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COMPARISON OF LOCAL DISCRIMINANT ANALYSIS AND SINGULAR VALUE DECOMPOSITION FOR CLASSIFICATION OF SURFACE EMG SIGNAL

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ABSTRACT

Electromyography (EMG) signal is electrical manifestation of neuromuscular activation that provides access to physiological processes which cause the muscle to generate force and produce movement and allow us to interact with the world. In this paper, an identification of six degree of freedom for evaluating and recording physiologic properties of muscles of the forearm at rest and while contracting is presented. The first step of this method is to analyze the surface EMG signal from the subject's forearm using Local Discrminant Analysis (LDA) and Singular Value Decomposition (SVD) to extract features from raw surface EMG(sEMG) signal. The second step is to import the feature values into multi class Support Vector Machine as a classifier, to identify six degree of freedom viz. open to close, close to open, supination, pronation, flexion and extension

Keywords: sEMG, LDA, SVD, Multi- Class Support Vector Machine(MSVM).

INTRODUCTION

Electromyography (EMG) signal is electrical manifestation of neuromuscular activation, that provides access to physiological processes which cause the muscle to generate force and produce movement and allow us to interact with the world[1][3]. Its application to control prosthetic limbs that can restore some or all of the lost motor functions of amputees has presented a great challenge due to the complexity of the EMG signal[2][5].

Feature extraction and function classification is the key in processing and analyzing the EMG signals. In this paper, we address the issue of wavelet packet transform using singular value decomposition, from which the function parameters can be computed by a multi class SVM. The success of our work is based on a combination on three factors: (1) a careful choice of muscle activity recording sites that are relevant to different functions of hand (2) the use of simple feature extraction and dimensionality reduction techniques (3) a state of art classification method based on multi class SVM. EMG signal is recorded from carefully chosen locations on the user's forearm. This stream of data is transformed into feature vectors using wavelet packet transform and classified by multi class SVM. Using the singular value decomposition, as the dimensionality reduction technique, results showed that an accuracy of over 96% could be obtained for a six degree of freedom classification problem. Figure 2 shows the overall representation of the work.

METHODOLOGY

A. Surface EMG (SEMG) Data Acquisition

EMG signals were collected by EMG signal detection module (Biopac Systems Inc.). For analysis, two channel SEMG was used to distinguish six hand motions. Ten volunteers in the age group of 23 to 27 years participated in the experiments. Two active electrodes were placed at the skin surface of

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Flexor Carpi Ulnaris and assigned as Channel 1 and the other two active surface electrodes were placed at the skin surface of Brachioradialis and assigned as channel 2.

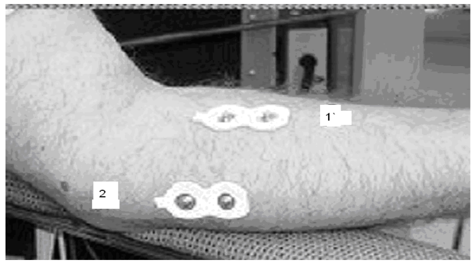

Figure1. Location of Surface Electrodes on the Forearm [1] Flexor Carpi Ulnaris [2] Brachioradialis

The sampling frequency for the purpose of recording was set at 2048 Hz. Number of samples recorded for the present work was 1024 with the time duration of 512 msec. The window of 256 msec was selected and computed the amplitude of each channel over this window.

B. Feature Extraction

The wavelet packet analysis [4] was employed to process the surface EMG signal. In this work, 'Symlet' (of order 5) mother wavelet was used in the Wavelet Packet Transform analysis and the decomposition level was set at the level '3'.

