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Prediction of Evoking Frequency from Steady-State Visual Evoked Frequency

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Abstract

The Brain-Computer Interface (BCI) is a system that enables individuals who cannot use the existing muscle and nervous system because of various reasons to communicate with the environment. Steady-state visual evoked potentials (SSVEP) from EEG signals have gained wide research interest due to their high signal-to-noise ratio and higher information transfer rate compared to other BCI techniques. Therefore SSVEP plays a major role in practical applications. In this study, the data set (AVI SSVEP Dataset) obtained through open access from the Internet (www.setzner.com) was analyzed. In the dataset, electroencephalography (EEG) signals were recorded in which the participants were looking at a flickering box at eight distinct frequencies (6, 6.5, 7, 7.5, 8.2, 9.3, 10 and 12 Hz) whose color changes rapidly from black to white. We extracted twenty-five features containing only time-domain properties from SSVEP signals to predict which frequency was applied to the subject. These features were applied to classifiers of Decision Tree, Discriminant Analysis, Naive Bayes, Support Vector Machines, k-Nearest Neighbors, and Ensemble Classifiers. We obtained the maximum accuracy of 42.9% for each subject separately. When we evaluate all subjects using the same classifier, we achieved a 20% accuracy. K-Nearest Neighbors and Ensemble Classifier give the best classification performance in all experiments in this study.

Keyword(s): Brain-computer interface, Steady-state visual-evoked potential, EEG, Evoking frequency detection.

Introduction

The Brain Computer Interface is a system and a research topic aimed at controlling various electronic devices by interpreting and interpreting human brain activity. With this interface, it is possible for individuals who are unable to control a part of their body due to paralysis or similar diseases but who are conscious, can communicate with the outside world and control the robot arm, wheelchair, computer and similar devices with thought power [1]. In general, the basic building blocks of this system based on the perception of some neurophysiological phenomena in the brain are bioactivity measurement software and hardware, signal processing methods and classification algorithms. Although EEG-based BCI studies around the world have a history of thirty years, SSVEP-based BCI studies are much more recent and less researched [2, 3].

Electroencephalography (EEG) signals are the most widely used signal types for BCIs because of their portability and ease of application. There are four typical EEG-based BCI paradigms: steady-state visually-evoked potentials (SSVEPs), slow cortical potentials (SCPs), the P300 component of stimulated potentials, and sensory motor rhythms (SMRs) [4]. The SSVEP signal is the response to a visual stimulator modulated at a frequency greater than 6 Hz [5] (or higher than 4 Hz [6]). The amplitude and phase characteristics of SSVEPs depend on the stimulus intensity and frequency. SSVEP-based BCIs have become a popular research area due to many advantages over other BCI systems, including higher signal-to-noise ratio (SNR) and faster information transfer rate (ITR). In the SSVEP-based BCI system, the participant is shown visual stimuli flashing at different frequencies. When the participant focuses on one of these stimuli, patterns may be observed in oscillating regions of the brain that show oscillations at the same frequency as the focused stimulus [6]. In this way, when different stimuli are differentiated, a simple computer interface enables the control of various electronic systems.

In the literature, various signal processing techniques have been used to convert SSVEP signals to BCI control signals. These techniques can be examined in three steps. The first is the signal enhancement step. In this step, the signal quality is improved by applying sampling, filtering, artifact removal and similar techniques. In the second step, the feature extraction, the information required for the BCI application is obtained from the data set. The final step is classification, in which the recorded signals are divided into various classes using the features obtained in the previous step.

In this study, signal processing analyzes were performed on data set (AVI SSVEP Dataset) obtained through open access from internet. In the data set, electroencephalography (EEG) signals were recorded in which the participants were looking at a flashing box at eight different frequencies (6, 6.5, 7, 7.5, 8.2, 9.3, 10 and 12 Hz) whose color changed rapidly from black to white. Twenty-five feature vectors containing time domain features were extracted to classify patterns generated by eight different frequencies in the image-related region of the brain, and SSVEP signals are classified into six basic classifiers. The classification results obtained were evaluated systematically and classifier performances were compared with each other. Classifier performances were evaluated by constructing a 10-fold cross-validation model and subtracting the error matrix.

