



# Reduction of Limb Position Invariant of SEMG Signals for Improved Prosthetic Control Using Spectrogram

E.F. Shair<sup>1\*</sup>, M.F.A. Suleiman<sup>1</sup>, A.R. Abdullah<sup>1</sup>, N. Nazmi<sup>2</sup>, N.Z. Saharuddin<sup>1</sup>

<sup>1</sup>Rehabilitation and Assistive Technology (REAT) Research Group,  
Centre for Robotics and Industrial Automation (CeRIA), Faculty of Electrical Engineering,  
Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, Durian Tunggal, 76100 Melaka, MALAYSIA

<sup>2</sup>Malaysia-Japan International Institute of Technology,  
Universiti Teknologi Malaysia, Jalan Sultan Yahya Petra, 54100 Kuala Lumpur, MALAYSIA

\*Corresponding Author

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**Abstract:** Prostheses are artificial devices that replace a missing body part, which might be lost through injury, infection, or a condition present at birth. It is proposed to re-establish the normal functions of the missing body part and can be made by hand or with a computer-aided design. As per the World Health Organization, around 160,000 individuals in Malaysia are required to use prostheses. One of the elements that influence the current prosthesis control is that the variety in the limb position and normal use results in different electromyogram (EMG) signals with the same movement at various positions. Consequently, the objective of this study is to ensure that amputees can control their prosthetics in an exact manner regardless of their hand movement and limb position. The raw EMG signals are taken from eight different hand movements' classes at five different limb positions and each of these hand movements has seven electrodes attach to it. This paper utilizes time-frequency distribution which is spectrogram to extract the EMG feature and six SVM classification learners; linear, quadratic, cubic, fine Gaussian, medium Gaussian, and coarse Gaussian were compared to find the most reasonable one for this application. The analysis performance is then verified based on classification accuracy. From the results, the overall accuracy for the classification is 65% (linear), 87.5% (quadratic) and 97.5% (cubic), 100% (fine Gaussian), 70% (medium Gaussian, and 45% (coarse Gaussian), respectively. It is believed that the study could fill in as knowledge to improve conventional prosthetic control strategies.

**Keywords:** Electromyogram, time-frequency distribution, support vector machine, prosthetic, hand movement, limb position

## 1. Introduction

To this day, interfaces between human-computer have been of great importance in allowing people to interact and manipulate a particular machine. Since many people with disabilities have trouble accessing current help-robotics and higher-development manual-machine interface, rehabilitation equipment with conventional user interfaces, such as joysticks and keyboards is required. It is evident that amputees or handicapped individuals can generate electromyogram (EMG) signal patterns that are repeatable but are varying gradually at different levels of static muscle contraction [1].

EMG is a type of diagnostic procedure that evaluates the health condition of muscles and the nerves that control them. The nerve cells or also known as motor neurons transmit electrical signals that cause the muscle to contract and relax. An EMG translates these signals using characteristics of EMG waveforms, thus helping doctors in their diagnosis.

\*Corresponding author: [ezreen@utem.edu.my](mailto:ezreen@utem.edu.my)

As previous researchers have suggested, an EMG signal is taken from humans muscles to develop a powered prostheses and rehabilitation instruments' control source [2-3]. The said interfaces directly sense and decode the recorded EMG signals. To differentiate between EMG signals that belong to various arm movements, a control scheme known as myoelectric control that employs a pattern recognition approach is used [4].

The principal assumption is that for a given pattern of activation, the EMG signals obtained during the extraction of features would generally be more or less the same. Also, at the same electrode location, the said features will not be similar from one pattern of muscle actuation to another [5]. This study focuses on the upper-limb position effects on EMG pattern recognition and the impact of the upper limb position as additional analysis of the EMG pattern recognition recorded by the previous researchers [6].

This study proposes a new approach for extracting features as an alternative solution for accelerometers. The method relies on the local and worldwide specificities of the EMG signal and the use of these features to establish a collection of invariants for EMG signals' changes that pertain to the same motion [7].

Many factors contribute to the formation of the research gap, where it can significantly affect the EMG pattern recognition performance thus resulting in an unusable controller. The variation in the limb position associated with normal use is an important contributor to the limited functioning of such controllers in practice, as it results in various EMG patterns for the same movements when they're done in positions. Electrode shifts caused by changes in muscle length, shape, and position will result in signal amplitude and frequency changes as different numbers of muscle fibers could be recruited.

