# A Windowed Eigenspectrum Method for Multivariate sEMG Classification During Reaching Movements

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***Abstract*—In this letter, we propose an eigenspectra-based feature extraction technique for classification of multivariate surface electromyographic (sEMG) recordings. The proposed method exploits the maximum eigenvalue vectors of the time-varying covariance patterns between sEMG channels. Together with a support vector machine (SVM) classifier, the proposed feature extraction technique is shown to be more reliable and robust, and it enhances classification between stroke and normal subjects, compared to the conventional univariate analysis methods that examine each muscle individually. In addition, analysis results show that the spatial whitening operation enhances the discriminability of eigenspectral features. This simple, easily-implemented, biologically-inspired approach is able to succinctly capture the subtle differences in muscle recruitment patterns between healthy and disease states. It appears to be a promising means to monitor motor performance in disease subjects.**

***Index Terms*—Classification, eigenvalues, multivariate analysis, stroke, support vector machine (SVM), surface electromyography (sEMG).**

## I. Introduction

PATTERN classification of surface electromyographic (sEMG) signals from the simultaneous recordings of several muscles has implications for neural prostheses development and diagnosis of diseases involving the motor system [1], [2]. Despite changes in arm dynamics after stroke obvious to trained clinicians, the abnormalities in the complex interference pattern of sEMG recordings during stroke can be subtle. In this study, we concentrate on the classification of reaching movements, rather than, e.g., unnatural sustained contraction, in healthy and stroke subjects.

A typical classification application is comprised of two components: features selection and decision-making algorithm (classifier). Many different classifiers have been proposed in the literature, which, in general, can be divided into two categories: data-driven and model-driven. The former is more widely used due to its simplicity and generality. It includes methods such as K-nearest neighbors, support vector machines (SVMs), and neural network analysis [3]. In this study, we use the widely-applied linear SVM algorithm since it is a powerful tool in classification and pattern recognition and has been shown to provide excellent classification performance [4].

A clear challenge, on the other hand, is to extract appropriate features from sEMG data for subsequent classification. We therefore appeal to contemporary developments in theoretical neuroscience for guidance. Recent work has suggested that complex movements are implemented by low-dimensional basis movements encoded in the spinal cord [5]. These basis movements or "muscle synergies" are distributed across several muscles. Examination of muscle synergies may provide a fruitful avenue to succinctly summarize the often complex changes in muscle activation that are seen in disease states, such as motor impairments after stroke. Despite the fact that sEMG recordings are conventionally examined individually in a univariate fashion, our previous study [6] shows that sEMG signals recorded from spatially distributed muscles may be correlated with each other. This observation motivates us to use features based on the covariance patterns.

Various factors can influence the amplitude of the sEMG: exact positioning of the electrodes, movement of the muscle with respect to the electrodes, the amount of subcutaneous fat, and the impedance of the skin [7]. These factors can potentially affect the reliability of amplitude-based classification schemes. On the other hand, examining the relationships *between* muscles may prove more robust and reliable in monitoring muscle function.

In this study, we propose a classification scheme which exploits time-varying covariance between sEMG recordings in healthy subjects and subjects recovering from differing severity of stroke. We demonstrate that the proposed method is more reliable than examining muscles individually, and it is monotonically related to the severity of stroke, as assessed by traditional subjective clinical scales.

## II. Methods

In this section, we propose a feature extraction technique which is based on the covariance patterns between muscles. We then describe the SVM classifier used for the sEMG classification.

### A. Whitening of Raw sEMG Data

In our preliminary investigation, the sEMG signals recorded while the subjects were at rest are shown to be spatially correlated between different channels. The correlated noise can potentially contaminate the covariance patterns of the sEMG data. As a countermeasure, a whitening filter is applied to remove any spatial correlations between channels observed during the non-movement part.

