A TIME-VARYING EIGENSPECTRUM / SVM METHOD FOR SEMG CLASSIFICATION OF REACHING MOVEMENTS IN HEALTHY AND STROKE SUBJECTS

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ABSTRACT

A method for classification of sEMG recordings based on the time-varying covariance patterns between sEMG muscle channels is proposed. The proposed eigenspectral feature vector appears to enhance classification of sEMG patterns with an SVM classifier. The method is shown to be more reliable, robust and enhances classification between stroke and normal subjects, compared to standard analysis methods that examine each muscle individually. This simple, easily-implemented, biologically-inspired approach appears to be a promising means to monitor motor performance in healthy and disease subjects.

1. INTRODUCTION

Pattern classification of surface electromyographic (sEMG) signals from the simultaneously recordings of the activity of muscles is a topic of great research importance in the area of motor behavior, with implications for neural prostheses development and diagnosis of diseases involving the motor system. Examples include the classification of upper arm movements [1] and classification of reaching abilities in spinal cord injury patients [2]. In this paper, we are particularly interested in classification of reaching movements in healthy and stroke subjects using sEMG data.

A typical classification application is comprised of two major components: features selection and the decision-making algorithm (classifier). The selection of the most appropriate features is often the most challenging. Many classifier approaches have been proposed in the literature, which can usually be divided into two categories: data-driven and model-driven. The former is most widely used due to its simplicity and generality and include such methods as self-organizing maps and machine learning based schemes such K-nearest neighbors, support vector machine and neural network analysis [3]. In this study, we focus on the widely-applied linear support vector machine (SVM) approach since it is a powerful tool in classification and pattern recognition, commonly used in many areas, and has been shown to provide excellent classification performance [4].

One of our major concerns was to extract appropriate features from sEMG data for this reaching classification problem and 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 "synergies" are distributed across several muscles. Moreover, examination of 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. Yet traditionally, sEMG recordings are examined individually, in univariate fashion. Based on the following statistic testing,

$$g(X) = \log\left(\frac{|COV\ (X)|}{|COV_{diag}\ (X)|}\right) \qquad (1)$$

a simple inspection of basic statistical properties of sEMG recordings (Figure 1) suggests strong covariance between muscles during natural movements that is relatively insensitive to preprocessing strategies. This observation motivates us to use features based on the covariance patterns.

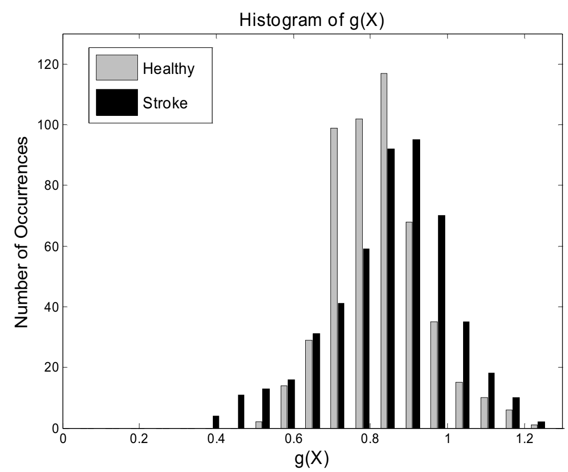

Figure 1: Covariance of sEMG recordings. A histogram of g(X) (Eqn 1), where X is a number of channels *by* timepoint *matrix of sEMG recordings (see Methods). Note that in all cases, a significant covariance between muscles can be detected.*

A number of factors influence the amplitude of the sEMG, affecting the reliability of this feature: exact positioning of the electrodes, movement of the muscle with respect the electrodes, the amount of subcutaneous fat, and the impedance of the skin. Examining the relationships *between* muscles may therefore prove more robust and reliable in monitoring muscle function.

We therefore propose a classification method which extracts features from the time-varying covariance between sEMG recordings in normal subjects and subjects recovering from differing severity of stroke. We demonstrate that the proposed method is more reliable than examining muscles individually, and is monotonically related to the severity of stroke, as assessed by traditional subjective clinical scales.

2. METHODS

In this section, we first introduce the experimental procedure for recording sEMG data. Next we propose the feature selection based on the covariance patterns between muscles and then the SVM classifier is explored for the sEMG classification during reaching movements.

