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Classification Method of Hand Gestures Based on Support Vector Machine

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ABSTRACT

This paper presents the EMG signal classification based on PCA and SVM method. The data is acquired from the 5 subjects and each subject perform 7 hand gestures includes the tripod, power, precision closed, finger point, mouse, hand open, and hand close. Each gesture is repeated 10 times (5 data as training data and the 5 Remaining data as testing data). Each of training and testing data are processed using 16 features extraction in time–domain and reduced using principal component analysis (PCA) to obtain new set of features. Features classification using support vector machine classify new set of features from each subject result 85% - 89% percentage of training classification. Training data classification is tested using testing data of EMG signals and giving accuracy reach 80% - 86%.

Keywords: Electromyography (EMG), Features extraction, Principal Component Analysis (PCA), Support Vector Machine (SVM), Pattern Recognition.

1. INTRODUCTION

Electromyography (EMG) signals have been widely used and applied as a control signal in numerous man – machine interface applications and have also been deployed in many clinical and industrial applications [1]. Widespread potential applications for surface EMG signal classification and control have been reported in the last two decades, including multifunction prosthesis, electrical wheel chairs, virtual mouse and keyboard, and virtual worlds [2].

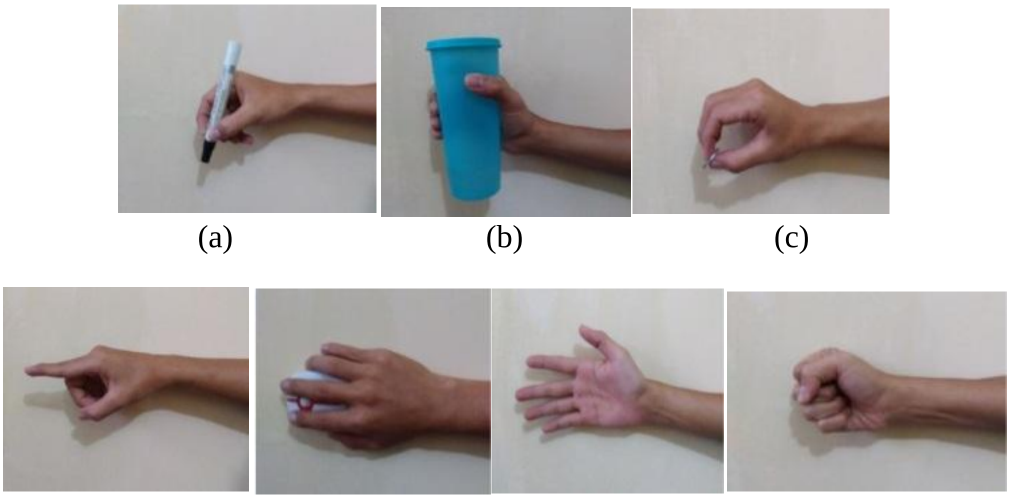
A number of studies in bionic hand have developed significantly. The purpose of the studies is mainly to interpret hand gestures. Peerdeman et.al. [3] developed a three-dimensional hand prosthesis model based on biomechanical structure of the human hand for the development of electromyography hand prosthesis control systems. The model's main purpose was as a test bed for the development of prosthesis control systems based on input from EMG sensing [3]. Matrone et.al. [4] demonstrated the real-time prehension control of a robotic hand employing two differential channels (four electrodes) EMG acquisition system and a PCA-based controller. The results showed that the robotic hand help amputees by allowing them at last to manage their hand prosthesis in a more intuitive and natural way.

The common used sensor for measuring the muscle activities is EMG sensor. The raw signals from EMG sensor is need further method to be analyzed. So, the implementation of pattern recognition method that can interpret the muscle activities has important role [5]. The pattern recognition method can provide the decision for actuator of bionic hand, where the input of pattern recognition method requires the EMG signal during muscle activities. In addition, the actuator and pattern recognition method will work effectively when an appropriate control system is used. This paper presents the EMG signal classification based on principal component analysis (PCA) and support vector machine (SVM).

2. METHOD

2.1 DATASET USED

Five subjects consist of three males and two females, aged between 20 and 25 years were involved in the experiment. The subjects were all normally limbed with no neurological or muscular disorders. All participants provided informed consent prior to participating in the study. Subject were seated on an armchair, with their arm supported and fixed at one position to avoid the effect of different limb position on the generated EMG signals [6].



