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Classification of Electromyography Signals Using Support Vector Machine

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ABSTRACT

In this paper, a classifier has been designed using Support Vector Machine (SVM) to classify Electromyography (EMG) signals. Given the EMG signals, the SVM-based classifier aims to classify ten individual and combined fingers motion command into one of the predefined set of movements. Prior to classification, EMG data is segmented with a sliding window technique and time domain features such as Mean Absolute Value (MAV), Root Mean Square (RMS), Integrated Average Value (IAV), Waveform Length (WL) and autoregressive model (4th order) are extracted for each window and combined to a feature set. Extracted features are used as inputs to the classification system. A linear SVM (one-against-one method) is used for the multiclass classification of EMG signals. Several window sizes that affect the classification performance have been reported. The best feature set that ensures maximum discrimination between the finger movements has also been reported. Validation shows that support vector machine can classify EMG signals correctly with a higher classification rate suitable for designing prosthetic and assistive devices.

Keywords: Classification, Electromyography, Feature Extraction, Support Vector Machine.

1. Introduction

Electromyography (EMG) signals are the measure of electrical activity in the muscle. The physiological variations across the muscle fiber membranes are responsible for creating electrical signals also known as myoelectric signals. These signals are produced by the exchange of ions across fiber membranes. The electrical potential that is produced on the muscle fibers is called action potential. An EMG signal is the summation of these action potentials of the muscle fibers. EMG signals can be determined by placing electrodes (both needle and surface type) on the skin.

The purpose of electromyography is to evaluate this electrical activity produced by the muscles. The electrical activity of a motor unit provides information for estimating neuromuscular disorders [1]. Other applications are motor control diseases, rehabilitation engineering, human machine interaction [2] etc. EMG signal classification gains an immense attention in the field of medical science, biomedical engineering, robotics etc. The classification of EMG signals has been widely used as the command signal to identify individual motions for controlling prosthetic and assistive devices. For achieving this purpose it is necessary to distinguish individual movements from the patterns of available EMG signals. Typically a pattern recognition system could be used to classify the acquired EMG signals into one of the predefined set of movements [3].

In recent years, significant works on EMG signal classification have been carried out. Many studies suggest that by classifying EMG signals it is possible to identify muscle diseases like neuromuscular disorder [4]. In most of the cases, the diseases have been identified as myopathy and neuropathy. Some other studies analyze the relative performance of SVM and neural network of EMG signal classification obtained from normal, myopathy, and neuropathy subjects [5]. A novel PSO-SVM model has been proposed that combines the particle swarm optimization and SVM to improve the EMG signal classification accuracy for diagnosis of neuromuscular disorders. Other studies that use EMG signals are human computer interfaces [2], a powered wheel chair controller, gait generation, interactive computer gaming etc [6]. For controlling peripheral equipments, hand gestures are often used. It is mainly done by capturing surface electromyography signals from the muscles.

In the recent past, myoelectric interfaces have attracted more attention for its application in the field of rehabilitation engineering, prosthesis devices, robotics etc. By the identification of EMG signals a myoelectric control system can be designed. It is mainly done into two parts. First part concerns the classification of EMG signals and second part covered the estimation of operator's joint angles. To classify a multi-channel surface electromyography signals with the aim of controlling myoelectric prostheses a support vector machine (SVM) approach has been applied. It is argued that this method is suitable for real-time application [7]. Recent attempts have been made to achieve more dexterous individual finger control. For classifying nine classes of individual finger movements 16-channels have been used and achieved 96% accuracy [8]. A pattern recognition system has been developed that can classify 10 classes of movements (five individual finger, four combined finger movement, and hand close) [9]. The features are time domain features and Support Vector Machine (SVM) for classification and Bayesian vote for post-processing have been employed with a classification accuracy is 92 % [9].

Feature extraction and classification have been considered as two key issues to design prosthetic/assistive devices or any useful application based on EMG [10]. Feature extraction is to define a feature vector from the original EMG signals, while classifier is to discriminate these feature vectors and group them into different classes. One of the main challenges in feature extraction and classification of EMG signals is its low quality. It is not always strictly repeatable, and may sometimes even be contradictory since it may be modified by many factors such as muscular fatigue, electrode shift, sweat, changing in thickness of skins, tissues. Sometimes it is difficult to extract useful features from the residual muscles of an amputee or disabled. Another challenge is to develop an EMG based myoelectric control system that can simultaneously allow movement of multiple degrees of freedom (DOFs). A number of EMG recognition methods, including feature extraction and classification have been proposed over time to time to achieve high recognition accuracy. But still a lot of research efforts are needed. To achieve more dexterity especially when controlling multiple DOFs, a pattern recognition system to discriminate multiple patterns has shown great promise.

