

Synchronous Emotion Pattern Recognition with a Virtual Training Environment

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Abstract - The use of Brain-Computer Interface (BCI) has been increasing exponentially in the recent years due to the use of low-cost commercial Fast Fourier Transform (FFT) based EEG headsets. The aim of this paper is to present a method and the results of applying binary Density Based Support Vector Machine (DBSVM) Classifiers in a 3D virtual environment designed for interacting with EEG predefined signal patterns. The environment trains the classifier by taking 180 second EPOCHs and classifying them into a successful/unsuccessful attempt per test subject. The test had a success rate of 80% for some of the obtained classifiers. Further work includes the study of different classifier features and implementation of a dynamic classifier. The target is to recognize a specific emotion pattern generated by a subject after learning his common wave pattern generations with the use of a 3D training application.

Keywords: BMI, MindWave, DBSVM, pattern recognition, Machine learning

1. Introduction

The use of FFT-BCI based 3D virtual environments has been implemented effectively in different application fields; it is rather a new technological tool, which may be exploited to enhance motor retraining [1].

A simple development with software like Unity3D can be combined with other assistance technologies or interfaces [2] in order to improve a specific system's performance with an end user's feedback.

These interfaces are either interacting with the preprocessed behavior signal output data stream from a processing IC with the aid of "slow adaptive algorithms" [3] like the TGAM1, or the RAW-EEG value obtained from an active electrode and then decomposed into a specific behavior according to the spectral density of the sample.

These main brain waves and frequency range for processing are specified in Table 1 [4].

There are algorithms that focus on detecting a specific emotion from the end user according to their mind-wave patterns.

Some of them can map and help to differentiate emotions like attention/inattention and meditation/uneasiness based on a simple beta/theta wave ratio [5].

Table 1: Basic human brain waves

Name	Frequency range [Hz]
Delta [δ]	0.5-2.75
Theta [θ]	3.5-6.75
Low alpha [$l-\alpha$]	7.5-9.25
High alpha [$h-\alpha$]	10.0-11.75
Low Beta [$l-\beta$]	13-16.75
High Beta [$h-\beta$]	18-29.75
Low Gamma [$l-\gamma$]	31-39.75
Mid Gamma [$m-\gamma$]	41-49.75

This paper describes the implementation and results of a Density Based Support Vector Machine Classifiers from a series of training data sets obtained from a 3D environment with the use of a different set of common-use kernels.

The classifiers' input data are a binary set of 180 long signal vectors (EPOCHs) corresponding to the preprocessed attention and meditation outputs from a one dry electrode EEG headset with the configuration as shown in Figure 1.

The aim of this research is to elaborate a method for recognizing mind behavior patterns for a synchronous password application development.

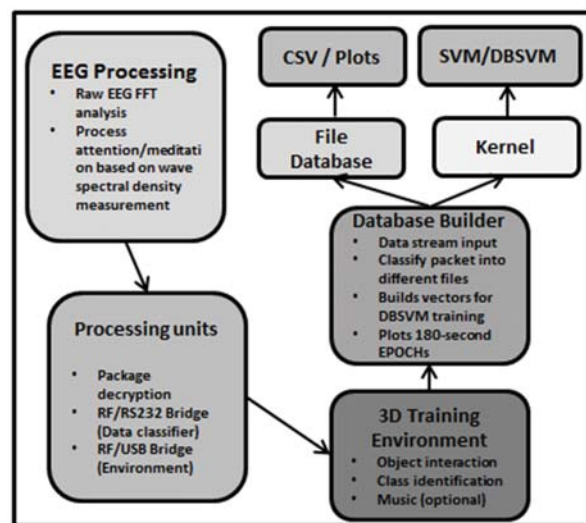


Figure 1: System description

2. Density Based Support Vector Machines

Machine learning techniques are generally helpful in feature extraction among EEG signals, since the recorded signals usually tend to have variable bias and uncertain changes, which make the feature classification difficult. The Support Vector Machine (SVM) model proposed by Dr. Vapnik has been used as a form of supervised learning models (SLM) in detecting certain features in the captured EEG data and in many other systems [6].

However, the sensitivity of SVMs to outliers is a weak point for this algorithm. One of the approaches for reducing this sensitivity is the Density Based Support Vector Machine (DBSVM) method, which is based in the simple expression of population density according to Equation (1) [7]:

$$\text{Population density} = \frac{\text{number of population}}{\text{area}} \quad (1)$$

Although the concept of population density is used to develop the DBSVM model, the formula is actually based on two separate algorithms. The removal of outliers is based on comparing a vector's total Euclidean or Mahalanobis distance between the average distances of the mapped vectors [8].

