Recognition of Hand Grasp Pattern via EMG Signals Using Neural Network Classifier

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Abstract
The aim of this study is the easy and efficient classification of five hand grasp pattern. For this aim, biomedical signals were used, which recorded via two-channel EMG sensors placed on the forearm muscles. At first stage of the study, a series of pre-processing steps (filtering and separating) was applied to the signals, then these signals were subjected to the feature extraction process. In this process, three-time domain and two frequency domain features were calculated for each channel. Finally grasp type was recognized using Neural Network (NN) classifier. Average classification success rate calculated as 96.40%. Based on this high success rate, it is said that bioelectrical based cognitive interaction method used in the study are suitable for prosthetic and orthotic devices control.

Keywords: sEMG, Pattern recognition, Grasp

1. Introduction

Prosthetics, which replace the shapes and functions of missing limbs, are manufactured which People lose limbs because of injuries, accidents, and medical conditions.

The complexity and the number of types of motion increase in direct proportion to the number of joints in a limb. For this reason, biological hand motion is quite complex. Prosthetics that imitate the motion of the human hand must have same capabilities. Prosthetic hand design consists of three basic steps. These are mechanical design, controller design, and user-prosthetic interaction network. However, no matter how good the mechanical design of the prosthetic devices and the controller design is, if the human prosthesis interaction is unsuccessful, it will never be able to complete many complex actions of a real human hand.

Electromyography (EMG) signal based human-robot interaction is the most used method for control of the prosthetic and orthotic devices. EMG signals carry information about muscle activities [1]. For this reason, it is suitable for use as an input signal to control the prosthetic. It is possible to decide with the EMG signals that the type of the human motion desire (hand closure, opening, cupping, etc.) [2]. The EMG signal is non-periodic, with a stochastic structure [1]. EMG signals are not repeated at specific time intervals. For this reason, it cannot be represented by a single mathematical expression [2] - [3]. During the recording of the EMG signal, environmental noise, magnetic effects, and vibration caused by the electronic recording device are incorporated into the structure of the raw EMG signal. To improve the diagnostic value of EMG data, signal processing techniques are used [4]. The processing of EMG signals basically is determined in three steps, i.e., pre-processing, feature extraction, and feature classification. The literature indicates that the pre-processing step, which includes sampling, rectification, and filtering of the data, is quite similar in almost all studies. However, researchers used different approaches and methods for the feature extraction and classification of EMG signals [5].

Classifier performance is very low when the raw EMG signal is applied to the classification algorithm, so researchers have used different types of features of the EMG signal as inputs to the classifier in efforts to improve its performance. In order to achieve the best classification accuracy, the ability of the selected EMG feature field should be examined with respect to its ability to separate the maximum class, its robustness, and the complexity of the calculation [6]. The features of the EMG signal are grouped under three different domain headings, i.e., time domain features, frequency domain features, and time-frequency domain features. Hudgins et al. (1993) were described mean absolute value, mean absolute slope, changes the slope sign, the wavelength and number of zero crossings as time-domain features of EMG signal [7-9]. When Hudgins features set is used as an input to the classifier, succeed in the classification is much higher than the raw signal [10,11].

In order to achieve the more accurate performance of classification by Englehart et al., time-frequency domain properties were proposed to use. Then they have compared their results, with the method of Hudgins [12]. Time-frequency domain features are effective for classification of bioelectric signals, but due to their high size and high resolution, it is often necessary to reduce the size of features dataset [13]. Frequency features such as the average frequency, median frequency, mean peak frequency, spectral moments, frequency ratio, power spectrum ratio and variance of the central frequency are effective for classification of EMG signals [14]. However, the performance comparison results of these three methods (time, frequency and wavelet transform) were 78.3%, 62.5% and 66.2%, respectively. [15]. For this reason, time domain feature extraction methods are used in this study.

The third step of this kind of research is the pattern recognition according to EMG features via classification algorithms. The types of classifiers that are used extensively to classify EMG signals are Artificial Neural Networks (ANNs), the Fuzzy Classifier, Linear Discriminant Analysis (LDA), Self-Organized Map (SOM), and Support Vector Machines (SVMs) [14]. Some of the researchers prefer SVM and LDA classifiers because of their simplicity and ease of training [16,17]. Del and Park have used the artificial neural network classification algorithm for real-time classification applications of EMG, they stated that ANN is a suitable technique [18]. Some researchers have used the network of multi-layered Perceptron-type artificial neural networks because of uncontrolled learning technique to recognize the test data automatically [19]. Tsuji et.al used the back-propagation artificial neural network model to recognize five forearm motion using entropy of EMG signals [20]. Nan, B. et al. have developed a new EMG classification method based on the Hidden Markov model, and named it as Recurrent Log-Linearized Gaussian Mixture Network [21]. To classify the wrist movements Naik et. al. has tried four methods and compared their results each other. These four methods are Fast ICA, JADE-ICA, Infomax-ICA, and Temporal Decor-relation Source Separation (TDSEP) [22]. Khezri et al. used a neural-based fuzzy logic classification algorithm to classify hand patterns via EMG signals [23]. Subasi et al. suggested to use two different classifiers together. these were the back propagation artificial neural network and the wavelet neural network [24]. In this study, Neural Network (FF) classifier used to recognize five grabs patterns.

