performs exploratory data analysis, pre-process data, post-process data and remove outliers in order to model the pattern of muscle recovery behaviour that obtained from pre experiment protocol to be the truth of normalization method. The 8^{th} order Gaussian function examination of all subject data, thus muscle recovery behaviour can be defined in mathematical form as in ((*1*).

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

Secondly, an exponential weight moving average (EWMA) filter is used to smooth the signal and remove unwanted line noise. The EWMA 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.

2.3. Statistical Analysis

After obtaining the data from actions and activity which recorded by using the EMG sensors. The statistical analysis methods had been applied to analyse muscle activation and they are good to indicate muscular activities. Statistical analysis consists of two methods and these methods are showing good results in previous work done. The statistical methods are one-way ANOVA analysis and boxplot analysis.

The EMG signal will go through an analysis and determination of the effect on the EMG signal classification performance of lumbar multifidus muscles by using one-way ANOVA method [22]. It also test the feature in order to observe the characteristic of each feature between different classes [23]. One-way ANOVA analysis integrated normalized EMG activities of lumbar multifidus muscle for each respective phase [24]. To do so, assumptions were made which is: The null hypothesis,H_o: $\mu_1 = \mu_2 = \mu_3 = \cdots = \mu_k$. The 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 mean 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 [25].

In boxplot, it shows the graphical layout which consists of five values. They are the minimum value and maximum value in the dataset, lower hinge (first quartile), upper hinge (third quartile) and median. It helps in summarizing the outliers and determination of trimmed mean value. An extreme observation can significantly affect the data measured in a larger data set [26]. The objective of boxplot is to understand the data distribution. The red line that divided the box.

3. Methodology

The experiment consists of 15 male subjects between 20 to 30 years old. There is no record of accidents or unhealthy between all subjects, particularly at their spine. Before proceed with the data gathering. There are two preparation sessions, the first session is briefing session while the second session is skin preparation. In skin preparation, fur at the electrode area will be removed and the alcohol was swept.

The experiment was conducted based on 0%, 25%, 50%, 75% and 100% MVC test and each test is repeated for three times for each subject. In order to determine and evaluate any inconsistent issue, the experiment applied the MVC normalization method. Fig. **2** shows the electrode position. Positive electrodes are connected to the muscle (lumbar multifidus), while negative electrode is connected to the bone. The Lumbar multifidus muscle was chosen because it is a small and powerful muscle, which related to upper limb movement and provide support to the spine [27].

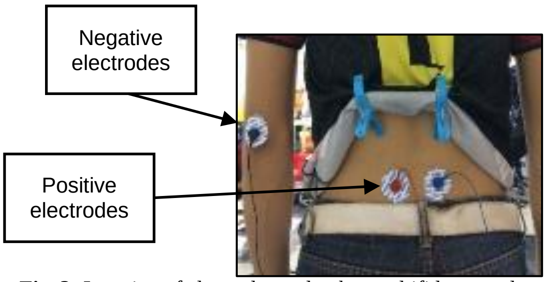


Fig. 2: Location of electrodes on lumbar multifidus muscle

The electrode is connected to the muscle sensor V3 kit that used to filter and rectified electrical activity of a muscle. For data acquisition, the digital oscilloscope was used. Collected data then will be analysed. The experiment started with the MVC normalization method. This procedure is followed the experiment procedure done by [28]. To make sure the results are consistent, all the experiment setup, task and activity must be the same. All the experiments are done in the laboratory. Firstly, subject is requested to stand in rest position for 1 second before lifting the weight for 3 second and hold it for another 1 second. Data and waveform from the oscilloscope (muscle sensor V3) are collected for 4 second starting from the rest position until holding the weight. After that, a subject is requested to rest for 1 minute before repeating the task. The task will be repeated for another two times. The experimental setup shown in Fig. *3*.

