EEG Based Brain Activity Monitoring using Artificial Neural Networks

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***Abstract*—Brain Computer Interfaces (BCI) have gained significant interest over the last decade as viable means of human machine interaction. Although many methods exist to measure brain activity in theory, Electroencephalography (EEG) is the most used method due to the cost efficiency and ease of use. However, thought pattern based control using is difficult due two main reasons; 1) EEG signals are highly noisy and contain many outliers, 2) EEG signals are high dimensional. Therefore the contribution of this paper is a novel methodology for recognizing thought patterns based on Self Organizing Maps (SOM). The presented thought recognition methodology is a three step process which utilizes SOM for unsupervised clustering of pre-processed EEG data and feed-forward Artificial Neural Networks (ANN) for classification. The presented method was tested on 5 different users for identifying two thought patterns; "move forward" and "rest". EEG Data acquisition was carried out using the Emotiv EPOC headset which is a low cost, commercial-off-the-shelf, noninvasive EEG signal measurement device. The presented method was compared with classification of EEG data using ANN alone. The experimental results show an improvement of 8% over ANN based classification.**

***Keywords*— Brain Computer Interface; Emotiv EPOC; EEG; SOM; ANN**

I. INTRODUCTION

Brain Computer Interfaces (BCI) are communication systems where humans interact with external devices using merely their brain activity [1], [2]. Therefore BCI enables humans to control machines without any peripheral muscular activity [3] ,[4]. BCIs can be of immense benefit to people who suffer from severe physical imparities by providing them with a method to interact with machines [5]-[7], design of prosthetic devices that can be controlled by thought [8]-[10] etc. Further, it has been shown that BCI can be used for tele-operation of robots [1], [11], gaming [12], [13] etc.

Theoretically, brain activity monitoring for BCI can be carried out by several measurements such as; electric field of brain (EEG), magnetic field of brain (MEG), functional magnetic resonance (fMRI), position emission tomography or functional near-field infrared spectroscopy(fNIR) [4], [14]. However, in practice, Electroencephalography (EEG) signal measurement is the most used method used for BCI due to the low cost measurement set up and low demanding technical requirements [4], [15]. Extensive research on EEG based BCI and modern technological advancements has resulted in development of low cost consumer grade EEG-BCI devices. Emotive EPOC [16], Neuroski Mindwave [17] and Myndplay BrainBand [18] are existing examples for such consumer grade hardware.

The accuracy of an EEG based BCI largely depends on its ability to identify different thought patterns of the user, since those thought patterns are transferred into commands [19]. The thought pattern identification process relies on the performance of the classification algorithm used [19]. EEG data are highly noisy and multi dimensional [4], [19] and can contain noise such as muscle movements, eye movements, eye blinks making it extremely difficult to identify the portion of signal pertaining to the intended BCI command [19].

Researchers have proposed various applications for EEG based BCIs. In [1], the authors proposed a BCI for mobile robot control. The authors investigated the feasibility of using a consumer grade EEG-BCI device and concluded by stating it is possible but significant improvements to the classification algorithm should be made. Various different classification methodologies have been explored in the past for different applications. In [20], the authors have proposed an EEG classification method which uses Support Vector Machines as the EEG classifier. Similarly, in [21], the authors have used Support Vector Machines based EEG classification for identifying epileptic seizures. The authors used a neural network classifier optimized with a genetic algorithm for EEG based BCI for wheelchair control in [22]. In [8], the author used Self Organizing Maps combined with Auto-regressive spectrum to distinguish between hand and foot movement through EEG classification.

This paper presents a methodology for identifying specific thought patterns which enables brain activity based mobile robot control that utilizes a combination of Self-Organizing Maps (SOM) [24], and feed-forward Artificial Neural Networks (ANN) [23] for thought patter recognition. The presented methodology can be divided into 4 steps: 1) data acquisition, 2) data pre-processing, 3) unsupervised clustering by SOM, and 4) classification by ANN. The SOM is used to cluster the pre-processed data in an unsupervised manner, and a separate ANN is trained for each of the clusters in the SOM which perform the final classification of the data.

The thought pattern identification method presented in this paper was implemented for recognizing two thought patterns; "move forward" and "rest" and was tested on 5 healthy individuals. Emotiv EPOC neuroheadset [16], which is a low cost, commercial-off-the-shelf, non-invasive EEG device, was used for EEG data acquisition. Furthermore, the presented methodology was compared to a thought pattern identification process using only ANN. The experimental results show an improvement of 8% over ANN based classification.

The rest of the paper is organized as follows. Section II introduces Self-Organizing Maps and its functionality. Section III describes the presented method. Section IV describes the implementation of the presented method. Section V presents the experimental results and finally, Section VI concludes the paper.