2.1 Outliers

Outliers are unusual data points that are inconsistent with other observations. In statistics an outlier is an observation with an abnormal distance from most observations.

Generally presence of an outlier may cause some sort of problems. An outlier may be due to gross measurement error, coding/recording error, and abnormal cases, but a frequent cause of outliers is a mixture of two distributions and they can be occur by chance in any distribution[9].

2.2 DBSVM with Mahalanobis Distance

The Mahalanobis distance is the distance between the x from the quantity μ . This distance is based on the correlation between variables or the variance-covariance matrix S .

For instance, let's suppose a set of n numbers of two-dimensional data $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$ is given. The Mahalanobis distance between two points is given by Equation (2):

$$D_m(x) = \sqrt{(x - y)^T S^{-1} (x - y)} \quad (2)$$

The next step is to sum up all the distances for each point (i.e. $d_1 = [D(1,2) + D(1,3) + \dots + D(1, n)]$) where n is the number of data points in the data set.

The total distance for all data points of one data set is needed to calculate the average distance that will be used to determine data points inside and outside of densely populated area. Equation (3) shows the expression to calculate this:

$$\text{Average}_d = \frac{\sum_{i=1}^N \sqrt{(x_i - y_i)^T S^{-1} (x_i - y_i)}}{n} \quad (3)$$

$$\text{if } d_i > \text{Average}_d \rightarrow x_i = \text{outlier}$$

After calculating Average_d by formula, those points that are not considered as outliers will become the new training data set in which the points will be considered important data points.

2.3 DBSVM with Euclidean distance

The Euclidean distance between two points is given by Equation (4):

$$D(1,2) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (4)$$

Therefore, as used for the Mahalanobis Distance average calculation, the average distance for excluding outliers is as described in Equation (5):

$$\text{Average}_d = \frac{\sum_{j=1}^N \sum_{i=1}^N \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}}{n} \quad (5)$$

The data sets obtained from the training environment will be tested with both population density methods for success rate comparison with hard margin SVMs. The application of this method can help for having a maximized margin and a better generalization of the EPOCH mapped values from the signal vector transformation.

3. The 3D training environment

The use of simulators for training with EEG Biofeedback is a common application and has been proven effectiveness in solving problems such as attention enhancement [10].

The proposed training environment was designed with the use of Blender for the animated models and structures and Unity3D for its ease of use and deployment. The environment has a series of features such as music and interaction with the experiment variables that are described as follows.

The environment setup was created for the test subjects to familiarize with the objects and understand the way of interacting with them; an additional relaxation music track can be used for aiming in obtaining higher meditation behaviors.

The purpose of the training task is to guide the player (training subject) throughout the predefined path, as specified in Figure 2.

