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Humanoid Robotic Hand (HRH) Based on EMG signal for Amputees Persons

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ABSTRACT

This paper proposes a system that designed and implemented to be used for persons who lost their limbs because of accident, wars or any other diseases. The idea of this paper is to design and implement Humanoid Robotic Hand (HRH). The HRH was built by using 3D printer technology of hard Polylactide (PLA) filament. The different components of the hands were separately built and then assembled, which gives easy manufacturing at the same time great latitude to choose materials, and also built by six servo motors while five servo motors used to move the fingers and the sixth servo motor used to rotate the wrist. The designed HRH system was controlled by electromyography (EMG) signals were utilized to classify seven classes of movements in offline mode and five movements in real-time. The EMG signals were measured by using three surface electromyography (sEMG) MyoWare muscle sensors, which were located on the forearm on three muscles (Extensor Carpi Ulna, Extensor Carpi Radius and Extensor Carpi Digitorum) and use Arduino Mega microcontroller as an analogue to digital converter to take the signal from the sensor and also use data collector to control the humanoid robotic hand. The proposed pattern recognition system was investigated in an offline mode to enhance it and to develop the classification accuracy of the system by using the (Integral Absolute Value (IAV), Mean Absolute Value (MAV) , Root Mean Square (RMS), Waveform length (WL), Zero Crossing (ZC), Slope Sign Change (SSC) and Autoregressive (AR) as feature extraction , Principal Component Analysis (PCA) as feature reduction, k-Nearest Neighbor (k-NN) and Linear Discriminant Analysis (LDA) algorithms as classifiers. Furthermore, the effects of electrodes' position on the forearm and the number of channels on the efficiency of the pattern recognition system were investigated too. The results showed that the performance of the LDA is better than the k-NN because the accuracy of LDA is 91.1056% and the accuracy of k-NN is 87.5849% these percentages are in the offline mode and in real time mode the accuracy is 84% when using LDA algorithm.

Key words: Electromyography, Pattern recognition, Electrodes, Myoware Muscle Sensor, Humanoid Robotic Hand.

1. INTRODUCTION

Robotics is the section of the engineering of a machine, the engineering of electrical and science of computer that deals with the design, structure, operation and applicability of robotics, [1] in addition, computer systems for their control, sensory feedback, and data processing [2]. Robots are automatic or semi-automatic mechanisms which mean responsible for purposeful movement returning to their surroundings in confused circumstances [3]. There are at least 30 million persons with amputations remaining in low-income nations, 80% of that cannot afford prosthetic care. Persons with amputations which remain in economically disadvantaged regions want a prosthetic hand that is not only valuable, but also affordable, simple to build, and easy to manage [4]. This paper presents a system that uses Humanoid Robotic Hand implemented by Electromyography (EMG) signal that is controlled by Myoware muscle sensor shown in Figure 1. EMG is the detection of the electrical activity associated with muscle contraction. It is obtained by measurement of the electrical activity of a muscle during contraction. EMG signals are directly linked to the desire of movement of the person [5].
The Myoware muscle sensor is a 3-lead muscle sensor from advancer technologies design, uniquely for microcontroller application. It is considered the latest version of these sensors that promises a very good collecting and signal processing with the high performance it is able of generating a rectified EMG signal that is completely suitable to be controlled by any controller as well as a raw EMG that could be utilized in analysis and studying the signal by feature extraction and classification [6].There are many algorithms to classify the signal in this paper. The k-NN algorithm that was applied, which is one of the most well-known and generally applied nonparametric pattern classification techniques[7] and the LDA algorithm simply checks the case where the within-class frequencies are unequal and their performances have been tested on randomly created test

data. This process maximizes the ratio of between-class variance to the within-class variance in any particular data set thereby guaranteeing maximal separability. The use of LDA for data classification is applied to classification problem in speech recognition [8]. The HRH was printed by using the 3D printer is a type of industrial robot. This technology provides low cost hand, fast production, low weight and customized design. Many of HRH is designed with the idea of decreasing cost, increasing manufacturability and using 3D printing technology.

In this paper, 3 sensors were connected to the electrodes that are proved on the human hand.