This study focus on the upper-limb position of an EMG pattern recognition on multiple subjects as an alternative to the use of accelerometers features extraction method. EMG signals from six subjects with five limb positions and each limb position have eight different types of hand movements are used.

|        |   |
|--------|---|
| EMG    | Electromyography  |
| SEMG   | Surface electromyography  |
| SENIAM | Surface Electromyography for the Non-Invasive Assessment of Muscles |
| ISEK   | International Society of Electrophysiology and Kinesiology          |
| TD     | Time Distribution   |
| FD     | Frequency Distribution  |
| TFD    | Time-frequency Distribution   |
| STFT   | Short-time Fourier Transform  |
| RMS    | Root Mean Square  |
| BC     | Bayesian Classifier   |
| SVM    | Support Vector Machine  |
| ANN    | Artificial Neural Network   |
| FL     | Fuzzy Logic   |
| LDA    | Linear Discriminant Analysis  |
| MLP    | Multilayer Perceptron   |
| KNN    | K-nearest Neighbor  |
| PCA    | Principal Component Analysis  |

## 2. Material and Methods

### 2.1 EMG Data

Researchers in the past two decades have studied the use of surface EMG (SEMG) signals to decode high limb activities [8]. SEMG is a non-invasive method for recording electric activities produced by skeletal muscle motor units [9]. The SEMG derived from the forearm is used to track hand movements and the location of the wrist and forearm joints through the use of machine learning techniques [10]. Although the subjects recruited have usually been limbed and have no musculoskeletal or neurological problems, it is clear to see the same strategy for trans-radial amputates.

The key point that is presented here is an EMG-based control scheme, not only for the use of amputees and prosthetics but that can also be used in various EMG-based monitoring systems (including muscular / computer game interfaces by Microsoft). For trans-radial amputees, however, the physiologically used muscles in the residual forearm are the best option to control multi-fingered prostheses, as are the flexes/extensions of the hand and wrist. As shown in Fig. 1, the data sets have therefore been captured using 7 EMG channels (Delsys DE 2.x EMG sensors series) mounted around the forearm circumference and analysed by Delsys Inc.'s Bagnoli Desktop EMG program [7].

The clinical significance of the proposed scheme is justified in return, which is also applicable to trans-radial amputees. The first EMG sensor has been mounted on each of the participants' Palmaris Longus muscles, while the rest of the sensors are positioned to maintain the same distance between them. The EMG signals obtained were amplified with a total gain of 1000 by a Delsys Bagnoli-8 amplifier [7]. The signal sample was then obtained by means of a 12-bit analogue to digital converter in 4000 Hz (National Instruments, BNC-2090) with MATLAB Technology. Data that are

used in this project are taken from an open-source which consists of 11 subjects (9 males, 2 females), aged between 20 and 37 years with normal body mass index (BMI). Each subject has eight different hand movements and seven electrodes each attach to their arm. The posterior and anterior electrode positions are shown in Fig. 2. All readings were repeated three times to ensure data reliability.

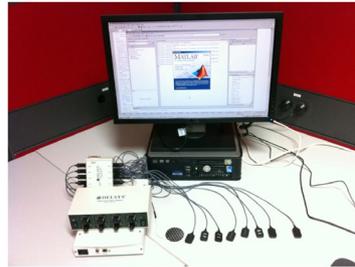


Fig. 1 - data acquisition set up

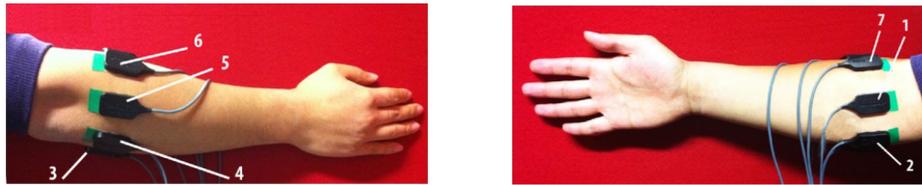


Fig. 2 - (a) posterior and (b) anterior electrodes position

## 2.2 Signal Pre-Processing

Before the extraction and classification steps, pre-processing is essential for handling data from an EMG signal. This is to improve the precision and response time of the information, such as data segmentation, filtering, and rectification. Such data must initially be separated into small segmented EMG signals [11]. The various window lengths of the EMG data have been suggested as it influenced error in classification [12]. This has been proven by previous researchers, that the performance of the EMG classification has been degraded by using a segment length that is less than 128 ms [11].

This is similar to the 2013 report, where classification accuracy improves with the segmental length increase from 125 ms to 500 ms [13]. This is because a larger segment provides additional details and creates a slight bias in the estimation of the function. Thus, results in a small variance. Due to the high precision of the segment state, the upper limbs can also be controlled in real-time [14].

From previous research, it has been indicated that the sample duration of EMG data at the beginning of the movement is set at 256 ms since it includes movement data information [15]. This follows the requirement that is set by other researchers, which states that the reaction time should not exceed 300 ms to meet the real-time limits for prosthetic limb control [11].

