Short latency hand movement classification based on surface EMG spectrogram with PCA

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Abstract— **Hand gesture recognition from forearm surface electromyography (sEMG) is an active research field in the development of motor prosthesis. Studies have shown that classification accuracy and efficiency is highly dependent on the features extracted from the EMG. In this paper, we show that EMG spectrograms are a particularly effective feature for discriminating multiple classes of hand gesture when subjected to principal component analysis for dimensionality reduction. We tested our method on the Ninapro database which includes sEMG data (12 channels) of 40 subjects performing 50 different hand movements. Our results demonstrate improved classification accuracy (by ~10%) over purely time domain features for 50 different hand movements, including small finger movements and different levels of force exertion. Our method has also reduced the error rate (by ~12%) at the transition phase of gestures which could improve robustness of gesture recognition when continuous classification from sEMG is required.**

I. Introduction

Modern prosthetic designs have provided dexterous solutions for amputees to restore their motor function. Because of its ease of use and non-invasiveness surface electromyography (sEMG) is a promising source of control signal for these prostheses [1]. However, sEMG can be sensitive to various factors, such as electrode placement, and recording environment. Despite these problems, EMG recordings at relatively high sampling rates, in the order of kHz, with multiple electrodes are commonly used to control the prosthesis [2, 3]. A wide range of pattern recognition techniques have been previously tested to classify the intended movements, with proper feature extraction from the high dimensional data key to accurate movement recognition. A variety of features which can extract the useful information embedded in the EMG signal and discard interference and unneeded parts have been tested [4]. These include both time domain and frequency domain features and have had different levels of success depending on the experimental design, number of electrodes, and types and number of movements [5, 6].

Hand movements are dynamic processes and hence, in order to produce more natural movements in real-life scenarios, systems which provide continuous recognition of movement are desirable. In such applications, time-frequency domain features could provide a more complete representation of the information contained within the data than either time or frequency domain only features. Time-frequency domain features have previously been shown to be applicable for forearm movement classification with a small number of movement classes [7] as well as for myopathy and neuropathy diagnosis in clinical applications [8]. However, high dimensionality and high-resolution in time-frequency features present a major hurdle to the computational efficiency required for real-time applications, hence, some form of dimensionality reduction is necessary [7, 9].

In this study, we suggest that spectrograms followed by principal component analysis (PCA) provides effective features for hand movement classification even with a large class of movements. We hypothesize that projection of EMG spectrogram onto subsets of principle components can improve information representation of sEMG while reduce computation load. The results are compared with time-domain inputs using standard classification method for short-latency continuous classification of hand movements from a publicly accessable database.

II. Methodology

The workflow of our method including data preprocessing, spectrogram calculation, normalization, PCA and support vector machines (SVM) classification is summarized in Fig. 1.

A. Ninapro Database 2

The Ninapro (Non-Invasive Adaptive Hand Prosthetic) database 2 used in this study contains surface EMG data recordings from 40 intact-subjects [10]. Each subject performed 49 movements: 8 isometric and isotonic hand configurations; 9 basic wrist movements; 23 grasping and functional movements; as well as 9 force patterns.

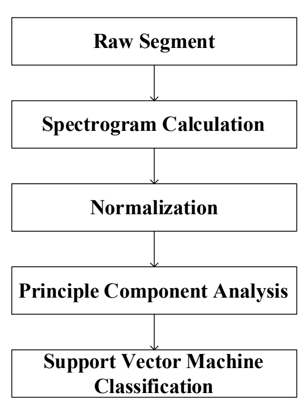

Figure 1. Flow chart of the proposed method.

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Classifications were performed on these 49 movements plus a rest posture. Each movement was repeated 6 times with a 3 s rest in between. The EMG data was recorded using 12 Trigno Wireless electrodes (Delsys Inc.) sampled at 2000Hz. The data was filtered using a Hampel filter to remove 50Hz (and harmonics) power line interference. The data was provided with two different sets of labels, the raw labels, taken from the stimuli, and a relabeling. The relabeled data realigned the movement boundaries by maximizing the likelihood of a rest-movement-rest sequence using an offline generalized likelihood ratio algorithm.