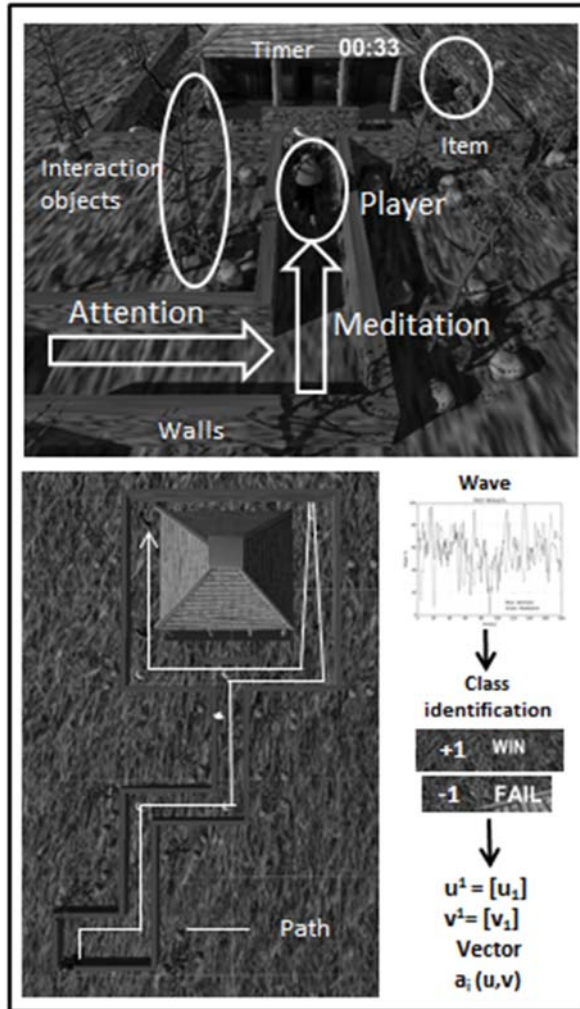


Figure 2: Environment description

When concentrated, the user can move the player forward and then move the player to the right if the user begins to enter meditation. In either case, the user can stop the player by blinking the eyes constantly until the player stops due to the artifact noise produced across the path, there are four main items that the subject requires to obtain.

If the series of mind-waves came into the expected pattern in the required time, the attempt will be classified as successful and the class $+1$ will be labeled for the output EPOCH. However, if the test subject is not able to perform the entire track along the timeframe, an unsuccessful attempt is recorded with the -1 label. The resulting vectors will be used as samples for later mapping in the SVM classifier.

Brain waves are dependent on each test subject, and so the performed wave patterns and headset calibration. Due to this factor, the training requires to be performed individually. Fortunately, the device has

a fast self-calibration routine [11] and a trained subject can easily adapt in controlling the headset in minutes. In order to have a good classifier, 30 samples were obtained from the test subject. In the case it is complicated to generate the attention or meditation patterns, the use of the additional music tracks can stimulate the brain for generating the necessary beta or alpha waves for the device.

The testing area was a quiet room with the test subject sitting in front of a screen displaying the 3D environment and the data processing script running in the background for obtaining the corresponding data sets. Whenever the test subject was ready to perform a test a red button was pressed to restart the environment and script.

4. Results

Once the test was performed, as there are two outputs from each result, matrix A consisting of attention values and matrix M with meditation values. Feature F from Equation (6) was used to relate both matrices:

$$F = \left[\frac{A^2(A-M)}{A+M} \right] \quad (6)$$

Assuming the condition if $A_i = -M_i$, $F_i = 0$ for avoiding division by zero. Once the matrices have been associated with the feature, the PCA matrix P is obtained for matrix F . The two main components the transform matrix B generated by Equation (7) were used to map the outputs in the two-dimensional space.

$$FP = B \quad (7)$$

For example, the first component of the first row of the matrix will be the x coordinate and the second component will be the y coordinate. The resulting hard margin SVM classifiers are presented in Figure 3.

The kernels that were used are the linear, RBF and polynomial degree 3. The LinearSVC kernel uses a different code library that allows a more flexible modeling and better choice of penalties and loss function scaling [12].

Once the DBSVM has been set, there was a test vector consisting of five test elements F_i , with their respective class label. This time the mapping coordinates were obtained by using the PCA matrix P described by Equation (7).

The corresponding success rate chart is described by Table. The performed classification had a success rate of 80% success for the test vector on the LinearSVC implementation.

The classification success rate for the test data set could be augmented if a soft margin is implemented.

