Investigation of Pattern Recognition System Based On Electromyography Signals for Optimal Electrodes' Number and Positions

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Abstract:-

This paper proposes a pattern recognition system for classification of six hand movements and rest by using only three Surface ElectroMyoGraphy (sEMG) sensors with the use of Arduino microcontroller as data collector. The performance of the Time Domain with Auto Regression (TDAR) and the recently proposed Time-Dependent Power Spectral Descriptors (TD-PSD) were compared as feature extraction and the k-Nearest Neighbor (KNN) and Linear Discriminant Analysis (LDA) algorithms as classifiers. In addition, the effect of electrodes' location on forearm and effect of channels number on performance of the pattern recognition system were investigated. Results showed that the performance of the TD-PSD and LDA is higher than that of TDAR and KNN where good classification accuracy was achieved by using only three channels (sEMG) which represented the best three electrode locations for recognizing the six hand movements and rest. Classification accuracy of 97 % was achieved by using only three sEMG channels using low cost components like Arduino and Myoware sEMG sensors which make the proposed system is low cost.

Keywords: Electromyography, Pattern recognition, Prosthetic hand, Arduino, Myoware sensor

1. Introduction

Worldwide, there are many people living with upper limb loss because of diseases and accidents which lead to amputate their limbs. To assist this segment of people, the field of prosthetics was existed and it is developing so rapidly to produce fully integrated, mechatronic and multifunctional prosthetic hand. Nowadays, to achieve these goals, pattern recognition based on muscle activity or Electromyography (EMG) signals is one of important methods which is used to control prosthetic hand so as to make prosthetic hand giving the patients the most possible functional capability back [16]. This approach is intuitive (more natural), reliable, fast and offers the ability to control multiple degrees of freedom of the

prosthesis [5]. The block diagram for the sEMG pattern recognition system is shown in **Fig.1**. To control and preform multi movements of prosthetic hands, there are many effects that must be taken into consideration. Some of these effects are sEMG electrodes location on forearm, the number of sEMG channels which were used to collect data and finally the techniques of features extractions and the classification methods used.

In [1], new feature extraction method was proposed which extracts power spectral descriptors of EMG signals directly from the time-domain to reduce computational cost. This method called Time Dependent Power Spectral Descriptors (TD-PSD).

Data Collection

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Data Segmentation

↓

Feature Extraction

↓

Classification

↓

Output smoother
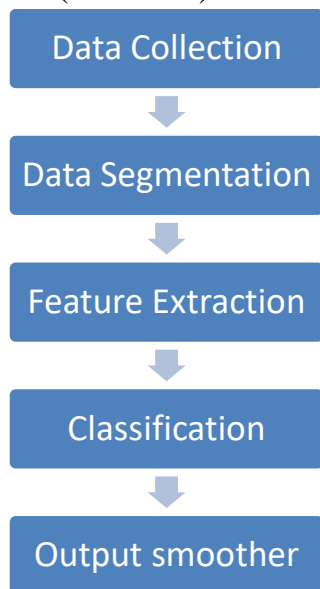
Fig. 1 Block diagram of the pattern recognition system

The performance of the proposed features was tested on EMG data collected from nine subjects performing six classes of movements. The results indicated that the proposed features can achieve significant reductions in classification error rates in 6% to 8% in the average.

Kim et al. [13] compared the k-Nearest Neighbor, Quadratic Discriminant Analysis, and Linear Discriminant Analysis algorithms for the classification of wrist motion directions such as up, down, right and the rest state. The forearm EMG signals for those motions were collected using two EMG channels system. Thirty subjects participated in their study. Thirty features with a window size of 166 ms were extracted. The recognition rates were 84.9% for kNN and 81.1% for LDA.In [3] the effect of the number and location of electrodes on finger movement classification was investigated during a typing task. .Eight electrodes were positioned around the forearm to detect muscle activity associated with the finger movements. The classification accuracy for each of the 255 possible electrode configurations was then determined using classification systems. The effect of electrode array size and arrangement on classification accuracy was also investigated for a four finger typing task. Advantages were found using array sizes of three and seven electrodes; electrodes located near bones were least commonly selected. But, electrodes were most commonly selected approximately over the flexor digitorum profundus. Classification accuracy of 92% was

found in the latter case across twelve subjects.