B. Data preprocessing

The data preprocessing followed the same procedures as those described in the Ninapro database [10], with each channel being processed independently. For each movement, the 1st, 3rd, 4th and 6th repetitions are used as the training set, while the other two are used as the testing set. Each movement is followed by a 3 s rest, giving a total of 294 repetitions of the rest posture. In order to balance the number of repetitions across all movements, six repetitions of the rest posture are selected randomly for the classifier training and testing sets. To compute the spectrogram the EMG signals are divided into 200ms (400 sample) segments with 100ms (200 sample) increments. The recognition system gives a prediction for each segment, such a short segment duration is chosen as this is desirable for continuous classification in real-life applications [11].

C. Spectrogram Calculation

The spectrogram of each segment is computed by 256 point fast Fourier transform (FFT) using a 256 sample Hamming window with 184 sample overlap. Thus, each 400 sample segment results in a spectrogram calculated at 129 different frequencies with 3 time bins. The energy of the EMG was observed to vary mainly over frequencies ranging from 0Hz to approximately 700Hz. Hence, to improve computational efficiency, we only use the first 95 points of the spectrogram which accounts for frequencies up to 736.43Hz, an example of the spectrogram over these frequencies is given in Fig. 2a. Thus, each data segment results in a 95×3 feature matrix.

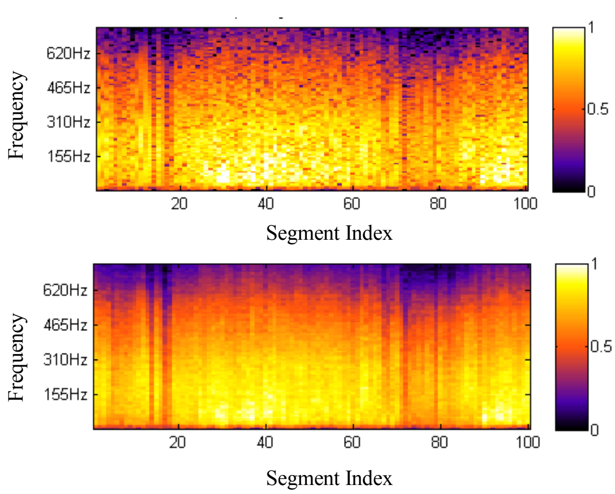

Figure 2. (a) Spectrogram of raw data and (b) the reconstructed spectrogram using the first 100 principal components.

D. Normalization

Before applying PCA to the spectrogram, the spectrograms of each channel are scaled into a range from 0 to 1 via a maximum-minimum normalization method. The 1st and 99th percentiles will be considered as minimum value and maximum value respectively. Values beyond this range will be forced to be 0 or 1. Hence, the normalized spectrogram, $Data^{i}_{norm}$, for channel i, is calculated by

$$Data^{i}_{norm} = \frac{Data^{i} - Min^{i}}{Max^{i} - Min^{i}} \qquad i = 1, 2, \cdots 12 \tag{1}$$

E. Principal Component Analysis

Normalized spectrogram matrices from each segment are then vectorized and all 12 channels are concatenated. The resultant vectors contain 95×3×12 elements making it computationally expensive to utilize all data to the classifier directly. Therefore, we will apply PCA to the spectrogram data to reduce the dimensionality of the data whilst also retaining the useful information from the EMG signals. For each subject principal component analysis is performed on all the segments across all the gestures in the training set. The weightings of the contributions of the principal components to each segment are then used for classification.

Fig. 3 shows an example of the variance accounted for and classification accuracy for increasing number of principal components (PCs). This result suggests that to achieve a good classification accuracy it is sufficient to use the first 40 – 120 components. In fact, including more components may compromise accuracy since these components possibly contain noise. In the following analysis, we retain the first 100 PCs, which account for on average approximately 57.45% of the variance for all subjects.

We also assume that both training and testing data share the same PCs. This is analogous to the observations that muscular synergies are robustly preserved across a variety of biomechanical or behavioral contexts [12]. Hence, testing data will be projected onto the PCs obtained from the training set when testing the accuracy of the classifier.

F. Support Vector Machine Classification

Previous results have shown that SVM has offered the highest classification accuracy for Ninapro Database [10].