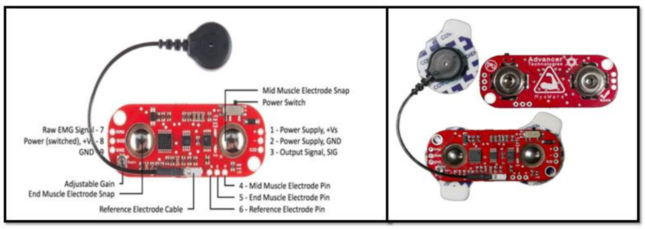


Figure 1: Myoware muscle sensor

1.1 General System Architecture

System block diagram is shown in Figure 2. The electrodes were put on the forearm muscle of the human. The Arduino mega microcontroller is connected to the myowarre muscle sensor through Input/Signal interface and it is also connected to a USB port with PC, and record the signal in the Matlab. So, the signal was registered in the Matlab and then the signal must be segmented, recognize and classify it by using the k-NN algorithm which is an easy but practical method for classification. Its low performance - being a slow learning method prevents and the LDA algorithm which is used to obtain a hyperplane that can divide the data points expressing various types. So, the Arduino mega sensor shield was put on the Arduino microcontroller and it is also connected to a USB port with PC. The humanoid robotic hand (HRH) was manufactured by using the 3D printer technology. The HRH servomotors were connected to Arduino through Pulse Width Modulation (PWM) signal and a reaction signal is repaid from the myoware muscle sensor to the PC.

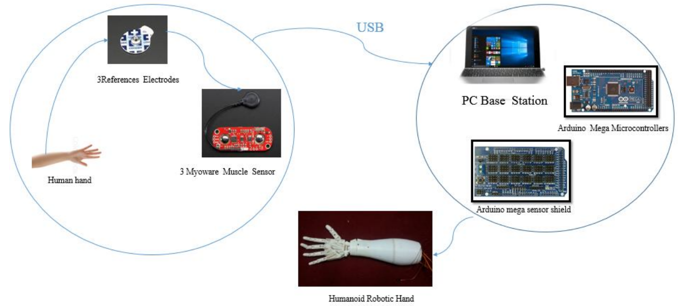


Figure 2: System Architecture

2. HUMANOID ROBOTIC HAND DESIGN

The humanoid robotic hand was designed to have five fingers (Little, Index, Middle, Ring and Thumb finger), Palm, wrist and forearm. Each finger of the hand is actuated by a servo motor located at the forearm. A servomotor has been utilized to perform each angle of movement for each finger (Q1→Q6).

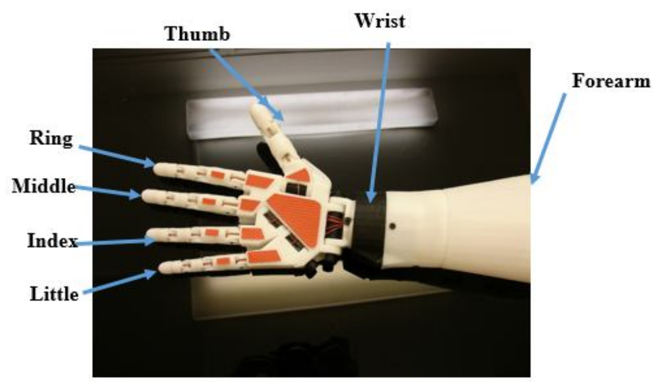


Figure 3: The location of fingers, wrist and forearm

The support filament with some part like the fingers and the palm was used to avoid the friction in the hand design, the Polylactide (PLA) 3D Filament was used to print the hand because PLA has many good features for 3D printing like a cheap melting temperature and glass transformation temperature.

As a result, PLA offers a high level of detail and exceptional print quality. Figure 4 show some parts of robotic hand designs.

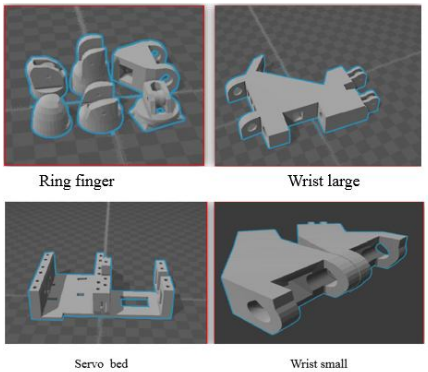


Figure 4: Robotic Hand Design

Figure 5. Shows all the parts of the robotic hand after printed by using 3D printer.