Fig 1 shows a typical pattern recognition framework. The performance of better discrimination between individual movements largely depends on the proper presentation of the EMG signals. It is done mainly in the pre-processing stage. Features can be extracted both in time domain and time-frequency domain. Many time domain features such as root mean square (RMS) value, slope sign change (SSC), zero crossing (ZC), waveform length (WL), willison amplitude, auto regressive (AR) model etc. and time-frequency domain features such as wavelet transform (WT), fast fourier transform (FFT) show good performance [11].

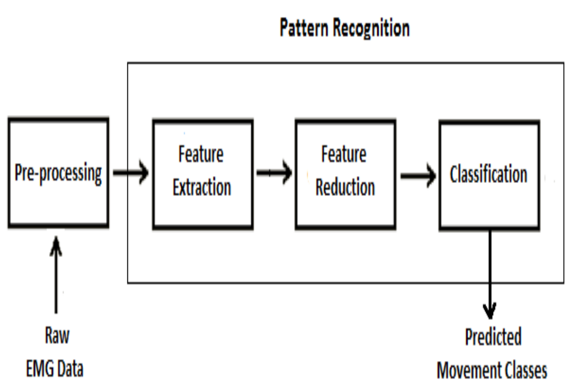

Fig. 1: A typical pattern recognition framework for EMG signal classification

The identification methods of individual movements fall into two categories. Supervised learning methods includes support vector machine (SVM), artificial neural networks (ANN) [12], k-nearest neighbor (KNN) etc. and unsupervised learning methods are K-means Clustering, Hidden Markov Models, Self Organizing Map etc. Some of the features are extracted from raw EMG data and recognition of individual movements can be carried out by using one of above learning methods.

In this research work a pattern classification system using support vector machine (SVM) has been designed and developed that can classify electromyography signals. The classifier can discriminate ten individual and combined finger movements.

2. Materials and Methods

2.1 Data Collection

The EMG signal dataset of ten classes of individual and combined finger movement has been collected from the work conducted by Dr. Rami Khushaba and his group of University of Technology Sydney [9].

The data was acquired by a data acquisition system from eight able bodied subjects (two females, six males). The collection of 2-channel EMG data was conducted by two Delsys DE 2.x series EMG sensors. Channel-1 signals mainly captured from the Extensor Carpi ulnaris and Extensor digitiminimi muscles while channel-2 from the Flexor digitorum superficials and Palmaris longus muscles.

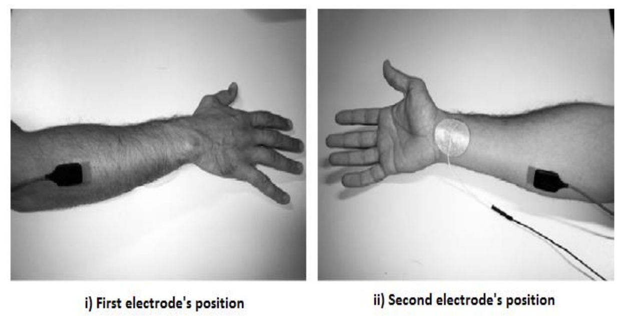

Fig. 2: Electrode Placements [9].

Fig. 2 shows the placement of electrodes for collecting two channels EMG data [9]. Ten classes of individual finger movements including Thumb (T) finger, Index (I) finger, Little (L) finger, Ring (R) finger, Middle (M) finger and combined finger movements including Thumb–Index (T–I) fingers, Thumb–Middle (T–M) fingers, Thumb–Ring (T–R) fingers, Thumb–Little (T–L) fingers, and Hand Close (HC) were performed on that experiment. Fig. 3 shows the individual and combined finger movements with their considered classes in this study.

The EMG data were provided in digitized format. For each class of movements there are six samples. Each number of samples includes two channel data. And each channel has 20,000 sampling points after digitization.