Analog filters are added to the raw signal, typically bandpass, before digitalisation. Filtering the band transfer separates high and low frequencies. The low-frequency filter eliminates baseline movement drift and prevents any DC offset. The low-frequency cut-offs are usually between 5 and 20 Hz. If the mean values of the signal are not zero before the filtering of a high pass or bandpass, they shall be subsequently as such filters exclude low-frequency components of the signal and thereby cause the average value to be null or almost null.

The high-frequency band-pass filter cuts away high-frequency noise and eliminates aliases in the sampled signal. The high-frequency is used to ensure that the EMG can still be easily detected with fast start-up bursts. Values are usually between 200 Hz and 1 kHz which follows the recommendation for EMG by the Surface Electromyography for the Non-Invasive Assessment of Muscles (SENIAM) and International Society of Electrophysiology and Kinesiology (ISEK) (Refer Table 1).

Table 1 - Filter recommendation by SENIAM and ISEK

| Organisation | Type of EMG                  | Filtering | Cut off Frequency |
|--------------|------------------------------|-----------|-------------------|
| SENIAM       | Surface EMG                  | Low Pass  | Near 500 Hz       |
|              |                              | High Pass | 10 - 20 Hz        |
| ISEK         | Surface EMG                  | Low Pass  | 500 Hz            |
|              |                              | High Pass | 5 Hz              |
|              | Intramuscular and needle EMG | Low Pass  | 1500 Hz or higher |
|              |                              | High Pass | Not specified     |

To improve the accuracy of the signals, the filtering of the signals is done. The standard SENIAM range of the bandpass frequency is from 10Hz and 20Hz to between 500HZ and 1000Hz. From that standard range frequency of 20Hz to 450Hz is chosen as the bandpass frequency for this study.

### 2.3 EMG Feature Extraction

Feature extraction plays an important role in signal processing analysis to achieve a better performance of classification for motion pattern recognition. Raw EMG signals are converted into an electrical vector during this process. Mainly, EMG analysis can be classified into three categories: time domain (TD), frequency domain (FD), and time-frequency domain (TFD). For TD characteristics, it is evaluated on the basis of a signal amplitude that depends on the time and signals amplitude during the observation process. To maintain complexities, many of the preceding studies centered on TD functions, and this function needs no further signal transformation. Table 2 shows the comparison between TD, FD, and TFD.

**Table 2 - Comparison between TD, FD, and TFD**

| Features                    | Advantages  | Disadvantages   |
|-----------------------------|---|---|
| Time Domain (TD)            | Low noise environment and lower computation complexity    | Non-stationary property of EMG signal                     |
| Frequency Domain (FD)       | Reducing interference and good localization of the signal | High noise environment                                    |
| Time-Frequency Domain (TFD) | Can overcome the limitation of the Time Domain            | High dimensionality and high resolution of feature vector |

The problem of finding the most compact and concise feature set, which can define the EMG signal accurately in a simplified representation, can be solved during feature extraction. Past researchers have indicated that the feature space for the set function to be matched to EMG-based regulation should have full class separability [11]. A major benefit of using the time domain function is the decrease in complexity associated with the feature extraction process. Though features extracted via time domain methods have been proven to be effective and sufficient for real-time control, some suggestion is that pattern identification results using these feature vectors may not bring high achievement in the literature.

Accordingly, in this study, the spectrogram which is a TFD is utilized in feature extraction. It is utilized to overcome the constraint of time and frequency representation for the nonstationary EMG signal. It is characterized as the squared magnitude of short-time Fourier transform (STFT) as expressed in (1).

$$S(t, f) = \left| \int_{-\infty}^{\infty} x(\tau) \omega(\tau - t) e^{-j2\pi f \tau} d\tau \right|^2 \tag{1}$$

where  $S(t, f)$ : time-frequency representation,  $x(\tau)$ : EMG signal, and  $w(t)$ : observation window.

The signals are extracted using TFD as it gives the most informative data contrasted to the others. In TFD, the time and frequency resolution can be acclimated to get valuable signal details.

There are two rapidly processed EMG features; the average rectified value and the root-mean-square voltage ( $V_{rms}$ ) [2]. Nevertheless, the  $V_{rms}$  is better because it isn't influenced by the cancelation of the amplitude that occurs when the positive and negative phases of the EMG signal are superimposed [16]. The  $V_{rms}$  was measured instantaneously over time based on the resulted time-frequency representation and the average values were taken for hand movement and limb position prediction. The average RMS voltage can be expressed as in (2).

$$V_{rms(avg)} = \frac{1}{T} \int_0^T V_{rms}(t) dt \tag{2}$$

where

$$V_{rms}(t) = \sqrt{\int_0^{f_{max}} S_x(t, f) df} \tag{3}$$

where  $V_{rms}(t)$ : instantaneous RMS voltage,  $S_x(t, f)$ : time-frequency representation, and  $f_{max}$ : maximum frequency of interest.