The motivation of this paper is to develop a control system based on pattern recognition of EMG for a prosthetic hand, studying the effect of electrodes' positions on forearm and finding best positions for electrodes to classify six movements (open, close, index, pinch, pronation, supination) and rest as shown in **Fig.2** .

Electrodes position and number play an important role in myoelectric based pattern recognition problem.

Fig. 2 Six movements and rest were investigated in this study.

2. MATERIALS AND METHODS

2.1 Proposed Method

The proposed pattern recognition system of this work includes five stages. Firstly, the sEMG signals were acquired by data acquisition device. Secondly, filtering and windowing of the collected data. Thirdly extract features from data segments. Then, classify the features using suitable algorithms and finally refine the classification result via the majority vote post-processing as shown in **Fig. 1**.

2.2 sEMG Data Collection

The EMG data in this work were acquired from six subjects, two females and four males. All subjects, which were aged between 25 and 45 years, were normally limbed with no muscle damage. To avoid the effect of position's movement on sEMG signals, subject's arm was supported and fixed at certain position [11].

In this study, three disposable EKG Ag/AgCl surface electrodes, with circular metal of 1 cm diameter for each of the three sEMG sensors, were used with bipolar configuration to acquire the sEMG signals as shown in Fig.3. Before putting the electrodes on forearm, the skin must be cleaned with piece of cloth and alcohol to remove dirt and oil. For increasing the conductivity and decrease the electrode-skin impedance, electrolyte gel was applied between the skin and the electrodes.


Fig. 3 sEMG electrodes.

2.3 sEMG sensors

Three Myoware, low cost sEMG sensors were used. each of them consists of one positive sign pole, one negative sign pole and one reference wire used as the path that transfer the sEMG signals from electrodes to the electronic condition circuit. The most common noises that can contaminate sEMG in the detection stage are motion artifact, poor skin contact, cable movement and poor reference.

To collect the raw sEMG signal, three MyoWare sensors were used to measure the muscle activity as shown in **Fig.4**, which designed to be wearable. The voltage supply for the sensor is +5Volt, current supply is 9mA with polarity reversal protection [21]. The MyoWare sensor amplifies the electrical activity of a muscle with gain 10000 and converts it into an analog signal that can be read via controller with an analog to digital converter.
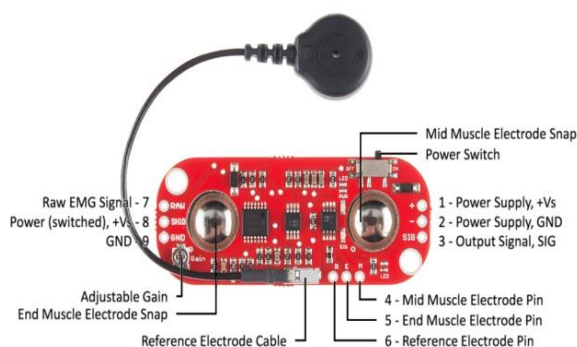
Fig. 4 Low cost MyoWare sEMG sensor [18].

2.4 Analog to Digital Convertor

In this work, Arduino M0 controller, as shown in Fig.5, was used to convert raw EMG signal to discrete signal. It is powered by Atmel's SAMD21 MCU, featuring a 32-bit ARM Cortex® M0 core operate at 3.3 volts with clock speed of 48 MHz and 6 inputs analog to digital convertor providing 12 bits of resolution (i.e. 4096 different values). By default, the analog inputs measure from ground to 3.3 volts [23].

Fig. 5 Arduino M0 microcontroller.

The Arduino reads analog signal from MyoWare sensor and converts it to digital signal, then send the data to computer via USB cable through serial port.

Handshaking method was used to avoid missing any data during the transmission. The Arduino waits until it gets a serial response from the computer which is an ASCII a (byte of value 49). Then, it sends sensor value as double bytes, and waits for another response from the computer. This operation is very important to be sure the Arduino and computer are synchronous and no data is missing, also if more than one channel of ADC is used. This method will keep the sequence of channels correct [22].

