

Hand Gesture Classification Using Emg Signal

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Abstract—The art of gesture recognition involves identification and classification of gestures. A gesture is any reproducible action or a sequence of actions. There are lots of techniques and algorithms to recognize gestures. In the project, gestures are recognized using biological signals generated by the human body. There are many biological signals that can be used for gesture recognition. Some of them are Electroencephalogram (EEG), Electrocardiogram (ECG), and Electromyogram (EMG). EMG signals are generally used because they have good signal strength (in the order of mV). Thus we use emg signal as the acquisition of EMG signals is easy and less complex as compared to the above mentioned signals. Five different gestures such as Six features such as . root mean square, mean, standard deviation, variance, maximum and minimum values are extracted from the emg signals. The classifier used under the study is SVM , giving classification accuracy of 96.8%.

Keywords- emg ; feature extraction; svm;

I. INTRODUCTION

Gesture recognition is the process by which specific movements executed by a user are used to convey information or to control an external device. Hand gesture recognition has numerous applications for human-machine interaction. Decoding hand gestures based on pattern recognition of biosignals are becoming increasingly important in many clinical and research applications, such as personalized health systems, robotic assisted physiotherapy, rehabilitation applications, and active control of prosthesis devices.

EMG is the signal produced when a muscle expands or contracts. This appears as a potential difference on the surface. By tapping the surface we can get an EMG for the particular gesture or action performed.

The myo-signals generated by the body have to be acquired into the system for processing and classification. The small electrical signal which comes from the active muscles is detected by electrodes placed on the skin directly above the muscles. The procedure that measures the muscle activity from the skin is referred to as sEMG.

The features used in this project are the RMS value, mean, standard deviation, variance, maximum and minimum values from the emg signals.

Support Vector Machines is a tool that is frequently used in order to classify a particular input data into various groups. The confusion matrix for the SVM classifier shows that it gives an accuracy of around 96%. The values have been taken for fifty training samples.

It was carried out a set of experiments to classify five movements at the upper-limb level. Five classes of individual fingers movements were implemented including: the flexion of each of the individual fingers, i.e., Thumb (T), Index (I), Middle (M), Ring (R), Little (L).

II. METHODOLOGY

The block diagram is shown in the figure below.



Fig.1. block diagram

The first step is data acquisition. It involves recording and reading of the emg signals. The input signal is processed and features are extracted. six features were extracted i.e. root mean square, mean, standard deviation, variance, maximum and minimum values of the given EMG signals. The feature vector is then given to the classifier. SVM classifier is used, the output of which is the predicted class.

III. DATA ACQUISITION

[1] Eight subjects, six males and two females, aged between 20 and 35 years were recruited to perform the required fingers movements. The subjects were all normally limbed with no

neurological or muscular disorders. All participants provided informed consent prior to participating in the study. Subjects were seated on an armchair, with their arm supported and fixed at one position to avoid the effect of different limb positions on the generated EMG signals (Scheme, Founger, Stavdahl, Chan, & Englehart, 2010). The EMG data was collected using EMG channels (Delsys DE 2.x series EMG sensors) and processed by the Bagnoli Desktop EMG Systems from Delsys Inc. A 2-slot adhesive skin interface was applied on each of the sensors to firmly stick the sensors to the skin. A conductive adhesive reference electrode (Dermatode Reference Electrode) was utilized on the wrist of each subject. The positions of these electrodes are shown in Fig.3. The EMG signals collected from the electrodes were amplified using a Delsys Bagnoli-8 amplifier to a total gain of 1000. A 12-bit analog-to-digital converter (National Instruments, BNC-2090) was used to sample the signal at 4000 Hz; the signal data were then acquired using Delsys EMGWorks Acquisition software. The EMG signals were then bandpass filtered between 20 and 450 Hz with a notch filter implemented to remove the 50 Hz line interference.



Fig.2. Fingers movements



Fig.3. placement of the electrodes

IV. FEATURE EXTRACTION

Feature extraction involves reducing the amount of resources required to describe a large set of data. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power, also it may cause a classification algorithm to overfit to training samples and generalize poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy.

The myo-signals generated by the body have to be acquired into the system for processing and classification. six features were extracted i.e. root mean square, mean, standard deviation, variance, maximum and minimum values of the given EMG signals.

A. Root mean square:

Root mean square (RMS) is another popular feature in analysis of the EMG signal (e.g. Boostani & Moradi, 2003; Kim et al., 2011). It is modeled as amplitude modulated Gaussian random process whose relates to constant force and non-fatiguing contraction. It is also similar to standard deviation method

the root mean square (abbreviated RMS) is defined as the square root of mean square (the arithmetic mean of the squares of a set of numbers).^[2] The RMS is also known as the quadratic mean.