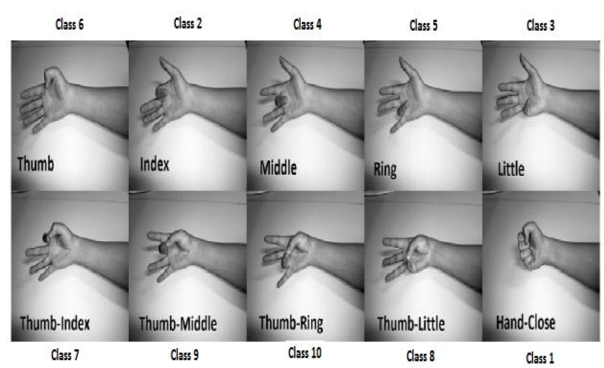

Fig. 3: Finger movement classes [9].

2.2 Segmentation/Windowing

The method of EMG signal classification using SVM can be visualized in Fig. 4. To successfully classify EMG signal it is necessary to represent data in an efficient manner. Classification accuracy largely depends on the productive representation of data. Pattern recognition of EMG signal starts with the segmentation of that signal. EMG signals are segmented with a suitable window size. Then features are computed from that particular window or segment of data. This approach is known as windowing approach [13]. There are two kinds of windowing approach exist.

a) Overlapping windowing,
b) Disjoint windowing [3].

It has been suggested that overlapping windowing technique gives better classification accuracy than disjoint windowing method [3]. The segmentation of raw EMG data is mainly performed by sliding window technique. The EMG data is windowed and feature is extracted from that particular window.

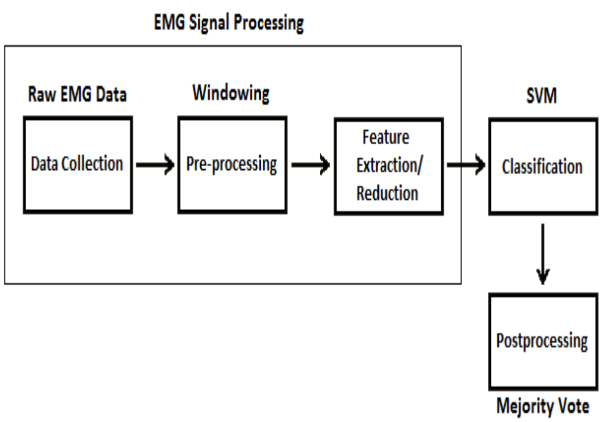

Fig. 4: Step-by-step procedure of EMG pattern recognition using SVM.

Then the window slides away to create another window of data that can be adjusted by window increment size. Classification accuracy differs significantly with window sizes (Section IV).

2.3 Feature Extraction

Successful EMG pattern classification to identify individual and combined motion commands depends on the correct feature extraction techniques. To separate the desired output classes a feature set (i.e. feature parameters) must be chosen wisely. One feature parameter can not represent the EMG signals to a motion command perfectly. To uniquely identify several motion commands various feature parameters are extracted and combined to form a large feature set. In this study, various time domain features such as Mean Absolute Value (MAV), Root Mean Square (RMS) value, Integrated Average Value (IAV), Waveform Length (WL), and Autoregressive Model (AR) with 4th order have been used to extract useful information.

The mathematics involved in the above time domain features are presented in the following:

a) *Mean Absolute Value:*

Mean absolute value of a surface EMG signal is calculated by taking the average of the absolute value of that signal. It is an estimation of the mean absolute value of the signal $x_i$in a segment $i$that is N samples in length.

$$MAV = \frac{1}{N}\sum_{k=1}^{N} |\, x_k|, \qquad where\ k = 1, \dots., I - 1 \qquad (1)$$

b) *Root Mean Square Value:*

Root Mean Square (RMS) is related to standard deviation by the following manner-

$$RMS = \sqrt{\frac{1}{N}\sum_{k=1}^{N} {x_k}^2} \qquad (2)$$

Where, N is the length of the signal and x_k represents the EMG signal in a segment.

c) *Integrated Average Value:*

The summation of the absolute signal value amplitude is known as integrated absolute value (IAV) of that signal. It is written as-

$$\begin{aligned} IAV &= \sum_{k=1}^{N} |\, x_k| \\ &= N.\frac{1}{N}\sum_{k=1}^{N} |\, x_k| \\ &= N.MAV \qquad (3) \end{aligned}$$

Where, the length of the signal is N and x_k represents the EMG signal in a segment.

d) *Waveform Length:*

The summation of the length of the waveform over the time segment is known as Waveform Length (WL). It is given by-

$$WL = \sum_{k=1}^{N-1} (|x_{k+1} - x_k|); \qquad (4)$$

e) *Autoregressive Model:*

Because of non-linearity and non-stationary nature of the EMG signal it is difficult to successfully examine the signal. But if the time interval is short then EMG signal can be represented as a stationary Gaussian random process. Each sample of the time series EMG signal is modeled as a linear combination of previous samples which is denoted by-

$$y_k = -\sum_{i=1}^{n} b_i y_{k-i} + g_k \tag{5}$$

Where b_i is AR co-efficient, n is AR order and g_k is white noise.