## 2.4 Classification

To distinguish various categories of the extracted features, classifiers ought to be deployed. The categories acquired will be applied as control commands for the controller in future works. A few techniques are used to classify data such as Bayesian classifier (BC), support vector machines (SVM), artificial neural networks (ANN), fuzzy logic (FL), linear discriminant analysis (LDA), multilayer perceptron (MLP), K-nearest neighbor (KNN), principal component analysis (PCA) and Hidden Markov Models (HMM) [11].

From past research, it has been expressed that the performance of feature extraction and dimensionality reduction is dependent upon the capabilities of a classifier [19]. LDA and PCA are also known as statistical classifiers had been used to classify hand movement. Although that LDA requires no heuristic architecture or training algorithm, it performs very well in a consistent manner. This is likely because of the PCA dimensionally reduction has an effect of linearizing by discrimination of the classifier. In the year 2013, a researcher had compared the performance of KNN, LDA, SVM, and multi-layer perceptron neural networks (MLP-NN) quadratic discriminant analysis (QDA) to classify ten upper limb motions [17]. And as a result, based on TD features LDA gained the highest classification accuracy. However, by using MLP to classify human forearm motion based on TFD features research had produced about 99% classification accuracy [18].

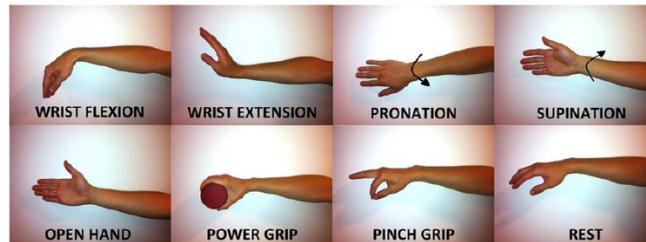
The theory of vector machines supports the simplest approach of neural networks architecture, removing domain knowledge requirements. SVM theory is applied to a single hidden layer of the MLP for pattern classification, regression, or density estimate. In contrast with BP, various cost functions are used to distinguish patterns and regression. Particularly, by using SVM learning, no hidden layer need to be selected.

To transform a nonlinear and separable pattern classification problem into a linearly separable, the hidden (feature) space is chosen for high dimensionality. Nonetheless, in a task of classification of the pattern, particularly the SVM learning algorithm selects support vectors to optimize the class separation range. For SVMs, quadratic programming can avoid the issue of the curse of the dimensionality that can harm the architecture of multilayer perceptions [19]. Its technique is used to resolve the linear weights of the output layer, based on the input data directly.

By utilizing the classification learner in MATLAB, a total of six different classifiers were utilized in this project to get the best accuracy, which is cubic SVM, quadratic SVM, linear SVM, fine Gaussian SVM, medium Gaussian SVM, and coarse Gaussian SVM. From the six subjects, 80% of the data is used for training, while the other 20% is for testing.