2.1. Experimental Setup and sEMG Data Collection

Twenty stroke subjects with ages ranging from 49 to 72 years were recruited. The severity of motor impairment of the paretic arm was assessed by upper extremity motor component of the Fugl-Meyer (FM) scale and by the Modified Ashworth Scale (MAS). In addition, ten healthy subjects of similar age were recruited to serve as the control group of the experiment.

After suitable consent was obtained, each subject was first seated in a chair with their hands on the thigh and was instructed to reach and touch a fixed target after 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 it is just within the workspace of the paretic arm of the stroke subject or non-dominant arm of the healthy subject. For every subject, the reaching movements were performed fifteen times on each side, resulting in thirty trials per subject.

The electrical activity of seven muscles (the anterior and lateral deltoid, the triceps (long head and lateral), the biceps brachium, latissimus dorsi, and the brachioradialis) was recorded using surface electrodes. A bipolar montage was used to minimize the effect of crosstalk. The 7-channel sEMG signals were amplified, sampled at 600 Hz, and high-pass filtered at 20Hz to reduce movement-related artifact. Pleaser refer to [6] for further details on the sEMG experimental procedures.

2.2. Feature Extraction

Conventionally, the classification of sEMG signals has been performed by using the linear envelope of the signal as the input feature. One widely used processing technique for extracting the linear envelope of single channel EMG is rectification and low-pass filtering, or nearly equivalently, the moving root-mean-square (RMS) method. The moving RMS value is found by sliding a window across the signal with a fixed step size, and at each time position, RMS of the data inside the window is calculated.

As previously mentioned, the studies in muscle synergies suggest that the muscles are activated in a coordinated fashion. One of our recent studies [7] and Fig.1 suggest that sEMGs recorded from spatially distributed muscles may be correlated with each other. These observations lead us to the following feature selection method which examines the covariance patterns between sEMG recordings:

1. Normalization: Since the amplitude information of sEMG itself is not reliable, we first normalize the raw sEMG signals to zero mean and unit variance, and then resample them such that all recordings have equal length to account for the slight variability in reaching times towards the target.

2. Extract feature vector based on the time-varying largest eigenvalue: For each trial, a moving window of width 300 points (~0.5s) is slid across seven channels with a step size of 25 points. At each time position, the covariance matrix and its largest eigenvalue, λ_{max}, are computed from the data points inside the moving window. As the window slides across, a vector of eigenvalues, **v**, is generated and it can be written as follows,

$$v \quad = \quad [\lambda(0), \lambda(T), \lambda(2T), \lambda(3T), \ldots \lambda(NT)] \in \Re^{N} \quad (2)$$

where T is the step size, and $\lambda(nT)$ denotes the largest eigenvalue of the covariance matrix calculated using the data from t = nT to t = $nT + 300$.

3. Further feature dimension reduction: Due to the duration of reaching movements, the resulting dimension of the largest-eigenvalue-based feature vector may be unacceptably high for suitable classifier learning. Thus we project the original feature vector to a lower-dimension space using principal component analysis (PCA) [8]. The resulting PC coefficients are used as features for final classification.

While a range of features based on the covariance matrix could be extracted (e.g. the entire eigenspectrum) preliminary investigations revealed that the largest eigenvalue most reliably distinguished between the non-paretic side and paretic side in stroke subjects (Figure 2). It therefore motivated us to employ it as an efficient feature to distinguish healthy and stroke subjects.

2.3. Pattern Classification

The classifier used in this paper is the linear Support Vector Machine (SVM). It attempts to separate members of two classes by first projecting the training samples in the input space to a higher-dimensional feature space. In the feature space, SVM finds a hyperplane that will maximize the margin between the hyperplane and the closest training samples to avoid the potential problem of overfitting. The hyperplane is represented as a linear combination of feature vectors on the decision boundary between two classes. Interested users are referred to [9] for details.

Inputs to the classifier are generated by applying the proposed feature selection method to the data collected from the paretic arm of stroke subjects and the non-dominant arm of control subjects, resulting in a set of time-varying eigenspectral vectors each containing 133 elements. The vectors were then collectively projected to a lower-dimension space using PCA and the resulting PC coefficients were used as features. Figure 4 shows an example where the vectors obtained from severe stroke subjects and healthy subjects are projected to a two-dimensional space by using the first two principal components. To investigate the effect of dimension reduction on classification, both the original eigenspectral vector and the dimension-reduced coefficient vector will be examined for classification between stroke and healthy subjects in Section 3.

