Design of an Intelligent Controller for Myoelectric Prostheses based on Multilayer Perceptron Neural Network

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Abstract. Myoelectric prostheses have been researched widely, and some cases have been implemented to be used by amputees in real life. However, natural control of an active prosthesis remains a challenge. This work presents an exploration of an intelligent controller for upper prostheses based on myoelectric signals. A simple intelligent classifier for a small control system is designed and incorporated into a hand prosthesis to be used by the amputees in Iraq and similar developing countries. To achieve this, a Multi-Layer Perceptron Neural Networks (MLPNN) classification system is developed. The proposed system uses pattern recognition based on features extracted from eight raw EMG signals collected using a Myo armband. Five different classes of hand gestures are recognised. The system also applies remove silence process and overlapped segmentation to the collected EMG data. Continuous real values that represent class types are sent to the controller to move the prosthesis. This work shows that, by adding appropriate pre-processing, a considerable increase in the accuracy of the proposed MLP classifier can be obtained. The required hardware circuits were assembled and software scripts written to implement the intelligent myoelectric hand prosthesis.

1. Introduction

Hand prostheses can be categorised into three types:

1- cosmetic (passive),
2- body-powered conventional prosthesis (passive), and
3- myoelectric prosthesis (active).

This research is interested in active prostheses, which can be either moved by the patient or have an external source of energy (electronic commands or myoelectric commands) [1]. Myoelectric prostheses are the next generation of upper-limb prostheses for amputees. The term myoelectric-controlled prosthesis refers to a prosthesis that can be controlled using the electrical signals generated by the remaining limb muscles of an amputee.

Recently, the myoelectric control system has been used more widely in upper limb prostheses for amputees, and the application of myoelectric prostheses with multifunction control system has developed from research laboratory conditions to embrace commercial applications [2, 3].

There are three main factors that determine the rate of acceptance of myoelectric prostheses by amputees; these are: the form of the designed prostheses, the level of patient training, and the control method.

Poor perceptions of control can lead to low acceptance rates [4, 5]. This work thus considers myoelectric control systems in more detail. Myoelectric signals offer important and effective input for...
the control systems of prostheses [4,6]. However, raw electromyography (EMG) signals contain huge amounts of data, and the beneficial information that can be extracted from this data is minimal compared to the amount of data available. In addition, raw EMG data input to the classification algorithm makes high computational demands, and pattern recognition processes are thus slow, with low classification rates [2]. It is thus common to use a number of carefully selected features extracted from the raw data as input to the classifier; these features represent the raw data in a reduced form with a focus on useful and appropriate information [2].

Generally, there are three major types of feature extraction that can be used in the analysis of an EMG signal: frequency domain, time domain, and time-scale (time-frequency) features [1].

The selection of features, method of extraction, and classifier type all directly affect EMG pattern recognition accuracy [7, 8]. Thus, both the classification and feature extraction methods must be selected carefully [2]. Extensive literature researched various features extraction and pattern recognition methods [9-14], with the aim of improving control of myoelectric prostheses systems. Many successful EMG classifiers have been presented in previous work, such as Support Vector Machines (SVM) [15-18], Linear Discriminant Analysis (LDA) [14, 11], k-Nearest Neighbour classifier (KNN) [13] and Random Forest (RF) [19] [20-22]. Some other researchers have used artificial neural networks (ANN) as EMG classifiers [23-26], along with fuzzy logic systems [20, 26-28], and hybrid neuro-fuzzy (NF) systems [23, 29-31].

While many components of prosthetics such as battery life, weight savings, and cosmetic features have been considerably improved recently, the basic myoelectric control of prosthetics has not changed considerably [32]. This work aims to implement a more precise control to develop a smart hand prosthesis with a relatively simple and low-cost myoelectric-based controller and interface devices for use by amputees in Iraq and similar developing countries. The outcome is a myoelectric prosthesis with natural movement which can distinguish between five gestures: fist, fingers spread, relaxed, waving left, and waving right, by using a Multi-Layer Perceptron Neural Networks (MLPNN) classifier based on features extracted from EMG data. The mechanical design and construction of the prostheses was supported by an open source project [33] and printed using a general-purpose 3D printer.

2. Experimental Work

2.1. Myo armband
The Myo armband is a device consisting of eight pairs of EMG electrodes placed on the inside of an armband that can be worn on a subject’s forearm, and which communicates with the PC to send EMG data via Bluetooth. The device can be used to recognise five different hand gestures: fist, wave right, wave left, fingers spread, and double tap, in addition to the relaxed state. The measured raw EMG data from the device can also be fed to custom classifiers such as the one used in this research.