Materials and Methods

Data Set Introduction

In this study, Adnan Vilic's steady-state visually-evoked potential data set (AVI SSVEP Dataset) was used [7]. In the data set, it is a free data set containing EEG measurements of healthy participants looking at the flashing target to trigger SSVEP responses. All data were recorded using three electrodes (Oz, Fpz, Pz). Using the standard 10-20 system for electrode placement, the reference electrode is positioned as Fz, the signal electrode as Oz and Fpz as the ground electrode. The reference and ground can be adjusted to other positions such as ear lobes and / or mastoids. Impedances are kept at 5kΩ or less. The amplifier used is g.USBamp from g.tec (Guger Technologies) set to a sampling rate of 512 Hz. Figure 1 shows the electrode cap used for all experiments and the layout of the electrodes. Figure 2 shows the hardware installation of the BenQ XL2420T LCD display with a 120 Hz refresh rate used in the experiments. The contrast and brightness were set to maximum and the screen brightness of 350 cd / m2 was achieved. The resolution is 1680x1050 pixels. The targets presented to the participants have an area of 2.89 cm2. The stimulus application was developed in Microsoft Silverlight and runs on a Windows 8 PC. The only process applied to the data is an analogue notch filter at mains frequency (50Hz).

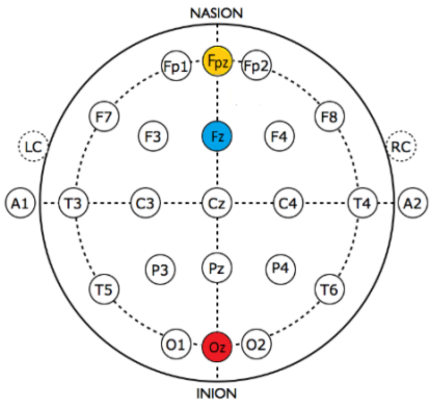

Figure 1 – International 10-20 electrode placement [7]

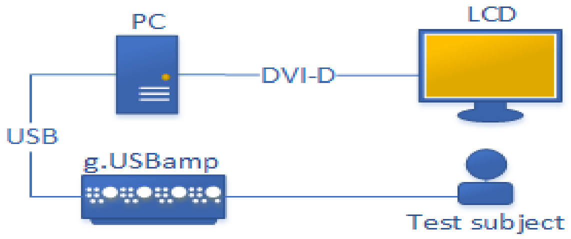

Figure 2 – Hardware installation for experiments [7]

In this experiment, participants were seated 60 cm away from a monitor where they looked at a single flashing target whose color changed rapidly from black to white. The stimulus of the experiment is a flashing box at 8 different frequencies (6, 6.5, 7, 7.5, 8.2, 9.3, 10 and 12 Hz) presented on the monitor. The data set consists of four sessions with four different participants. Each trial in a session lasts 30 seconds and participants take a short break between trials. Experiments were repeated at least 3 times for each frequency. Table I presents a list of some physiological data (gender and age) of healthy individuals participating in the experiment.

Table 1 –List of SSVEP test participants

List of Participants in Single Target Stimulation				
Participant	1	2	3	4
Gender	Male	Male	Male	Female
Age	32	27	27	31

Feature Extraction

Time and frequency information of EEG signals is used to generate feature vectors in steady-state visually-evoked potential based brain computer interface systems [8, 9]. Feature extraction uses the distinctive features of SSVEP signals to interpret and identify the purpose of controlling an individual's brain signals and an external electronic device. In other words, feature extraction is the process of extracting important features from the obtained SSVEP data and obtaining feature vectors [10].

