Classification of Finger Activation for Use in a Robotic Prosthesis Arm

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***Abstract*—Hand amputees would highly benefit from a robotic prosthesis, which would allow the movement of a number of fingers. In this paper we propose using the electromyographic signals recorded by two pairs of electrodes placed over the arm for operating such prosthesis. Multiple features from these signals are extracted whence the most relevant features are selected by a genetic algorithm as inputs for a simple classifier. This method results in a probability of error of less than 2%.**

***Index Terms*—Assistive devices, electromyography (EMG), genetic algorithms (GA).**

I. Introduction

In cases of hand amputation, there is a need for a way to control a robotic replacement hand. Although the hand is missing, the muscles in the forearm, which are responsible for finger movement, usually remain, and can be flexed. This muscle activity can be read as electomyographic (EMG) signals by placing electrodes on the forearm. The objective of this study is to use these EMG signals to successfully identify when a finger is activated and which finger is activated.

The physiological basis for this paper is that the muscles operating articulations of the limbs are located above them. For example, amputation below the wrist does not usually damage the muscles operating the fingers, which are situated in the arm. However, previous studies [1]–[4] have shown that there is no one-to-one mapping of muscles to fingers. Operating a finger causes activation in a number of muscles, some of which are associated with other fingers. Thus, it is imperative that the processing algorithm be capable of correctly associating the activation caused by several muscles to the correct finger movement.

Most previous studies of EMG classification to specific movements have focused on extraction of forearm movement using the EMG recorded from upper arm muscles [5]–[7]. One study which attempted to classify finger movements [8] used several learning techniques, such as perceptron linear separation and a backpropagation-type neural network. These techniques yielded probabilities of misclassifications too high for a realistic implementation (recent studies reached approximately 15% error).

In this paper, a combination of a K-nearest neighbor (KNN) classifier and a genetic algorithm (GA) for feature selection is used, resulting in an average error rate of approximately 2%, thereby making it feasible to operate a robotic replacement arm with relatively few errors using only two pairs of electrodes.

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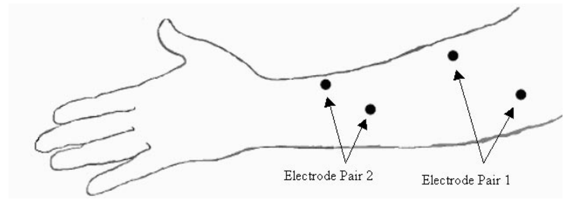

Fig. 1. Location of the recording electrodes. The electrode pairs are attached to the superficial layer of flexors. This is advantageous compared to recording locations over the extensor muscles because the flexor muscles are triggered before actual movement of the finger.

II. Materials and Methods

A. Experimental Protocol

Four healthy subjects (males, aged 19 to 27 years old) participated in the study. The subjects did not suffer from neurological or muscular disorders. Informed consent was obtained from the subjects.

Subjects were seated in an armchair, with their arm supported and their right hand fixed to a board with five microswitches, one under each finger. The microswitches required 400 [gm] of pressure for activation. Their maximal movement was 1 [mm]. The subjects were asked to randomly select and press one of the five buttons with a brief delay between each press. No feedback was provided except for the microswitch movement. The subjects were instructed not to use maximal force as it was found that this causes muscle coactivation of other fingers and produced inferior results. No multiple switches were closed at the same instant.

Passive electrodes were placed over the flexor muscles of the right forearm (as can been seen in Fig. 1), with one pair approximately 5 cm distal to the elbow (denoted as electrode pair 1) and another pair approximately 5 cm proximal to the wrist joint (denoted as electrode pair 2). The electrodes (Myo-Tronics Duo-Trode) were Ag-AgCl surface electrodes, circular, with a 6-mm diameter. The electrode pairs were placed 4 cm apart, at an angle of 45 degrees to the arm. This electrode location was chosen so as to record activity from a variety of forearm muscles, which were found to give the best classification results.

The EMG signals were amplified 2500 times and sampled (after antialiasing filter with a cutoff frequency of 250 [Hz]), together with the microswitch states, using a Bio Pac Student Lab PRO kit at a sampling frequency of 500 [Hz].

At least 30 presses from each finger were recorded. In order to decrease the effect of fatigue, the subjects paused briefly after each minute of recording.

B. Data Processing

Data processing was done in three stages: Detection, where the intervals of finger presses were detected; Feature extraction, where the most relevant features for classification were extracted; and classification, to determine which of the five fingers were pressed. The stages of data processing were performed separately for each subject.

1) Finger activation identification: The objective in this stage is to find the intervals of finger activity (without regard to identity). This was achieved using envelope detection on the EMG signal recorded from both electrode pairs. The calculation of the envelope of the signal is a three-staged process. First, the signal is passed through a high-pass FIR filter with a cutoff frequency of 30 [Hz]. Then, the absolute value of the resulting signal is taken. Finally, the signal is passed through a low-pass FIR filter with a cutoff frequency of 2.5 [Hz].