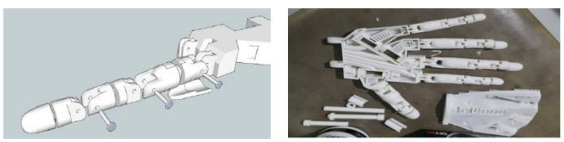


Figure 5: Finger Joints

Figure 6. Shows the assembly of the hand after connect each part together.

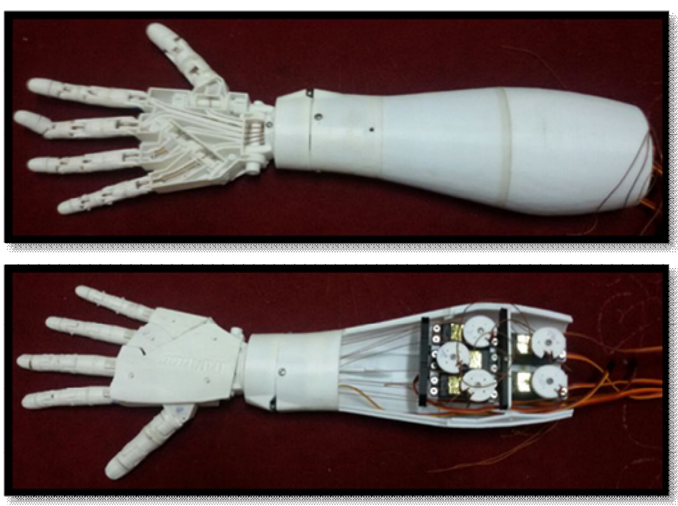


Figure 6: Complete Humanoid Robotic Hand Design with servos

And the hand has been installed on a stand made of wood as shown in Figure 7.

Figure 7: The Humanoid Robotic Hand installed on the stand

3. SOFTWARE SYSTEM DESIGN

1. Data segmentation: Contains many ways and systems that are done to check data before feature extraction to enhance efficiency and response time [10].

2. Feature extraction: This module measures and shows pre-selected features for a classifier. Features rather of raw signals, are supplied into a classifier to enhance classification performance. Choice or extraction of deeply practical features is one of some various important steps in myoelectric control design. In this paper, seven type of feature extraction was used [10] :

- Integral Absolute Value (IAV): Integral Absolute Value (IAV) is determined as the collection of the absolute values of the sEMG signal amplitude. It is related to the sEMG signal sequence firing point, which can be expressed as [10]:

$$\mathrm{IAV} = \sum_{i=1}^{N} |X_i| \tag{1}$$

- Mean Absolute Value (MAV): is alike to average rectified value (ARV). This can be determined to utilize the moving average of full-wave rectified EMG. As well as, this is determined by using the average of the absolute value of sEMG signal [10].

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

- Root Mean Square (RMS): RMS is connected to fixed power and non-tiring contraction. It links to standard deviation, which can be expressed as[11]:

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} X_i^2} \tag{3}$$

- Waveform length (WL): is the total length of the waveform above the time section. WL is linked to the waveform amplitude, frequency and time. It is given by[10]:

$$\mathrm{WL} = \sum_{i=1}^{N-1} |X_{i+1} - X_i| \tag{4}$$

- Zero Crossing (ZC): is the digit of times that the amplitude rate of the sEMG signal passes the zero y-axes. During EMG feature, the threshold provision is implemented to avoid the experience noise. It can be formulated as [10]:

$$ZC = \sum_{n=1}^{N-1}\left[sgn(X_n \times X_{n+1}) \cap |X_n - X_{n+1}| \geq threshold\right]$$

$$sgn(x) = \begin{cases} 1, & \text{if } x \geq \text{threshold} \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