In this study, time domain informations of the signals were used as feature vectors and feature vectors containing twenty-five different statistical properties were created. These features [10-14] are listed in the following table (Table 2):

Table 2 – Features extracted from SSVEP data

No.	**Features**	**No.**	**Features**
1.	EEG minimum value	***14.***	Kurtosis of EEG signal
2.	EEG maximum value	***15.***	EEG signal skew
3.	EEG average value	***16.***	Hjorth identifiers: 1) Activity
4.	EEG standard deviation value	***17.***	Hjorth identifiers: 2) Mobility
5.	Integrated EEG value	***18.***	Hjorth identifiers: 3) Complexity
6.	Average absolute value	***19.***	Signal range (max-min.)
7.	Simple square integral value	***20.***	Inter-quarter intervals 1st Quarter
8.	EEG variance value	***21.***	Inter-quarter intervals 2nd Quarter

9.	Root square average value	***22.***	Inter-quarter intervals 3rd Quarter
10.	Wave shape length value	***23.***	Zero-crossing
11.	Average amplitude change value	***24.***	Slope-change value
12.	Mode value of the signal	***25.***	Maximum fractal length
13.	Absolute difference in standard deviation		

Classification

In order to recognize an EEG signal and convert it to a command, that is to use it as an output, classification is performed after the feature extraction [15]. For the classification process, the datasets formed by a certain number of feature vectors known to which class belong to are passed through a training process. As a result of this training, a decision mechanism is used to assign the unknown sign to the appropriate class [16, 17].

In this study, feature vectors extracted from SSVEP signal were classified with six basic classifiers and a total of twenty four different classification methods were tried due to the different sub-parameters of the classifiers. These classifiers can be listed as follows:

1) Decision Trees

-Fine Tree, -Medium Tree, -Coarse Tree

2) Discriminant Analysis

-Linear Discriminant, - Quadratic Discriminant

3) Naive Bayes Classifier

-Gaussian Naive Bayes, -Kernel Naive Bayes

4) Support Vector Machines-SVM

-Linear SVM, -Quadratic SVM, -Cubic SVM,

-Fine Gaussian SVM, -Medium Gaussian SVM, -Coarse Gaussian SVM

5) k-Nearest Neighbour-KNN

-Fine KNN, -Medium KNN, -Coarse KNN, - Cubic KNN, - Cosine KNN, - Weighted KNN

6) Ensemble Classifier

-Bossted Trees, - Bagged Trees, - Subspace Discriminant, - Subspace KNN, - RUSBoosted Trees

Evaluating Classifier Performances

In this study, k-fold cross validation and confusion matrix evaluation criteria were used to evaluate the performance of the classification algorithms used.

k - fold cross validation: The purpose of separating the data set as a training and testing set is to avoid possible overfitting and to understand how the model performs on a data set that it has not seen before. However, there may be some errors due to data distribution during the training and testing phase of the model. To minimize these errors, the k-fold cross-validation technique is used. The training divides the data set into random k segments. k-1 is used for training, 1 part is used for test set and this process is repeated k times. The values obtained at each iteration are summed and averaged. In this way, the performance of the model is evaluated [14].

In this study, the data set is divided into 10 equal parts. At each iteration, the blue painted area was allocated to the test set, while the other parts were reserved for training. At the end of each iteration, the performance values from the classifier were recorded in E variable. When all the iterations were over, the arithmetic mean of E showed the performance of our model.