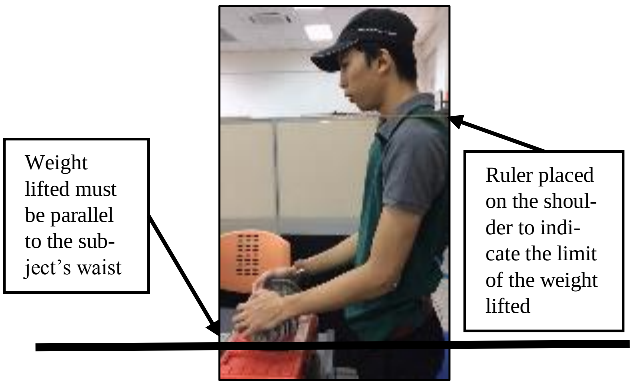


Fig. 3: Movement of subject in lifting object

4. Results and Discussion

Fig. **4** shows the average result of 0%, 25%, 50%, 75% and 100% of MVC test among 15 subjects which had been filtered by muscle sensor V3 kit.

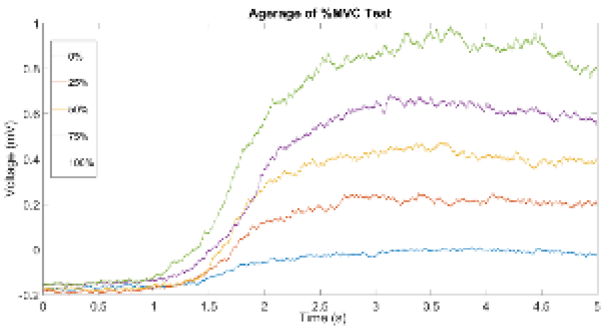


Fig. 4: Average of %MVC Test

The normalized amplitude is higher when %MVC is greater. It shows that the greater the load, the greater the myoelectric generated by the muscle. At 0% MVC, the normalized amplitude is falling below 0V due to the greater distance between positive and negative electrode location. However, this setup was consistently used for others %MVC where it will not affect the recognition process.

4.1. 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 Fig. **5**, the p value is 4.48069e-243 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.

ANOVA Table

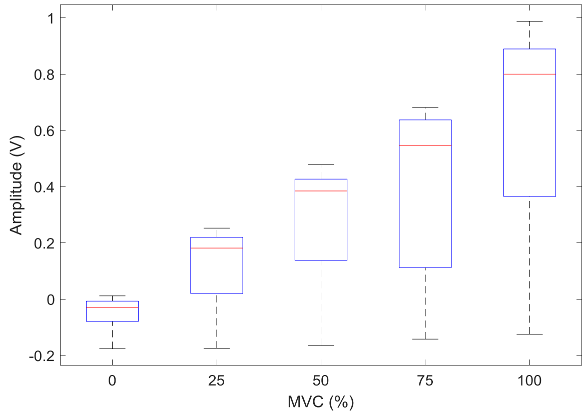
Source	SS	df	MS	F	Prob>F
Columns	383.65	14	27.4039	107.45	4.48069e-243
Error	635.04	2490	0.255		
Total	1018.69	2504			