- Slope Sign Change (SSC): is the other way to express the frequency data of sEMG signal. The calculation is defined as [10]:

$$SSC = \sum_{i=2}^{N-1}\left[f\left[(X_i - X_{i-1}) \times (X_i - X_{i+1})\right]\right] \quad (6)$$

$$f(x) = \begin{cases} 1, & \text{if } x \geq \text{threshold} \\ 0, & \text{otherwise} \end{cases}$$

- Autoregressive (AR): is a Frequency Domain Feature Extraction. AR model explained every unit of sEMG signal as a linear sequence of former units plus a white noise wrong session. The model is basically of the following form[10]:

$$X_n = -\sum_{i=1}^{p} a_i x_{n-i} + w_n \quad (7)$$

3. Feature reduction: The method of feature extraction may (and often does) result in feature vectors with great dimensionality. Feature reduction is applied to decrease the dimensionality, explaining the job of the classifier and diminishing effect of the ban of dimensionality (i.e. the exponential increment in the feature area with the addition of specific new feature). Further to enhancing the signal nature and decreasing the noise, feature reduction may also try to decrease repetitions in the feature vector. In this paper, Principal Component Analysis (PCA) method was used to reduce the dimension of the EMG signal if it is found [10].

4. Classification: This module realizes signal patterns and classifies them inside pre-defined sections. Because the difficulty of biological signals, and that impact of physiological and physical conditions, the classifier must be sufficiently strong and ready. This must be capable to modify itself to variations in long-term work, by utilizing offline and/or online training. In this paper, two type of classification was used [9]:

- Linear Discriminant Analysis (LDA): The aim of LDA is to obtain a hyperplane that can distribute the data points describing various classes. This hyperplane can be achieved by searching for a projection which maximises the distance between the mean of the classes and minimizes the variance within the class below the assumption of normal data relationships [11].

- k-Nearest Neighbors (k-NN): is an easy but efficient technique for classification. Its low performance - being a slow learning method prohibits it in several applications such as dynamic web mining for a large repository, and its dependence on the choice of a "good value" for k [13]. The principle work of k-NN algorithm determines the nearest neighbours to the training samples by computing the minimum distance between two samples which is called Euclidean distance in n-dimensional space is defined by [13]

$$x1=(x11,x12,\ldots,x1n),x2=(x21,x22,\ldots,x2n)$$

$$(x1,2)=\sqrt{\Sigma(x1i-x2i)2ni=1}\ldots\ldots\ldots(2.15)$$

The k-NN algorithm is made for the classification of upper arm motions [14].

5. Controller: Creates output groups based on signal patterns and control systems. Post-processing techniques, like majority voting, which is usually done next classification to reduce negative leaps and produce a continuous product, are also involved in this module. In spite of any closed-loop control projects, like trouble avoidance can be done applying sensory feedback, myoelectric control structured bears from a shortage of feedback. High-level feedback, like visible or response data, can enhance the degree of control and ability. Because of goals in implementing feedback to a neuromuscular operation, knowledge melting utilized in MES, and equivalent sensory feedback can develop control execution. Any specified module should an essential and necessary function. But, sometimes, modules may be discarded or mixed together [7].

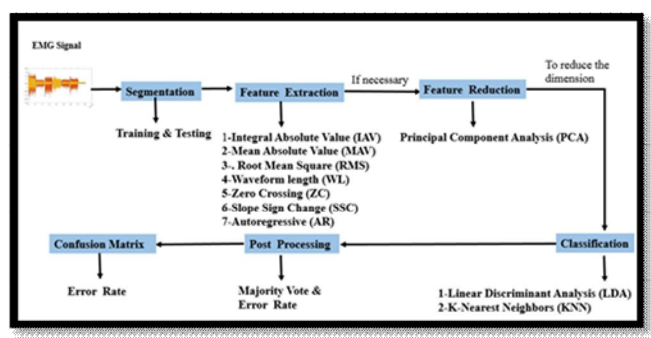


Figure 8: Block diagram of software system

3.1. The Hand Movement

The upper limb is anatomically classified into three subparts, the arm, the forearm and the hand. The first; ranges from the shoulder to the elbow, the second is the part from the elbow to the wrist and the third and final portion is positioned below the forearm. The hand is working for grasping and holding and consists of the wrist, palm, four fingers, and an opposable thumb [15]. The movements of the hand are shown in figure 8. The places that were chosen to prove the myoware muscle sensor on the hand are on three muscles: Extensor Carpi Radius, Extensor Carpi Digitorum and Extensor Carpi Ulna as shown in figure 9. The electrodes have to be placed on the skin firstly, ensure that the skin sites are dry clean and free of excessive hair, then connect the lead wires to the electrodes after removing the plastic cover and position the electrode on the skin.