Fourth order AR model is widely used but other orders are also employed occasionally. The main advantage of AR model is that EMG signal can be modeled as a list of parameters. Instead of using original EMG data model, parameters can be fed to the classification algorithm for recognition purposes which reduces computational burden.

2.4 Dimensionality Reduction

The higher dimensional data representation describes an action or gesture clearly but it is not computationally efficient since a large amount of time is required to process the data. Feature extraction is not enough for reducing the size of the data. A dimensionality reduction technique could be used. Principle component analysis (PCA) has been used to reduce the dimension of the features extracted from EMG data for classification purposes. The classification performance varies with the number of PCA reduced features. Since reduction of the number of features describes data poorly, an optimum reduced feature size should be chosen carefully.

2.5 Classification and Post Processing

The EMG data after processing in a signal processing stage is ready for classification. The extracted features after PCA reduction are classified by a SVM based classifier.

The data classification using SVM is performed by the construction of the best possible hyper plane that separates all data points from one class of the other class. The best hyper plane for an SVM means the one with the largest margin between the two classes. The maximal width of the slab parallel to the hyper plane that has no interior data points is called Margin. Data points that are closest to the separating hyper plane are called support vectors. These points lie on the boundary of the slab. These definitions are illustrated in Fig. 5 with filled small circles indicating data points of class 1 and blank small circles indicating data points of class 2. For two class problem consider the training sample dataset, $\{\boldsymbol{x_i}, y_i\}$, where i=1, 2,…, n, and $\boldsymbol{x_i} \in \boldsymbol{R^d}$ represents feature vector. And y_i are labels with $y_i = +1$ for one class and $y_i = -1$ for another class simply putting, $y_i \in \{+1, -1\}$. As choosing optimal hyper plane another aim of SVM is to maximize the margin to distinguish data. A hyper plane can be defined as follows-

$$f(\boldsymbol{x}) = \omega.\boldsymbol{x} + b = 0 \tag{6}$$

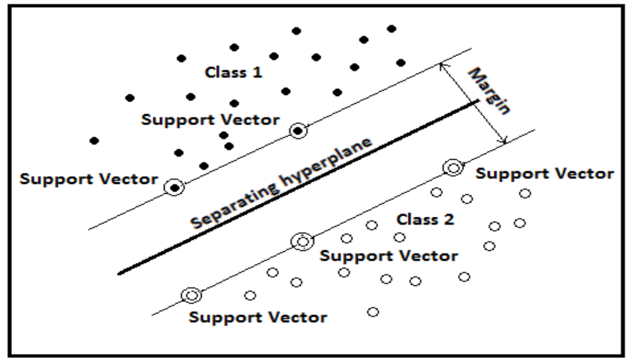

Fig. 5: Support Vector Machine

Where, $sign(f(\boldsymbol{x}))$, can be regarded as a decision function. And ω is normal to the hyper plane (Fig. 6) also $\frac{|b|}{\|w\|}$ is the perpendicular distance from the hyperplane to the origin. Now let us define d^+ and d^- be the shortest distance from the separating hyperplane to the closest examples. So the margin of a separating hyperplane would be d^++d^-.The solution of the largest margin can be formulated as follows:

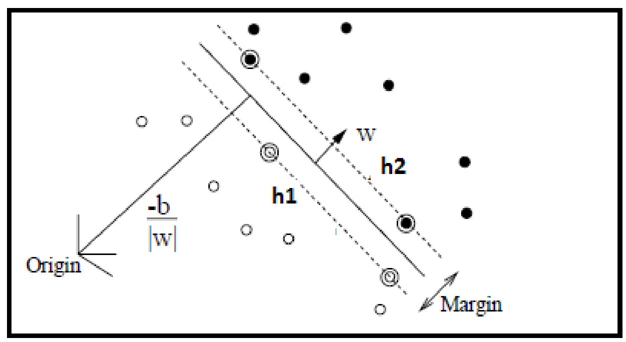

Fig. 6: Separating hyperplanes with support vectors [14].