(a) (b) (c)

(d) (e) (f) (g)

FIGURE 1. Hand gestures photograph during EMG signal data acquisition: (a) Tripod, (b) Power, (c) Precision closed, (d) Finger point, (e) Mouse, (f) Hand Open, and (g) Hand close.

Dataset of EMG signal was loaded from one channel EMG sensor of BITalino plugged kit. The EMG signals was collected with the sampling rate at 1000 Hz. The participants were instructed by an auditory due to elicit a contraction from rest and hold that gesture for a period 10 s, with the transition from a relaxation state to a movement also included in the collected data. Each movement was repeated ten times with a resting period of 5 to 7 s between trials. The seven hand gestures are shown in Figure 1.

2.2 FEATURES EXTRACTION

Some researches presented the features extraction of EMG signals divided in two domains: (1) time-domain features and (2) frequency-domain features [7]. Time domain features were used in this paper. The definition and the equation are presented in this paper as follow; Integrated EMG, Mean Absolute Value, Modified Mean Absolute Value Type 1, Modified Mean Absolute Value Type 2, Simple

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Square Integral, Variance of EMG, Root Mean Square, Waveform length, Difference absolute standard deviation value (DASDV), Autoregressive coefficients (AR), Hjorth Activity, Hjorth Mobility, and Hjorth Complexity.

Integrated EMG (IEMG) is normally used as an onset detection index in EMG non–pattern recognition and in clinical application [7, 8].

$$IEMG = \sum_{i=1}^{N} |x_i| \tag{1}$$

Mean absolute value (MAV) is one of the most popular used in EMG signal analysis. It is similar to IEMG feature which is used as an onset index, especially in detection of the surface EMG signal for prosthetic limb control [7, 8].

$$MAV = \frac{1}{N} \sum_{i=1}^{N} |x_i| \tag{2}$$

Modified mean absolute value type 1 (MAV1) is an extension of MAV feature [7, 8] is defined as,

$$MAV1 = \frac{1}{N} \sum_{i=1}^{N} w_i |x_i|$$
$$w_i = \begin{cases} 1, & if \quad 0.25N \le i \le 0.75N \\ 0.5, & else \quad if \end{cases} \tag{3}$$

Modified mean absolute value type 2 (MAV2) is an expansion of MAV feature which is similar to MAV1 [7, 8] and simple square integral (SSI) or integral square uses energy of the EMG signal as feature [7, 8] are defined as follow,

$$MAV2 = \frac{1}{N} \sum_{i=1}^{N} w_i |x_i|$$
$$w_i = \begin{cases} 1, & if\, 0.25N \le i \le 0.75N \\ 4i/N, & else\ if\ \ i < 0.25N \\ 4(i-N)/N, & otherwise \end{cases} \tag{4}$$

$$SSI = \sum_{i=1}^{N} x_i^2 \tag{5}$$

Variance of EMG (VAR) is another power index. Generally, variance is defined as an average of square values of the deviation of that variable; however, the mean value of EMG signal is close to zero (~10^{-10}) [7, 8]. The VAR value can be described as,

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N} x_i^2 \tag{6}$$

Root mean square (RMS) is another popular feature in analysis of the EMG signal. It is modeled as amplitude modulated Gaussian random process whose relate to constant force and non–fatiguing contraction [7, 8].

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{7}$$

Waveform length (WL) is a measure of complexity of the EMG signal. It is defined as cumulative length of the EMG waveform over the time segment and difference absolute standard deviation value (DASDV) is look like RMS feature, in other words, it is a standard deviation value of the wavelength [7, 8] can be formulated as,

$$WL = \sum_{i=1}^{N-1} \left| x_{i+1} - x_i \right| \tag{8}$$

$$DASDV = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1} \left(x_{i+1} + x_i \right)^2} \tag{9}$$

Autoregressive coefficients (AR) is a common approach for modeling univariate time series as AR model follows [7, 8]. Where a_1 to an are the autoregressive coefficients, y_t is the time series under investigation, n is the order of the AR model (n = 4) and ε is the residual which always assumed to be Gaussian white noise. The activity parameter represents the signal power, the variance of a time function. This can indicate the surface of power spectrum in the frequency domain [6]. All values is defined as follow,

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$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + ... + a_n y_{1-n} + \varepsilon_t = \sum_{i=1}^{n} a_i y_{t-1} + \varepsilon_t \tag{10}$$

$$Hjorth\_1 = \sigma_x^2 = \frac{1}{N} \sum_{i=1}^{N} \left(x_i - \bar{x} \right)^2 \tag{11}$$