2.5 Electrode placement

Three MyoWare sEMG sensors were used in this study to collect raw sEMG signals from six positions on forearm in two stages, by using three sensors in three positions 1,3 and 5. Then, the experiment was repeated again for another three positions 2, 4 and 6 as shown in Fig.6 and **Fig.8**. The reasons to use three sensors instead of six are to reduce the cost, reduce the computation time which is needed to analysis the data. It is suitable with Arduino capability when six sensors which are used the sampling rate reduced to half about 400 per channel and this cause aliasing [9] so the sampling rate must be at less twice than sEMG signal maximum frequency which its range between 20 and 400 Hz.

These sensors are connected with ADC pins of controller (Arduino (M0). The signal sources were obtained from two electrodes with a conductive adhesive reference electrode placed in the elbow as shown in **Fig. 7**.
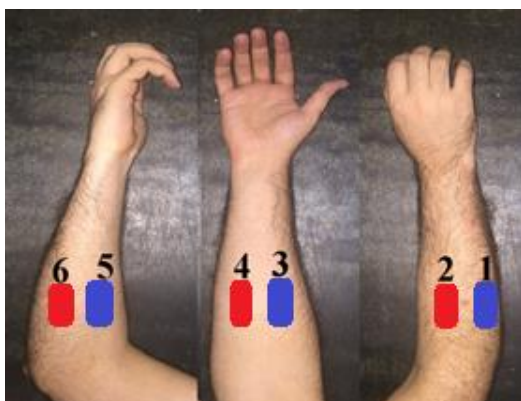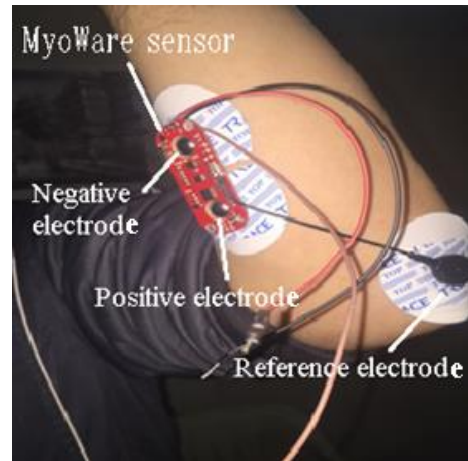

Fig. 7. sEMG sensor with electrodes fitted on forearm and reference electrode fitted on the elbow.

The electrodes placement is as shown in **Fig.6**. In first experiment, the three sensors were placed on positions 1, 3 and 5 on the forearm.six hand movements and rest were investigated in this study as shown in **Fig.2**. which include hand open, hand close, index finger, fine pinch, pronation, supination and rest. The subjects performed a hand movement which was started from a relaxation state and then followed by holding certain movement for a period of 5 seconds. The subject repeated the same movement four times with 3 seconds resting period between movements. The data has been collected twice in sessions, one session was used for training data and second session was used for testing data each one contained data for 7 movements repeated 4 times. The previous procedure was repeated again for the second stage for 2, 4, and 6 positions as shown in **Fig. 8**.

**Fig. 6 sEMG electrodes' locations**
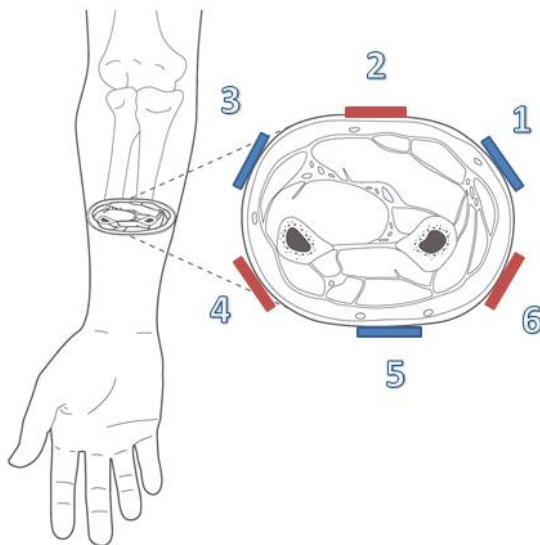
Fig.8. Six electrodes' locations on right forearm of the subject.