Although the application of a whitening filter can effectively remove the spatial correlation in the noise, it can possibly also

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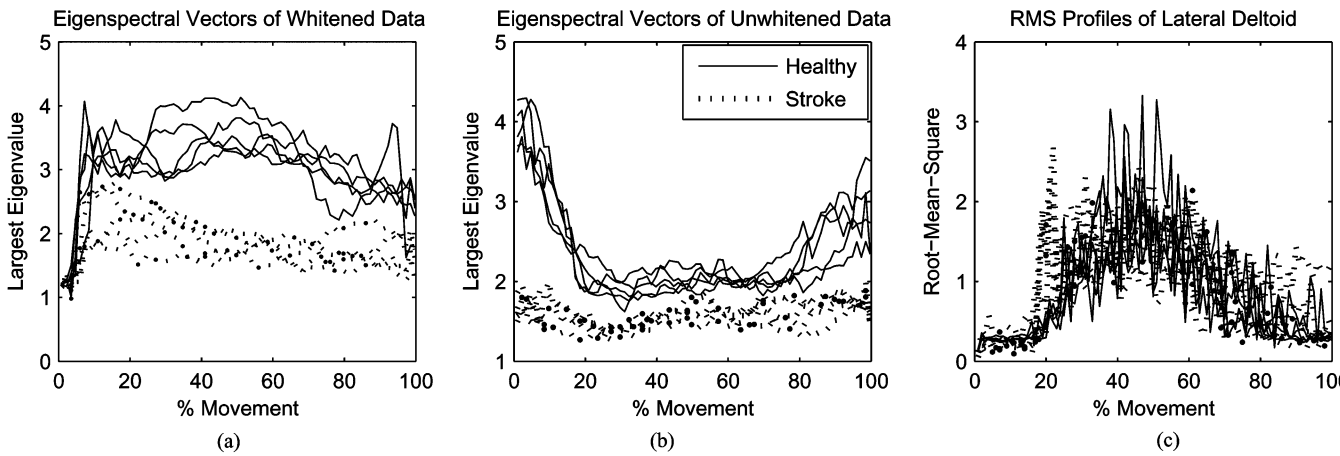


Fig. 1. (a) Time-varying eigenspectral patterns extracted from the whitened data of one healthy subject (solid lines) and one stroke subject (dotted lines), where each line represents the eigenspectral pattern extracted from a single reaching trial. Note the consistency across the five reaching trials for both subjects. (b) Eigenspectral patterns extracted from the unwhitened data of same subjects. (c) RMS profiles obtained from the same healthy and stroke subjects. The RMS profiles are almost indistinguishable between the healthy subject and the stroke subject.

remove the correlation associated with muscle co-activation during reaching movements. To overcome this complication, we assume that the sEMG noise observed during the non-movement part remains stationary throughout the entire recording period and was superimposed on the desired sEMG signals. Thus, the whitening of an sEMG recording is done by first constructing the whitening filter using the non-movement part of the raw data. The filter is subsequently applied to the entire sEMG recording.

Let $\boldsymbol{Y} \in \mathbb{R}^{M\times N}$ denote $M$-channel raw sEMG recordings of one trial and $\boldsymbol{R} \in \mathbb{R}^{M\times P}$ denote the non-movement segment of $\boldsymbol{Y}$, where $M$ is the number of channels, $N$ is the total number of timepoints in the raw data, and $P$ is the number of timepoints in the non-movement segment. Assume that both $\boldsymbol{Y}$ and $\boldsymbol{R}$ are zero-meaned. The covariance matrix of $\boldsymbol{R}$, denoted by $\boldsymbol{C}$, is given by $\boldsymbol{C} = E\{\boldsymbol{R}\boldsymbol{R}^T\} \in \mathbb{R}^{M\times M}$. $\boldsymbol{C}$ can be decomposed by eigenvalue decomposition into $\boldsymbol{C} = \boldsymbol{V}\boldsymbol{L}\boldsymbol{V}^T$, where $\boldsymbol{V} \in \mathbb{R}^{M\times M}$ is an orthogonal matrix containing columns of eigenvectors, and $\boldsymbol{L} \in \mathbb{R}^{M\times M}$ is a diagonal matrix consisting of eigenvalues of $\boldsymbol{C}$. The whitening filter, denoted by $\boldsymbol{W}$, is given by

$$\boldsymbol{W} = \boldsymbol{V}\boldsymbol{L}^{-1/2}\boldsymbol{V}^T = \boldsymbol{C}^{-1/2} \in \mathbb{R}^{M\times M}.$$

The whitened sEMG data, $\widetilde{\boldsymbol{Y}}$, can be obtained by

$$\widetilde{\boldsymbol{Y}} = \boldsymbol{W}\boldsymbol{Y} \in \mathbb{R}^{M\times N}. \tag{1}$$

All subsequent analysis is performed on the whitened sEMG data, $\widetilde{\boldsymbol{Y}}$.