The mobility parameter represents the mean frequency, or the proportion of standard deviation of the power spectrum [6]. The complexity parameter represents the change in frequency. The parameter compressed the signal's similarity to a pure sine wave, where the value Converge to 1 if the signals is more similar [6].

$$Hjorth\_2 = \frac{\sigma_{x'}}{\sigma_x} \tag{12}$$

$$Hjorth\_3 = \frac{\sigma_{x''} / \sigma_{x'}}{\sigma_{x''} / \sigma_x} \tag{13}$$

2.3 FEATURES REDUCTION USING PCA

The two commonly used techniques for data classification and dimensionality reduction are principal component analysis (PCA) and linear discriminant analysis (LDA) [9]. PCA in general term, is a technique using sophisticated underlying mathematical principles to transforms a number of possibly correlated variables into a significant smaller number of uncorrelated variables called principal components [10, 11]. PCA technique lies in multivariate data analysis, but it has a wide range of applications, such as de-noising signals, blind source separation, cluster analysis, visualization of high-dimensionality data, regression, data compression and pattern recognition [9]. Let a set of centered data input vectors x_t (t =1, …,l and $\Sigma x_t = 0$), each of which is of m dimension $x_t = [x_t(1), x_t(2), \ldots, xt(m)]T$ usually m<l, s_t linearly transforms each vector x_t as in Equation (14)

$$\mathbf{s}_t = \mathbf{U}^T \cdot \mathbf{x}_t \tag{14}$$

where **U** is the $m \times m$ orthogonal matrix whose *i*th column, $\mathbf{u}_i$ is the eigenvector of the sample covariance matrix **C**. The **C** matrix can be calculated using (15)

$$\mathbf{C} = \frac{1}{l} \sum_{t=1}^{l} \mathbf{x}_t \cdot \mathbf{x}_t^T \tag{15}$$

The eigenvalue problem in PCA can be solved using equation (16)

$$\lambda_i \mathbf{u}_i = \mathbf{C} \cdot \mathbf{u}_i , \quad i = 1, \ldots, m \tag{16}$$

where λ_i is one of the eigenvalues of **C**. The components of $\mathbf{s}_t$ are then calculated as the orthogonal transformations of $\mathbf{x}_t$ based on the estimated $\mathbf{u}_i$

$$\mathbf{s}_t(i) = \mathbf{u}_i^T \mathbf{x}_t , \quad i = 1, \ldots, m \tag{17}$$

The new extracted components are called principal components. The number of principal components in $\mathbf{s}_t$ can be reduced using only the first several eigenvectors sorted in descending order of the eigenvalues.

2.4 FEATURES CLASSIFICATION USING SVM

Support Vector Machine (SVM) is a classifier which requires training of the model for testing of the samples and such technique in which training is given called as supervised learning technique [8,11, 12]. In this case, model is firstly trained to learn according to the features of classes that be reduced by PCA and which need to be classified. Then that trained model is exploited in the classification process. Learning given to the classifier provides better result. This classifier is simple and easy to understand as it constructs a hyperplane between the different classes which need to be classified. The classifier used may be linear or non–linear. In linear SVM, training samples of the classes are linearly separable. But it is very difficult in practical situations that a straight line is sufficient to classify each and every sample. For such case, non–linear classifier is exploited [11, 12].

Kernel function used to build linear boundaries through non-linear transformations or mapping to finding the best classes for decision plane. The SVM select the classes with maximal margin. The SVM is a supervised learning method. It is widely used for classification and regression. SVM applies the input vectors that are non-linearly mapped a very high dimension feature space. The data input is given by $\mathbf{x}i$ (i = 1, 2, …, M), M is the number of samples. It is assumed that there are two classes namely positive class and negative class. The two classes are denoted by yi = 1 for positive class and yi = -1 for negative class, respectively. For linearly data, it is possible to determine the hyper plane function of $f(\mathbf{x}) = 0$ splitting the given data as in (18).

$$f(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + b = \sum_{i=1}^{M} w_i x_i + b = 0 \tag{18}$$

The M-dimensional vector **w** and scalar b are used to define the position of separating hyper plane. It is created by decision function of sign $f(\mathbf{x})$ to classify the input data either in positive or negative class. The constraint should be fulfilled by separating hyper plane that can be written in (19)

