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Design and Implementation of Hand Movement Detection and Classification Method using Electromyogram Signal for Human-Computer Interface

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Abstract:- One of the methods of artificial hand prosthesis control is the use of a surface electromyogram signal. There are many methods to control the prosthesis, each of which has advantages and disadvantages. In this study, first, the surface electromyogram signal of people's hands, which is related to the 6 movements that are the most active in daily movements, is recorded and then stored. To identify the movement pattern, 8 temporal features are extracted from the signal, and then the best feature is selected using a blind search of sources and given to the input of the neural network. The results showed that the average classification accuracy by multilayer perceptron and PCA output is 96.77%, while the average classification accuracy using all features is 82.77%.

Keywords:- Pattern recognition, hand movement detection, electromyogram signal.

I. INTRODUCTION

Due to the industrialization of today's lives and the growth of devices and machines, various disabilities have also increased, one of which can occur in the hand [1] . Although disability or hand muscle defect does not cause the loss of a person's life, it strongly affects the quality of a person's life and makes a person suffer from social problems. With the progress of science and technology, scientists are looking for a way to execute movement commands from the body to the machine. There are various methods for obtaining commands, which can be mentioned using EMG, EEG, and EOG signals [2-3]. To implement these commands, it is necessary to obtain the signals first, and then pre-processing operations to strengthen and remove noises from the signal, and at the last stage, the classification operation is done. Also, efforts have been made in methods without using biological signals. is done by using the head and mouse movement. Many people in the world suffer from various disabilities every day, and one of these disabilities can occur in the hand [5]. It can record the electrical signals of the hand muscle using various tools and methods and give it to the input of artificial prostheses and other equipment to control various objects. The classification of different hand movements can be used in many applications such as militaries, industrial, medical, etc. [5]. In another research used Fourier series using non-linear differential equations and gave the formed Fourier series to their designed CPG model, and the output of their research was to create a pathway for hemiplegic patients that can be used in exoskeleton robots [6]. Special cases of classification can be used to control artificial prostheses or vehicles for people with amputees [7]. Many features are hidden in the electromyogram signal and it is difficult to choose the best feature for work classification. Despite the research presented and the various methods that have been proposed, there is still a long gap in the real world, and providing a method that can use many features in the EMG signal and select the most optimal ones is a serious challenge. [8-9]. Vital signals provide a lot of information about the organs, and since the recording of vital signals is generally done by non-invasive methods, the study of these signals is widely used to obtain information about the functioning of the body system, as well as to investigate and diagnose diseases [10]. For a long time, doctors have been examining patients using recorded brain or heart signals or listening to heart and lung sounds. Nowadays, the field of vital signals has become very diverse and numerous, some of which have a clinical aspect and others part has a research aspect. As you know, due to the low amplitude of the electromyogram signal during recording, the data is recorded with a lot of noise and it is difficult to extract the original signal [11]. Now, before classification, the extracted signal must be pre-processed. Also, according to the various articles that have been reviewed, choosing the best feature or features for classification is difficult and controversial. There is still a serious challenge in choosing the best features in the articles that are presented, and which features can make the best classification. If the classification is provided with very high accuracy, it can be used in the control of artificial prostheses, and the lives of people who have suffered limb amputation will be seriously affected.

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Reference	Signal	Network	Movement	Accuracy	Participant	year
[12]	EMG(wrist)	Convolution neural network (CNN)	**Rock, Scissors, Paper**	94.5%	8 people	2018
[13]	EMG	Feed Forward	5 hand movement	94.45%	120 people	2020
[14]	Semg Image	CNN+LSTM , CNN only	30 movement	97.34% for CNN+LSTM, 93.32% for CNN only	25 male and 3 female	2020
[15]	Semg	Support vector machine	6 movement	87.5%	60 people	2019
[16]	EMG	LSTM, Neural network	6 movement	9% error	9 people	2020
[17]	EMG foot gesture	SVM	Five foot gesture	90.04%	47 male, 22 female	2019

Table 1: DATA

II. MATERIALS AND METHODS

A. Data recording protocol:

In this study, a recording protocol is proposed that records the EMG signal in a non-invasive way. for this purpose, 6 hand movements include closing the hand, opening the hand, picking up a heavy object, picking up a thin object like a credit card, picking up an object like a pencil, and picking up a light object. two electrodes are placed on the Wrist and the signal related to the hand muscles is recorded with a sampling frequency of 512 Hz. The signal is recorded for 6 seconds and each test is repeated 30 times.

B. Preprocessing:

Considering the nature of biological signals, signal preprocessing plays an important role in creating a correct signal that is given to the input of the neural network. According to the nature of the EMG signal, a Butterworth filter with a low cut-off frequency of 0.15 Hz and a high cut-off frequency of 150 Hz will be used.