The device can theoretically recognize more gestures, as many of the muscles located in the forearm contribute to the movement of the wrist and hand. However, it is not possible to mimic all hand movements using a prosthesis, and a more practical approach is to enable the patient to control the basic movements that allow interaction with common objects well [1].

2.2. Segmentation
Segmentation is an important process in pattern recognition. It separates the input data into sequences before feature extraction. Variance and bias in the estimation of a feature may occur if the duration of a segment is too short; conversely, segmentation with long durations can enforce high computational costs and may not be suitable for real-time applications [1]. Segmentation can be applied in either disjoint or overlapped segment lengths.

2.3. Data Collection
Conventional commercial prosthetics provide two hand gesture such as opening and closing of the hand. In this paper, five gestures are implemented: fist, fingers spread, wave right, wave left, and relaxed, as shown in figure 1.
Figure 1. The five hand gestures (from left to right): fist, fingers spread, wave right, wave left, and relax.

For the data collection process, the Myo armband device was used. A MATLAB script was then written to acquire the EMG data from the device via Bluetooth for future processing. Each gesture was performed for a time period of 5 seconds with a data sampling rate of 200 HZ. This yielded eight sets of EMG data, each with 1,000 elements per gesture. For the purposes of this research, the data were collected from three body-able volunteers with full arm movement and capability.

2.4. Pre-Processing

The first step of the proposed pattern recognition for the collected EMG data was to remove the silences from it. This was carried out by calculating the mean value of the EMG data and subtracting this from the original EMG data. After this, all data were expected to be of the same length for the segmentation process. To achieve this, two methods could be used:

1- Zero padding small data vectors to be equal to the largest vector, or
2- Removing redundant values from all vectors to make them equal to the smallest vector.

In this work the second approach was used. Finally, the data were divided into 50 ms length vectors with 5 ms overlap between segments, yielding a total of 180 segments (vectors).

2.5. Feature Extraction

In this work, several feature extraction methods were used to feed the classifier and to characterise the acquired signal. The features Root Mean Square (RMS), Standard Deviation (STD), Maximum, and Minimum were extracted to use as input for training the MLPNN classifier. Each feature was calculated for all eight sensors of the Myo armband. Thus, the length of each input data vector was 32 (4 features by 8 sensors), and for 180 collected vectors, the result of the overlapping process, the input data had a size of 32 x 180. Table 1 shows the formal definitions of the extracted features used in this work for the proposed myoelectric control system.

| Feature               | Definition                                                                 |
|-----------------------|---------------------------------------------------------------------------|
| Root Mean Square (RMS)| $\text{RMS} = \sqrt{\frac{1}{M} \sum_{m=1}^{M} V_m^2}$                   |
| Standard Deviation (STD)| $\text{STD} = \sqrt{\frac{1}{M - 1} \sum_{m=1}^{M} (V_m - \bar{V})^2}$  |
| Maximum               | $V_{\text{max}} = \max(V_1, V_2, ..., V_M)$                              |
| Minimum               | $V_{\text{min}} = \min(V_1, V_2, ..., V_M)$                              |
2.6. Classification
The proposed controller is based on pattern recognition; it receives and classifies the input data represented by features extracted from the raw EMG signal, and outputs a real value between 1 and 5 indicating class type. The classifier is based on a fully connected MLPNN architecture, and various structures of MLPNN classifier were designed for the collected data. The simplest and fastest of these structures was then chosen to classify the selected sets of features, resulting in a lower recall time for the class number. The recall time, added to the feature extraction process time, must be acceptable to ensure a fast response time in the proposed controller.

3. Neural Network Training
The hidden layer perceptron of MLPNNs is generally used as a universal approximator. This was thus chosen as the fundamental construction of the proposed classifier. To realise the input-output data mapping, an additional hidden layer was then added to the network. A trial process was used to determine the required number of hidden nodes, but to simplify the network and to reduce computational time, the minimum sufficient number of hidden neurons was chosen. Fig. 2 shows a graphical representation of the MLPNN.

Different transfer functions were tested with various learning algorithms. Sigmoid activation function and tangent activation function were chosen in the first and second hidden layers, respectively, with a linear transfer function used in the output layer. The available data were divided up, with 70% used as training patterns and 30% used as testing patterns. The training error was calculated using the RMS of the difference between the actual obtained values and the desired output values. The following parameters were used as the stop condition for training: the maximum number of epochs was set to 100 and RMS error was set to less than or equal to 10 to 15. Fig. 3 shows the training performance of the MLPNN.

Figure 2. Graphical diagram of MLPNN. 
Figure 3. Training performance of MLPNN.