### B. Feature Extraction

Conventionally, the classification of sEMG signals has been performed by using the linear envelope of a single channel as input features, which can be extracted by the moving root-mean-square (RMS) method. This feature extraction technique examines each muscle in isolation, and it does not take into account the correlation between muscle recordings. As previously mentioned, sEMG signals recorded from spatially distributed muscles are typically correlated with each other. These observations lead us to a new feature selection method which examines the covariance patterns between sEMG recordings. The method is outlined as follows.

1) *Normalization*: To minimize trial-to-trial variability, we first normalize the sEMG signals to zero mean and unit variance. In addition, to account for the slight variations in reaching times of each trial, the normalized signals are resampled such that all recordings are of equal length.
2) *Extraction of feature vector based on the time-varying largest eigenvalue*: Let $\widetilde{\boldsymbol{Y}}$ denote the sEMG recording matrix for one trial whose dimension is *number of channel* , $M$, by *number of timepoints*, $N$. For each trial, a moving window of width $T$ points is slid across all $M$ channels with a step size of $\delta$ points, where $T, \delta < N$. For each time position of the moving window, the covariance matrix and its largest eigenvalue, $\lambda$, are computed from the data points inside the moving window. As the window slides across, a vector of eigenvalues, $\boldsymbol{v}$, is generated and it can be written as follows:

$$\boldsymbol{v} = [\lambda(0), \lambda(\delta), \lambda(2\delta), \ldots, \lambda(n\delta)] \in \mathbb{R}^{n+1} \tag{2}$$

where $\lambda(i\delta)$ denotes the largest eigenvalue of the covariance matrix calculated using the data from $t = i\delta$ to $t = i\delta + T$.

While a range of features based on the covariance matrix could be extracted (e.g., the entire eigenspectrum), our preliminary investigations [6] revealed that the largest eigenvalue most reliably distinguished between the non-paretic side and paretic side in stroke subjects (see Fig. 1). It therefore motivated us to employ it as an efficient feature to classify healthy and stroke subjects.

### C. Extraction of sEMG Amplitude

Clancy *et al.* [8] have suggested that a univariate sEMG signal $y(k)$ recorded during voluntary dynamic contractions usually can be considered as a zero-mean, band-limited, and wide-sense stationary stochastic process, $x(k)$, multiplied by the sEMG amplitude, $m(k)$, where $k$ denotes time. The amplitude information $m(k)$ is commonly regarded as a good representation of muscle activity and is often used for further analysis or modeling in sEMG studies. In this work, in addition to the whitened, unrectified sEMG data, $\widetilde{\boldsymbol{Y}}$, we will also analyze the amplitude sEMG.

In the literature, there have been several techniques proposed for accurate estimations of the amplitude sEMG $m(k)$ [9]. In this work, we use the RMS, with a moving window applied. As its name suggests, the RMS technique computes the root-mean-square value of a single-channel sEMG recording over a time window of width $S$ points. As the time window is slid across the signal, the resulting RMS profile is a time series of RMS values, one for each time position of the window. Given that our sEMG data, $\widetilde{\boldsymbol{Y}}$, consist of multiple channels, the RMS processing is performed repeatedly for each channel of $\widetilde{\boldsymbol{Y}}$.

### D. Pattern Classification

The classifier used in this study is the linear support vector machine (SVM) which is widely applied in many different areas due to its robustness and reliability [10]. The goal of the SVM is to find a hyperplane in the input space which can maximally separate members of two classes. Specifically, the hyperplane is defined as follows:

$$\boldsymbol{v} : \boldsymbol{w} \cdot \boldsymbol{v} + b = 0 \tag{3}$$

where $\boldsymbol{v}$ is a vector in the feature space, $\boldsymbol{w}$ is a weight vector normal to the hyperplane, and $b$ is the bias. The term $\boldsymbol{w} \cdot \boldsymbol{v}$ represents the dot product of $\boldsymbol{w}$ and $\boldsymbol{v}$. In most cases, there are infinitely many hyperplanes which can separate two classes. However, in order to avoid the potential problem of overfitting, the optimal hyperplane is defined as the one with maximal margin of separation between two classes. It can be found by solving the following quadratic optimization problem:

$$\begin{aligned} &\text{minimize} \quad \|\boldsymbol{w}\|^2 \\ &\text{subject to} \quad z_i(\boldsymbol{v}_i \cdot \boldsymbol{w} + b) - 1 \geq 0, \quad \forall\, i \end{aligned} \tag{4}$$

where $\boldsymbol{v}_i$ is $i$th training sample and $z_i \in \{-1, 1\}$ is the corresponding class label. The resulting decision function for the test sample, $\boldsymbol{v}$, has the following form:

$$h(\boldsymbol{v}) = \sum_i \alpha_i z_i \langle \boldsymbol{v} \cdot \boldsymbol{v}_i \rangle + b \tag{5}$$

where $h(\boldsymbol{v})$ is the decision value for $\boldsymbol{v}$, and $\alpha_i$ is the Lagrange multiplier associated with $i$th inequality constraint in (4). Further details on SVM classifiers can be found in [10].

In this work, the classification performance is evaluated using the leave-one-subject-out cross-validation (LOSOCV) technique, which works as follows: Assume that each subject performed $K$ reaching trials in the experiment. In each round of classification, LOSOCV leaves out all $K$ trials of a subject as the test set while the remaining trials of other subjects are used to train the classifier. The test trials are classified one at a time, and the class label of the test subject is determined by the majority vote of the classified test trials. This procedure is repeated until all subjects have been classified. The overall classification rate is defined as the percentage of correctly classified subjects.

## III. Results and Discussion

In this section, we study the performance of the proposed classification scheme by examining the sEMG data collected from stroke and healthy subjects. The experiment protocol and classification results for each experiment are described below.

### A. Experimental Protocol

Nine healthy and 11 stroke subjects were recruited from the community to perform reaching tasks. Motor impairment of the stroke subjects was assessed by the upper extremity motor component of the Fugl–Meyer (FM) scale [11]. During the experiment, the subjects were first seated in a chair with their hands resting on the thigh and they were asked to reach and touch a fixed target upon hearing an auditory cue. The target was located in the subject's mid-sagittal plane at shoulder height, and its distance with the subject was adjusted such that the target was just within the workspace of paretic arm of a stroke subject or the non-dominant arm of a healthy subject. The reaching task was performed five times for each subject. A total of 45 sets of sEMG data were collected from healthy subjects, and 55 sets were from stroke subjects. In this study, we focus on the comparison of the non-dominant arm of healthy subjects with the paretic arm of stroke subjects. While the dominant arm of healthy subjects may also be used, the dominant arm is often overtrained for simple tasks such as reaching, and thus, the non-dominant arm is more comparable with the paretic arm of stroke subjects in terms of their motor capability [12].

The electrical activities of the following seven muscles were recorded during the reaching movement using surface electrodes: anterior and lateral deltoid, long head and lateral triceps, biceps brachium, latissimus dorsi, and brachioradialis. A bipolar montage was used to minimize the effect of crosstalk. The seven-channel sEMG signals are amplified, sampled at 600 Hz, and high-pass filtered at 20 Hz to reduce the movement-related artifact. Further details on the experimental procedures can be found in [12].

### B. Classification Results

The proposed feature extraction technique described in Section II-B is applied to the sEMG data with $\delta = 30$ timepoints and $T = 300$ timepoints ($\sim 0.5$ sec). The amplitude sEMG is extracted using the RMS technique described in Section II-C, with the time window of width $S = 30$ timepoints. The resulting time-varying eigenspectral vectors from a healthy and a stroke subject are shown in Fig. 1(a) and (b). The eigenspectral vectors are relatively consistent across trials for the same subject, yet the difference between the healthy and stroke subjects is evident. On the other hand, although the lateral deltoid was reported as revealing significant differences between healthy and stroke subjects using the same data set [12], the RMS profiles from this single muscle are almost indistinguishable between the healthy and stroke subjects, as shown in Fig. 1(c).

To investigate the relationship between the severity of motor impairment and the covariance patterns of sEMG data, we divide the stroke subjects into three classes based on their FM scores: *Severe* with FM scores below 25, *Moderate* with FM scores between 25 and 50, and *Mild* with FM scores above 50. The characteristics of subjects in each class are summarized in Table I. Fig. 2 illustrates the average eigenspectral vectors extracted from each subject class using the whitened data.