C. Feature extraction:

Considering that extracting the pattern from the original EMG signal is very difficult, we extract the following features from the signal to extract the pattern:

Kurtosis: $$\text{VAR} = \frac{1}{N-1}\sum_{k=1}^{N} emg_k^2 \tag{1}$$

Skewness: $$\text{MAV} = \frac{1}{N}\sum_{K=1}^{N} |emg_k| \tag{2}$$

$$\text{WL} = \sum_{K=1}^{N-1} |emg_{k+1} - emg_k| \tag{3}$$

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{w} {x_i}^2} \tag{4}$$

Zero Crossing: $$zc = \Sigma f(x)_{,}\ where$$

$$f(x) = \begin{cases} 1,\ if, (x_k > 0\ AND x_{k+1} < 0) \\ \quad OR (x_k\ < 0\ AND\ x_{k+1}\ > 0 \\ 0,\ otherwise \end{cases} \tag{5}$$

for k = 1, 2, 3, … , N – 1

Slope Sing Changes (SSC):

$$\text{SSC} = \sum f(x) where$$

$$f(x) = \begin{cases} 1,\ if, (x_k\ < x_{k+1}\ AND\ x_k\ < xk - 1) \\ \quad OR (x_k\ > x_{k+1}\ AND x_k\ > x_{k-1}) \\ 0,\quad otherwise \end{cases} \tag{6}$$

for k = 1, 2, 3, … ,(N – 1)

$$k = \frac{E(x-\mu)^4}{\sigma^4} \quad (7)$$

$$s = \frac{E(x-\mu)^3}{\sigma^3} \quad (8)$$

The obtained features are stored in a matrix with the same name. These 8 features are put in a matrix and according to the overall error percentage of the neural network and according to the feature extraction methods, the best feature is selected, and also the dimensions of the features are reduced by using principal component analysis.

D. Feature Selection:

The issue of feature selection is one of the issues that is raised in the topic of machine learning and also pattern recognition. This issue is very important in many applications (such as classification) because in these applications there are a large number of features and many of them are either useless or do not have much information. with not removing these features, does not create a problem in information of signal, but it increases the calculation load for the intended application. And in addition, it causes us to store a lot of useless information along with useful data. For the feature selection problem, many solutions and algorithms have been presented. The problem of some algorithms when they were presented was their high computational load, although today with the advent of fast computers and large storage resources, this problem is not visible, on the other hand, data sets Very largely for new problems make it still important to find a fast algorithm for this task. The blind source separation [18] technique is divided into three methods: forward selection, backward selection, and two-way selection. According to the limited observations that we have of the electromyogram signal, we use the first method in such a way that first the feature vector is assumed to be empty and then classified according to the accuracy, any feature that has the most accuracy in discrimination is selected.

III. RESULTS

In this study, 6 main stages have been done: the first stage is data collection. Surface electromyogram data with 2 electrodes of 5 healthy people during 6 movements captured. The electrodes are placed in the area of theFlexor carpi ulnar and Extensor Capri radialis. Also, this database includes 6 movements of holding a spherical tool, grabbing an object like anautomatic, holding a thin object like a card, holding a cylindrical object, holding a heavy object, and holding small tools, which were taken from 5 healthy people, including 2 men and 3 women, with an approximate age of 20-22 years, and each test was repeated 30 times. The second stage is the pre-processing of the raw data collected from the first stage. For this purpose, a Butterworth low-pass filter with a low cut-off frequency of 15 and a cut-off frequency of 500 Hz, and a notch filter of 50 Hz have been used to remove city electricity noise. In the third step, each hand movement is labeled and targeted. The fourth step is extracting features from the obtained signal. A set of features mentioned below is extracted from the cleaned signal, and since the number of electrodes and features is large, the feature space reduction method based on principal component analysis is used. The set of extracted features is considered as the input of the classifier structure which forms the sixth stage of this study Using the multilayer perceptron classifier, we first feed the features extracted from the raw electromyogram signal to the neural network and check the results. Then the features are combined with each other and we check the results using principal component analysis and its output. The learning algorithm of the neural network was an error during the post-propagation check period and will not change. Also, in the results section of the feature combination, the number of hidden layer neurons is checked in numbers 5, 10, and 20. The example of electrode placement and registration is as follows, which is taken as an example:

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Fig. 1: multi-layer perceptron neural network

Using a multi-layer perceptron neural network, the features act as input to the neural network. The activation function of the middle layer and the hidden layer is sigmoid, of course, we used various functions such as Purelin and... as the activation function of the middle layer and the output layer, which increased the percentage of neural network output error. MATLAB software has been used, and the result of the value of the output layer is classified as follows:

movement name	output	Class
Holding a spherical tool	0.1667	Class one
Taking an object like a pencil	0.3333	Class two
Taking a thin object like a card	0.5000	Class three
Maintaining a cylindrical object	0.6667	Class four
Holding a heavy object	0.8333	Class five
Holding small tools	1.0000	Class six

Table 2: of the neural network output range

The range of each class is calculated according to the tolerance of 0.0.85 with its center, for example, if the output of the network shows the number 0.75, it means that the desired movement was to hold the heavy object, and the range of movement will be 0.7517-0.9183 This issue has been included for all six movements in programming. Also, 70% of the data has been used for neural network training, 15% for testing, and 15% for evaluation, which has been constant in all results.