The output of the simulated intelligent controller is the identified class number. A MATLAB code was developed to allow the prosthesis to perform the gesture determined by the MLPNN output. An Arduino UNO was used as a controller for the prosthetic hand, with servo motors of type SG901. An open source prosthesis designed per [33] was used, being constructed using a 3D printer as shown in Fig. 4 for use for testing purposes only. The movable parts of the prosthesis are the fingers, with two degrees of freedom, where the thumb and the index finger moving together constitute one movement and the other three fingers constitute a separate movement of the prosthesis. A plastic material was used to build the prosthesis, with two servo motors added to fulfil the movement function. Fig. 5 shows the

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1 Operating voltage of +5V typically, torque: 2.5kg/cm operating speed is 0.1s/60° and rotation: 0°-180°
algorithms used in the training of the MLPNN and the complete implemented myoelectric control system.

Figure 4. The 3D printed prosthesis (a) Individual parts, (b) Assembled prosthesis.

4. Results
The actual output of the trained MLPNN, the class of the performed gesture, is shown in figure 6. The classification is perfect for all input training data due to the high accuracy of the network, which had training performance error rate of just $1.87 \times 10^{-11}$, as shown in figure 3. Thus, the network’s accuracy was greater than 99%, superior to the classifier accuracies reported in [2]. As a further example [24] reported an accuracy of 98.21% using back propagation artificial neural networks.

The execution time of the pre-processing part computations was calculated as less than 0.2 sec, while the overall response time for the proposed controller is estimated at less than 1 second.
The MLPNN classifier was trained with 130 patterns (26 patterns for each of the five gestures) and tested with 50 unknown patterns (10 for each gesture). Figure 7 presents the results of the testing process and it shows that all the unknown gestures were successfully recognized.

![Figure 6. Output of MLPNN training process.](image1)

![Figure 7. Output of MLPNN testing process.](image2)

The gesture in which the classifier thinks it was intended by the user is transferred to the Arduino microcontroller, and each of the indicated gestures is mapped to a movement of the prosthetic hand, achieved by setting the rotation angle of the servo motors to accomplish the required movement. Table 2 shows the mapping between the identified class number and the servo motor rotation angles set by the Arduino. Figure 8 shows the experimental prosthesis movement for the implemented system.

**Table 2. MLPNN output and servo motors angles.**

| Desired Output | Actual Output | Servo 1 Angle (fingers) | Servo 2 Angle (thumb) | Gesture | Mapped Movement |
|----------------|---------------|-------------------------|-----------------------|---------|-----------------|
| 1              | 1.0000        | 180                     | 180                   | fist    | fist            |
| 2              | 2.0000        | 0                       | 180                   | fingers open | close thumb    |
| 3              | 3.0000        | 0                       | 0                     | relax   | relax           |
| 4              | 4.0000        | 180                     | 0                     | wave left | close fingers  |
| 5              | 5.0000        | 90                      | 90                    | wave right | half close fingers and thumb |
Figure 8. The prosthesis in action. Relaxed gesture on the left and fist on the right.

5. Conclusions
This work aimed to develop an intelligent controller for a smart prosthesis based on pattern recognition. A new approach to classifying EMG signals was presented in which five different gestures are recognized using MLPNN based on extracted features.

A myoelectric prosthetic hand controller was designed with the ability to receive control commands that could perform the five gestures. This number of movement patterns may be increased depending on the learning and generalisation properties of MLPNN. The results showed good generalisation ability within the MLP network and a high rate of pattern recognition. This capability should allow the recognition of new movements for the amputee with whom the system is trained and no other amputee; this is not likely to be a problem, as a prosthesis is usually trained to be used by only one person.

A straightforward comparison of the results of this work with results in the literature is not possible due to the variety of amputee cases and diverse types of gestures studied, not to mention the different EMG devices available. However, the results do show an excellent recognition rate. In addition, the results show that the required storage capacity is minimal, which is an advantage for embedded devices as in the proposed control system.

The proposed pre-processing for selected feature extraction offers low computational time compared to other works, and the simple intelligent controller is designed with a low error level that allows the application of designed prosthesis for clinical purposes.

The developed prosthesis in this work can thus be considered an essential step towards a reliable controller. However, the small sample database of three non-amputee persons and offline operation of the proposed system creates a major limitation for this work. To improve the performance of the myoelectric controller based on MLPNN recognition, several further developments are also required, such as selecting the most effective extracted features, using a dimensionality reduction process to reduce the number of features in vector spaces, and using additional classifiers such as fuzzy logic or a neuro-fuzzy approach.

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