Analysis and Classification of Multiple Hand Gestures using MMG Signals

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***Abstract*—This research aimed to find out whether the MMG signal is useful in recognition of multiple hand gesture. The following hand gestures are Hand closing, wrist flexion, wrist extension, opening, pointing. MMG is reflects the intrinsic mechanical activity of muscle from the lateral oscillations of fibers during contraction. However, external mechanical noise sources such as movement artifact are known to cause considerable interference to MMG compromising the classification accuracy. First aim to develop various feature extraction algorithms software that can identify multiple hand gesture using MMG signal. The main purpose of this work is to identify the hand gestures that are predefined using the artificial neural network, which is particularly useful for classification purpose. The MMG patterns are extracted from the signals for each movement, the features extracted from the signals are given to the neural network for training and classification since it is the good technique for classifying the bio signals. The features like mean absolute value, root mean square, variance, standard deviation and root mean square are chosen to train the neural network.**

***Index Terms*—Artificial Neural Network; Classification; Hand Gestures; Mechanomyography.**

I. INTRODUCTION

Skeletal muscles create sounds particular to their action it is called MMG signal. Mechanomyography (MMG) is an appropriate skill for elucidating mechanical activity based on muscle contraction. The prediction of muscle tissue state can find out by using MMG, based on a technique that muscular mechanical waves created when fiber stretching and contraction take place over skin surface [1]. The reason for this research is to investigate various methods of muscle movement through MMG signal to recognize multiple hand gestures. A major focus is on mechanomyography based on measurements of mechanical responses of muscle activity. It is well archived that muscle generates low-frequency vibrations range of (5-100) Hz when muscle contract [2]. The mechanomyogram signal is observable at the surface of the muscle due to the movement of the muscle fibers underneath. There is also another definition for the MMG which is mechanical oscillation recording that associate with contraction of muscle [2], it is also can be detected on the skin overlying the muscle, so this MMG signal is easier to detect. However, it contains a lot of noise since the various muscle that moves at once. This signal can be detected by using some devices, such use of a microphone and accelerometer to measure the signal from the muscle [3]. New findings become important to upgrade the efficiency of MMG DAQ systems and implement their application in the rehabilitation of strokes patients, and hospitalities.

II. METHODOLOGY

A. DAQ System

The shimmer is a device used to collect raw EMG data and MMG data from the hand from which performing gesture. The shimmer is a self-contained device that has an inbuilt accelerometer, gyroscope, EMG sensors and much more. Data sensed by these modules can be transmitted through Bluetooth to a PC running Matlab. Each Shimmer device can support two channels of EMG and a 3-axis accelerometer. Accelerometers were placed in the arm as shown in Figure 1. One channel of an accelerometer placed in the Extensor digitorum muscle and the other placed over the Flexor digitorum. The Shimmer unit placed near the wrist so that it can measure the accelerometer activity as shown in Figure 2.

Figure 1: Position of triaxile Accelerometers in hand

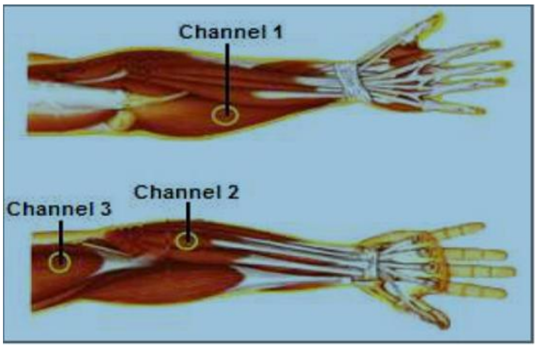

Figure 2: Forearm muscle sensors placement. Channel 1, 2 & 3: Flexor carpi Ulnaris, Extensor Carpi Radialis Longus, and Biceps respectively [4]

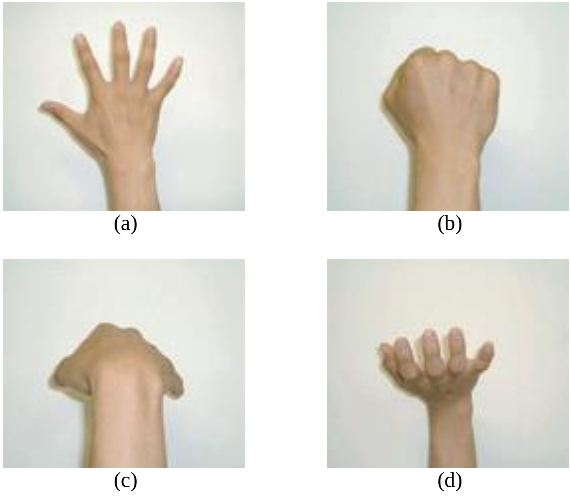

Figure 3: Proposed hand gesture; (a) Hand opening (b) Hand grasping (c) Wrist flexion (d) Wrist extension [5]

10 right-handed subjects were selected to take part in this experiment. First, the subjects were asked to sit on the chair. Their right hand of a subject placed on a table (perpendicular to the surface of table Each motion gestures as shown in Figure 3 are performed for a duration of 25s. To ensure that muscle fatigue was not an issue, participants given up to 120 s of rest between each (5 times) gesture performance.