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$$y_i f(\mathbf{x}_i) = y_i(\mathbf{w}^T \mathbf{x}_i + b) \geq 1 \quad \text{for } i=1,2,\ldots M \qquad (19)$$

The optimal separating hyper-plane is the maximum distance between the plane and the nearest data, i.e. the maximum margin created by separating hyper-plane. An example of the optimal hyper-plane of the two data sets can be seen in Figure 2. A series data points for two different classes are presented in Figure 2, black circle for positive class and white circle for negative class. The SVM tries to place a linear boundary between the two classes, and orients it in such way that the dash dotted line is maximized. Moreover, SVM tries to orientate the maximum of the distance between boundary and the nearest data point in each class. The boundary is located in the middle of margin between two points. Support vectors are the nearest data points used to define the margin. In Figure 2, support vectors are represented by square black circle and square white circle. In this linear system, the normal vector to the hyper plane is **w** and the perpendicular distance from the hyper plane to the origin is $\frac{-b}{|\mathbf{w}|}$

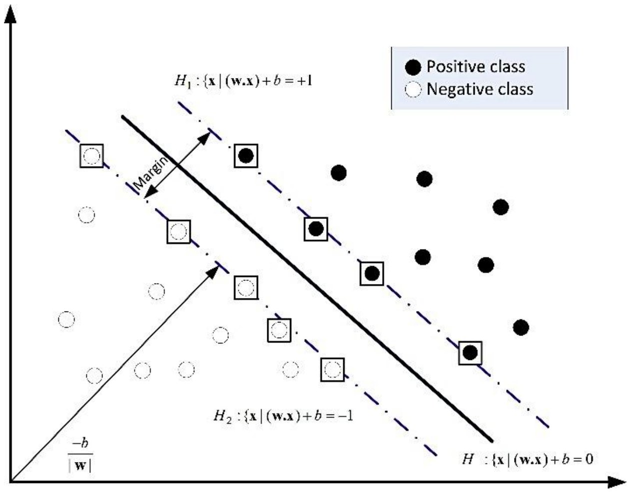

FIGURE 2. Classification of two linearly separable classes using SVM

The noise with slack variables ξ□*i* and the error penalty *C*, the optimal hyperplane separating the data can be calculated using Equations (20) and (21)

$$\text{Minimize } \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{M} \xi_i \qquad (20)$$

$$\text{subject to} \begin{cases} y_i(\mathbf{w}^T \mathbf{x}_i + b) \geq 1 - \xi_i, i = 1, \ldots M \\ \xi_i \geq 0, i = 1, \ldots M \end{cases} \qquad (21)$$

where ξ_i is measuring the distance between the margin, the calculation can be simplified into the Lagrangian dual problem as in Equation (22) using Kuhn-Tucker condition.

$$\text{Min } L(\mathbf{w}, b, \boldsymbol{\alpha}) = \frac{1}{2}\|\mathbf{w}\|^2 - \sum_{i=1}^{M} \alpha_i y_i (\mathbf{w}.\mathbf{x}_i + b) + \sum_{i=1}^{M} \alpha_i \quad (22)$$

The task is to minimize Equation (20) and (21) with respect to **w** and *b*. The saddle point at optimal point can be calculated using Equations (23) and (24)

$$\text{Maximize } L(\alpha) = \sum_{i=1}^{M} \alpha_i - \frac{1}{2} \sum_{i,j=0}^{M} \alpha_i \alpha_j y_i \mathbf{x}_i.\mathbf{x}_j \quad (23)$$

$$\text{Subject to} \quad \begin{aligned} &\alpha_i \geq 0, i = 1, ..., M \\ &\sum_{i=1}^{M} \alpha_i y_i = 0 \end{aligned} \quad (24)$$

Solving the dual optimization problem, the coefficients α*i* is obtained which is required to express the **w** to solve Equations (20) and (21). The non-linear decision function becomes Equation (25) as follow;

$$f(\mathbf{x}) = sign\left(\sum_{i,j=1}^{M} \alpha_i y_i (\mathbf{x}_i \mathbf{x}_j) + b \right) \quad (25)$$