Subjecting six channels of data at the same time is definitely the best, but this does not necessarily mean the inability to be measured in two stages because both phases were carried out under the same conditions and with the same equipment and software, taking into consideration synchronization of sEMG signals recording, the start and end of each movement exactly. These tests were conducted on six people were get the results and took her average, and this strengthens the final results have been reached.

2.6 Pattern recognition of EMG signals procedures

2.6.1 Segmentation

The collected data of EMG signals were windowed by using disjoint window. A 200 ms analysis window was used to form the pattern recognition system in this study as shown in **Fig. 9**.
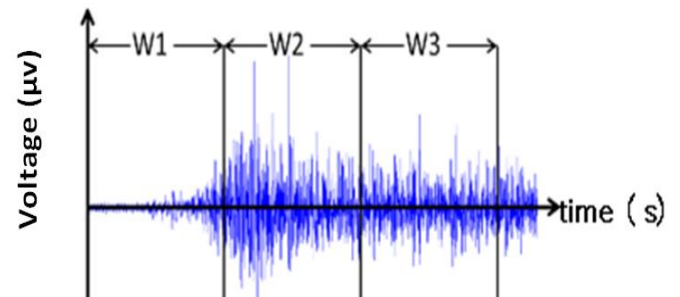
Fig. 9 Disjointed windowing method used in this study.

2.6.2 Feature extraction

Two different sets of feature extraction methods were investigated in this work.

a)-Time domain with Auto Regression (TDAR) feature extraction:

The first one was time domain features (TDAR) used to avoid a high complexity of processing [20]. There are five time domain features which include Mean Absolute Value (MAV), Root Mean Square (RMS), number of Zero Crossings (ZC), Waveform Length (WL), auto Regressive (AR) model parameters.

Mean Absolute Value (MAV) is the estimation of the mean absolute value of the sEMG segment

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \qquad (1)$$

The mathematical definition of the RMS feature is given by

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2} \qquad (2)$$

Waveform Length (WL) is defined as the cumulative sum of the differences over the time segment.

$$WL = \sum_{i=1}^{N-1}|x_{i+1} - x_i| \qquad (3)$$

Zero Crossings (ZC) are estimated by calculating the number of times the values of the amplitude cross the zero amplitude level.

Auto Regression (AR) features are based on the spectral statistics of the signal, and they have information about the location of the peaks of the signal on the signal spectrum. The order of AR model was 6 [17].

b)-Time dependent power spectrum descriptors (TD-PSD):

The second feature extraction set was (TD-PSD) [12][1], which offered a time-dependent spectral feature extraction method that extracts a set of power spectrum characteristics directly from the time-domain to reduce the impact of variation of limb position, while keeping a low computational cost. This method produces six features as following formulas.

$$f_1 = \log(m_0) \qquad (4)$$
$$f_2 = \log(m_0 - m_2) \qquad (5)$$
$$f_3 = \log(m_0 - m_4) \qquad (6)$$
$$f_4 = \log(\frac{m_0}{\sqrt{m_0 - m_2}\sqrt{m_0 - m_4}}) \qquad (7)$$
$$f_5 = \log(\frac{m_2}{\sqrt{m_0 m_4}}) \qquad (8)$$
$$f_6 = \log(\frac{\sum_{j=0}^{N-1}|\Delta x|}{\sum_{j=0}^{n-1}|\Delta^2 x|}) \qquad (9)$$

Where m_0, m_2 and m_4 are roots squared of EMG signal samples and (x) is EMG signal sample. for more information about TD-PSD, the reader is referred to [1].