Experiment Procedure steps:

Step 1: Set-up the Data Acquisition system.

Step 2: The test subject requested to sit in the seat.

Step 3: Place the Subject's right-hand perpendicular to the table.

Step 4: Place each sensor on Channel 1: flexor carpi radialis (FCR), Channel 2: extensor carpi radialis (ECR) muscles.

Step 5: Subjects asked to perform hand gestures according to the list below

i) Hand closing (5times in 25s, rest 120s)
ii) Wrist flexion (5times in 25s, rest 120s)
iii) Wrist extension (5times in 25s, rest 120s)
iv) Hand opening (5times in 25s, rest 120s)

Step 6: Repeat step 5 for each subject

Step 7: All the data recorded using personnel laptop.

B. Signal Processing

After the raw MMG signals captured using the accelerometer, it needed to undergo feature extraction and classification process for better precision and accuracy. The MMG (X-axis) signal converted into Fast Fourier Transform (FFT) to identify the noise that influences the signal. Then the signal split into two equal parts due to mirror similarity. The signal normalized for better clarification for the range that filter off. After that, the signal applied with Butterworth Filter stop reject. Ma, Martin et al. found that Butterworth Filter is good compared to Bessel and Chebyshev Filters [6]. The filtered signal then applied with a bandpass filter to improve the signal. In the last section, the filtered signal undergo rectification and smoothing.

For the Y-axis MMG signal converted into FFT and applied with Butterworth low pass filter in order to improve the signal. Then, the signal applied with Butterworth bandpass filter. At last, the filtered signal undergo rectification and smoothing. Z-axis MMG signal converted into FFT and applied with low pass filter to reduce noise. This project focuses on Y-axis MMG signal because the Y-axis appears less sensitive to muscle vibration than the X-axis. According to Chris Murphy et al., Y-axis MMG signal was more sensitive to limb movements due to the ankle and calf moving upward and forward because of the H-reflex, causing vibrations to travel in the y-direction. Whereas the x-axis measured the lateral, oscillations of the soleus muscle and was less sensitive to limb movements [1].

For the feature extraction part, root mean square (RMS), variance, mean absolute value (MAV), standard deviation (STD), root sum square (RSSQ) methods were used. These features are extracted from the filtered signal so that it can be classified accordingly. For example, RMS is a method that has the capability of calculating the value of finite sampled of the signal sampled at the uniform sampling rate. It is used for calculating the optimal value of the maximum potential of outputs. This method is used to narrow down the data that obtained from the signal recording to required and useful data only. The equations that used for features extraction are as follow.

RMS feature is an average value of root mean square of the MMG signal amplitude, which defined as [2]:

$$RMS = \sqrt{\left(1/N \sum_{i=1}^{N} x_i^2 \right)} \tag{1}$$

where: N = Total no. of Data
i = Length of MMG signal
x_i = MMG signal in a segment

Then MAV feature is an average of the absolute value of the MMG signal amplitude, which defined as [7]:

$$MAV = \frac{1}{N} \sum_{i=1}^{N} |x_i| \tag{2}$$

where: N = Total no. of Data
i = Length of MMG signal
x_i = MMG signal in a segment

Variance is defined as an average of square values of the deviation of that variable; it is also can be defined as [8]:

$$VAR = \frac{1}{N-1} \sum_{i=1}^{N} x_i^2 \tag{3}$$

where: N = Total no. of Data
i = Length of MMG signal
x_i = MMG signal in a segment

Standard deviation value of the wavelength as can be defined by [8]:

$$STD = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (x_{i+1} - x_{i)}{}^2} \tag{4}$$

where: N = Total no. of Data
i = Length of MMG signal
x_i = MMG signal in a segment

Root Sum Square or RSSQ is usually used for statistical tolerance, which is defined by [8]:

$$RSSQ = \sqrt{\sum_{i=1}^{N} |x_i|^2} \tag{5}$$

where: N = Total no. of Data
i = Length of MMG signal
x_i = MMG signal in a segment

Artificial Neural Network (ANN) is used in the classification process, which comes under the title soft computing. The network was trained with 200 set of data. Soft computing includes a number of techniques and methods used to solve any complex problem and difficulty same as human being. Multilayer ANN consists of three layers, input layer, hidden layer, output layer known with input and output function. Classification accuracy for different features calculated for MMG signal and applied to Levenberge - Marquardt algorithm based neural network for hand-movement realization. The success rate of classification is reported in results and discussion section.