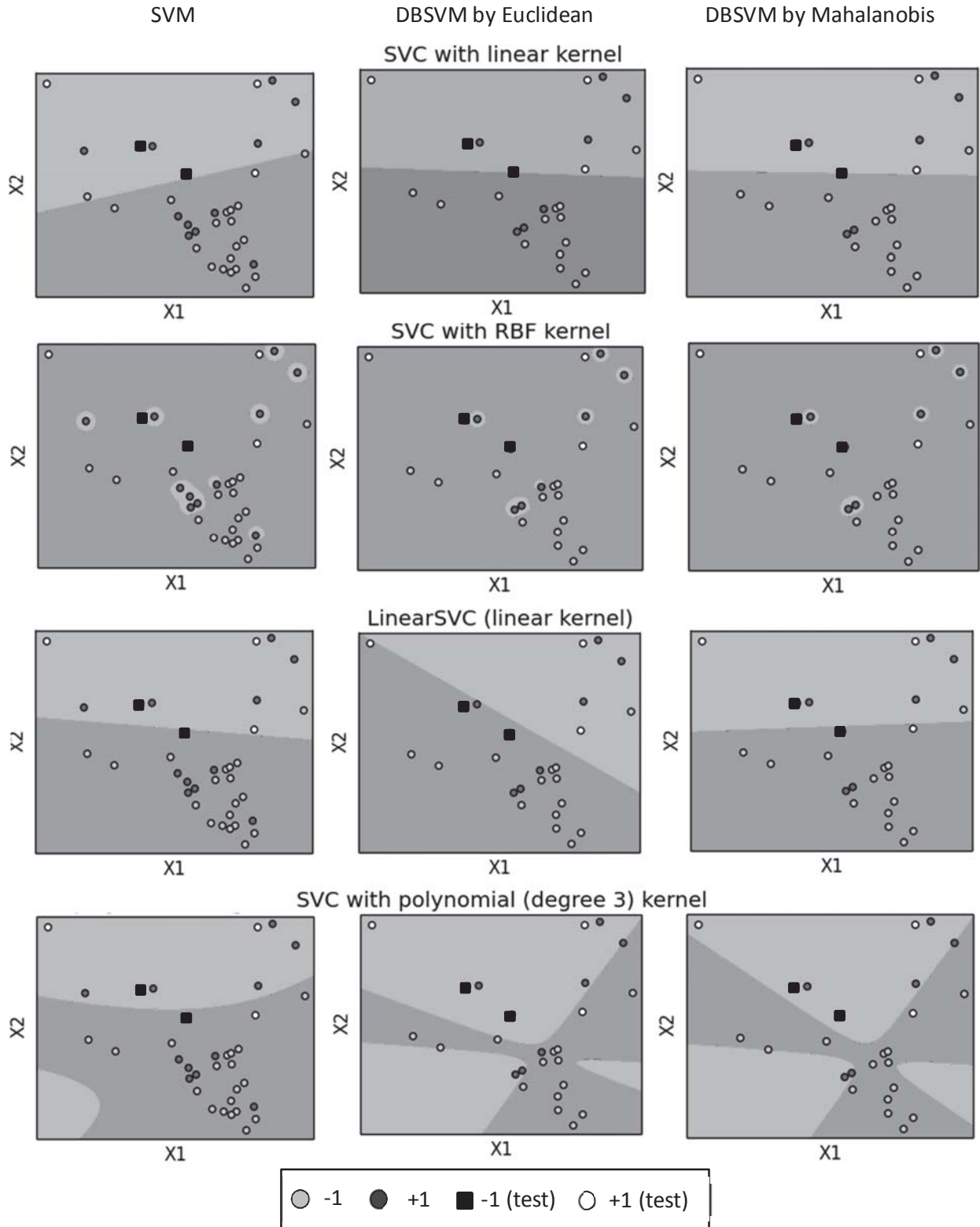


Figure 3: SVM and DBSVM classifiers

Table 2: SVM Classification success rates

<i>Kernel</i>	<i>Normal</i>	<i>Euclidean</i>	<i>Mahalanobis</i>
Linear	20%	60%	60%
RBF	40%	40%	40%
LinearSVC	80%	80%	60%
Polynomial	60%	20%	20%

5. Conclusions

This paper presents a way to use the Density Based Support Vector Machine Classifiers for a synchronous mind pattern classification problem. One of the main disadvantages the SVMs is the selection of a particular feature that can reduce the classification error. By choosing the correct feature, data sets can be condensed in specific regions and clusters in which the Euclidean and Mahalanobis outlier discrimination algorithm can perform as expected.

For this particular problem, the selected feature was the one that worked best after trying various models with the use of PCA. There can be other mapping approaches that can be performed based on the Attention/Meditation signal correlation. The use of a more flexible linear kernel for the training could obtain a higher learning rate without soft margin. If soft margin was included, the learning success would be 100%. However, the number of test vectors should be increased for a better test accuracy.

However, the use of the raw EEG data sets could represent a better way for classification derived from training.

The performed test demonstrates the effective use of low-cost, single electrode commercial FFT-based EEG headsets for simple classification tasks with the aid of a simple training environment with optional music feedback. Nonetheless, it is important to choose a specific feature to reduce the error.

6. Further work

From the DBSVM, a more specific feature will be determined based on the Attention/Meditation wave behaviors on the obtained EPOCHs. The resulting classifier will be used with different test vectors that will be based on performing in the training environment; by either moving the player or imaging the player's relative position and movement.

If successful, the end user will be performing an Attention/Meditation pattern recreation without the aid of the environment. This will be performed by the end user with the use of single and multiple channels FFT based EEG tools for performance analysis.

Also, the use of Independent Component Analysis for Raw EEG data will be implemented for different brain regions in order to generate a better feature based on specific active electrode positions.

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