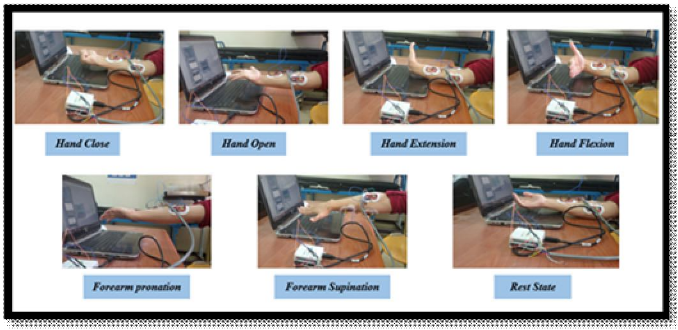


Figure 9: The 7 Hand Movements

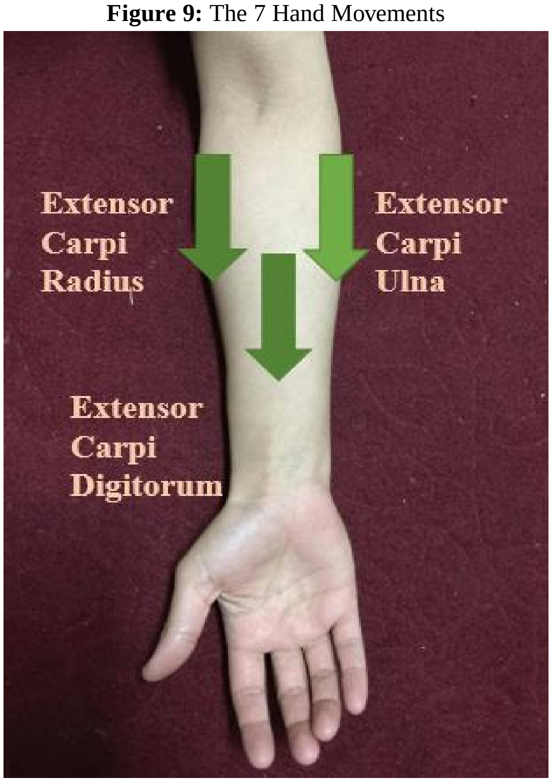


Figure 10: Muscles location

3.2 The EMG Signal Results

The raw EMG signal from three myoware muscle sensors that are connected with the NI data acquisition (DAQ)-6009 A/D converter microcontroller for seven movements (Close, Open, Extension, Flexion, Supination, Pronation and rest state) and the electrodes were placed on three muscles of the forearm these muscles are (Extensor Carpi Ulna, Extensor Carpi Radius and Extensor Carpi Digitorum) shown in Figs.(12,13 and 14).

