Analysis of Visual Colour Perception using EEG Spectral Features

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Abstract

Electroencephalography signals are the electrophysiological measures of brain function and used to develop a brain machine interface (BMI). BMI system is used to provide a communication and control technology for the differentially enabled people having neuromuscular disorders. In this paper, a simple BMI system based on EEG signal emanated while visualizing of different colours has been proposed. The proposed BMI uses the color visualization tasks (CVT) and aims to provide a communication link using brain activated control signal. For each EEG signal, using spectral analysis, alpha, beta and gamma band frequency statistical spectral features such as spectral energy, mean spectral energy and standard deviation spectral energy are obtained. The extracted features are then associated to different control signals and a probabilistic neural network model has been developed to observe the classification accuracy of this three features.

Keywords— Spectral Features, Brain Machine Interface, Colour Visualization Tasks, Neural Network.

I. Introduction

Electroencephalography (EEG) is defined as an electrical activity recorded from the scalp using surface electrodes [1]. EEG signals are the electrophysiological measures of brain function. While performing visual, mental and physical actions, EEG signals are produced. Thus the difference in EEG signals while performing various actions helps us to develop a brain machine interface (BMI). BMI is a system that provides communication link between the human brain and a digital computer. BMI aims to help the people who are suffering with neuromuscular disorders such as paralysis, quadriplegics, amyotrophic lateral sclerosis brain stem stroke, and spinal cord injury to drive computers directly by brain activity rather than by physical means. In recent years many research works have been carried out in developing BMI systems and it is mainly involved in recording an EEG signals using surface electrodes [2]. Many significant technological advancement have occurred in the past decade towards developing a BMI, such as using visual evoked potential (VEP), slow cortical potential (SCP), P300 evoked potential, sensorimotor activity mental tasks and multiple neuromechanisms [3-6]. Few researchers have investigated the effect of colour on the EEG signal activity and analyzed whether different colours affect can the behavior of EEG signals [7]. Using this theoretical concept, the BMI using CVT has been proposed and analyzed to help the differentially enabled people.

In this paper, a simple protocol has been proposed for visualization of different colors namely black, blue, cyan, green, magenta, red, white and yellow. As a preliminary of the research, these eight colours were chosen as it emanates high brain activity responses [7]. The features corresponding to the alpha, beta and gamma bands were

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extracted from the EEG signals using spectral energy entropy. The extracted features are fed as input to probabilistic neural network (PNN) model. The block diagram of the proposed BMI system is shown in Figure 1. The rest of the paper is organized as follows: Section II describes the data collection and feature extraction method. Section III illustrates the designed network model and its performances. Section IV and V presents the results and conclusion, showing the potential of EEG signals derived from vision perception for BMI.

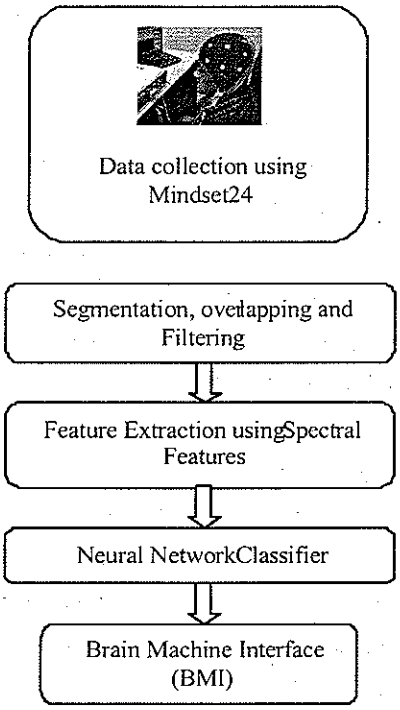

Figure 1. Block diagram of proposed BMI system

II. Feature Extraction

A. Protocol and Data Collection

EEG brain signals were recorded using the Mindset-24 topographic neuro-mapping instrument along with an electrode cap [8, 9]. This instrument is also called as 1.5 to 34 Hz data acquisition system. Ten healthy volunteers (10 men), aged between 21 and 25, have participated in this experiment. All the ten subjects had no prior experience in EEG experiments. The subjects were requested to get seated in a silent room and also requested not to make any overt movement while performing the CVT. A 19 channel (FP1, FP2, F7, F3, FZ, F4, F8, T3, T5, C3, CZ, C4, T4, T6, P3, PZ, P4, O1 & O2) electrode cap was used for recording the brain signals from the scalp as per the 10-20 system of electrode placement [10] and the measurements were made with reference to electrically linked mastoids, A1 and A2. A 19 channel electrode cap along with the internal 10-20 electrode positions are shown in Figure 2.