All the training data satisfy the following constraints-

$$f(\boldsymbol{x_i}) = \boldsymbol{x_i}.\omega + b \geq +1 \quad for\ y_i = +1 \tag{7}$$

$$f(\boldsymbol{x_i}) = \boldsymbol{x_i}.\omega + b \leq -1 \quad for\ y_i = -1 \tag{8}$$

These form the following inequalities-

$$y_i(\boldsymbol{x_i}.\omega + b) - 1 \geq 0 \quad \forall i \tag{9}$$

Now considering the points satisfying equation (7) and (8) and lying on the two hyper plane say $h_1 and\ h_2$, the shortest distance can be found as d^+=d^-= $\frac{1}{\|\omega\|}$. So, the margin is simply $\frac{2}{\|\omega\|}$. The Lagrangian formulation can be written as follows,

$$L_p = \frac{1}{2}\|\boldsymbol{\omega}\|^2 - \sum_{i=1}^{l} \alpha_i y_i(\boldsymbol{x_i}.\boldsymbol{\omega} + b) + \sum_{i=1}^{l} \alpha_i \tag{10}$$

Where $\alpha_i$is a positive lagrangian multipliers.

Here L_p is need to be minimized with respect to $\boldsymbol{\omega}$ and b. It also requires that gradient of L_p with respect to α_i vanishes such that $\alpha_i \geq 0$.

3. Implementation

3.1 Window Size Selection

The collected EMG data is windowed with suitable window size and features are extracted within each window. All of the extracted features are then concatenated to form a larger feature set. To select the best window size several sliding windows are chosen as 128 ms, 256 ms, 384 ms, 512 ms, 640 ms, 768 ms, 896 ms, 1024 ms window and their performance on EMG signal classification accuracy have been evaluated respectively. Window increment has been considered as 128 ms for all the cases. For each subject, the classification rate of finger movements has been estimated five times with each of the window sizes. Then the average classification rate has been computed. Next, the average of all subject's data for each of the window has been calculated. The results are presented in results and discussion (Section IV).

3.2 Feature Parameters Selection

The choice of feature parameters affects the classification accuracy. To assess this, time domain features are organized into eight feature sets for performance evaluation as shown in TABLE I. For each feature set the average classification rate of ten individual and combined finger movements is calculated. The process is repeated for each (five) subjects. Then the total average classification rate is determined across all subjects for that particular feature set. The process is repeated for eight feature sets and the total average classification rate or error rate for each of the eight feature sets is calculated (Section IV).

3.3 Feature Vector Calculation

The classification of EMG signals depends upon the finding of right feature vectors that are unique for them. By considering different feature parameters (i.e. RMS, MAV, IAV, WL and autoregressive model), features are extracted from EMG data within each window. In this study, the collected EMG signal consists of 2-channel (ch1 & ch2) EMG data. So features are calculated from each of the EMG data channel by using these feature parameters. At first a window of data is selected and feature parameters considered above for example are estimated for that particular window.

Then the window slides away (i.e. by a window increment) to consider a new window of data and the calculation for feature values for each feature parameters is repeated.

TABLE II and TABLE III show the calculated features from one class of EMG data (i.e. 'Hand Close ') only for 1st window, 50th window, 100th window and 150th window as an example. The calculated feature values are then concatenated to form a large feature vector.

Table 1. Feature Sets

Feature Set	Feature Parameters
Set 1	WL, AR Model (Order 4)
Set 2	RMS, MAV, AR Model (Order 4)
Set 3	RMS, WL, AR Model (Order 4)
Set 4	MAV, WL, AR Model (Order 4)
Set 5	RMS, IAV, WL, AR Model (Order 4)
Set 6	RMS, MAV, ,WL, AR Model
Set 7	RMS, IAV, WL,MAV
Set 8	RMS, IAV, WL, MAV, AR Model

Table 2. Calculation of Feature parameter values for 1st window and 50th window

Feature Para-meter	1st Window		50th Window	
	ch1	ch2	ch1	ch2
RMS	0.000369	0.000556	0.000325	0.000465
MAV	0.000286	0.000433	0.000261	0.000342
IAV	0.146196	0.221547	0.133595	0.174854
WL	0.013255	0.018492	0.010951	0.013865
AR Model (4^{th} order)	-1.45421	-1.8524	-1.87688	-2.76986
	0.302385	0.732129	0.787649	2.816215
	0.244419	0.415169	0.355063	-1.17604
	-0.02654	-0.25907	-0.23435	0.140626