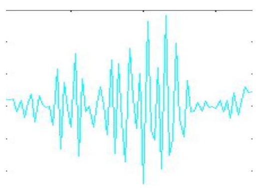

Figure 2. Close to Open

Figure 3. Open to Close

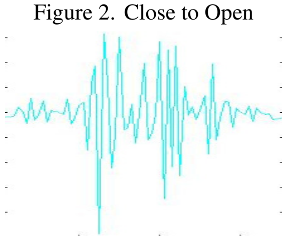

Figure 4. Pronation

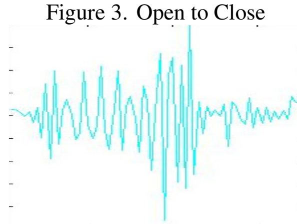

Figure 5. Supination

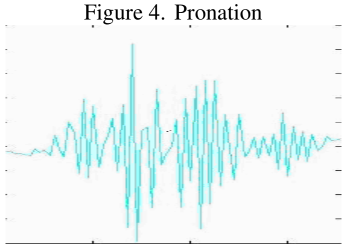

Figure 6. Flexion

The figure 2-6 shows the results of the wavelet decomposition for the different motions of forearm. The features were extracted using Singular Value Decomposition (SVD)and LDA. Singular value decomposition is a linear algebra technique that decomposes matrices into constituent parts, a left-hand and right-hand matrix separated by a descriptive diagonal matrix, the singular values, as their weighting. It takes a rectangular matrix of data (defined as X, where X is a n x p matrix) in which the n rows represent the text of SEMG data, and the p columns represent the wavelet coefficients. The SVD theorem states:

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$$\mathbf{X}_{nxp}=\mathbf{U}_{nxn}\,\mathbf{S}_{nxp}\,\mathbf{V}^{\mathbf{T}}_{pxp}$$

Calculating the SVD consists of finding the eigenvalues and eigenvectors of XX^T and X^TX. The eigenvectors of X^TX make up the columns of *V*, the eigenvectors of XX^T make up the columns of *U*.

C. Local Discriminant Analysis

The best basis algorithm developed by Coifman and Wickerhauser was mainly for signal compression [8, 9]. This method first expands a given signal or a given collection of signals into a library of an orthonormal basis, i.e. a redundant set of wavelet packets or local trigonometric functions having a binary tree structure where any set of nodes of the tree represents a subspace with specific time–frequency localizations. Then a complete basis (so called *best basis*) is searched from this binary tree, minimizing a certain information cost function (e.g., here entropy was used as cost function).

Local Discriminant Basis Algorithm

1. Expand **x** (Processed SEMG signal) into the library of orthonormal bases *W* and obtain coefficients $\{W_{jj,n}\,.\boldsymbol{x}\}$, $0 \leqslant j \leqslant J$, $n=0,\ldots,2^j-1$.

2. Define A_J as the initial basis constituted by all sub-bases $\{W_{J,n}\}$,$n=0,\ldots,2^j-1$.

3. Determine the best basis using the bottom search strategy as follows:-

For each level $j=(J-1),\ldots,0$, and each node $n=0,\ldots,(2^j-1)$, the best sub-basis $A_{j,n}$ is obtained by

$$A_{j,n}=\begin{cases} W_{j,n} & \text{if } M\left(W_{j,n}\mathbf{x}\right)\leqslant M\left(A_{j+1,2n}\mathbf{x}\right)+M\left(A_{j+1,2n+1}\mathbf{x}\right), \\ A_{j+1,2n}\oplus A_{j+1,2n+1} & \text{if not,} \end{cases} \quad \ldots\ldots(3.11)$$

The principal component analysis is designed in such a way that the data set may be represented by a reduced number of effective features and yet retains most of the intrinsic information content of the data.