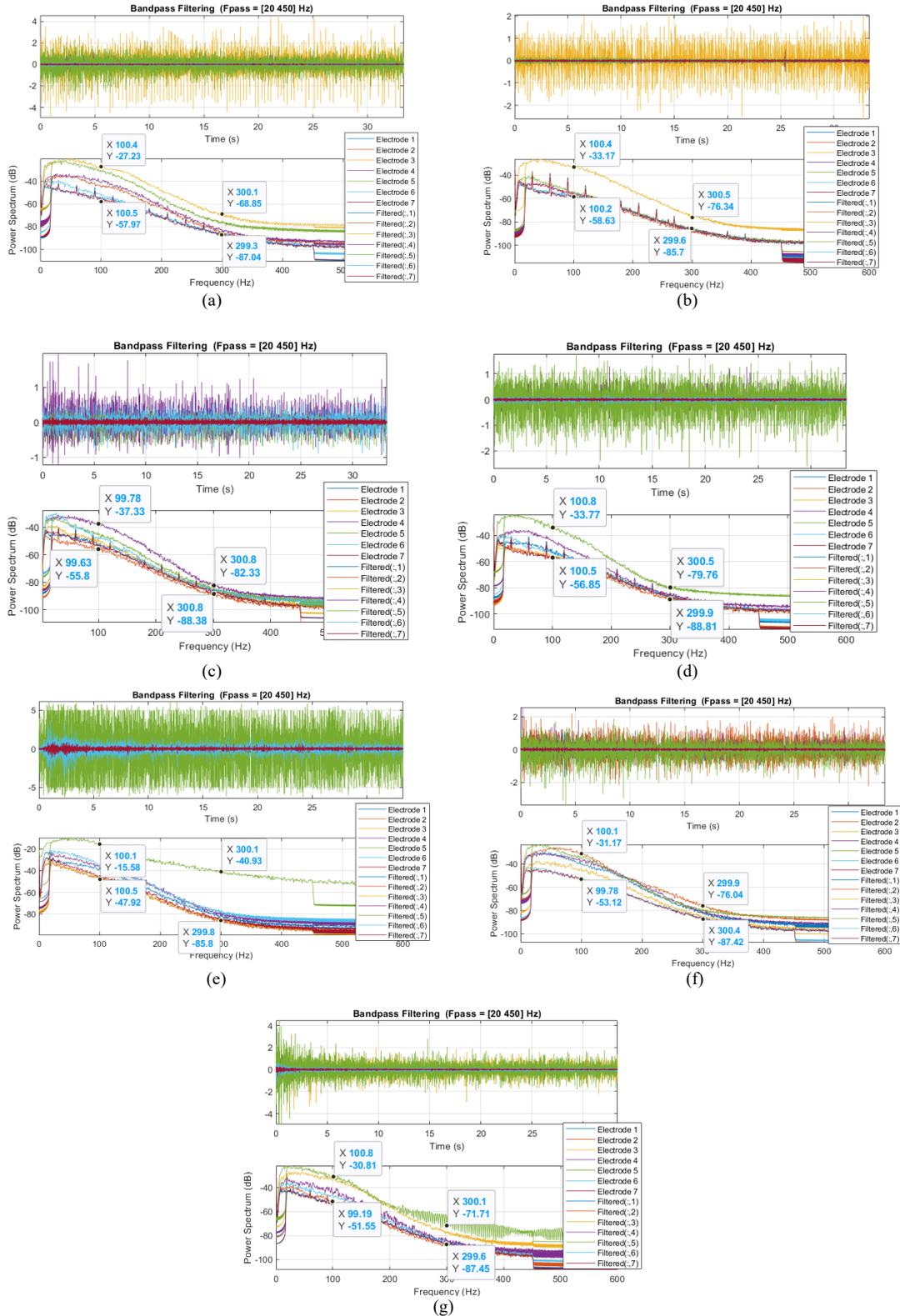
## 3. Results and Discussions

The raw EMG signals are taken from eight different classes of hand movements as shown in Fig. 3 and each of these hand movement has seven electrodes attach to it. For accuracy purposes, each of the hand movements is simulated six times.



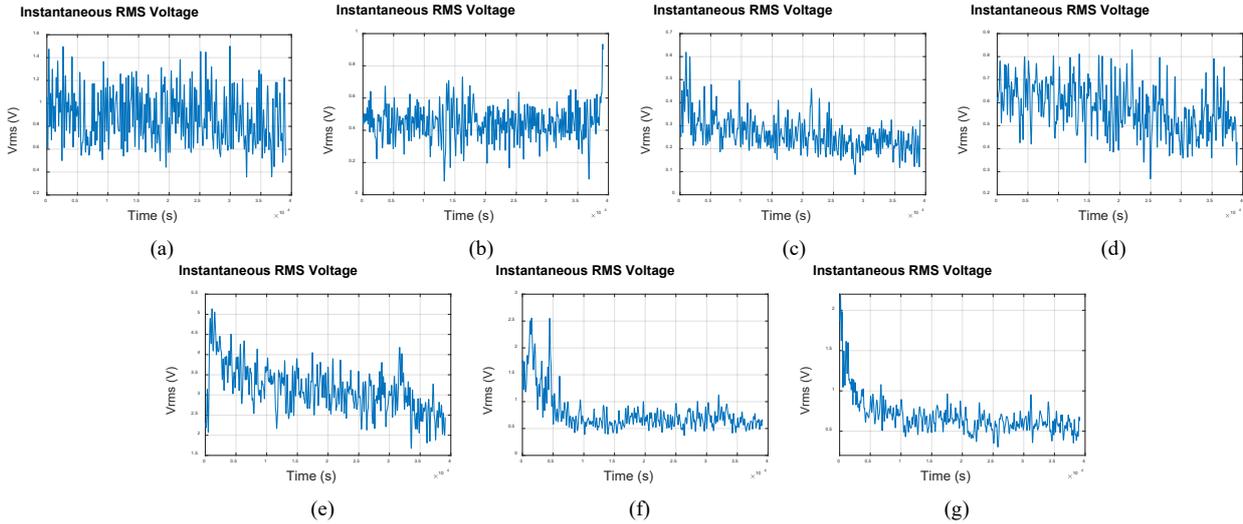
**Fig. 3 - Different hand movements**

The raw EMG signals are filtered using a bandpass filter between 20 and 450 Hz with a sampling frequency of 4000 Hz to avoid aliasing. Fig. 4 shows the filtered signal of subject 1 for different hand movements. The seven signals in Fig. 4 represent seven different electrodes attached to the arm. The upper graph of Fig. 4 shows the raw signal while the bottom shows the filtered signal.