In the following table, the results obtained from a single feature in the neural network are checked and the results are reported:

Property	Training	Test	Validation	ALL
VAR	89.64	79.30	81	82.97
MEAN	83.20	69.13	68.17	72
WL	97	93.60	94.22	93.15
MAV	98.70	95.20	96.80	96.09
Zero Crossing	89.35	82.36	81.77	86.70
STD	99.97	97.60	93.20	96.92
Kurtosis	84.39	71.40	72.29	75.10
Skewness	81.69	80	87	86.30

Table 3: The neural network accuracy rate for different features

After the results of each feature, we extract the best available feature vector using the BSS [18] technique, which is one of the subsets of the PCA method. Using the PCA output, we designed the neural network again and checked the results. In this step, the dimensions of the data were reduced and the features that had more output errors were removed. The results using the PCA output are as follows:

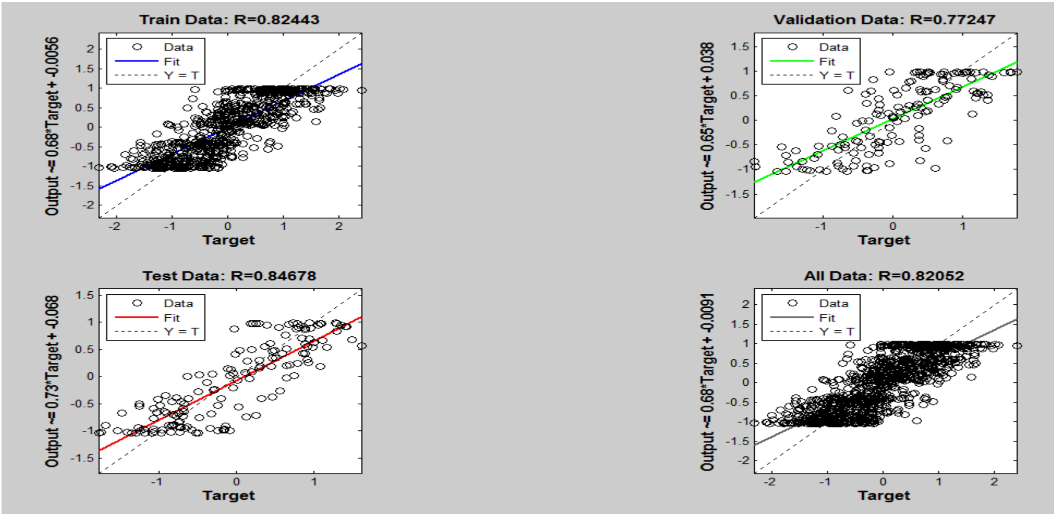

Fig. 2: MLP neural network results using all features

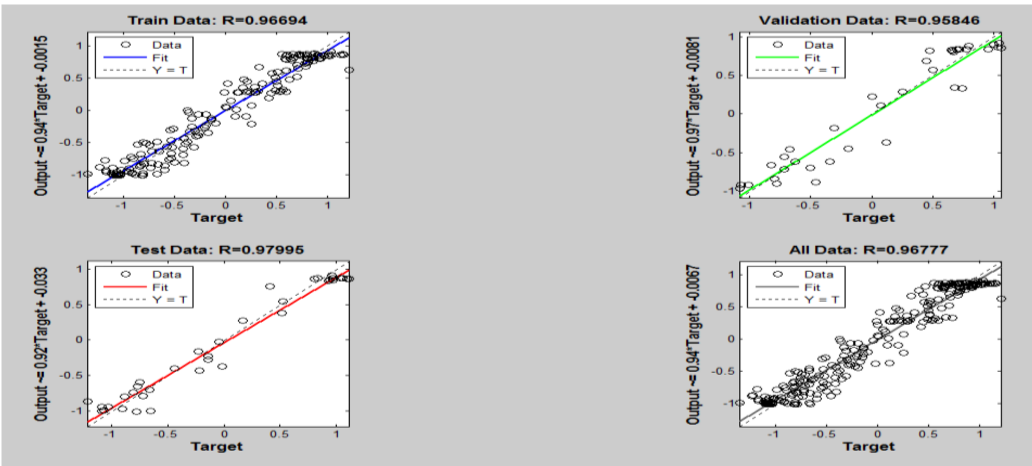

Fig. 3: MLP neural network results using PCA output

IV. CONCLUSION

An EMG-based hand position detection system is an EMG signal analysis system that is accurate, simple, fast, and reliable. This study proposes the development of a framework for hand posture detection that uses surface EMG. This framework uses electrodes placed on the hand to measure EMG signals from the hand. For EMG signals, which are complex data sets, feature extraction is probably a better solution. The aim of this study is to investigate the potential of using neural networks for EMG data classification. The six important hand movements that do the most work during the day were examined. The classification accuracy of six hand movements in this study is 96.77%, which is more accurate than the research studied [2-6-10].

Our results showed that:

- The use of a single feature is not suitable for classification.
- We remove the features that are similar to each other for the neural network and the amount of network error is the same.
- The use of PCA output as neural network input increases the speed and accuracy of program execution.
- The characteristics of MAV, SSC, WL, and STD had the best performance according to the results.
- In this study, an EMD-based noise removal method was used to remove EGG artifacts.

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