The interval of finger activation is the interval in which the envelope of the signal in at least one of the electrode pairs surpasses a threshold. In order to separate noise from finger activation the subjects were instructed to remain still for approximately 3 [s]. The threshold was set 10% higher than the maximum envelope of the quiet EMG signal recorded in this time period.

2) Feature extraction: After identification of the time intervals in which finger activity was present, features for classification were extracted from the EMG in these intervals. By trial and error it was found that the best interval from which to extract features was between 0.4 [s] and 1.6 [s] after the envelope crossed the threshold. The characteristic features in this study were derived from two main sources. The first is the amplitude of the discrete Fourier transform (DFT) of the EMG signal: The frequency region between 0 [Hz] and 250 [Hz] was divided into 20 equal sections of frequencies and each section was characterized by its mean and variance values.

The second main source for features is the coefficients of an eleventh-order autoregressive (AR) model [9]. This order was chosen heuristically.

Each electrode pair was assigned an additional binary feature to represent whether or not finger activation was detected in that electrode pair.

3) Classification: A modified KNN classifier used the above features in order to ascertain which finger was activated (each finger is given a different label). A standard KNN classifier [10] measures the distance between a test measurement and the labeled training examples and the label which appears most frequently in the K nearest examples is chosen as the label of the test measurement. The modified KNN classifier is different from the standard KNN classifier only when there are an equal number of appearances of two or more labels in the K nearest training examples. In this case, the average distance between the above training examples and the test measurements is used as a tiebreaker.

The error rate of the classifier was determined using fivefold cross validation [10]: The data was divided into five equal subsets. One of the subsets was used for testing and the other four for training the classifier. The error rate was the average error of this procedure repeated for each of the subsets.

4) Feature selection: The signals from a total of 150 finger-presses samples were recorded (30 per finger) and for each such press 102 features were measured: For each electrode pair there were 20 DFT bins of mean amplitude, 20 DFT bins of the variance of the amplitude, the coefficients of an eleventh-order AR model, and one binary feature. This relatively small ratio of samples to features poses a generalization problem for the classifier [13]. Hence, it is imperative to use a smaller number of features for classification. In this paper, a genetic search algorithm was used for selecting the best subset of features for use by the classifier.

A genetic algorithm attempts to simulate a process similar to nature's evolutionary process [11], [12]. The algorithm works by encoding many possible solutions to the problem and iteratively improving them. In this paper, solutions were encoded using a binary vector of length N (the number of features), where "1" terms in the solution indicate inclusion of the appropriate feature for use by the KNN classifier. A certain number of solutions were iteratively evaluated and ranked according to the number of misclassifications of the KNN classifier, when using the features denoted by the solution. The solutions that have the worst error rates are discarded, and are replaced by solutions, which are crossovers or mutants of the remaining solutions. This process is iterated until termination, which occurs when most of the solutions are identical, which implies that the algorithm has converged, or when a certain predetermined number of iterations (generations) is reached.

III. RESULTS

The GA feature selection resulted in a classifier that had a relatively low error rate, but still used about 50 features (as can been seen in Fig. 2). This number of features was deemed too high, and so the GA was run again using only the features selected in the first execution of the GA. The number of features obtained after this second execution dropped to about 28 and the error percentage improved slightly, indicating that some overfitting was present in the first execution of the GA.

In the second execution of the GA the average error percentage (across all subjects) was 1.9% (s.d. 1.5%). This was reached using an average of 28 (s.d. 2) features. The average error percentage for the thumb was 7% (s.d. 5.5%) and 0.5% (s.d. 0.8%) for other fingers. The high error percentage for the thumb is probably due to the electrode location, however a better location was not found. This error percentage also suggests that if four fingers are sufficient for a given application, the error rate can be as low as 0.5%.

Fig. 3 shows that the AR features were utilized more frequently compared to other features. The binary features were often used because some fingers' signals (for example, the thumb) appear in electrode pair 2 but not in pair 1 and vice versa.

It was calculated that 38.5% of the selected features were chosen from electrode pair 1 and 61.5% from electrode pair 2. This is logical because electrode pair 2 is located closer to the activating muscles. Tests conducted with either one of the two electrode pairs resulted in prohibitively high error rates (approximately 15%).