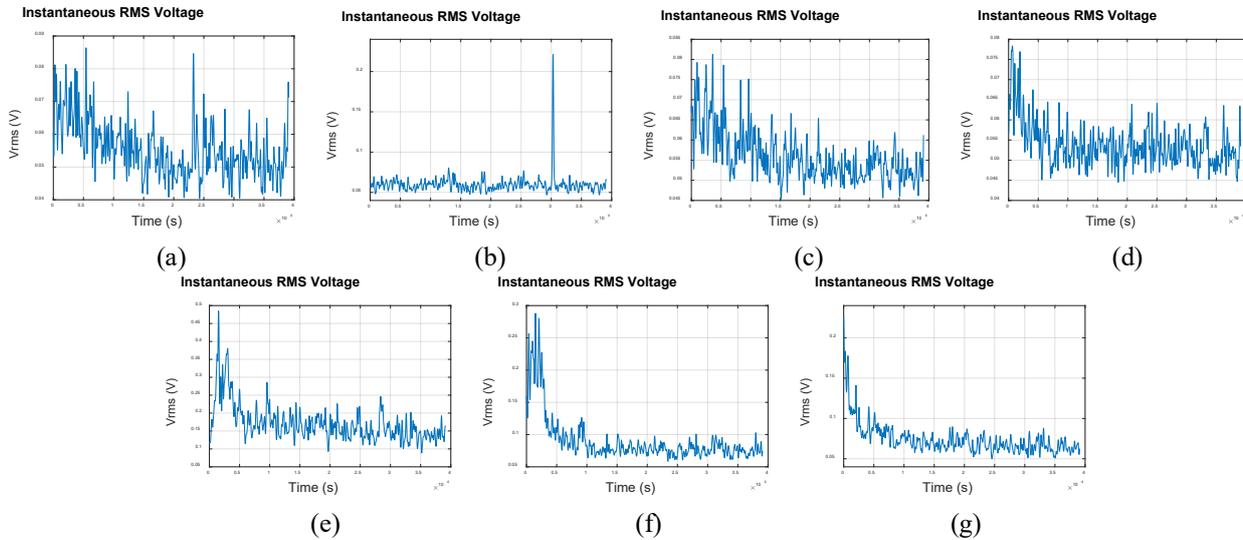


**Fig. 4 - Raw and filtered EMG signals during (a) hand open; (b) hand rest; (c) object grip; (d) pitch grip; (e) wrist extend; (f) wrist pronation; (g) wrist supination**

The filtered EMG signal is then processed to extract the EMG feature;  $V_{rms}$ . Fig. 5 and Fig. 6 show the instantaneous  $V_{rms}$  that has been extracted from electrode 5 and 7 for each hand movements, respectively.



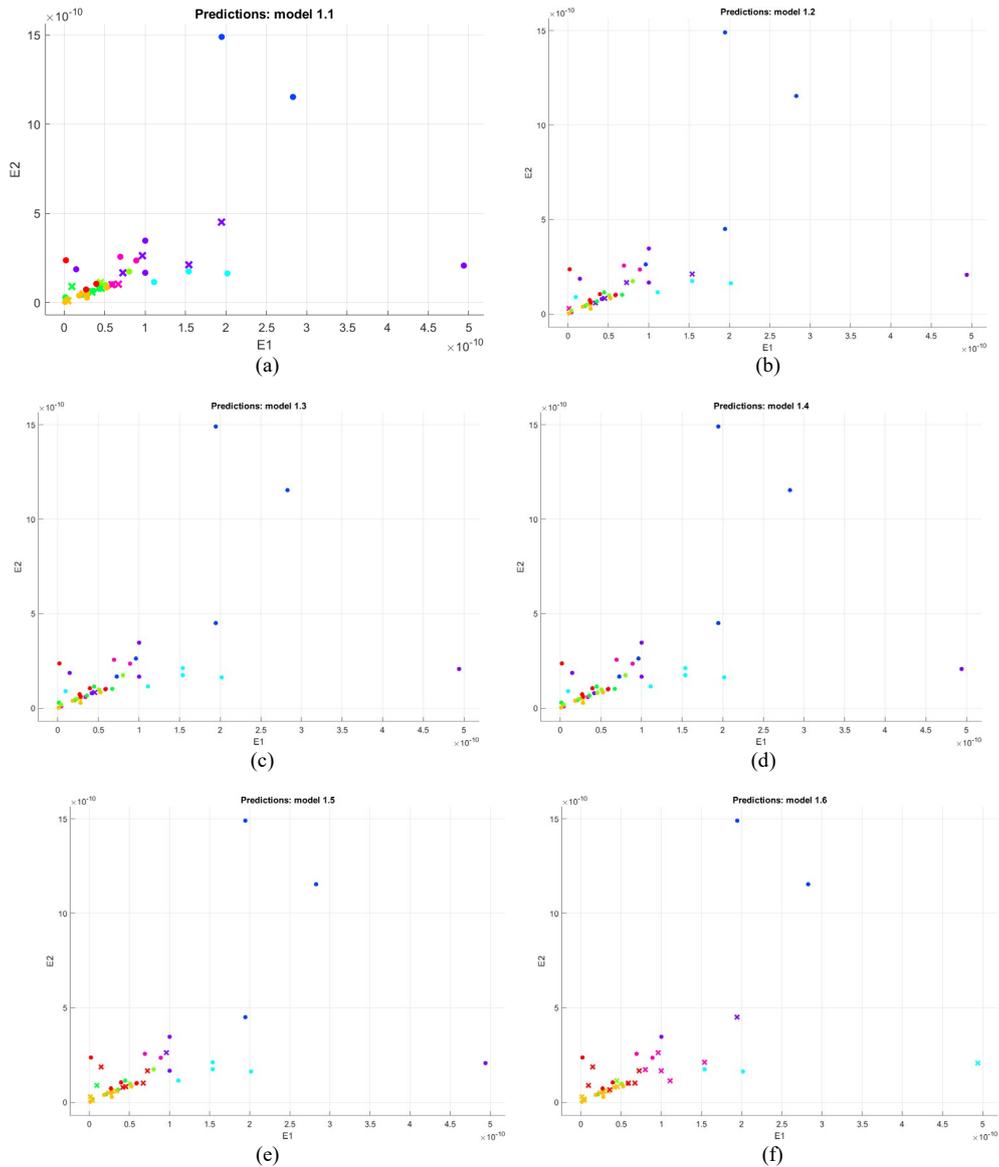
**Fig. 5 - Instantaneous  $V_{rms}$  extracted from electrode 5 during (a) hand open; (b) hand rest; (c) object grip; (d) pitch grip; (e) wrist extend; (f) wrist pronation; (g) wrist supination**