Fig. 5: One-way ANOVA analysis

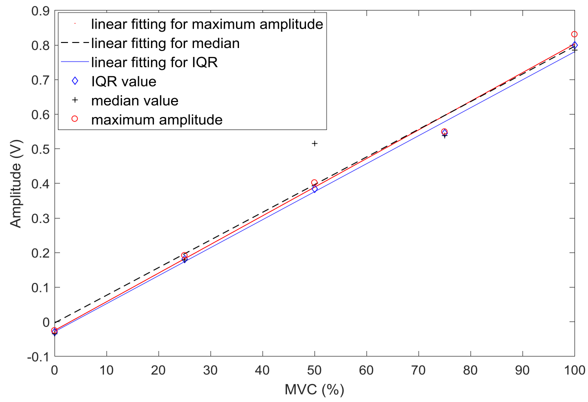
4.2. Boxplot analysis

Only the boxplot analysis was done to the average of all 15 subject normalized amplitude signals based on %MVC. The Interquartile range (IQR), maximum amplitude, and median are observed to identify the signal characteristic for each %MVC. The normalized amplitude than go through 1) 8th order Gaussian function and 2) EWMA filter before the Interquartile range (IQR), maximum amplitude, and median is observed. The value will be compared to identify the best method to recognize the signal.
Fig. **6**(a), (c) and (e) show the boxplot analysis for ent %MVC test. From the analysis, it shows that the characteristic in term of maximum value, 1st quartile and 3rd quartile was nearly the same for all three graphs. The minimum IQR is when subject lifting the object at 0% MVC.
The boxplot for 50% MVC and 75% MVC cross at the 1st quartile in which the minimum value was nearly the same. This is due to the subject need to use nearly the same force in completing the task. This is based on increasing of cross data from 0% MVC to 100% MVC for each boxplot analysis. However, the IQR is significantly different between each % MVC.
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 [29]. 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 has higher consistency. For the average IQR different from 0% until 100%, the signal undergo EWMA filter is the smallest, 0.106648 while the signal undergoes 8th order Gaussian function in curve fitting is the highest, 0.121189. It shows that the EMG signal undergoes 8th order Gaussian function in curve fitting has a lower consistency of data, but more variable the data set is.
The detailed for each variable on each boxplot analysis in Fig. **6**(a), (c) and (e) represented in Fig. **6**(b), (d) and (f). Variables that observed are the Median, inter quartile range and maximum amplitude. These variables can represent the signal identity in the classification process. To do that, the variable should be significantly different between each MVC%. Fig. **6**(b), (d) and (f) had used linear fitting based on the three variables state before. From the linear line, the RMSE was calculated to represent the consistency of the data to the linear line. Larger the RMSE more inconsistent the data record. If the RMSE is too high, it will be difficult for the

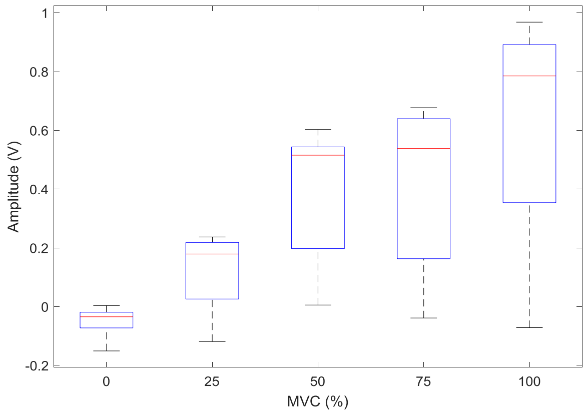
classification process. This was due to the variable may lays on different MVC%.



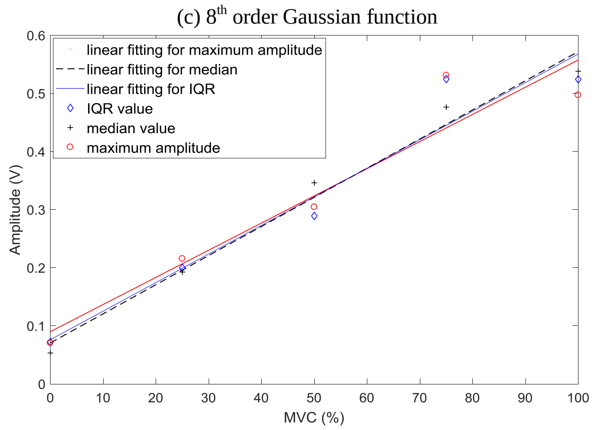
(a) Without any filter



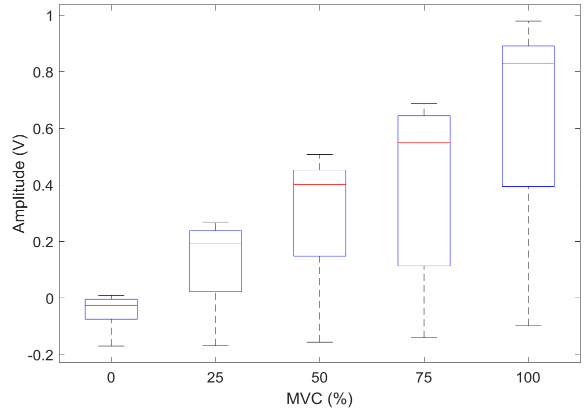
(b) Variables from boxplot without any filter



