Myoelectric Signal Based Finger Motion Discrimination by using Wavelet's and Pattern Recognisition

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Abstract

This paper details a strategy of discriminating finger gestures using surface electromyography (EMG) signals, which could be applied to controlling the advanced multi-fingered myoelectric prosthesis for hand amputees. Finger motions discrimination is the key problem in this study. The EMG signal classification system was established based on the surface EMG signals from the subject's forearm. Four pairs of electrodes were attached on the subjects to acquire the signals during six types of finger gestures, i.e. Thumb Extension (TE), Thumb Flexion (TF), Index finger Extension (IE), Index finger Flexion (IF), Middle finger Extension (ME) and Middle finger Flexion (MF). Record electrode signals from the extension digitrum, flexor carpi, extensor pollicis brevis, flexor digitrum superficialis are noise filtered and transformed into features using wavelet transforms. Feature sets for six different finger gestures are classified by minimum distance classifier technique. Features construction, recognition accuracy and an approach for an extension of the technique to a variety of real world application areas are presented.

Key words: Surface Electromyography, wavelets, SEMG signal features, Pattern Recognition, Prosthesis.

1. Introduction

The main control functions of the prosthesis are hand closing and hand opening, palmar flexion and palmar dorsiflexion, wrist pronation in action [1], [8],[13]. In order to discriminate these functions, investigators have used various EMG features including Entropy, Standard Deviation, EMG frequency characteristic, power spectrum analyzed by Fast Fourier Transform (FFT) method[8], [3], and coefficients of an EMG AR model [1], [12]. The classification n tools covered linear discriminate functions, neural networks [1],[8],[3], and fuzzy systems [6]. Chan et al. [2] used a hidden Marko model to process four channels continuous EMG signal, with the task of discriminating six classes of limb movement. There are some strategies for myoelectric controlling a dexterous hand. Discrimination of different types of grasp motions has been studied .Huang et al. used a three-channel EMG signal to distinguish several grasp motions, such as power grasp, hook grasp, centralized grip, three-jaw chuck, cylindrical grasp and so on. Human hand motion control includes not only grasping but also individual finger motion. Farry et al.[7] presented the results with a 90% correct grasp selection rate and an 87% correct thumb motion selection by using the myoelectric spectrum. The thumb motion is very important but not enough for controlling a dexterous robot hand. So classification of multi-finger movements based on the recognition of EMG patterns has been also successfully accomplished [3]. In this paper Feature sets for six different finger gestures are classified by minimum distance classifier technique with satisfied results.
2. Methodology

The real-time scheme of SEMG pattern recognition system used in this work is shown in figure 1. The four major components are sensing, preprocessing, feature extraction and classification. The EMG signal of the performing arm muscles is detected by electrodes connected to a sensor.

![Image](image1.png)

Figure 1. General procedure of a bio-signal based recognition system.

In order to qualify the incoming raw signal for further processing the signal is preprocessed first. The goal of preprocessing step is to prepare and amplify the signal for the subsequent steps and reduce noise artifacts. The features were extracted from the SEMG signal and the incoming patterns, which represent gesture movements, are matched by using the minimum distance classifier technique.

2.1 Extracting the MUAP

We used Trident Tech Labs EMG sensor which enables to record EMG signals of upto 1600µV in an active range of 20 to 500Hz. For the recording the EMG signal, four pair of pre-gelled Ag/Agcl electrodes was fixed on the skin of the subject. One pair of electrodes are connected to observe muscles, mainly the flexor Carpi radialis and the Palmaris longus, both of which are responsible for wrist movements, as well as the flexor digitorm superficialis, which is used for finger movements[9]. All the electrodes are situated in a line in the middle of the forearm parallel to the length of the forearm muscle fibers. By placing the first electrode near the wrist, it is possible to examine the muscles of the forearm between their tendon insertions and their motor points, which seems to be the best location for constant measurements[10].