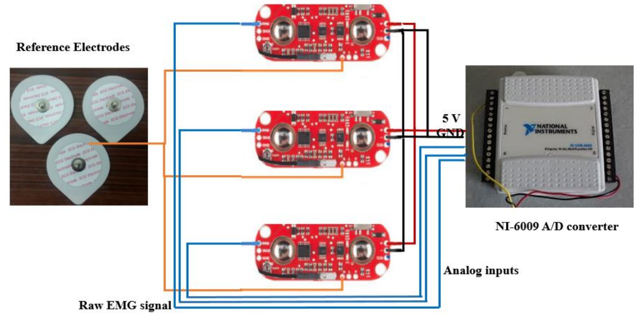


Figure 11: Circuit diagram of data acquisition instrument

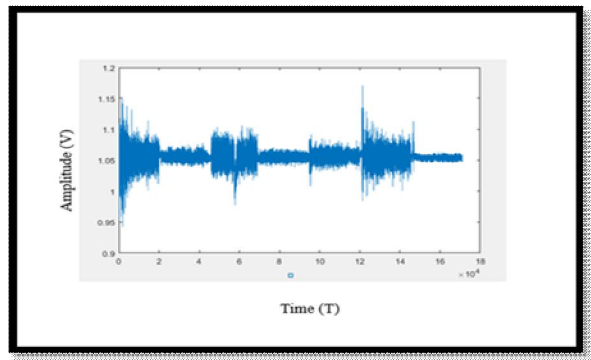


Figure 12: The raw EMG signal for Extensor Carpi Digitorum

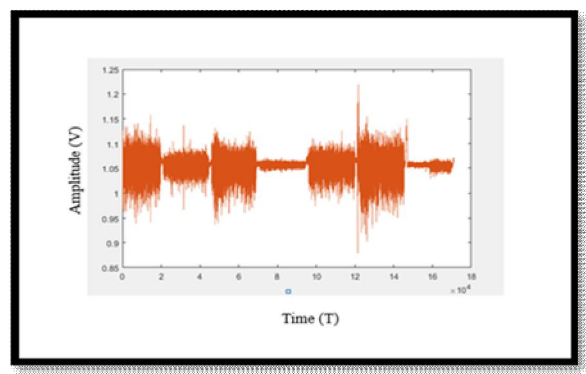


Figure 13: The raw EMG signal for Extensor Carpi Ulna

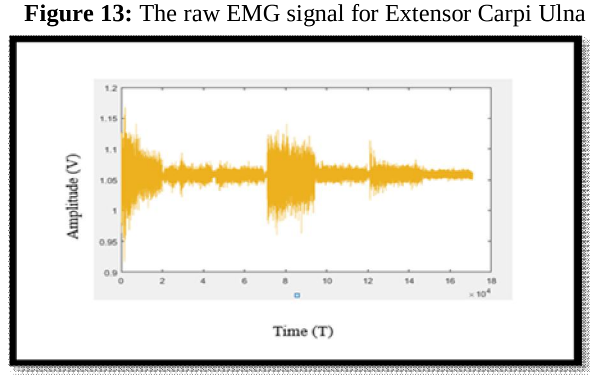


Figure 14: The raw EMG signal for Extensor Carpi Radius

3.3 Recognition, Classification Results and its Discussion

Figure 15 shows the correct and incorrect classification per each motion class for LDA classifier and PCA reduction. The Y-axis is the motion class number, while the X-axis is the window sample number. Each window sample is tested for all of the different motion classes and classification results are recorded. Correct classification is shown in green dot while an error is drawn as red x.

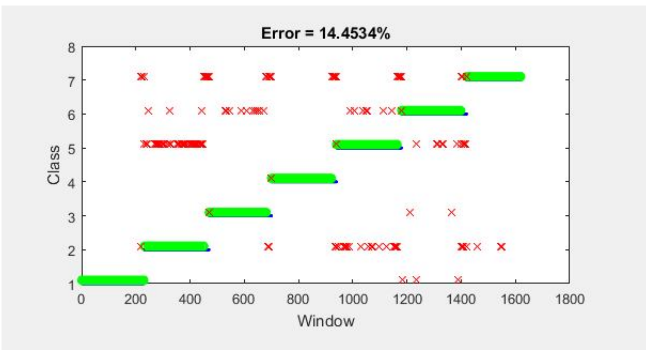


Figure 15: Classification error rate using LDA

The classification error was 14.4534%. To improve classification accuracy, majority vote post-processing has been used and thus error reduced to 8.8944% as shown in Figure 16.