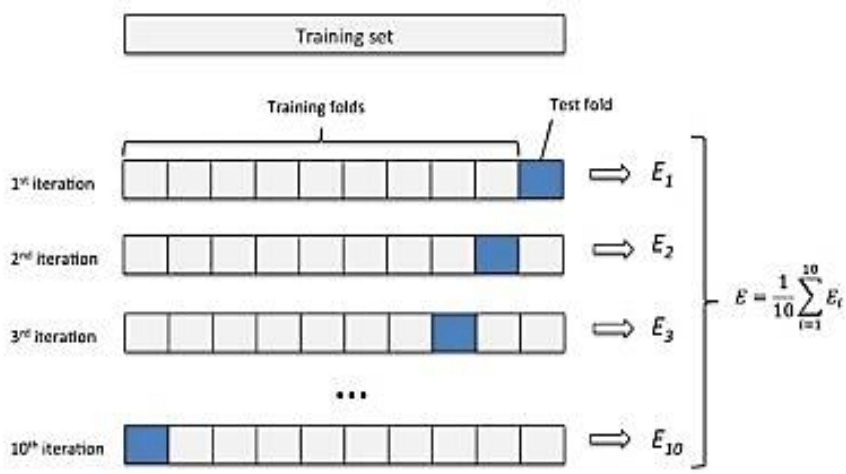

Figure 3 – 10-fold cross validation model used in classification

Confusion matrix: Another criterion used to evaluate the performance of the classifier is the confusion matrix. It is a table with four different combinations with predicted and actual values. The following are formulated as accuracy (ACC), sensitivity (SEN) and specificity (SPE), respectively [18, 19]:

$$\mathrm{ACC} = \frac{\mathrm{TP+TN}}{\mathrm{TP+FN+FP+TN}} \quad \text{(Eq. 1)}$$

$$\mathrm{SEN} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \quad \text{(Eq. 2)}$$

$$\mathrm{SPE} = \frac{\mathrm{TN}}{\mathrm{TN+FP}} \quad \text{(Eq. 3)}$$

The above formulas are expressed as accuracy (ACC), sensitivity (SEN) and selectivity (SPE), respectively. All values in the equations are calculated in Matlab environment using

’Confusion Matrix’. TP belongs to a class and represents the number of data assigned to the same class by the classifier and FN represents the number of data assigned to a different class in error. The number of data belonging to a different class and assigned to a different class by the classifier is represented by TN, and the number of data assigned by mistake to the same class is represented by FP [18, 19].

Results and Discussion

The SSVEP data used in this study were obtained from the “www.setzner.com” [7] site with the knowledge of the owner of the data set and the algorithms generated for the analyzes were tested using MATLAB program and the classification performance criteria were examined with the same program. The performance of each classification algorithm was evaluated using criteria of accuracy, sensitivity and selectivity. The time domain-specific parameters selected as features and the results of the classifier obtained from six basic classifiers are presented in Figure 4.

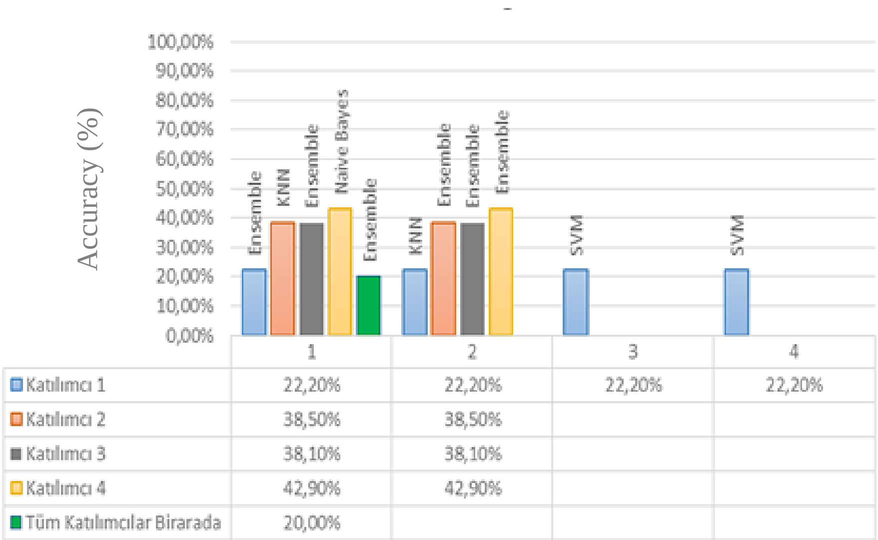

Figure 4 - Highest performance of classifiers (%)

Future studies that are not examined in this study and which will be added to the analysis section in future studies and which will increase the performance of SSVEP based BCI applications due to their classification performance are as follows:
- Filter design and application in accordance with signal characteristics in signal pre-processing step,
- Extracting the frequency domain and time-frequency domain features from the SSVEP signal,
- Feature selection and / or reduction.

Conflict of Interest: The authors declare that they have no conflict of interest.

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