The classification performance was evaluated using the leave-one-out cross-validation technique.

3. RESULTS AND DISCUSSION

In this section, we study the performance of the proposed classification method by examining the sEMG data collected during the reaching movements.

First, we demonstrate that the feature vector extracted from multiple muscles simultaneously provides more insight into the different reaching movement patterns of healthy and stroke subjects than one from a single muscle. As shown in Figure 2, the time-varying eigenspectral patterns are consistent across trials on the same side, and the difference between the paretic and non-

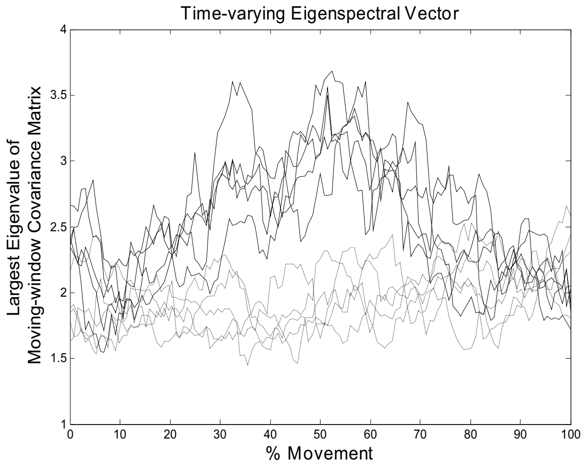

*Figure 2. Time-varying eigenspectral patterns obtained from non-paretic side (*solid line*) and paretic side (*dotted line*) of a stoke subject. Note the consistency between reaching trials.*

paretic sides is evident. On the other hand, though the lateral deltoid muscle was reported as revealing significant differences between healthy and stroke subjects using the same data set [6], the moving-RMS profiles from this single muscle for the paretic and non-paretic sides of the same subject are almost indistinguishable (Figure 3). Moreover, the trial-to-trial variability was significantly larger compared to the eigenspectral patterns.

To measure the correlation between the severity of stroke and the classification performance, the stroke subjects were divided into three categories based on their FM score: *Severe* with FM score below 25, *Moderate* with FM score between 25 and 50, and *Mild* with FM score above 50. Classification was then performed comparing *Severe*, *Moderate* and *Mild* separately to normal subjects.

We now proceed to evaluate the classification performance of the proposed scheme. In comparison with Figure 4, the projected PCA coefficients based on the RMS feature vectors from a single sEMG channel data is shown in Figure 5. It is clear that the

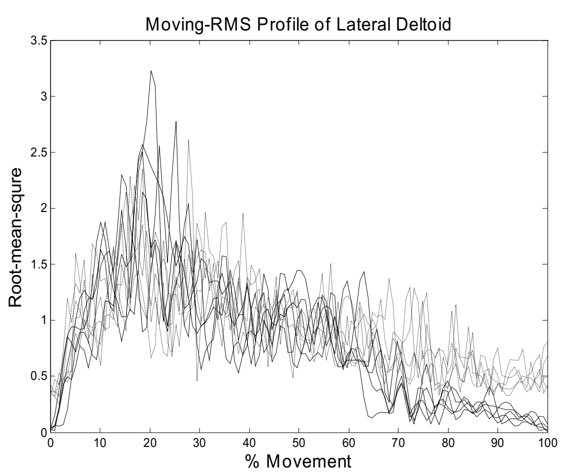

*Figure 3. Moving-RMS profiles patterns obtained from non-paretic side (*solid line*) and paretic side (*dotted line*) of a stroke subject.*

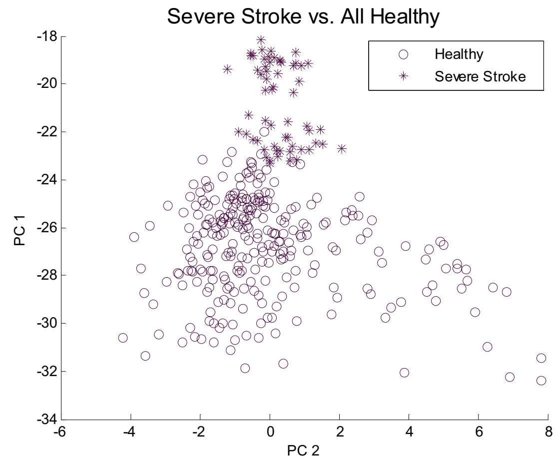

Figure 4. An example of PCA-based dimension reduction. The original time-varying eigenspectral vectors are projected into a two-dimensional space.