The eigenspectral patterns can be intuitively interpreted as a representation of the strength of the dominant muscle synergy. As shown in Fig. 2, the eigenspectral patterns of *Healthy* and

TABLE I
CHARACTERISTICS OF STROKE CLASSES

| Class | Range of FM Scores | Average FM Score | Number of Subjects | Total Number of Trials |
|---|---|---|---|---|
| *Severe* | $< 25$ | $18.5 \pm 0.6$ | 4 | 20 |
| *Moderate* | $25 - 50$ | $41.0 \pm 3.0$ | 3 | 15 |
| *Mild* | $> 50$ | $62.8 \pm 2.1$ | 4 | 20 |

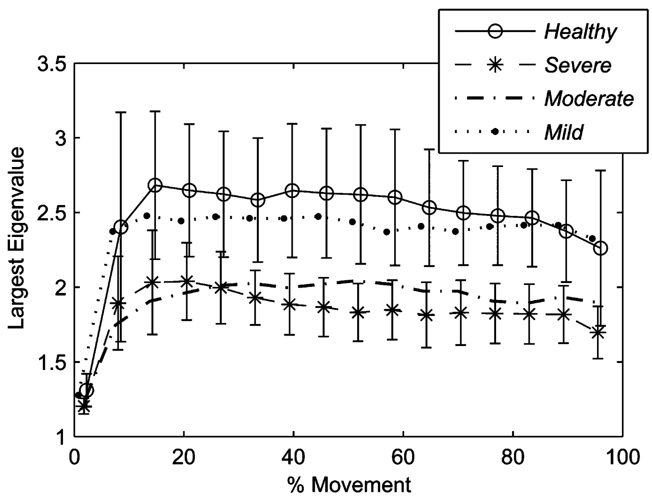


Fig. 2. Average eigenspectral vectors extracted from whitened data of different subject groups. The vertical error bars represent the standard deviation.

TABLE II
CLASSIFICATION RATES BETWEEN STROKE AND HEALTHY SUBJECTS

| Preprocessing | Whitened sEMG | | Unwhitened sEMG | |
|---|---|---|---|---|
| | *Unrect.* | *Amplitude* | *Unrect.* | *Amplitude* |
| Severe vs. Healthy | 93.33% | 93.33% | 86.67% | 80.00% |
| Moderate vs. Healthy | 91.67% | 100.00% | 50.00% | 75.00% |
| Mild vs. Healthy | 71.43% | 71.43% | 71.43% | 42.86% |

*Mild* classes have significantly larger magnitude than those of *Severe* and *Moderate* classes, suggesting that in healthy and mildly impaired stroke subjects, the reaching movement was dominated by few strongly activated muscle synergies. On the other hand, in severely impaired subjects, more muscle synergies were recruited to complete the task, as indicated by the flatter eigenspectrums. This result coincides with the observations reported by Eng *et al.*. In [12], Eng *et al.* observed that in stroke subjects, additional muscles are typically recruited to compensate for the weaker muscles in order to complete the reaching task.

Classification is then performed to compare *Severe*, *Moderate*, and *Mild* separately to healthy subjects using the SVM classifier. The classification rates given by whitened and unwhitened sEMG data are summarized in Table II. Overall, the spatial whitening operation improves the classification performance for raw and amplitude data. Moreover, the classification rates are monotonically related to the severity of motor impairment as assessed by FM scores, particularly in the case of the whitened, unrectified sEMG signals (see Column 2 of Table II). This observation suggests that the proposed method may provide a quantifiable metric of motor performance.

## IV. CONCLUSION

Performing a reaching task is a complex interplay between brain regions subserving motor planning, vision, attention, and motor execution, and impairment of some of these will not be captured by the traditional clinical scale. Finding features that are relatively invariant to inter-individual differences, yet still sensitive to detect severity of impairment, is a challenge. The proposed method is a first step towards this goal, as the exact combination of muscles may vary across subjects, but this may not affect the eigenvalues (as opposed to the eigenvectors) of the sEMG recordings over a specific time window. Also, by looking at the eigenvalues, the results would be expected to be relatively insensitive to the exact positioning of the electrodes, a problem plaguing amplitude-based classification schemes.

The proposed eigenspectral feature vector appears to be suitable for classification of sEMG patterns with an SVM classifier. Moreover, since the classification decision values are monotonically related to the severity of stroke (as estimated by subjective clinical scales), it suggests that this method could be extended into a quantifiable assay of motor performance.

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