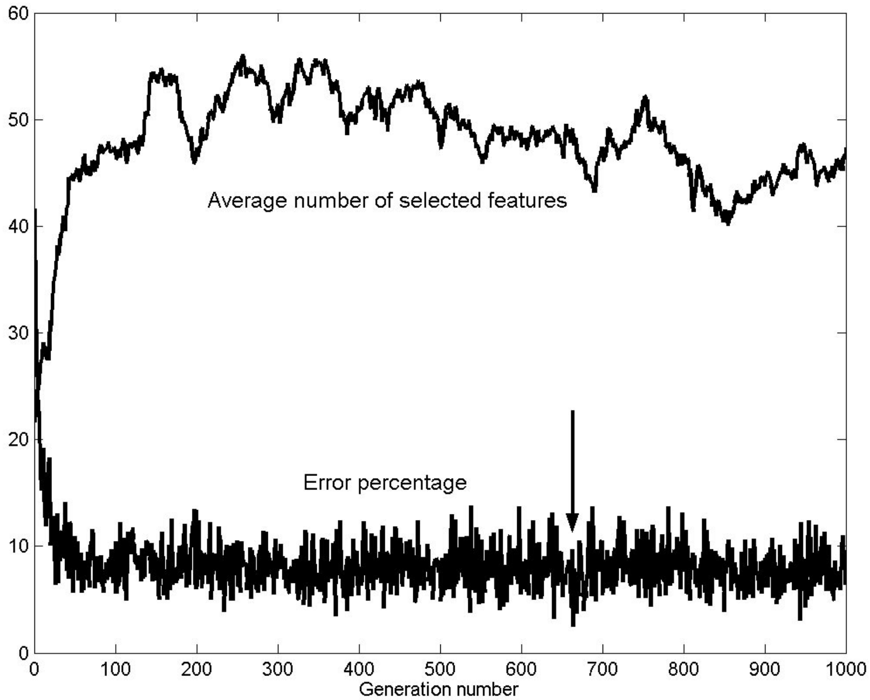

Fig. 2. A demonstration of the search process during the first execution of the GA. The bottom line shows the classification error (in percent). The top line shows the average number of selected features and the arrow indicates the iteration in which the lowest percentage of classification error was obtained.

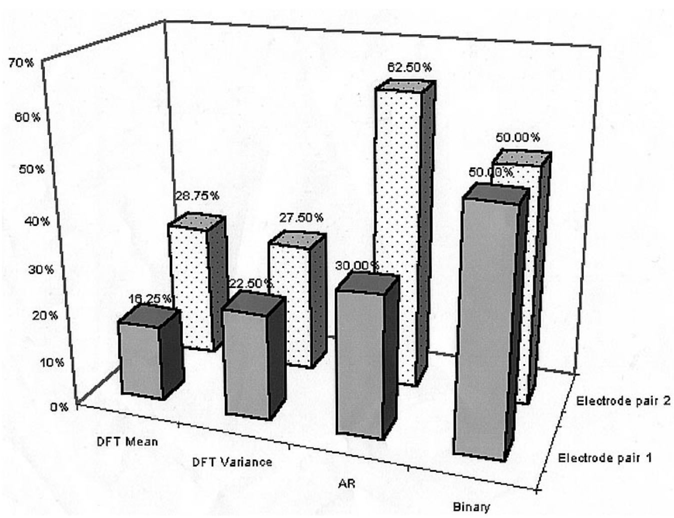

Fig. 3. Average percentage of selected features by type. This graph shows that AR was the most useful feature for classification. Standard deviation of the selected features was less than 15%, except for binary features, where it was 58%.

IV. Discussion

In this paper, the possibility of using a small number of surface electrodes for operation of hand prosthesis was demonstrated. We have shown that it is possible to obtain sufficiently small error rates by using a simple classifier coupled with a feature selection algorithm.

As noted earlier, the first 0.4 [s] (200 samples) were not utilized for feature extraction. This was done because their inclusion raised the probability of misclassification, probably due to the transient nature of this interval.

During the testing of the above algorithm, it was found that the genetic algorithm never converged and always had to be terminated after reaching the maximum number of iterations (set to 1000). This indicates that either a highly local solution exists or that the convergence criterion (80% identical solutions) was too high. In order to make use of this algorithm without it converging, the best overall solution was saved (marked by an arrow in Fig. 2).

We chose to use 1000 iterations as a compromise between a more thorough search of the solution space and processing time. Yet if 1000 generations seem like a high value, a simple calculation can show that the GA searches only through approximately 10^{-25} percent of all possible feature combinations.

It is interesting to note that if the choice of features is completely random, the probability of misclassification error is about 25%. Manual selection of the features by observation yielded a probability of misclassification of around 15%. The genetic algorithm, after reviewing only approximately 10^{-25} percent of all the possible combinations of features, managed to lower the probability of misclassification to only 2%.

We are currently in the process of building a real-time version of the algorithm. Such a system would (hopefully) reduce the number of errors even further, as the user interacts with the system. Additional studies are also planned to test this system with hand amputees.

During work with an on-line system, fatigue will become a factor to be dealt with by the system. It is thought that by running the feature selection and classification algorithms every several movements (in a bootstrap-like technique [10]) will enable the system to cope with the nonstationary nature of EMG.

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