Table 3. Calculation of Feature parameter values for 100th window and 150th window

Feature Para-meter	100th window		150th window	
	ch1	ch2	ch1	ch2
RMS	0.000414	0.000326	0.000292	0.000259
MAV	0.000323	0.000256	0.000223	0.000215
IAV	0.165423	0.13101	0.113938	0.110195
WL	0.009497	0.007148	0.008074	0.006482
AR Model (4^{th} order)	-2.65778	-1.9543	-1.79114	-2.853
	2.50027	0.882446	0.665951	3.080835
	-0.89712	0.335687	0.315306	-1.47939
	0.061697	-0.2467	-0.15997	0.259955

Table 4. Concatenation of Feature values (Feature values of ch2 below Feature values ch1)

Feature parameters	1st Window		
RMS	0.000369		-1.45421
	0.000556		0.302385
MAV	0.000286		0.244419
	0.000433	AR Model (4^{th} order)	-0.02654
IAV	0.146196		-1.8524
	0.221547		0.732129
WL	0.013255		0.415169
	0.018492		-0.25907

At first for each feature parameter, the calculated feature values of channel 1 and channel 2 are concatenated one below another. TABLE IV shows the concatenation of feature values of 2-channel for 1^{st} window.

Then all of the combined feature values for all feature parameters are concatenated one below another to form the feature vector. TABLE V shows the feature vectors for all 4 windows as example:

Table 5. Feature Vectors for 1^{st} window, 50^{th} window, 100^{th} window and 150^{th} window

1^{st} Window	50^{th} Window	100^{th} Window	150^{th} Window
0.000369	0.000325	0.000414	0.000292
0.000556	0.000465	0.000326	0.000259
0.000286	0.000261	0.000323	0.000223
0.000433	0.000342	0.000256	0.000215
0.146196	0.133595	0.165423	0.113938
0.221547	0.174854	0.13101	0.110195
0.013255	0.010951	0.009497	0.008074
0.018492	0.013865	0.007148	0.006482
-1.45421	-1.87688	-2.65778	-1.79114
0.302385	0.787649	2.50027	0.665951
0.244419	0.355063	-0.89712	0.315306
-0.02654	-0.23435	0.061697	-0.15997
-1.8524	-2.76986	-1.9543	-2.853
0.732129	2.816215	0.882446	3.080835
0.415169	-1.17604	0.335687	-1.47939
-0.25907	0.140626	-0.2467	0.259955

3.4 Classification Algorithm

Support vector machine is a linear classifier that classifies data that poses only two classes. It can be extended to multiclass classification. Among two popular approaches, one-against-one method has been used in this study. A majority voting strategy has been used as a post processing stages after all the classifiers are trained with samples of all classes. The new sample is assigned to the class with the largest vote.

The classification rate of ten individual and combined finger movements is calculated ten times for each subject. Then the average classification rate is calculated for that subject. The process is repeated for the remaining subject's. TABLE VI shows the average classification rate for all five subjects.

Table 6. Average classification rate using support vector machine with the designed parameters

Data Subject	1	2	3	4	5	6	7	8	9	10	Avg.(%)
Subject 1	85	90	90	85	90	85	85	90	95	90	88.50
Subject 2	95	90	90	90	75	100	90	90	90	95	90.50
Subject 3	85	90	90	100	90	95	85	95	90	90	91.00
Subject 4	95	90	95	100	95	85	95	90	90	95	93.00
Subject 5	95	90	95	95	95	95	100	90	90	95	94.00
										Avg	**91.40**

4. Results and Discussion

4.1 Window Size vs Classification Rate

Fig. 7 shows the variation of classification rate by changing window sizes. It is seen that classification rate increases if we increase the window size with fixed window increment. The classification rate is increasing upto 512 ms window size. It does not improve much after 512 ms window if we increase the window sizes. Since 512 ms window gives better classification rate and choosing larger window gives nothing but a larger processing time it has been chosen as window size with fixed window increment 128 ms in this study.