It is possible to use SVM in non-linear classification with application of kernel functions. The data is mapped onto a high dimensional feature space using nonlinear vector function of $\mathbf{\Phi}(\mathbf{x}) = (\phi_1(\mathbf{x}), ..., \phi_i(\mathbf{x}))$. The decision function can be calculated using Equation (26) below,

$$f(\mathbf{x}) = sign\left(\sum_{i,j=1}^{M} \alpha_i . y_i (\mathbf{\Phi}^T(\mathbf{x}_i) . \mathbf{\Phi}(\mathbf{x}_j)) + b \right) \quad (26)$$

High dimensionality will cause over fitting and computational problem will occur due to large vectors. The problem can be solved by using kernel function $K(\mathbf{x}_i, \mathbf{x}_j) = \left(\mathbf{\Phi}^T(\mathbf{x}_i) . \mathbf{\Phi}_j(\mathbf{x}_j) \right)$. The decision function will be,

$$f(\mathbf{x}) = sign\left(\sum_{i,j=1}^{M} \alpha_i y_i K(\mathbf{x}_i, \mathbf{x}_j) + b \right) \quad (27)$$

3. RESULTS

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In this study, SVM classifier is utilized for the classification of seven different types of EMG signals. The seven EMG signals are related to different hand gestures. As the features extraction required to describe the EMG signals in statistical analysis. Then the features are reduced by PCA and classified using the SVM. The hand gesture classification pattern recognition is designed by arranging the 16 features as rows and 35 data samples as column in matrix 16 x 35. That matrix is used as training data and testing data for further analysis in PCA.

In PCA, the eigenvalue of 16 features was computed and arranged consecutively. So that, it can be determined that the highest eigenvalue can be assumed as number of principal component in PCA. As shown in Figure 3 that three eigenvalues used to assume for 3 principal components in PCA.

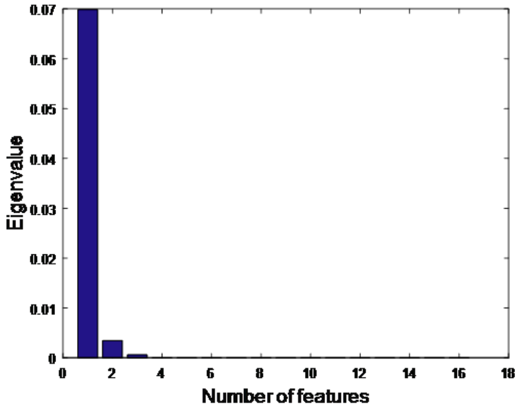

FIGURE 3. Eigenvalue of 16 features in sequence

The 16 features were reduced into 3 principal components. The principal components are plotted in 3-dimensional axis, where x-axis is principal component 1 (PC1), y-axis is principal component 2 (PC2) and z-axis is principal component 3 (PC3). It can be seen from Figure 4 and 5 the hand gestures are separated and can be distinguished clearly.

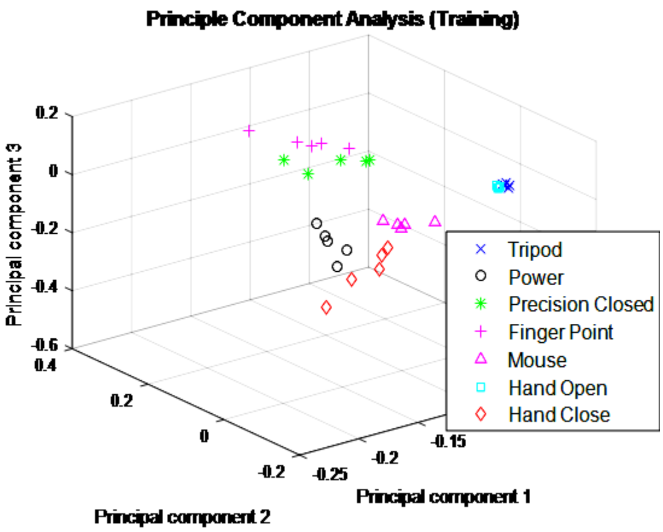

FIGURE 4. Three principal components of EMG seven hand gesture signals dataset training