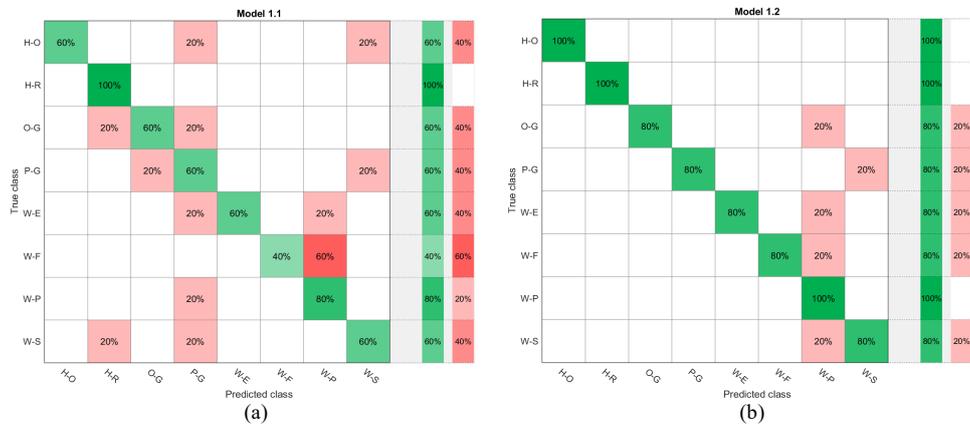
**Fig. 6 - Instantaneous  $V_{rms}$  extracted from electrode 7 during (a) hand open; (b) hand rest; (c) object grip; (d) pitch grip; (e) wrist extend; (f) wrist pronation; (g) wrist supination**