2.6.3 Classification

In this study, the k-Nearest Neighbor (k-NN) and Linear Discriminant Analysis (LDA) algorithms were used to classify the six hand movements (close, open, index, pinch, pronation, supination) and rest.

a)- Linear Discriminant Analysis (LDA):

The principle work of LDA is to detect a hyper-plane that can assign the data points into different classes. The hyper-plane will find a projection which extends the gap between the mean of the classes and reduces the variance within the class under the supposition of normal data distribution [10]. LDA constitutes the best classifier under the statement of multivariate Gaussian feature distribution for each class [2]. It has been applied to the control of multifunctional upper limb prosthesis, and was reported to achieve good results for the classification of sEMG signals [8][5] because it has a simple implementation with low computational requirements, and because of its suitability to real-time implementations [8]. The discriminant function rule is applied in this stage for a k sample given by

$$f_i = U_i \ Pcov^{-1} \ x_k^T - \frac{1}{2}U_i \ cov^{-1} \ U_i^T + \ln(P_i) \qquad (10)$$

Where U_i represents the mean of the class, $Pcov^{-1}$ represents the inverse of the pooled covariance matrix, x_k^T is the input data sample and P_i is the prior probability vector given by

$$P_i = \frac{n_i}{n_{total}} \qquad (11)$$

The input sample of number k will be classified to class i when it has maximum f_i .

b)- k-Nearest Neighbor (KNN):

KNN classification is a "lazy" learning method because training data is not preprocessed in any way [14]. The algorithm of k-NN is widely used in non-parametric pattern classification methods [13, 14] [7]. The principle work of KNN is that it guesses the testing samples class with reference to the k training samples, which are the nearest neighbors to the testing samples by measure the distance between their samples as given formula (12), and classifies it to the class that has the largest class probability[14].The KNN rule classifies testing samples by assigning the label that most frequently represented among the k nearest samples; this means that, a decision is made by examining the labels on the K-nearest neighbors and taking a vote [7].

$$dist(x_1, x_2) = \sqrt{\sum_{i=1}^{n}(x_{1i} - x_{2i})^2} \quad (12)$$

Where x_1 is the training samples and x_2 is the testing samples.

2.6.4 Post-processing

Majority vote was employed to smooth the classification output [4]. It uses the results from three previous states and the present state and produces a new classification output based on the class which appears most frequent. This operation produces the hand movement class that removes bogus of wrong classification. Besides majority vote, the transition states in the classification results are removed too. This method gives the recognition system that works in steady state only regardless of the transition state [4].

The error rates of the classification can be determined by the formula:

$$Error\ Rate = \left(\frac{Classes - Classification\ result}{Length\ of\ classes}\right) * 100\%$$
(13)

Where classes are optimal required result of classification.

3. RESULT AND DISCUSSION

In this section, we will display the results of investigating the hand movement's recognition performances by using LDA or KNN classifiers and TDAR or TD-PSD feature extraction methods. The experiments were performed on a processor 2.4 GHz Intel Core i5 based with 4 GB RAM. The exercises were guided by a computer program, written in MATLAB R2015a.

Five experiments were done in this study.

A-Experiment one:

There are lots of methods of "classification" and "feature extraction", which are used to identify patterns of EMG signals. Most prominent of them are employed in this study to classify the hand movements based on EMG signals. This research differs from other researches by the type of devices (hardware) which include

sensors and Arduino controller "" and pattern recognition algorithms were utilized to classify movements as well as the types and number of movements So, this kind of comparisons is performed to make sure the best scheme of features and classification that works well on our EMG signals.

First experiment was to compare the performance of four sets where each set is a combination of one type of feature extraction and one type of classifier .The four sets include:

1) TDAR with LDA.
2) TDAR with KNN.
3) TD-PSD with LDA.
4) TD-PSD with KNN.

The aim is to find the best which gives minimum error rate and best performance to recognize the seven hand movements.