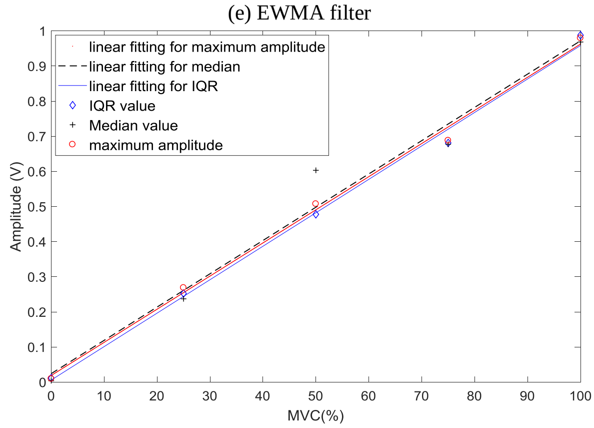
(c) 8th order Gaussian function



(d) Variables from boxplot after go through 8th order Gaussian function



(e) EWMA filter



(f) Variables from boxplot after go through EWMA filter

Fig. 6: Figure (a), (c) and (e) are the Boxplot analysis from 0% to 100% MVC based on 15 sample data. Figure (b), (d) and (f) are the linear fitting plot based on the boxplot analysis.

From Fig. **6**(b), the RMSE for the median is smaller compared to IQR and maximum amplitude which is 0.02286V. However, IQR becomes the smaller value when go through 8th order Gaussian function which is 0.03144V. When the signal goes through EWMA filter, the minimum RMSE is 0.0279V where came from the maximum amplitude. Table 2 shows all the RMSE for the variables observed in Fig. **6**.

From Table 1, it can be said that the EWMA filter is the best method due to the average RMSE for all three variables is 0.0428V. However, if refer to the variables, median is more consistent based on the average RMSE from all three types of signal is 0.0359V.

In order to proceed with classification process, EWMA filter is recommended to be used with the maximum amplitude value of the boxplot. The RMSE is 0.027V, the smaller among variables go through EWMA filter and 2nd from all data gather in here. However, it is the best to use more than one variable to represent the signal. For example, median and maximum amplitude can be used to ensure the accuracy of the classification. From the analysis, it also shows that IQR are not consistent for most of the time. This can be seen from the RMSE value and the boxplot analysis in Fig. **6**. In term of filter used, 8th order Gaussian function is not suitable in this case because the average RMSE is greater.

Table 1: RMSE between linear fitting and the variables

Filter	median	IQR	Max	Average
normal	0.0228	0.0794	0.0326	0.0449
8th order Gaussian	0.055	0.0314	0.0648	0.0507
EWMA	0.0290	0.0715	0.027	0.0428

5. Conclusion

The experiment shows that the boxplot analysis able to differentiate the signal based on %MVC. Despite the inconsistency of raw data collected effected the boxplot, it still has a significant difference. When the signal undergoes two types of filters, it shows that there is advantages and disadvantages for each. When median, IQR and maximum amplitude taken from the boxplot, the variables are in positive linear line. To ensure the best filter and variable that can be used to represent the signal, RMSE was calculated. The RMSE was taken from the value observed from the boxplot with the linear fitting of the variables i.e. median, IQR and maximum amplitude. It shows that the EWMA filter has average RMSE 0.0428. With minimum RMSE came from the maximum amplitude. This method is sufficient to use as classification between percent MVC when lifting an object. However, if there is more motion, such as swinging [22] or punching need to be classified, this might create inaccuracy on the classifying the signal. It is recommended to use a higher level of filter and pattern recognition method before analysing the signal. This will increase the consistency of the signal gather. Secondly, the classification also need are proper artificial intelligence method due to the EMG signal was surely having high inconsistency and noise. This work will be used as the reference data for the classification process.

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