Increasing performance of a pattern recognition system using a sEMG signal by setting multi-references

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Abstract – This paper proposes a special technique for pattern classification problems using the sEMG signal from human forearm muscles. For improvement of classification accuracy, a multi-reference is set for each class so that the classifier can cover a wide range of obtained signals for training. The results of classification accuracy through an off-line simulation were analyzed to validate the proposed concept.

Keywords – sEMG signal, pattern classification, Bayesian classifier

1. Introduction

An EMG signal is generated when muscles contract. It can be easily detected over the skin surface and as such is one of the most widely used bioelectric signals. Using this signal, human motions can be decoded with proper pattern classification techniques. The use of surface electromyography (sEMG) signals for the control of exoskeleton robots or multi-functional artificial limbs has been widely investigated.[2][7] For using a sEMG signal as a control command for these applications, the pattern classification problem must be solved with appropriate feature and learning algorithms.[4][8] To successfully classify an EMG signal, selection of proper features and classifiers should be carefully considered. Numerous studies have tried to find the optimal features, combinations of features, and the optimal classifier for the sEMG signal.[1][3] However, few works have intensively studied the inner characteristics of sEMG signals.

The goal of this research is to increase the classification accuracy by following the transition of the features of the signal in a given period of time. That is, providing additional references with the same features and classifier can improve the performance. In this study, we introduce this approach to improve the performance of the Bayesian classifier, which is statistically based.

Fig. 1. sEMG interface with 8 electrodes and a band
Fig. 2. Nine target hand configurations: (a) rock, (b) scissors, (c) paper, (d) ulnar deviation, (e) radial deviation, (f) wrist flexion, (g) wrist extension, (h) wrist pronation, (i) wrist supination

2. Background

2.1 Data acquisition

A total of four healthy male subjects (age 25 to 30, all right-handed) participated in this experiment. For data acquisition, eight self-designed circuits [5] with a dry-typed electrode were randomly placed on the right forearm of the subjects and another electrode was mounted on the left arm as a reference, as shown in figure 1. A total of nine hand configurations including rock, scissors, paper motion, radial deviation, ulnar deviation, wrist pronation, supination, wrist extension, and flexion were classified by the proposed pattern classification algorithms.

In the training session, each movement lasted for three seconds and the time interval for rest between two adjacent movements was also three seconds. Among nine motions, a randomly chosen picture was displayed without overlap on a screen to give a motion cue to users.

The sEMG signals were sampled at 1000Hz frequency by an A/D data acquisition system (Model S526, Sensoray Co). The signals in this study were processed by a PC-104 Computer (Poseidon EPIC SBC, Diamond System Co.) running a MATLAB xPC real time operating system.
2.2 Pattern recognition system

The conventional pattern classification system consists of four main steps, as shown in figure 3: 1) signal pre-processing, 2) feature extraction, 3) classifier, and 4) class assignment. The information of the feature is learned by the classifier in the training session and it is utilized as a reference for determining the identity of unknown signals.

A. Preprocessing

At the preprocessing step, first, a raw signal is passed through a band pass filter, where the target range of frequency is 15-500Hz. The magnitude of filtered signals is squared to make the signal positive. At the last, samples of the signal are filtered by moving average filter (window size: 200). The algorithms are explained in detail in [6].

B. Feature Extraction

In the feature extraction process, Mean of Absolute Value (MAV) and Principal Component Analysis (PCA) are selected for feature extraction and feature projection. With projection by the PCA algorithm, the dimension of the feature vector can be reduced from 8 to 3.

C. Learning Algorithms

From the PCA results, the feature vector of the data sample can be represented as a point vector in 3d vector space. Each sample thus represents one point vector in 3d space. The data of one sample motion are shown in Figure 4 (a). With the assumption that samples are scattered in the form of a Gaussian distribution, the Gaussian parameters - mean and variance of distribution - can be estimated according to samples by the maximum likelihood estimator. Therefore, setting the number of samples according to the estimate, the means and variances of each sample group are calculated. The Bayesian classifier stores these parameters to be used as references of the motion classes. Figure 4(b) shows that five Gaussian ellipsoids are set to cover the sample data for three seconds. Fifteen Gaussian ellipsoids for the same data are drawn in Figure 4(c). Naturally, the latter ellipsoids efficiently cover the given data without empty space. For this reason, setting many references makes it possible to distinguish one class among others precisely.

D. Classifier

For any unseen test sample, the classifier computes the posterior probability of that sample belonging to each class. After the classifier computes all the probabilities with each distribution, it then determines the label of the class that has the largest probability. In our algorithms, there is a predefined number of Gaussian distributions that belong to each motion.

3. Methods & Algorithms

3.1 Data Analysis

The feature vectors of nine motions can be visualized in 3d space as a trajectory in a time series. As described in Figure 5 (a), it appears that the trajectories of data are not covered with just one mean vector (MAV feature) because the direction of each trajectory is not consistent. We should therefore add more references to the classifier to include more information about each class. To include as much direction information of data as possible, the number of references can be increased by the user. For example, five Gaussian ellipsoids are fit to the signal in Figure 5 (b). In this study, the performance of the classifier is examined with 3 to 24 references.
3.3 Multi-references

We just add new references to the classifier as if there are more classes to classify than the actual number of classes. Equally cut signals are exploited to make references. The relation between the number of references and performance accuracy is shown in the next section.

3.3 Decision rule

The determinant function of the Bayesian classifier must examine the probability with all references. Due to this calculation process, the computation time for classification inevitably increases according to the number of references. Among the calculated results, the class is assigned to a new signal according to the reference with maximum probability.

4. Simulation Results

In this simulation, the classification success rates are computed in more a tougher condition, as the accuracy of all data samples in the entire experimental period, or three seconds for each motion.

To guarantee the performance of the Bayesian classifier, the classification accuracy was compared with that of the Extreme Learning Machine (ELM) classifier, which has been demonstrated to provide high performance [6]. Although the ELM classifier showed, on average, 92% accuracy, the Bayesian classifier with many references showed better performance. The performance of the Bayesian classifier becomes superior when the number of feature references is approximately nine. The performance of classification accuracy increased to more than 95%. The simulation results for classification accuracy are provided in Table 1.

![Fig. 5. (a) Three-dimension trajectories for 9 motions.][image1]

![Fig. 5. (b) Five Gaussian models for 9 motions.][image2]

![Fig. 6. Classification accuracy according to the number of references.][image3]

**Table 1 Classification accuracy results**

<table>
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<tr>
<th>Ref</th>
<th>3</th>
<th>6</th>
<th>9</th>
<th>12</th>
<th>15</th>
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However, there exists a trade-off relation between computation time and classification accuracy with the multi-reference Bayesian classifier. This approach might be difficult to utilize in real time applications requiring high speed. At present, this technique guarantees sufficient speed for real time application with a 2-3 second delay.

5. Conclusion

This paper introduced a pattern recognition system using the sEMG signal to decode nine human hand configurations with a statistical classifier. By setting a multi-reference, we can contain almost the entire range of features of the obtained data. Off-line simulation results verified that the proposed technique improved the classification performance. However, the problem of slow
computation speed has to be resolved for fast real time applications.

References