For a set of n numbers or values of a discrete distribution x_1, \dots, x_n , the root-mean-square (abbreviated "RMS" and sometimes called the quadratic mean), is the square root of mean of the values x_i^2 , namely

$$x_R = \sqrt{\frac{x_1^2 + x_2^2 + \dots + x_n^2}{n}}$$

$$= \sqrt{\frac{\sum_{i=1}^n x_i^2}{n}}$$

$$= \sqrt{\langle x^2 \rangle},$$

where $\langle x^2 \rangle$ denotes the mean of the values x_i^2 .

B. Mean:

Mean value is the integral of a continuous function of one or more variables over a given range divided by the measure of the range.

C. Standard deviation:

The standard deviation is a measure that is used to quantify the amount of variation or dispersion of a set of data values.^[3] i.e. Standard deviation is a measure of the dispersion of a set of data from its mean. It is calculated as the square root of variance by determining the variation between each data point relative to the mean.

The symbol for Standard Deviation is σ (the Greek letter sigma).

The formula for Standard Deviation is as follows:

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \mu)^2}$$

σ : standard deviation.

x : individual data point

μ : mean of data points

N : total number of data points

D. Variance of EMG

Variance is a measurement of the spread between numbers in a data set. The variance measures how far each number in the set is from the mean. Variance is calculated by taking the differences between each number in the set and the mean, squaring the differences (to make them positive) and dividing the sum of the squares by the number of values in the set.

$$\sigma^2 = \frac{\sum (X - \mu)^2}{N}$$

σ^2 : variance.

X : individual data point

μ : mean of data points

N: total number of data points

Variance of EMG (VAR) is another power index (e.g. Park & Lee, 1998; Zardoshti-Kermani et al., 1995). Generally, variance is defined as an average of square values of the deviation of that variable; however, mean value of EMG signal is close to zero (10^{-10}). Hence, variance of the EMG signal can also be defined as

$$VAR = \frac{1}{K-1} \sum_{m=1}^K X_m^2$$

E. Maximum:

The value of the function at a maximum point is called the maximum value of the function.

F. Minimum:

The value of the function at a minimum point is called the minimum value of the function.

V. CLASSIFICATION

Support Vector Machine

In machine learning, support vector machines (SVMs, also support vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. Given a set of training examples, each marked as belonging to one or the other of two categories, an SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall.

In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

When data are not labelled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups, and then map new data to these formed groups. The clustering algorithm which provides an improvement to the support vector machines is called support vector clustering and is often used in industrial applications either when data are not labeled or when only some data are labelled as a pre-processing for a classification pass.

Support vector machine basically deals with pattern classification which means that this algorithm is mainly used for classifying the different types of patterns. The main aim of SVM is to maximize the margin hence the SVM can correctly classify the given patterns.

VI. RESULTS AND CONCLUSION

The scatter plot for the six features are shown.

Where X- axis denotes the category of finger movement and Y- axis denotes the features.