III. Results and Discussion

The signals from X-axis appeared less sensitive to muscle vibration than the signals from Y-axis. The signals from Y-axis were more sensitive to limb movements due to the ankle and calf moving upward and forward because of the H-reflex, causing vibrations to travel in the Y-direction. Whereas the signals from X-axis were measured from the lateral, oscillations of the soleus muscle and was less sensitive to limb movements [1].

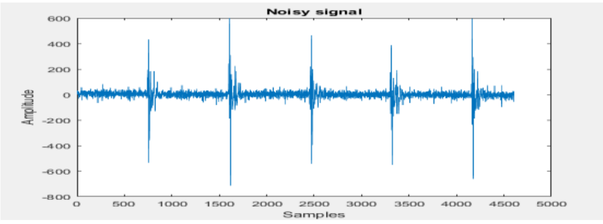

Figure 4: Y-axis raw signal

Figure 4 shows the raw Y-axis signal that collected during the experiment. The signal used for pre-processing such as filtering, rectifying and smoothing.

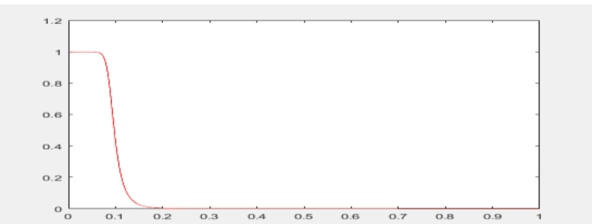

Figure 5: Butterworth low pass filter

This is the range was used for the low pass filtering as the Figure 5 which is start from 0.09 with 7th order filter which is this filter was needed based on the FFT of the raw signal.

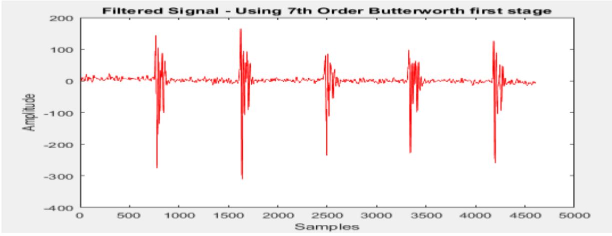

Figure 6: Signal after low pass filter

This is the signal pattern got after the low pass filter applied as Figure 6, in order to improve the signal, we applied the next stage filter.

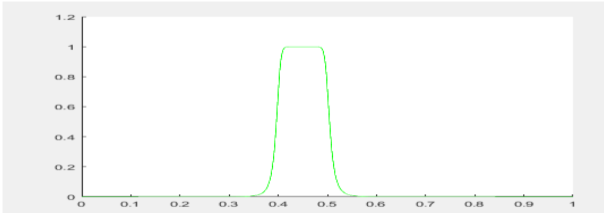

Figure 7: Butterworth band pass filter

In this stage, band pass filter applied and its range as shown in Figure 7, which between 0.4 to 0.5.

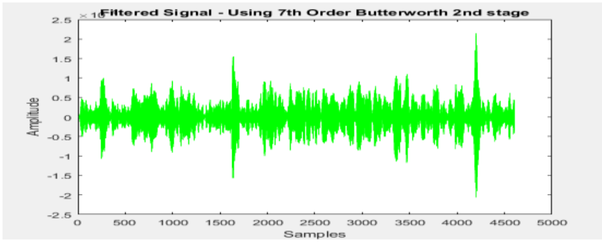

Figure 8: Signal after second stage of band pass filter

As the Figure 8, after the second stage filter, the signal is improved and the noise reduced.

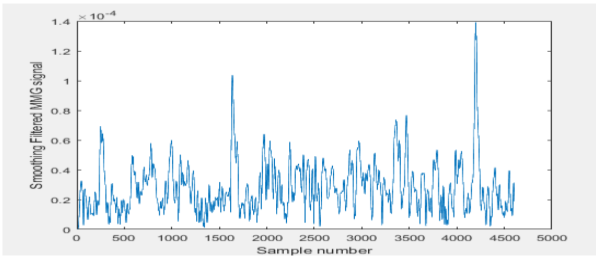

Figure 9: Final signal after rectified and smoothing

At last, for the signal as Figure 9 the final signal was look like this, from this signal the important data is now standing out.

Figure 10 shows the RSSQ feature that extracted from Channel 1 and 2.