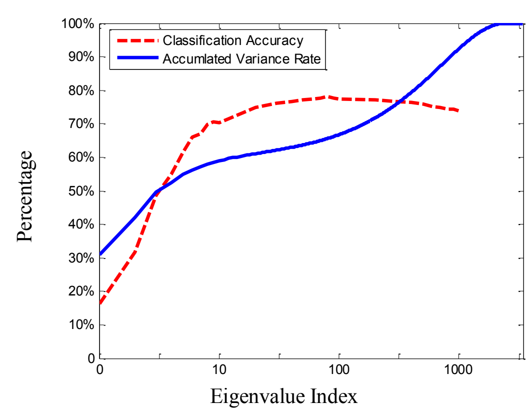

Figure 3. Accumulated variance accounted for and average classification accuracy of the first subject

Open source C++ library LIBSVM [13] is used in this study to implement the SVM classifier. To obtain the optimal values for the hyper-parameter pair (c, γ) for the SVM classifier, following the approach from [14], a grid search is performed for each subject over the range,

$$\begin{aligned} c &= 2^{i}, i = -2, -1, \cdots, 13, 14 \\ \gamma &= 2^{j}, j = -12, -11, \cdots, 6, 7 \end{aligned} \tag{2}$$

A 4-fold cross-validation method is used to select the best combinations of (c, γ).

III. RESULTS

Fig. 2 shows the spectrograms for both the raw data and the reconstruction of the first 100 PCs. For simplicity only the first time bin of each segment is shown. While the major time-frequency content defining the movement has been retained in the reconstructed spectrogram (Fig. 2b) the reconstruction provides a smoothed representation of the data.

Root mean square (RMS) of the EMG signal has been shown to be a useful and simple time-domain feature for hand movement classification in previous studies [5, 10]. As such, RMS was used as a benchmark for our method. The RMS of the EMG is computed for each 200ms segment, and is then normalized and classified using SVM in the same way as described in Section II.

Classification was performed using both the raw labeled and relabeled data with either the spectrogram/PCA or RMS as features. The overall accuracies, averaged over all subjects and all movements, are summarized in Table I. .

The average accuracy of our proposed method on the relabeled data is 77.41%, which is 9.75% higher than when using the RMS as a feature. Note also that we have obtained higher overall accuracy than the best results reported by Atzori *et al.* when using the same dataset with a combination of four different sets of features [10]. As relabeling can only be obtained offline, for real-life applications, accurate classification of the raw labeled data is critical. Our method also offers over 10% higher overall accuracies on the raw labeled data than when using the RMS.

Table I. Overall Accuracy

Accuracy	RMS	Spectrogram PCA
Relabel	67.66%	77.41%
Raw Label	63.65%	74.18%

To further investigate the performance of the proposed approach we next consider the classification accuracy for each type of movement separately. Fig. 4 shows that on average, the spectrogram with PCA performs better in every movement except resting (index 1), which is slightly lower in accuracy (65.03% vs. 68.46%, $p>0.01$, paired t-test). This is probably a result of the random selection of a subset of rest posture for training the classifier.

Table II shows the classification accuracy for the three different types of movement: basic movements; grasping and functional movements; and force patterns. For the first 40 movements (index 2 to 41) which includes the isometric and isotonic hand configurations, basic wrist movements, as well as the grasping and functional movements, our results using the spectrogram with PCA show >11% improvement in the average classification accuracy when compared to using the RMS ($p<0.01$, paired t-test). The improvement in the 9 force pattern movements (index 42 to 50) is smaller but still statistically significant (88.15% vs. 82.88%, $p<0.01$, paired t-test).

Significantly, we note that the largest errors are found in the classification of the segments close to the transition phase of movements, that is, the beginning and the end of a movement. We divided each movement into 7 parts and evaluated the classification accuracy for each of them. Each of the first 3 parts contain 4 segments, starting from the beginning of the movement. The last 3 parts contain the corresponding 12 segments before the end of the movement. The remaining segments are considered the middle of the movement. The average classification errors over all subjects and all movements were computed for each of these 7 parts. Fig. 5 verifies that the largest classification errors are found at the transition phases of movements, and as the movement

Table II. Classification accuracy for different types of movements

Movement Type	RMS	Spectrogram PCA
Basic movement (index 2 to 18)	64.71%	75.74%
Grasping and functional movement (index 19 to 41)	55.13%	67.61%
Force pattern (index 42 to 50)	82.88%	88.15%