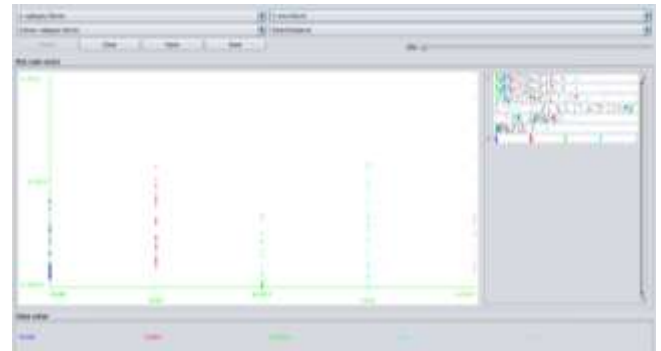


Fig.4. scatter plot for root mean square

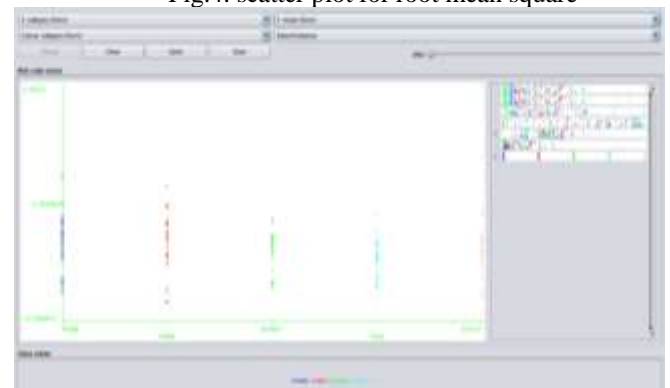


Fig.5. scatter plot for mean value

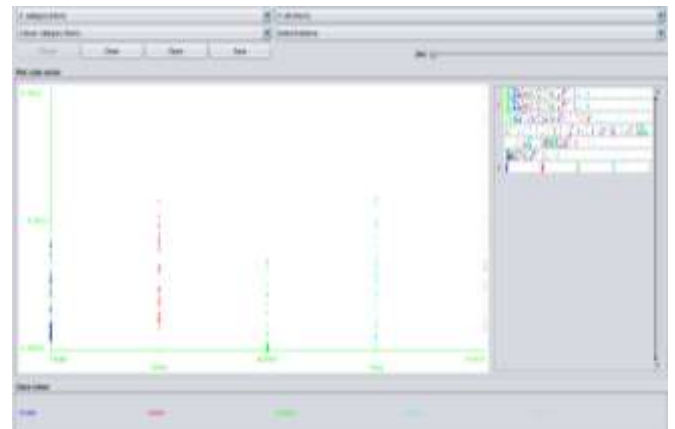


Fig.6. scatter plot for standard deviation

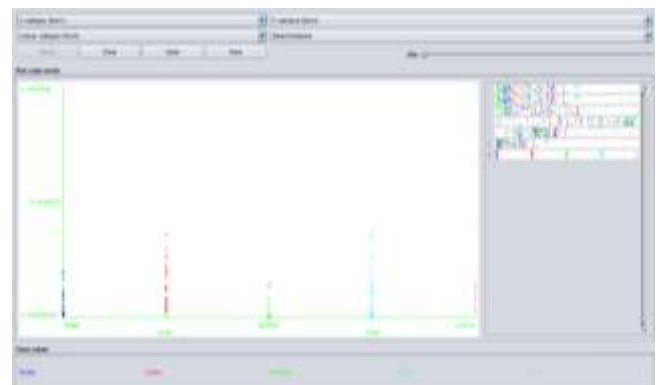


Fig.7. scatter plot for variance

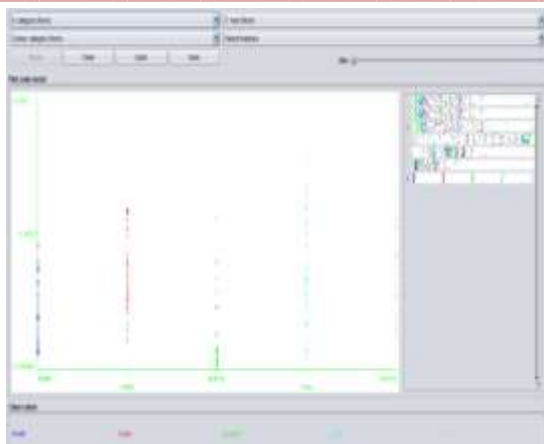


Fig.8. scatter plot for maximum value

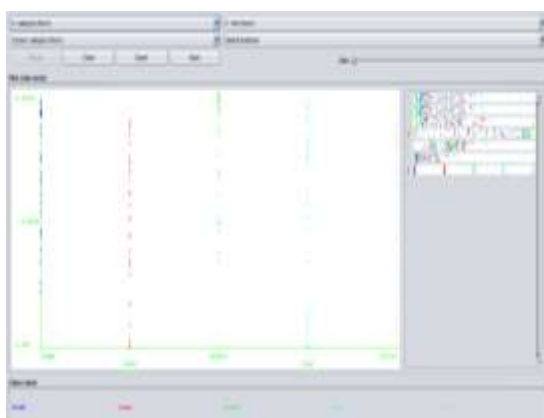


Fig.9. scatter plot for minimum value

Result for svm classifier

The confusion matrix for svm classifier is given in figure below. The confusion matrix for the SVM classifier shows that it gives an accuracy of around 96%. The values have been taken for fifty training samples.

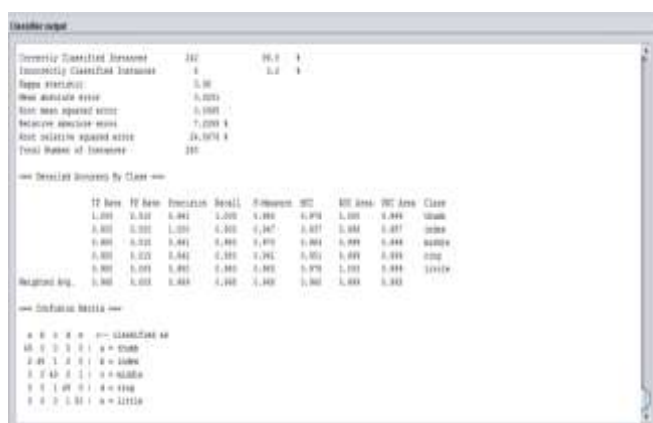


Fig.10. confusion matrix for svm classifier

It can be seen from the above classifier output that out of the total 250 signals 242 signals are correctly classified with accuracy of 96.8% and only 3.2% or 8 signals from the total 250 signals are classified incorrectly.

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