The four sets were applied on data which were collected from six channels across six subjects. **Fig. 10** represents the error rates of the four sets. Based on the graph, the LDA with TD-PSD combination gives the minimum error rate by regarding the error rate around it, therefore, TD-PSD was chosen as a feature extraction and LDA as a classifier to perform the subsequent analysis in this paper.
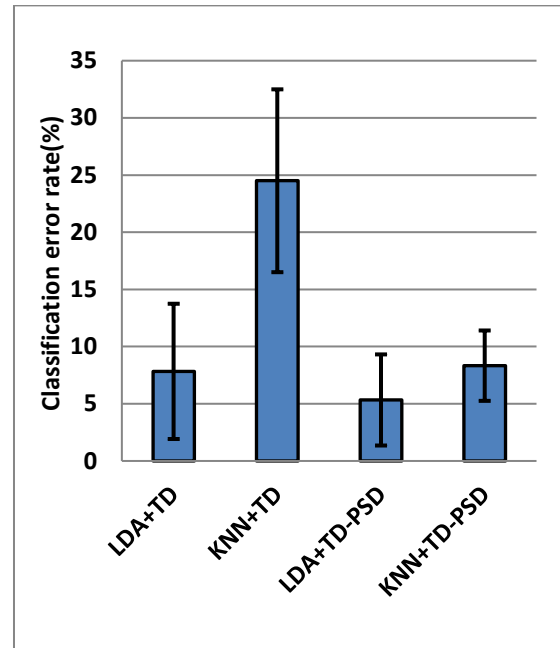
Fig. 10 Average classification error rate of the four sets for 6 subjects with 6 EMG channels. Standard deviation across 6 subjects is shown with error bars.

B- Experiment two:

The second experiment investigated the effect of electrodes location and compared the performance and the error rate of six channels separately which represented six electrode locations on forearm by using TD-PSD as a feature extraction and LDA as a classifier which give best performance as described in the previous experiment. **Fig. 11** shows the error rates of the six channels separately. According to this experiment, the locations 2, 4 and 5 gave the best performance with the minimum error rate compared to other locations to perform six hand movements and rest. The error rate of location 2 was around 37%, error rate of location 4 was around 44% and error rate of location 5 was around 39%. The reason of high

error rates in this experiment because the pattern recognition was performed on data from each channel separately. This experiment suggests that more than 1 sEMG channel is needed to improve the performance.

C- Experiment three:

The third experiment investigated the effect of number of channels on pattern recognition performance and the classification error rate, using the LDA as classifier and TD-PSD as feature extraction with window size 200ms. As shown in **Fig.12** the error rate of pattern recognition system reduced when the number of channels increased.
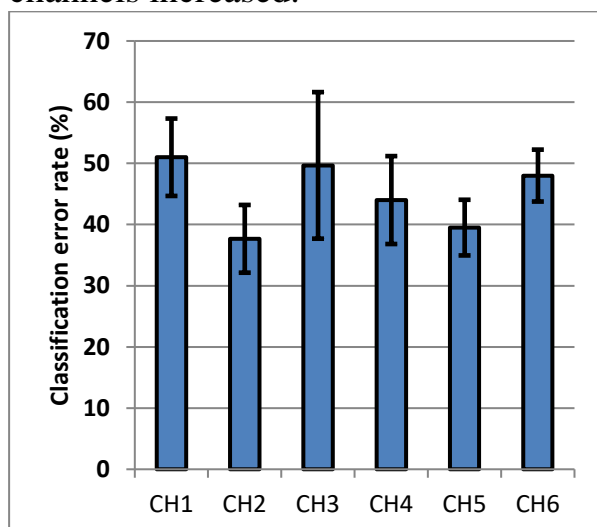
Fig. 11 Effect of the 6 electrode locations on error rate for 6 subjects. Standard deviation across 6 subjects is shown with error bars.

When applying the pattern recognition on data of channel (2) which represents best electrode location compared with other locations, the error rate was 38 %. When the pattern recognition was

applied to channels (2) and (5) which represent best two locations, the error rate was reduced more than half only 18%. When adding channel 4, the error was reduced to 13%. When applying pattern recognition to data of all six channels combined, the error rate was only 5%. The use of three channels located on best location on forearm was more advantageous than using six sEMG channels. This will reduce the cost and it's more suitable with Arduino capability when increasing the number of channels to more than three when connected with Arduino. In this case the sampling rate reduced to half (400 Hz). This is undesired because the sampling rate must be twice than sEMG signal frequency which its range between 20 and 400 Hz. The difference of error rate between using three channels and using six channels was 8% and this difference can be reduced using techniques which will be explained in next paragraphs. One of the goals of this research is to use the fewest possible channels of sEMG to reduce the cost and the size of the input data to reduce the computation time which will be suitable for mobile application in the future work. On other hand, to increase the classification accuracy of the system modern methods of identifying patterns can be used without the need to increase the number of channels. As shown in this study, using three channels is suitable with the possibilities of the "Arduino". It is not considered

limiting for the study because the sampling rate in this research is within the acceptable range of 500Hzaccording to [15].