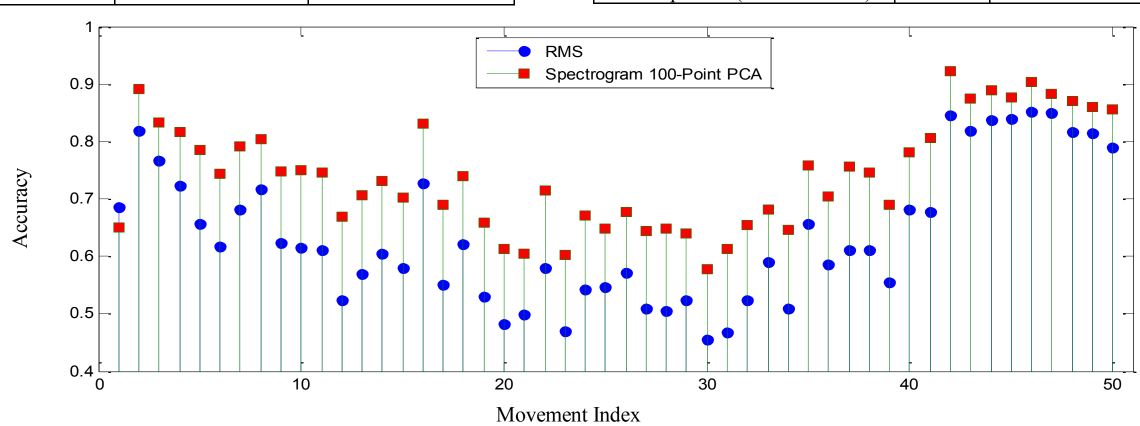

Figure 4. Average accuracy over 40 subjects for rest posture (index 1) and each of 49 movements (isometric and isotonic hand configurations (index 2-9), basic wrist movements (index 10-18), grasping and functional movements (index 19-41), and force pattern (index 42-50)).

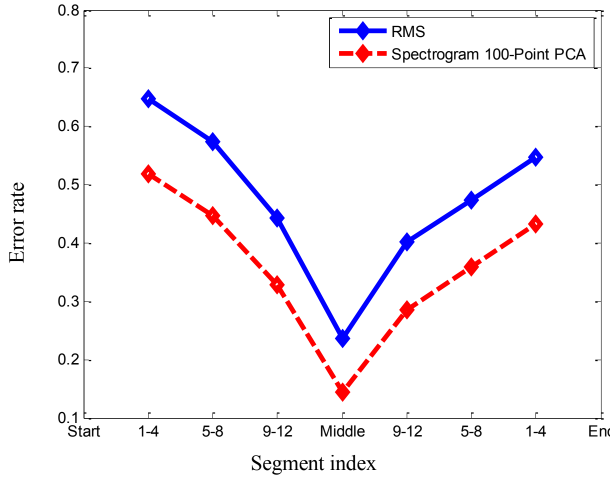

Figure 5. Classification error at different phase of a movement. “Start” and “End” denote the onset and termination of a movement respectively.

progresses, classification accuracies improve. While this is true regardless of the method used, the spectrogram with PCA consistently has smaller errors compared to the RMS throughout the execution of movements ($p<0.01$, paired t-test), hence, providing more robust movement recognition when continuous classification is required.

IV. CONCLUSION

The results presented here show that time-frequency features of surface EMG can provide improved hand movement classification over solely time domain features, partly due to noise rejection in the spectrogram. With appropriate dimensionality reduction, it can also become a computationally efficient approach. Our results are consistent with the findings by Englehart *el al.* [7]. However, we have demonstrated higher performance here for much larger electrode numbers (4 vs. 12) and larger variety of movements, including finer movements (4 classes of elbow and forearm movement vs. 49 classes of functional hand/finger movements and force patterns).

The choice of number of principal components to be included in the classifier is important. Excessive number of components would increase computational load as well as deteriorate classification accuracy, probably as a result of overfitting to noise. Our results have shown that there were minor effects on the classification accuracy when we used 40-120 components. Hence, in practice, we can further speed up the classifier by using a smaller number of components without compromising performance. However, the small PCs being discarded in our experiments may actually contribute to the skillfulness of movement execution [15], and hence may be useful when fine-tuning of joint movement is needed, for example, when manipulating different objects.

Surprisingly, classification error in the rest posture was not improved when using spectrogram/PCA compared with RMS. We observed that the rest postures were commonly misclassified as the movement which that particular rest was neighboring. It is possible to circumvent this limitation by adding another binary classifier to distinguish resting and action based on some time domain features.

To offer reliable continuous movement classification for real world prosthetic application, it is important not only to classify the movement per se, but is also important to provide accurate onset and termination of a movement. From the results obtained in this study these transition phases present the biggest challenge to accurate classification of movement from EMG, regardless of the features used or the types of movement of interest. The time-frequency domain features have provided more useful information than time domain features in capturing the onset and offset timing of movement and further improvement may be possible using a longer segment.

The combination of spectrogram/PCA/SVM offers a simple yet efficient framework for hand movement classification problems with potential for real-time application.

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