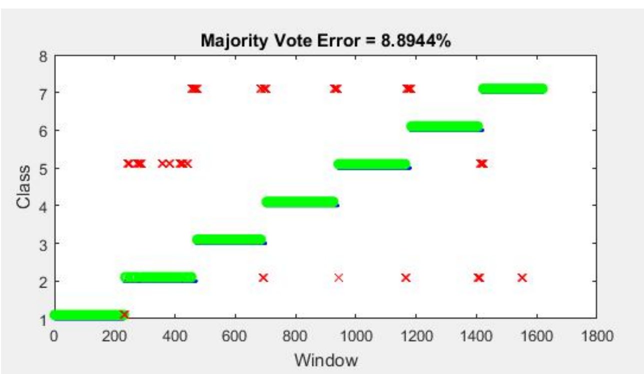


Figure 16: Classification errors after majority-voting post-processing

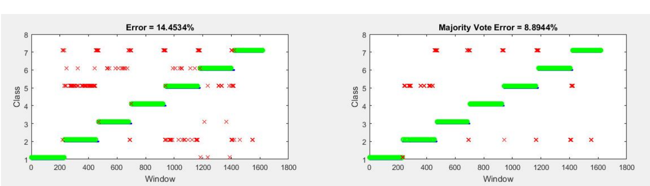


Figure 17: Classification & Recognition using PCA reduction and Classification errors using testing data from real EMG signal

These results demonstrate that a relatively simple pattern classification system can achieve high classification accuracy may change by changing the pattern recognition components in the system.

For comparison purposes, a pattern recognition using k-NN algorithm was done. Figure18 shows the error percentage and results obtained from k-NN algorithm, implying that LDA is superior to k-NN in classifying accuracy.

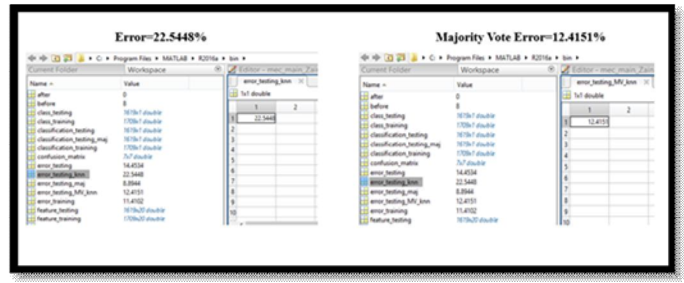


Figure 18: Classification using k-NN algorithm

These results show that the LDA classification clearly gives better performance than k-NN classification. So, the following table summarize this comparison.

Table 1: Comparison between k-NN classifier and LDA classifier

	Error (%)	Majority Vote Error (%)
k-NN Classifier	22.5448%	12.4151%
LDA Classifier	14.4534%	8.8944%

3.4 The Confusion Matrix

A confusion matrix is a technique for summarizing the cmatrix can give you ctypes of errors it is making. Figure 19 shows the error rate when using the LDA algorithm and Figure 20 shows the Confusion matrix errors after majority-voting post-processing and Figure 21 shows the Confusion matrix errors using testing data & Recognition using PCA reduction from real EMG signal.

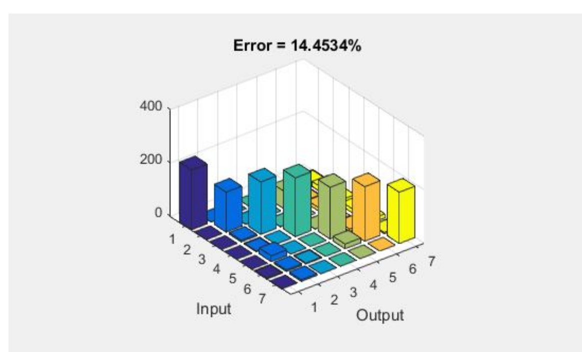


Figure 19: Confusion matrix error rate using LDA

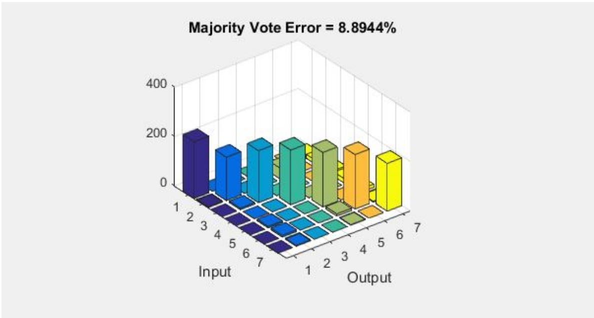


Figure 20: Confusion matrix errors after majority-voting post-processing.