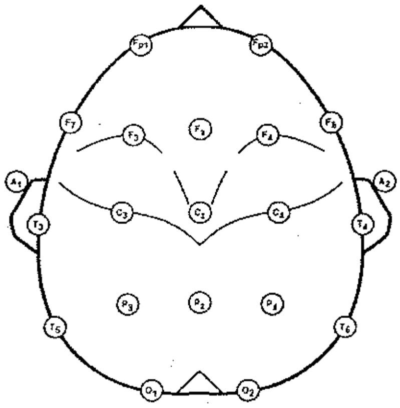

Figure 2. Electrode position from International 10-20 Standard [10]

In the experimental study, the subjects were asked to perform eight different CVTs and their corresponding EEG signals were recorded. All the subjects were free from illness at the time of EEG recording. Before starting the data collection, the data collection procedures were explained clearly to the subject. The subjects were seated comfortably in front of a color LCD monitor and were asked to view the displayed colors. All the ten subjects were asked to view the colour screen in a relaxed condition during the data collection. Before starting the real data collection, for each colour task, a sample data collection was conducted to find the difficulties in performing the tasks and a feedback was also obtained from the subjects. Each color was displayed on the color

LCD and subjects were asked to visualize each colour for 10 seconds and the EEG signals were recorded. Before recording the next CVT, the subjects were asked to be in a relaxed state for 20 seconds and this process was repeated for all the trails. For each subject, EEG signal was recorded for 10 seconds at a sampling frequency of 256 Hz [9] and ten such trials session were performed for all the tasks. After completing each session, the subjects were asked to sit in a relaxed manner for 2 to 5 minutes.

A. Feature Extraction Process

In this section, feature extraction processes using spectral features are described and carried out. Three spectral features namely spectral energy, mean spectral energy and standard deviation spectral energy were proposed and analyzed based on the statistical approach [16]. First the raw EEG data was preprocessed and then feature extraction was performed. The recorded signals were segmented into number of frames with a overlapping of 75% [11]. Each frame has 256 samples (corresponding to 1 second). The segmented signals were then filtered using passband elliptic filters and the alpha (7 to 14 Hz), beta (14 to 21 Hz) and gamma (21 to 34 Hz) from all the 19 channels [1, 11]. In this spectral feature extraction process, the filtered data, $x(j)$ were first Fourier transformed to $X(m)$ using Equation (1),

$$X(m) = \sum_{j=1}^{N} x(j)\ w_N^{(j-1)(k-1)} \qquad (1)$$

where $w_N = e^{(-2\pi i)/N}$ is the complex exponential and N is the total number of data in the filtered signal. For the Fourier transformed signal $X(m)$, the spectral energy (SE) value is calculated using Equation (2),

$$SE = \sum_{m=1}^{N} [X(m)]^2 \qquad (2)$$

Then the corresponding mean spectral energy (MSE) and standard deviation spectral energy (SDSE) is calculated using Equation (3) and (4) respectively,

$$MSE = \sum_{m=1}^{N} [X(m)]^2 / N \qquad (3)$$

$$SDSE == \sqrt{\frac{1}{N-1} \sum_{m=1}^{N} [X(m)^2 - \overline{X(m)^2}]^2} \qquad (4)$$

where $N = 256$, is the number of samples.

Similarly, the features corresponding to the CVTs performed by all the ten subjects (for all trials) were extracted and associated to their respective colour codes. Each CVT has 57 (19 channels x 3 bands) feature values and it is given as input to the network model.