2. Material Method

2.1. Overview of Study

In this study, sEMG for Basic Hand movements Data Set of UCI Machine Learning Repository data bank was used. Used Dataset were recorded an NI analog/digital conversion card NI USB- 009, mounted on a PC by C. Sapsanis et al. [25]. Figure 1 shows an overview of this study.

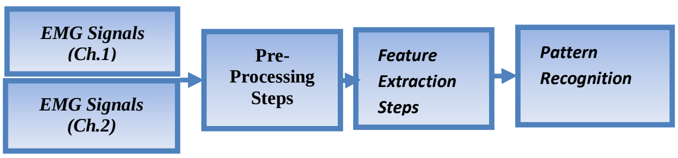

Figure 1. Overview of the study

In the first step the band pass filter was applied to the signals. Then time domain and frequency domain features were extract. Finally, hand grasp patterns were recognized using NN classification algorithm, and performance ratios of the algorithm compared with other studies.

2.2. Description of Dataset

EMG signals were recorded by C. Sapsanis et al. Dataset has the following properties.
Hardware Instrument: The signals were taken from two-channel differential EMG sensors via Delsys Bagnoli.
Electrode type: Electrodes used are Delsys Trigno Mini Sensors which dimension of the electrode is 25 × 12 × 7 mm. This type of electrode is designed for use in the treatment and diagnosis of disease.
Electrodes Placement: Surface EMG electrodes were placed in the muscles of the two forearms. (Flexor Capri Ulnaris, Extensor Capri Radialis Longus and Brevis) [18].
Subject Information: Data were obtained from 5 healthy subjects (two males and three females). Subjects were the same age approximately (20 to 22-year-old).
Grasp patterns type: 6 hand movements (grasp motions) were asked to each of subjects. The measured time of each grasp motion was 6 second. Each subject has repeated the same grasp motion 30 times. Thus 180 × 3000 data matrix was created for each subject. Grasp motions can be seen in Figure 2.
Recording sample rate: Sampling rate was 500 HZ

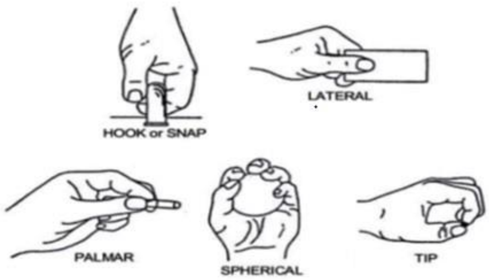

Figure 2. Photographs of Recognized Hand Patterns

2.3. Pre-Processing

The signals were band-pass filtered using a Butterworth Band Pass Filter. The low and high cut-off frequency was 50 Hz and 500 Hz respectively.

2.4. Feature Extraction

In this study, three-time domain and two frequency domain features were calculated. These features (energy, maximum value, variance, median frequency, mean frequency of signal) are widely used as input data for motion classifier algorithms in the literature [29-33].

2.5. Classification of EMG Signals

Neural Network (NN) was used with the aim of determining hand pattern in this study. NN has the ability to converge non-linear models to any continuous function or its derivatives. NN is successful especially in dealing with the classification and estimation problems, which is making it suitable for EMG classification [32-33] In this study an NN was designed, which contains input, hidden and output layers. The input layer is the layer that holds the data that enter the NN, the hidden layer, or layers that perform the operations according to the desired result, and the output layer shows the output values. The layer's weight, superscript number, weight matrix, and activation function are denoted w, k, w_{ij} , and g, respectively.
Total of inputs to perceptron are calculated as Eq. (1).

$$a_{\mathrm{q}} = \sum_{i=0}^{N} \omega_{qi}^{(1)} x_i \quad (1)$$

The output of the hidden perceptron z_q (Eq. (2)) is found by applying its activation function, $g^{(1)}$, to the nodes total input, a_q.

$$z_q = g^{(1)} a_q \tag{2}$$

As the same way, the second layer of perceptron's is estimated, and the output of the NN can be calculated as Eq. (3).

$$y_m = g^{(2)} \sum_{q=0}^{Q} \omega_{mq}^{(2)} z_q \tag{3}$$

Output of Two layer NN can be estimated as Eq. (4)

$$y_m = g^{(2)} \left(\sum_{q=0}^{Q} \omega_{mq}^{(2)} g^{(1)} \left(\sum_{i=0}^{N} \omega_{qi}^{(1)} x_i \right) \right) \tag{4}$$

3. Experemental Result and Discussion

The dataset included 150 motions and was separated into two parts. 50 of the motions were selected as training sets, and the remaining 100 motions were selected as the test sets. NN classification algorithms were tested offline with the test datasets.