D- Experiment four:

Forth experiment was done to find the minimum error rate of pattern recognition by applying various values of window sizes. From 100ms to 500ms as shown in **Fig.13**. When increasing the window size, the error rate is reduced until 400 ms where the error rate becomes stable with little change. This experiment performed on data of 3 channels using TD-PSD and LDA in pattern recognition.
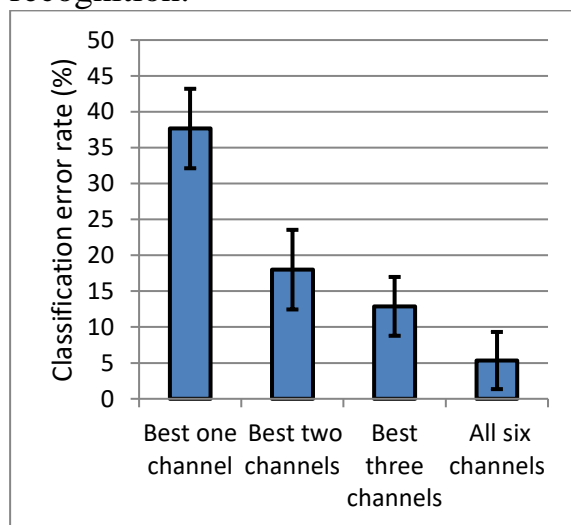

Fig. 12 Effect of the number of sEMG channels on the classification error rate. Standard deviation across 6 subjects is shown with error bars.

The error rate is reduced to half which is another advantage of increasing the window size. A too short window would increase classification error, while a too long window would produce excessive user-perceived delays, the optimal window length was found to be

between 150 and 250 ms, which is within acceptable controller delays for conventional multistate amplitude controllers [19].so in this study, 200 ms window size was adopted which is within the acceptable range.

E- Experiment five:

In last experiment, the majority voting post processing technique was used to smooth the classification results. It uses the results from three previous states, the present state and three next states to produce a new classification result. This technique reduced the error rate more than half as shown in **Fig. 14**.
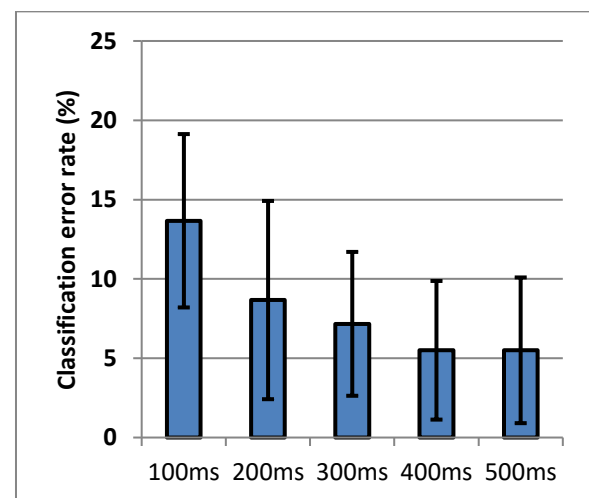

Fig. 13 Window sizes of segmentations. Standard deviation across 6 subjects is shown with error bars.
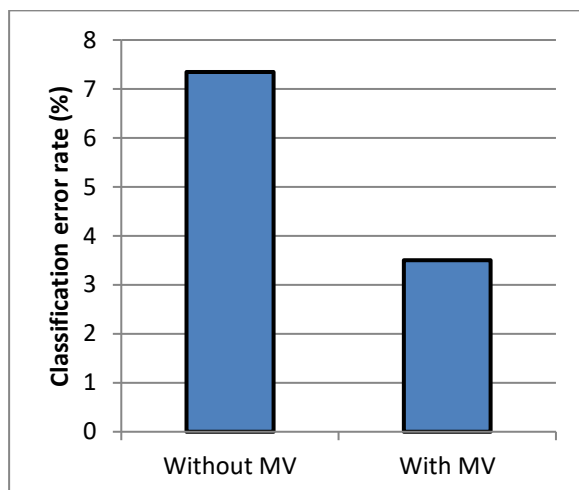
Fig. 14 Majority vote effect.