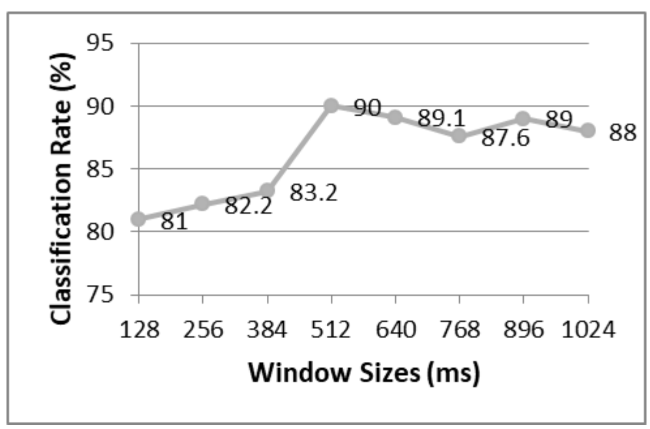

Fig. 7: Relation between classification rate and window sizes

4.2 Feature Parameters vs Classification Rate

Fig. 8 shows the dependency of classification rate or error rate on the selection of feature parameters. It is clearly seen that increasing feature parameters reduces the average error rate. More interesting result is found if we see feature parameters of feature set seven and eight (TABLE I).

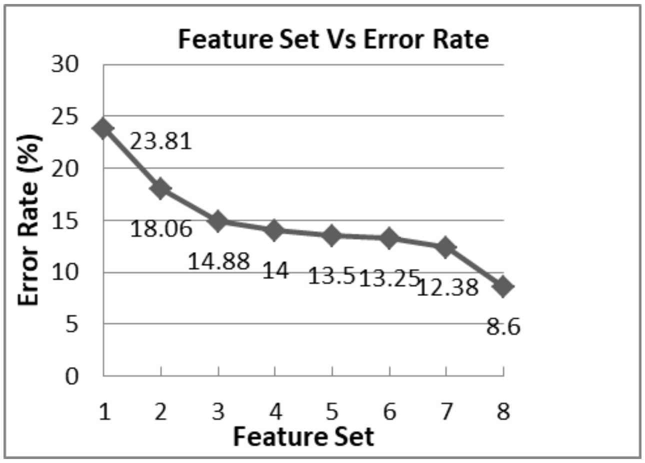

Fig. 8: Relation between error rate and feature set

The reduction of average error rate is less if we consider feature set seven to eight. AR model is included in feature set eight. But error rate is not reduced significantly if we use feature set eight. In this study feature parameters of feature set eight has been considered to classify EMG patterns.

4.3 Average Classification Rate

The overall average classification rate across all subjects is approximated which is equal to **91.40 %** (TABLE VI).

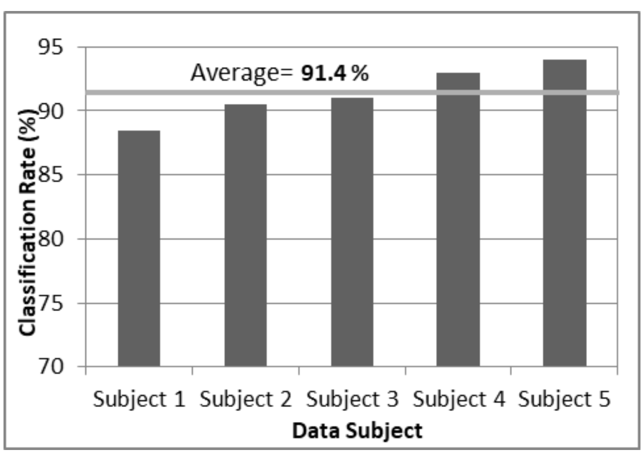

Fig. 9: Average classification rate of eight subjects using SVM based classifier.

Fig. 9 shows the average classification rate for each subject. The x-axis represents data subject. Along y-axis, each value represents the classification rate for each subject. A horizontal line is drawn through the vertical bars in order to represent overall average classification rate.

5. Conclusion

A support vector machine (SVM) based EMG signal classification method has been designed in this work. The classification method starts with collected EMG data segmentation with a sliding window technique. Features are extracted using time domain feature representation for each sliding window. Among several window sizes suitable window has been selected by investigating their influences on the classification accuracy. Best feature set (i.e. feature parameters) that ensures maximum separation between finger movements has also been investigated. The classification accuracy of individual and combined finger movements using SVM based classifier is of ≈**91.40 %** across all subjects. So it can be concluded that support vector machine based pattern recognition system is suitable for discriminating hand motions with the little cost of average classification rate.

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