In order to choose optimal parameter for NN algorithm to yield successful results, the parameters were tested experimentally (Figure 3). Selected parameter values used for the classification algorithms are given in Table 1.

Table 1. NN Parameters

Parametre	Değeri
Data Division	3
Training	Bayesion Regularization
Calculations	Mex
Layer Neuron Count	7,6,5
Transfer Function each Layer	{'tansig','purelin','purelin'},'trainbr
Performance Function	MSE
Eproach	70

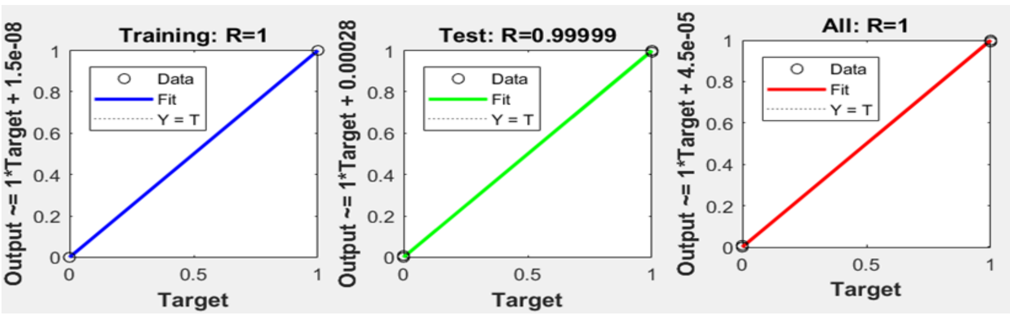

Figure 3. NN training regression

In the medical decision-making process, the Receiver Operator Characteristics Curve ROC analysis method is used to determine the discrimination of the test or the classification algorithm [34]. In this classification problem, there were five motion classes, and the performances of the NN algorithms, according to the ROC analysis. The performance values for each hand motion were calculated using Eqs. (8) [34].

Accuracy(ACC) = (A+ D) / (A+B +C+ D) (8)

The five outcomes for each classifier can be formulated in a 2 x 2 contingency table. All contingency matrixes for each motion are shown in Tables (2) and NN Classifier accuracies rage of five grasps were presented in Figure 4.

Table2. Contingency Matrixes for NN

Grasp 1			Grasp 2			Grasp 3			Grasp 4			Grasp 5		
A 18	B 0	18	A 18	B 3	21	A 18	B 1	19	A 20	B 2	22	A 17	B 3	20
C 2	D 80	82	C 2	D 77	79	C 2	D 79	81	C 0	D 78	78	C 3	D 77	80
20	80	100	20	80	100	20	80	100	20	80	100	20	80	100
ACC=0.98			ACC=0.95			ACC=0.97			ACC=0.98			ACC=0.94		

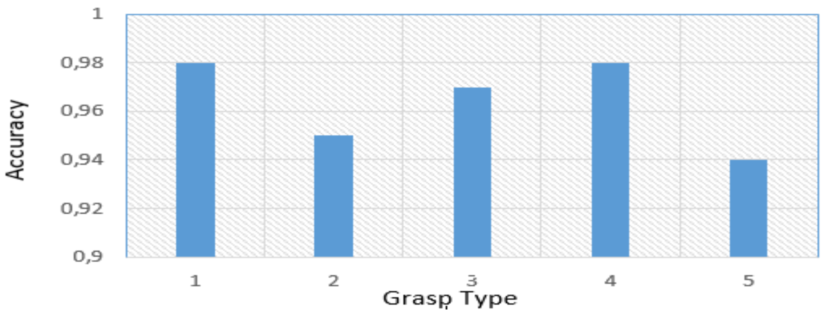

Figure 4. NN Classifier accuracies rage of five grasp

4. Conclusion

Cognitive interaction is the most important component of studies concerning the control of prosthetic devices because such a network allows the effective use of the prosthetic. Thus, the objective of this work, i.e., the processing and classification of EMG signals in order to recognize human motion desire, was achieved. This study shows that the grasp motions can be classified easily with a simple 2-channel sEMG device with high accuracy. Average accuracy rate for five in this study is 96.40 %. Also, results also have showed the relationship between the grasp motions and forearm muscles. The results obtained by the proposed method can be used to give support to some medical decision. Apart from all these, proposed method can support the studies in literature related with prosthetic design.

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Ethical approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Ethics Committee Permit Document for this study is attachment.
Funding: There isn't any founding source
Data Availability: The data used to support the findings of this study are available from the corresponding author upon request.

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