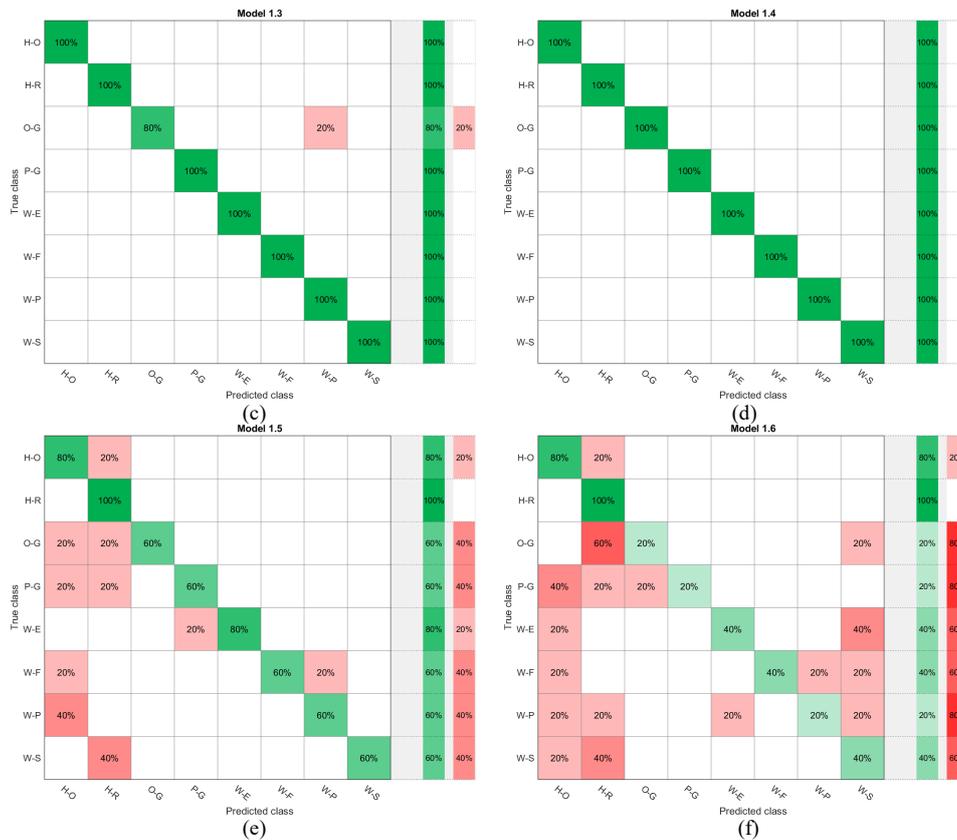
Subsequent to extracting the  $V_{rms}$  for every movement from all subjects, an analysis based on the average  $V_{rms}$  is done. The higher the average  $V_{rms}$  on a single electrode indicates that it has a significant influence in classifying the movements involved and the least will assume a minor role to classify the movement. From the result, six out of the eight movements record the highest average  $V_{rms}$  value from electrode 5. This indicates that electrode 5 records the most number of highest average  $V_{rms}$ . This is then followed by electrode 7 with two out of the eight movements record the highest average  $V_{rms}$ .

For the classification, there are six types of SVM classifiers used to classify the eight movements. These classifiers comprise linear SVM, quadratic SMV, cubic SVM, fine Gaussian SVM, medium Gaussian SMV, and coarse Gaussian SVM. The EMG feature is used as input to the classifier with 80% for training and 20% for testing. The performance of the classifiers is compared based on accuracy. The performance of the SVM classifiers is shown in the scatter plot and confusion matrix in Fig. 7 and Fig. 8, respectively.



**Fig. 7 - Scatter plot of (a) linear SVM; (b) quadratic SVM; (c) cubic SVM; (d) fine Gaussian SVM; (e) medium Gaussian SVM; and (f) coarse Gaussian SVM**





**Fig. 8 - Confusion matrix of (a) linear SVM; (b) quadratic SVM; (c) cubic SVM; (d) fine Gaussian SVM; (e) medium Gaussian SVM; and (f) coarse Gaussian SVM**

For the linear SVM, most of the data has a false-negative rate of over 40%, and a 60% value of true positive with the hand rest movement is the only one without any false-negative data. The highest inaccuracy occurs during wrist flex with false-negative rate of 60%. For the quadratic SVM, the majority of the data has an accuracy of over 80%, with false-negative rate of 20% with the hand open, hand rest and wrist pronation movement are the only ones without any false negative data. For the cubic SVM, the majority of the data has an accuracy of over 100% with the open grip movement are the only one with inaccurate data, which is 20%. For the fine Gaussian SVM, all the data has an accuracy of 100% with no false-negative value. For the medium Gaussian SVM, the majority of the data has an accuracy of over 60%, and over 40% value of false-negative with the hand rest movement is the only one with inaccurate data, which is 20%. For the coarse Gaussian SVM, the majority of the data has a rate of false-negative of over 60%, and only 20% value of true negative with the hand rest movement is the only one with no false-negative rates data. From the results, it can be summarized that the fine Gaussian SVM is the most suitable classifier for this application with 100% accuracy, followed by cubic SVM (97.5%), and quadratic SVM (87.5%), respectively.

#### 4. Conclusions

In conclusion, this study has presented research on the impact of upper limb position on SEMG pattern recognition performance. The analysis shows that several factors influences the EMG signal’s performance at different hand movement. The first factor is the consistency of the extracted features and their ability to distinguish robustly hand movements in different limb positions. Changes in the EMG signal characteristics at various limb positions may prompt to a change in signal shape, amplitude, scaling time, and translation of the frequency spectrum.

The subsequent aspect is the differences in the recruitment of muscles, with various muscle types employed to perform a particular function to stabilize their limb in specific limb positions. EMG feature based on the time-frequency domain derivation is used to address the effects of the aforementioned factors and fine Gaussian SVM is regarded as the best classifier that can be used to classify as many as eight hand movements.

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