III. Neural Network

To discriminate the colour perception using visualization tasks, probabilistic neural network (PNN) has been developed. PNN is a supervised neural network proposed by Donald F. Specht [14, 15] and it is a variant of radial basis network suitable for classification problems. The PNN is a direct continuation of the work based on Bayesian classification and classical estimators for probability density function [14]. The only factor that needs to be selected for training is the smoothing factor/ spread factor which affects the classification accuracy. The network structure of PNNs is similar to that of backpropagation [12, 13]; the primary difference is that uses exponential activation function instead of sigmoidal activation function and also the training time is lesser compared to multi-layer feed forward network trained by back propagation algorithm.

PNN consists of four types of units, namely, input units, pattern units, summation units, and an output unit. The pattern unit computes distances from the input vector to the training input vectors, when an input is presented, and produces a vector whose elements indicate how close the input is to a training input. The summation unit sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, a complete transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 for that class and a 0 for the other classes. Furthermore, the shape of the decision surface can be made as complex as necessary, or as simple as desired, by choosing an appropriate value of the smoothing parameter.

In this paper, PNN architecture and the feature extraction process are constructed and analysed using MATLAB software. For the CVTs, the eight different colours are to be classified into eight different clusters. This problem requires 57 input neurons. In the experimental study, EEG signals corresponding to eight different visualization tasks were recorded and separate neural network model was developed for each subject. The master data set has 2960 samples. The network is trained with 1776 samples of data and tested with 1184 samples with a testing tolerance of zero. The accuracy results of each subject for the corresponding smoothing parameter (K) ranges from 0.10 to 0.20 are tabulated in Table 1, 2 and 3.

60% (1776 samples) of training samples are taken randomly from the total samples and the remaining 40% (1184) samples are tested using the network models. This process of training and testing is repeated for 10 times. From the Table 1, 2 and 3, the highest classification performance of three features and its smoothing parameter value for each subject were highlighted. The highest average classification accuracy of SE, MSE and SDSE features has been tabulated in Table 4.

TABLE 1. CLASSIFICATION PERFORMANCE OF PNN USING SE FEATURE

K	Sub 1	Sub 2	Sub 3	Sub 4	Sub 5	Sub 6	Sub 7	Sub 8	Sub 9	Sub 10
0.10	83.14	81.01	82.01	84.74	91.23	81.26	83.33	84.90	88.95	83.36
0.11	81.70	83.00	84.26	84.88	90.64	79.20	81.47	83.85	90.67	77.32
0.12	83.14	84.49	83.83	85.61	92.61	78.74	81.06	84.63	88.82	83.02
0.13	82.25	85.07	83.87	84.01	89.61	81.29	83.30	85.03	**91.23**	81.75
0.14	**84.36**	84.65	**84.70**	**86.04**	91.59	**83.56**	**85.84**	**88.44**	89.38	82.50
0.15	81.38	85.21	82.42	83.26	93.25	75.82	77.72	86.01	85.22	**86.89**
0.16	83.18	84.58	81.01	83.76	92.36	76.90	79.19	86.95	89.18	84.25
0.17	81.73	81.45	77.37	82.50	92.75	70.88	73.33	82.59	90.56	83.88
0.18	80.42	82.41	73.51	78.24	**93.43**	77.64	79.37	83.24	86.44	85.23
0.19	78.00	**85.59**	73.51	80.39	92.01	80.65	82.37	81.33	86.14	81.25
0.20	76.07	81.05	77.23	79.58	89.60	74.63	77.22	81.14	87.61	80.05