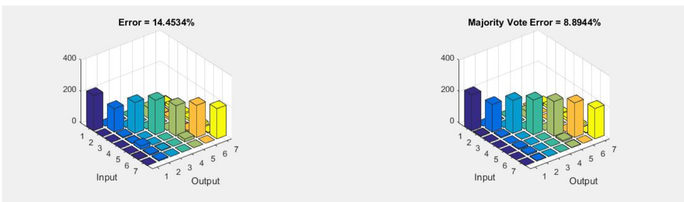
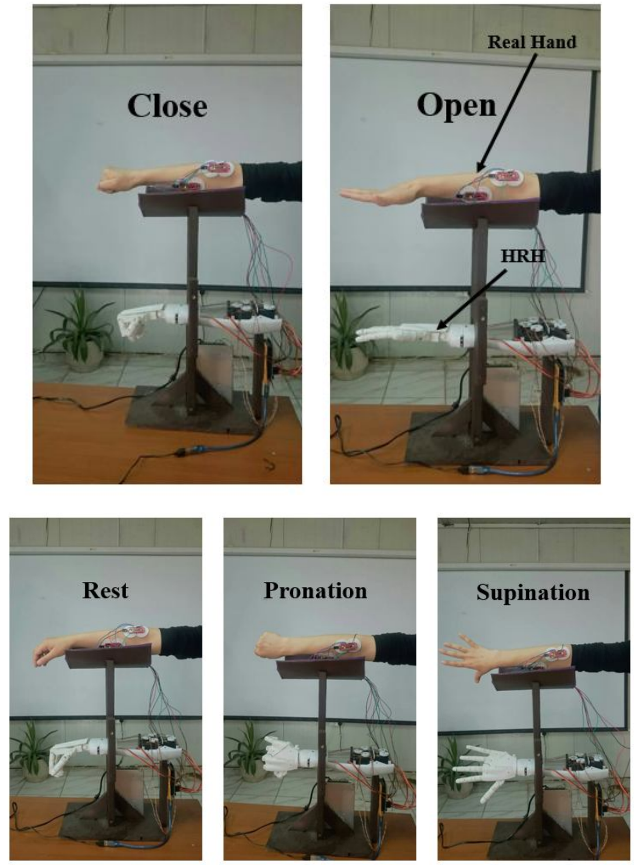


Figure 21: Confusion matrix errors using testing data & Recognition using PCA reduction from real EMG signal

4. EXPERIMENTAL TEST RESULTS

In this paper, the pattern recognition control was performed in online mode based on sEMG signals with applying the best pattern recognition methods from previous studies in offline mode to classify and recognize five hand movements. In addition, the electrodes were placed on best locations on the forearm and employed less number of channels with keeping of classification accuracy steady.

In real time, the testing data as the case in offline mode was replaced with online data. Each segment was 200 samples of sEMG signal. This signal segment was compared with the training data which was recorded previously, the feature extraction was used to learn the machine and LDA also used as classifier method to classify them into movements' classes. The real time data segment was prepared by using two type of filters: the notch and band pass filters. This operation was performed by using the LDA classifier to classify the real time data segments into hand movements' representation. Like the offline mode, the result of classification was also applied on majority vote to refine it by choosing the most repeatedly between the two previous and present results. The flow chart of real time program can be presented in Figure.21.In offline work, seven motion can obtained and implemented the pattern recognition & classification, but in the real time work two of seventh motion (the wrist extension and wrist flexion motions) could not implemented on the HRH because these motions need servo in the palm so, just five motion can implemented on HRH. The accuracy of real time is 84%. So, this HRH can be used for the amputee's person in the future work.



(a) **Figure 21:** The five classes of movements were tested on online with HRH

5. CONCLUSION

The goal of this study was to design and implement a humanoid robotic hand that performs feature extraction, feature reduction and classification of EMG signals that can be applied on the robotic hand. The conclusions were that:

- Environment interference and mainly power line highly affect EMG signal especially in surface probes so, the noise can be reduced the by turn off the power in the room and remove the charger from the calculator.
- LDA algorithm presented lower error rate in comparison to k-NN, especially when used with PCA as a dimensionality reduction technique.
- Majority voting method provided a relatively good way to removing transitional errors in classification.
- The technology of using 3d printer provides low-cost hand, fast production, one day assembly, low weight and customized design instead of buying ready robotic hand.

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