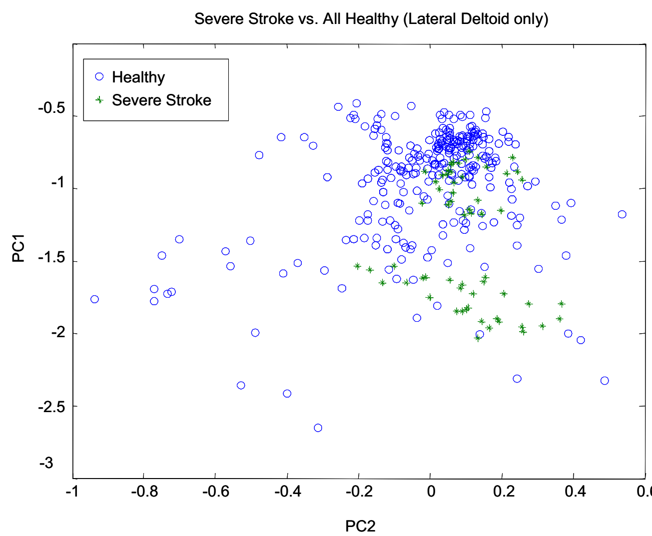

Figure 5. An example of PCA coefficients map based on a single channel of sEMG data. Compare to Figure 4.

patterns of the healthy and stroke subjects are not easily distinguishable from Figure 5. For the proposed scheme, to examine the effect of dimension reduction, two feature vectors are computed to train the SVM classifier: the original eigenvalue vector, and the coefficient vector after PCA projection. Classification rates obtained from applying SVM to the original feature vectors and the dimension-reduced ones is shown in Table 1. In general we can see that the two types of feature vectors yield similar classification performance. For the reduced ones, different choices of vector dimension, ranging from 2 to 70, are investigated to examine the effect of dimension reduction. No general tendency can be concluded. However, it seems that the classification performance was relatively insensitive to the dimension of input features, and we suggest to use N=3 or 4 for the good trade-off

Table 1. Classification rates for different severities of impairment using different feature vectors.

	Number of Dimensions				Mean
	N = 3	N = 30	N = 50	No dimension Reduction	
Severe vs. Healthy	97.89	97.29	97.29	96.99	97.37
Moderate vs. Healthy	80.27	80.55	75.07	80.00	78.97
Mild vs. Healthy	69.57	67.0	71.82	74.19	70.64

between performance and computational complexity. The average classification rates for *Severe*, *Moderate* and *Mild* vs. *Healthy* was 97.37%, 78.97%, and 70.64%, respectively. Note that the classification rates are monotonically related to the severity of the impairment.

When all stroke and healthy subjects are classified jointly, the histogram of the decision values (Figure 6) also confirms the correspondence between the classification performance and severity of impairment. This observation suggests that the proposed method may provide a quantifiable metric of motor performance.

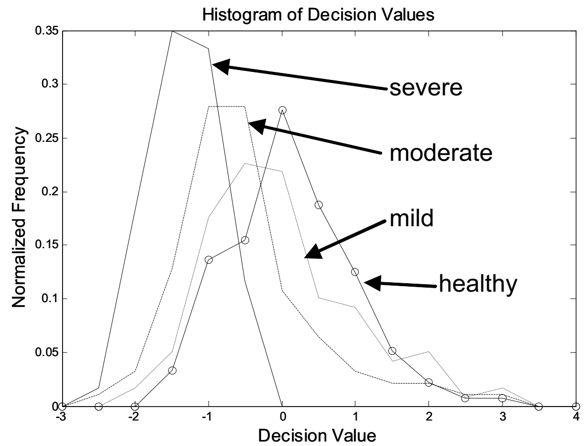

Figure 6. Histogram of decision values for various groups of subjects: Healthy (open circles), Severe (solid line), Moderate (dashed line), and Mild (dotted line).

4. 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 clinical scale used here to monitor functional independence. 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 will 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 enhance classification of sEMG patterns with an SVM classifier. Moreover, since the classification rate was monotonically related to the severity of stroke (as estimated by subject clinical scales) it suggests that this method could be extended into a quantifiable assay of motor performance.

5. ACKNOWLEDGEMENTS

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