TABLE 2. CLASSIFICATION PERFORMANCE OF PNN USING MSE FEATURE

K	Sub 1	Sub 2	Sub 3	Sub 4	Sub 5	Sub 6	Sub 7	Sub 8	Sub 9	Sub 10
0.10	86.34	84.54	88.95	89.39	94.81	85.94	88.24	**91.04**	89.31	83.49
0.11	86.54	85.69	89.72	90.10	**95.04**	**87.86**	89.45	88.31	90.27	85.85
0.12	82.62	86.22	**92.10**	**90.71**	94.29	86.88	89.01	84.21	89.10	87.13
0.13	86.14	86.74	89.82	90.45	90.78	84.85	86.94	87.68	89.41	85.73
0.14	87.06	86.41	91.45	90.53	89.55	86.08	87.93	86.78	**92.44**	84.60
0.15	85.20	84.89	89.00	89.81	85.61	87.31	89.16	84.64	89.18	88.75
0.16	85.64	87.63	89.93	89.99	83.59	86.15	87.66	83.57	88.43	**90.45**
0.17	86.20	89.32	91.23	89.35	83.06	86.73	89.33	82.76	88.63	86.36
0.18	86.70	85.81	88.43	90.61	83.30	85.46	87.69	86.05	87.43	83.86
0.19	**89.61**	89.62	89.40	89.95	79.47	87.50	**89.90**	82.80	87.14	85.36
0.20	88.35	**90.35**	87.67	88.01	80.56	85.99	88.30	80.97	86.38	84.38

TABLE 3. CLASSIFICATION PERFORMANCE OF PNN USING SDSE FEATURE

K	Sub 1	Sub 2	Sub 3	Sub 4	Sub 5	Sub 6	Sub 7	Sub 8	Sub 9	Sub 10
0.10	83.17	79.96	83.29	**88.78**	90.76	81.51	87.15	83.01	88.51	83.53
0.11	81.08	80.84	85.84	87.39	90.55	79.49	84.92	81.62	90.06	76.95
0.12	81.03	82.33	85.24	83.86	90.22	80.53	84.27	83.03	89.49	82.41
0.13	82.84	83.22	85.54	85.07	90.68	80.96	86.69	82.64	**91.16**	81.09
0.14	**84.56**	82.79	**86.66**	83.76	91.06	**82.36**	**89.28**	**86.61**	89.74	82.06
0.15	76.94	**83.93**	84.89	83.47	91.13	79.23	81.88	83.49	85.26	**86.77**
0.16	79.34	82.90	83.08	83.24	88.99	80.53	83.24	85.04	88.95	84.94
0.17	73.37	80.01	80.09	80.58	**91.69**	79.40	77.35	80.40	89.94	83.54
0.18	79.18	81.20	75.63	79.19	90.74	78.12	83.68	80.56	86.55	85.75
0.19	82.67	83.09	74.75	79.35	89.57	76.23	86.57	80.00	86.63	81.06
0.20	76.71	78.97	79.14	79.81	88.46	73.72	80.62	78.83	88.31	79.85

Table 4 : Classification Results Of Se, Mse and SDSE Features

Subject	Mean Classification Accuracy %		
	SE Feature	MSE Feature	SDSE Feature
Subject 1	84.36	89.61	84.56
Subject 2	85.59	90.35	83.93
Subject 3	84.70	92.10	86.66
Subject 4	86.04	90.71	88.78
Subject 5	93.43	**95.04**	91.69
Subject 6	83.56	**87.86**	82.36
Subject 7	85.84	89.90	89.28
Subject 8	88.44	91.04	86.61
Subject 9	91.23	92.44	91.16
Subject 10	86.89	90.45	86.77

IV. RESULTS

To discriminate the colour perception using visualization tasks, PNN has been developed. In this case, eight-class classification was carried out using PNN to categorize these different CVTs. The highest mean classification accuracies of three spectral features for each subject were tabulated in the Table 4. While comparing the classification accuracy of three features, it has been also observed that MSE feature performs well when compared to other two features (SE and SDSE) for all ten subjects.

From the Table 4, it could be observed that, the highest mean classification accuracy of 95.04% (for subject 5) and the lowest mean classification accuracy of 87.86% (for subject 6) were obtained for MSE feature. Further, it can be observed that the performance of the subject 5 is better than the other subjects.

V. Conclusion

In this paper, SE, MSE and SDSE features were extracted from the EEG signal while performing the CVTs and the results were compared. The extracted features were associated to their respective tasks and the neural network models were developed successfully. The performance of the neural network models were tabulated and compared. From the above experimental study, it has been observed that the MSE feature using PNN model performs better when compared to the other two features. The proposed BMI using CVT is new in the development of BMI and it will be easy to implement, hence it involves less mental stress and no need of special training to control the BMI. In future, the proposed system will be implemented in a real time analysis.

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