MUAPS using wavelets

EMG signal is time series data. Therefore, it is not easy to infer operator’s intension of motions from raw EMG signal; electrodes placed on a muscle, measure a superposition of single Motor Unit Action potentials (MUAPs), artifacts and background noise. Basic shapes of surface MUAPs can be represented by only a few wavelet functions[11]. The clinically interesting features of the EMG signal are the number of active motor units and the MUAP waveform [5]. Quantitative analysis in clinical electromyography (EMG) is very desirable; with the development of computer aided EMG equipment different methodologies in the time domain and frequency domain have been followed for quantitative analysis. Wavelet transform provides two dimensional time-frequency representation. Wavelet transform has the ability to localize in the statistics of non-stationary signals and it provides an alternative to short-time Fourier Transform (STFT) which uses a single analysis window. The wavelet transform uses short window at high frequency and long window at low frequencies. In the case of db4, WT coefficients at the highest-frequency scales provide high time-resolution of only four signal samples. This allows the db4 wavelet to effectively track the MUAP main spike transient signal at a time resolution that the STFT simply can’t match [4]. In our work we have used db4 for four levels to decompose the signals.
2.3 Feature extraction
To be able to classify a performed gesture some distinctive features have to be found and taken from each matched pattern. Therefore several features were extracted, including common statistical feature like RMS, Entropy and Standard Deviation.

2.4 Classification using minimum distance classifier
The single nearest neighbor technique bypasses the problem of probability distance completely and simple classifies an unknown sample as belonging to the same class as the most similar or “nearest” sample point in the training set of data [5]. Nearest can be taken to mean the smallest Euclidean distance in n-dimensional feature space and in this work the city block distance technique of minimum distance classifier is taken by
\[ d_{cb}(a,b) = \sum_{i=1}^{n} |b_i - a_i|. \]

2.5 Experimental setting
We conducted a more comprehensive experiment with a total of 16 subjects. First of all, we collected personal information about the subjects, including age (average 21 year’s) gender (08 females and 08 males), weight (Average: 50.44Kg) and performing hand (16 right hands, nil left hander).

The experiment consisted of two phases. ten subjects participated in the first phase and for each subject, we recorded six Finger gestures of hand position and total 60 gesture are taken from each gesture we have taken three feature values which was averaged and finally the average of 10 subject’s feature were taken as a standard samples. The remaining 06 subjects with 6 gestures of finger of right hand were taken as test samples.

3. Results
The following table (1) shows the classification rates of the simple minimum distance classifiers.

<table>
<thead>
<tr>
<th>Recognition results</th>
<th>R.M.S in%</th>
<th>Entropy in%</th>
<th>Standard Deviation in%</th>
</tr>
</thead>
<tbody>
<tr>
<td>TE</td>
<td>83.33</td>
<td>100</td>
<td>83.33</td>
</tr>
<tr>
<td>TF</td>
<td>100</td>
<td>100</td>
<td>83.33</td>
</tr>
<tr>
<td>IE</td>
<td>66.66</td>
<td>100</td>
<td>83.33</td>
</tr>
<tr>
<td>IF</td>
<td>83.33</td>
<td>83.33</td>
<td>100</td>
</tr>
<tr>
<td>ME</td>
<td>66.66</td>
<td>83.33</td>
<td>66.66</td>
</tr>
<tr>
<td>MF</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

Table (1) represents the recognition results

<table>
<thead>
<tr>
<th>Finger Gesture Matching rate</th>
<th>RMS</th>
<th>Entropy</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sub1</td>
<td>5</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>Sub2</td>
<td>6</td>
<td>6</td>
<td>5</td>
</tr>
<tr>
<td>Sub3</td>
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<td>6</td>
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<tr>
<td>Sub4</td>
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<td>6</td>
<td>5</td>
</tr>
<tr>
<td>Sub5</td>
<td>5</td>
<td>5</td>
<td>4</td>
</tr>
<tr>
<td>Sub6</td>
<td>4</td>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>

Table (2) shows the test subject Finger Gesture, matching rate

From the above results it was concluded that entropy of Finger gestures is the best feature for gestures classification, which matches with 94.44% and overall finger gesture classification rate 88%.

4. Conclusion
We have described a system that demonstrates the SEMG classification by using min distance classifier technique. It is able to classify the signals by 88% accuracy. The enabling technologies were surface sensors used to measure the EMG signals, signal processing used to transform the signals in to feature sets, and pattern classifier to provide sufficient robustness for the non linear and non stationary nature of the
underlying signal data. The significant challenges were to apply this classification for HCI for the beneficial of human beings, improve the classification by applying multilevel neural networks.

References

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