After using the TD-PSD as a feature extraction and LDA as a classifier, we apply them on data of 3 channels which represent electrode locations 2, 4 and 5 across six subjects while the window size was constant at 200 ms, It can be seen from **Fig. 15** that on average, the system was able to recognize the different hand movements with classification accuracy from 92% to 99 %.

This accuracy lies within the accuracy of a usable pattern recognition system [6].
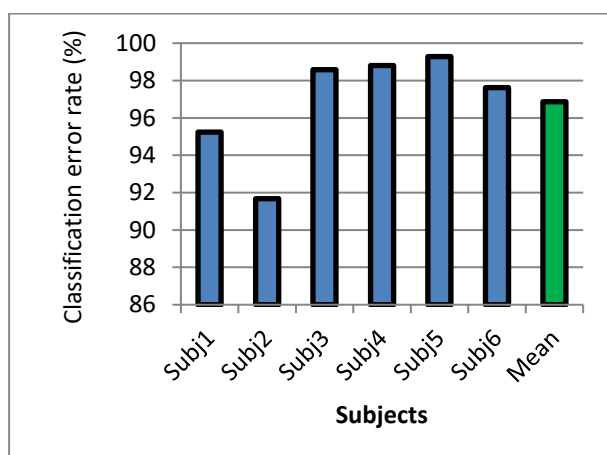
Fig. 15 System accuracies of 6 subjects.

The results of this study can be compared with previous literature as

shown in **Table .1**. Note that for this comparison, the devices which used to collect and analysis data were different and types of movements were also different.

Table. 1 Comparison between this study and other researches.

	This study	Al-Timemy et al.[1]	Kim et al. [13]	Andrews et al. [3]
Classifier	LDA	LDA	LDA	LDA
Feature extraction	TD-PSD	TD-PSD	TD	TD
Window size (ms)	200	150	166	256
Number of movements	7	6	5	4
Number of channels	3	16	2	4
Using of majority vote	Yes	No	No	No
Classification accuracy	97%	94%	81%	92.7%

4. CONCLUSION

In this study, five experiments were performed to improve the pattern recognition system and to obtain high classification accuracy by choosing the best feature extraction method (TD-PSD) and classifier (LDA). Then, we found the best electrodes' location on the forearm where electrodes 2, 4 and 5, were located almost over the flexor digitorum profundus muscles. With only 3 sEMG channels and window size of 200 ms. In addition, the effect of using majority vote was investigated which reduced the error rate to half. The average of system accuracy of six subjects was around 97 %. This is a good result for only three sEMG channels by using low

cost components like arduino and MyoWare EMG sensors which make the proposed system low cost

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الخلاصة

تقترح هذه الدراسة نظام التعرف على الانماط لتصنيف ست حركات اليد مع وضع الراحة باستخدام ثلاثة أجهزة استشعار كهربائية العضلة (sEMG) مع استخدام متحكم الاردوينو لجمع البيانات. تم مقارنة أداء المجال الزمني (TDAR) مع واصفات الطاقة الطيفية معتمدا على الوقت (TD-PSD) كمستخرجات انماط و أقرب جار (KNN) و تحليل التمايزالخطي (LDA) كمصنفات الخوارزميات. حيث بحثنا في تأثير موقع الأقطاب على الساعد وتأثير عدد القنوات المستخدمة على أداء نظام التعرف على الانماط. حيث توصلنا الى ان أداء TD-PSD وLDA هو أعلى من TDAR وKNN حيث تم تحقيق دقة تصنيف جيدة باستخدام ثلاث قنوات فقط من أجهزة استشعار (sEMG) التي تمثل أفضل ثلاثة مواقع على الساعد ممكن من خلالها التعرف على حركات اليد ستة والراحة. وقد تحقق دقة تصنيف 97٪ باستخدام ثلاث قنوات فقط sEMG باستخدام مكونات منخفضة التكلفة مثل أجهزة الاستشعارMyoWare والمتحكم اردوينو التي تجعل من النظام المقترح قليل الكلفة.