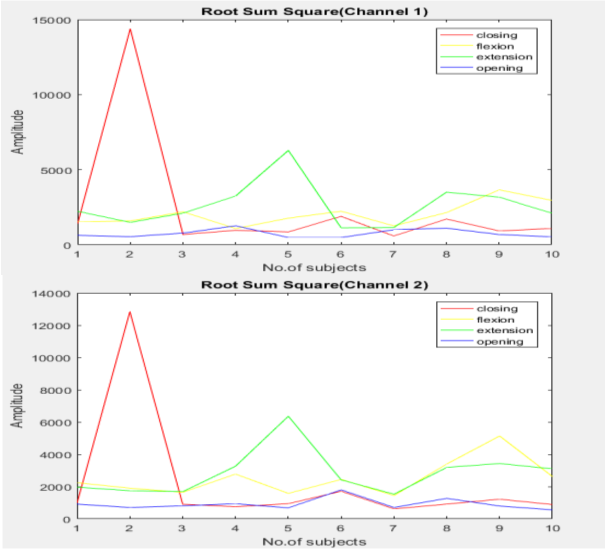

Figure 10: Average of root sum square for four different hand gestures

Tables 1 to 5 show the classification accuracy on each extracted feature. RSSQ is the feature that gives the highest accuracy in the ANN classification as compared to the other four extracted features.

Table 1
VAR Classification Accuracy for Y-Axis Data

Training (%)	Testing (%)	Hidden layer	Average of 5 trials (%)
90	10	15	86.19
80	20	15	91.25
70	30	15	87.58

Table 2
MAV Classification Accuracy for Y-Axis Data

Training (%)	Testing (%)	Hidden layer	Average of 5 trials (%)
90	10	15	89.50
80	20	15	89.00
70	30	15	88.08

Table 3
RMS Classification Accuracy for Y-Axis Data

Training (%)	Testing (%)	Hidden layer	Average of 5 trials (%)
90	10	15	90.75
80	20	15	86.75
70	30	15	85.00

Table 4
STD Classification Accuracy for Y-Axis Data

Training (%)	Testing (%)	Hidden layer	Average of 5 trials (%)
90	10	15	86.00
80	20	15	86.50
70	30	15	90.24

Table 5
RSSQ Classification Accuracy for Y-Axis Data

Training (%)	Testing (%)	Hidden layer	Average of 5 trials (%)
90	10	15	89.00
80	20	15	91.70
70	30	15	89.50

Clustering can be used in most unsupervised learning problems because it deals with finding in a structure in a collection of unlabeled data. The goal of clustering is to determine the intrinsic grouping in a set of unlabeled data. The cluster is collections of subjects, which are similar between and dissimilar to the objects, belong to other groups or classes. In this work, four different hand gestures can be grouped according to MMG signal. The MMG signal from four different hand gestures are clustered accordingly so that the machine can identify and recognize each of the hand gestures.

The clustering chart in Figure 11 shows the red dots signify hand closing, the blue dots signify wrist flexion, while the turquoise and pink represent the wrist extension and hand opening respectively. This step is just as the preceding step to develop the algorithm for supervised learning and test the accuracy and learning outcomes as well as the efficiency of the system.

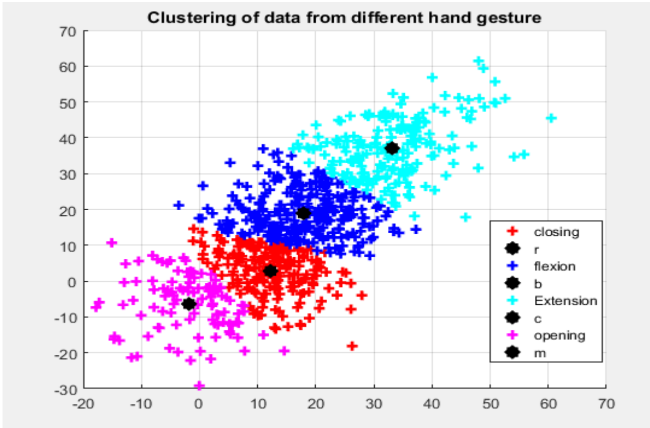

Figure 11: Clustering of the Data from Different Hand Gestures

IV. CONCLUSION

A study that monitors muscle activities and incorporates machine learning for the purpose of hand gesture recognition is completed. RSSQ is the selected feature from MMG signal to become input to the ANN classifier because it gives highest classification accuracy, which is 91.70%. The system can identify the hand gesture based on clustering method. A wearable band equipped with MMG sensors can be developed based on this study in the future, in order to produce a good hand gestures recognition system for rehabilitation purpose.

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