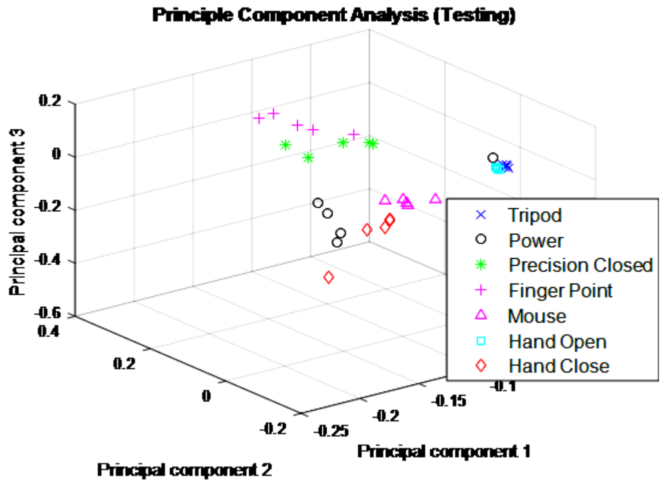

FIGURE 5. Three principal components of EMG seven hand gesture signals dataset testing

Prior to SVM classification, the best two principal components were selected as an input features initially. The best principal component was a pair of principal component 1 (PC1) and principal component 2 (PC2). The features dataset was divided into two that are training datasets and testing datasets. In training process, the feature was then classified using SVM equation with radial basis function (RBF) as a kernel function. The classification result which include the hyperplane that separate hand gestures is shown in Figure 6. Each area separated by the hyperplane indicates a species hand gesture. It can be seen from Figure 6 than some features are located in different area e.g. Hand Close and Precision Closed. This result to the decrease the of the classification accuracy.

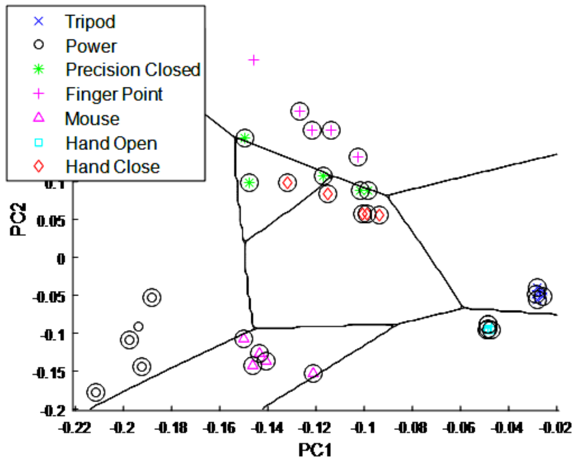

FIGURE 6. Dataset of training with hyperplane in SVM

The classification accuracy is presented in Table 1. The SVM classification was tested in 5 subjects. The five subjects show the classification accuracy of range from

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85.7% to 88.57%. Once the model of SVM classification was obtained, the testing feature datasets were classified in the testing process. The result of testing process is presented in Figure 7. In addition, Figure 7 shows that some of the Hand Close and Precision Closed features were still located in different area. The accuracy of testing process achieved 80% - 85.71%. The *k* for cross validation parameter was tuned from small to high number. The optimized value of *k* is selected as 900.

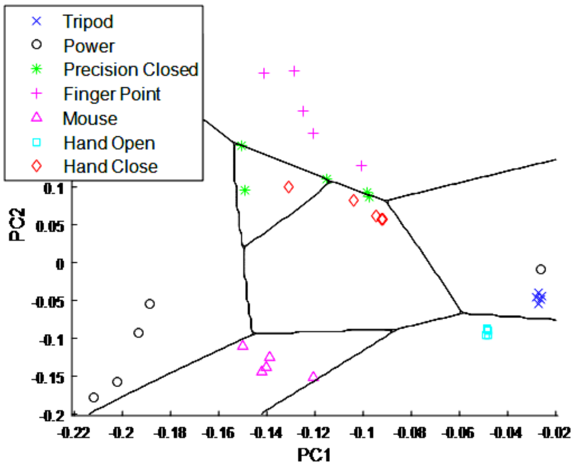

FIGURE 7. Dataset of testing with hyperplane in SVM

TABLE 1.
Accuracy of training and testing in SVM

Subject	1	2	3	4	5
Train	88.57%	85.71%	88.57%	85.71%	88.57%
Test	82.86%	80%	80%	85.71%	80%

4. CONCLUSION

EMG signal processing using pattern recognition method that includes (1) features extraction, (2) features reduction, and (3) features classification has been presented. Each of training and testing data are processed using 16 features extraction in time–domain. The 16 features are reduced using principal component analysis (PCA) to obtain new set of features. Features classification using support vector machine classify new set of features from each subject result 85% - 89% percentage of training classification. Training data classification is tested using testing data of EMG signals. The accuracy result varies from 80% to 86%.

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