D. Multi-Class SVM

For multi class SVM, one against all [6][7] method was implemented. The ten untrained data was given to precisely classify the six different motions of hand. The kernel function used in this work was 'Gaussian Kernel'. One-against-all method constructs k SVM models where k is the number of classes. The i^{th} SVM is trained with all of the examples in the i^{th} class with positive labels, and all other examples with negative labels. Thus given l training data, $(x_1, y_1),\ldots\ldots,(x_l, y_l)$, where x_i ε R^n, $i=1,\ldots\ldots\ldots,l$ and y_i

ε $\{1,\ldots\ldots\ldots,k\}$ is the class of x_i, the i^{th} SVM solves the following problem:

$$\min_{w^i,b^i,\xi^i} \quad \frac{1}{2}(w^i)^T w^i + C\sum_{j=1}^{l}\xi_j^i (w^i)^T$$

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$$(w^i)^T \phi(x_j) + b^i \geq 1 - \xi_j^i, \quad \text{if } y_i = i$$

$$(w^i)^T \phi(x_j) + b^i \leq -1 + \xi_j^i \quad \text{if } y_j \neq i$$

$$\xi_j^i \geq 0, \quad j = 1, \ldots\ldots, l$$

where training data x_i are mapped to a higher dimensional space by the function ϕ and C is the penalty parameter.

Minimizing $(1/2)(w^i)^T w^i$ means that we would like to maximize $2/\|w^i\|$, the margin between two groups of data .When data are not linear separable, there is penalty term $C\sum_{j=1}^{l}\xi_j^i$ which can reduce the number of training errors. The basic concept behind SVM is to search for a balance between the regularization term $(1/2)(w^i)^T w^i$ and the training errors.

RESULTS

In 2-channel identification, the signals from Flexor Carpi Ulnaris and Brachioradialis were used. The recorded data was classified into the required six degree of freedom viz. open to close, close to open, supination, pronation, flexion and extension. After the wavelet packet analysis, features were selected using singular value decomposition. For multi class SVM, one against all method was implemented. The concept of kernel function is very powerful. It allows SVM models to perform separations even with very complex boundaries. The use of kernel function is to map the data into a different space where a hyperplane can be used to do the separation. The kernel function may map the data into high dimensional space to make it possible to perform the hyperplane. The goal of SVM model is to find the optimal hyperplane that separates clusters of vector in such a way that cases with different categories are distinctly classified. The kernel function used in this work was ‘Gaussian Kernel’. The benefit of using this function is that the number of basis function (the number of support vectors), the centres and the weights in the output layer are all determined automatically. The five untrained data was given to precisely classify the six different motions of hand. It was demonstrated that the multi class support vector machine could accommodate the diverse sets of the EMG patterns produced while contracting and at rest for different motion of the forearm muscle. During the training, the classifier was able to adapt each subject’s motion of the forearm. During testing with the untrained data, the multi class support vector machine was unaffected by little variations in the feature values. The overall rate of correct class testing was 97%.

Table 1. Results From The Multi-Class SVM , Method:- SVD

S. No.	*Motion of the hand*	*Output For tested Data For Each Motion*					*Success Rate (%)*
1	CO	1	1	1	1	1	100
2	OC	2	2	2	2	2	100
3	P	3	3	3	3	3	100
4	S	4	4	4	4	**1**	80
5	F	5	5	5	5	5	100
6	E	6	6	6	6	6	100
Overall Success Rate							**96.667**

Where CO- close to open, OC- open to close, P- pronation, S-supination, F- flexion, E- extension

Table 2. Results From The Multi-Class SVM, Method:- LDA AND PCA

S. No.	Motion of the hand	Output For tested Data For Each Motion					Success Rate (%)
1	CO	1	1	1	**2**	1	80
2	OC	2	2	2	2	2	100
3	P	3	3	**1**	3	3	80
4	S	4	4	4	4	**3**	80
5	F	5	5	5	**6**	5	80
6	E	6	**5**	6	6	6	80
Overall Success Rate							**83.33**

CONCLUSION

The study brings out that the method of singular value decomposition produces better accuracy to classify the six different motions of hand using both the multi-class SVM**.** More investigations are being carried out focussing on different settings or setups of the data acquisition system to view how they influence the overall results. The work is being carried out for the realization of an interface between the peripheral nervous system (PNS) and the artificial device (i.e., a "natural" neural interface [NI]) to record and stimulate the PNS in a selective way for more accurate classification.

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