II. Self-Organizing Maps

The Self-Organizing Map (SOM) was developed by Kohonen [24] which employs unsupervised learning. The SOM comprises of a topological neuron grid typically arranged in a 1D or 2D lattice [25], which defines the spatial neighborhood of each neuron. SOM adjusts itself to the topological properties of the input data set using unsupervised *winner take all* learning algorithm together with cooperative adaptation.

For a C dimensional input space, a synaptic weight vector, $\vec{w} = \{w_1, \ldots, w_C\}$, is maintained by every neuron. A dataset B containing G data points can be expressed as:

$$B = \{\vec{b}_1, \vec{b}_2, \ldots\ldots, \vec{b}_G\} \tag{1}$$

where $\vec{b}_g$ represents the gth data point. Each $\vec{b}_g$ has C dimensions. Thus $\vec{b}_g$ can be expressed as:

$$\vec{b}_g = \{v_{g,1}, v_{g,2}, \ldots\ldots, v_{g,C}\} \tag{2}$$

where $v_{g,c}$ is the c^{th} dimension of $\vec{b}_g$.

Initialization of all neurons is done randomly and they are adapted iteratively based on the training input data set. The training process can be described in several steps as follows [25]:

Step 1 - Initialization: Randomly initializing all synaptic weight vectors in the input domain.

Step 2 - Sampling: Selecting a random input pattern $\vec{b}_g$ from the training dataset.

Step 3 – Competitive Learning: Finding the Best Matching Unit (BMU) for the current input pattern $\vec{b}_g$. The BMU is the neuron where the Euclidean distance between its synaptic weight vector $\vec{w}$, and the input pattern $\vec{b}_g$, is minimal. The BMU can be expressed as,

$$BMU(\vec{b}_g) = \arg\min_j \left\| \vec{b}_g - \vec{w}_j \right\|, \quad j = 1, 2, \ldots, J \tag{3}$$

where, $BMU(\vec{b}_g)$ is the best matching unit for input pattern $\vec{b}_g$, operator $\| \ \|$ denotes the Euclidian distance norm, and J is the number of all the neurons in the SOM.

Step 4 – Cooperative Updating: Updating the synaptic weight vectors of all neurons in SOM using the cooperative update rule:

$$\vec{w}_j(i+1) = \vec{w}_j(i) + \eta(i)\, h_{j,BMU(\vec{b}_g)}(i)\, (\vec{b}_g - \vec{w}_j(i)) \tag{4}$$

where, i denotes the iteration, $\eta(i)$ is the learning rate and $h_{j,BMU(\vec{b}_g)}(i)$ is the value of the neighborhood function for the neuron k centered at $BMU(\vec{b}_g)$.

Step 5 – Convergence Test: Checking whether the specified convergence criterion is met. If the criterion is met, learning process is terminated. If not, algorithm is moved back to **Step 2**.

The learning process is controlled by two parameters; 1) neighborhood function h and 2) dynamic learning rate η. A Gaussian function centered at the selected neuron as the BMU

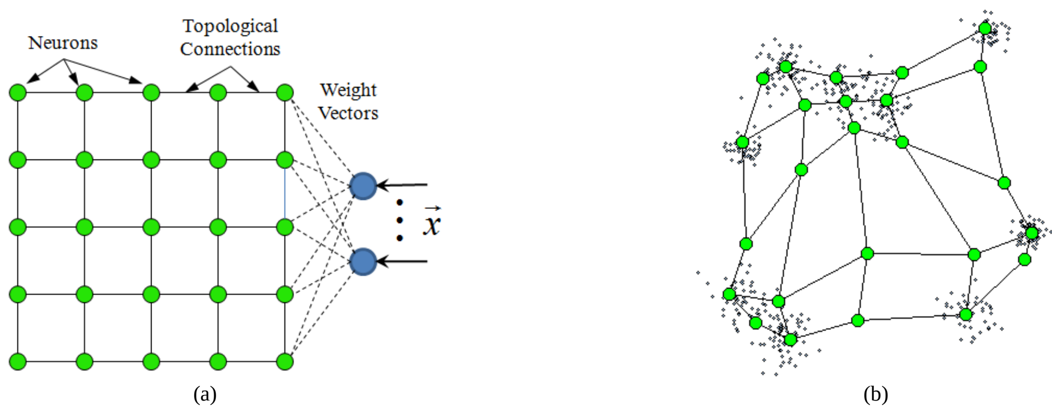

Fig. 1 Self-Organizing Map displayed in the output space (a) and in the input space adapted to 2D distribution of input points (b).

is typically used as the neighborhood function. Its amplitude applied to neuron *k* can be expressed as,

$$h_{j,BMU(\vec{b}_g)} = \exp\left(-\frac{\left\| \vec{w}_j - \vec{w}_{BMU(\vec{b}_g)} \right\|^2}{2\sigma^2} \right) \quad (5)$$

The size of the Gaussian neighborhood function is determined by parameter σ . When parameter σ is decreased, the size of the neighborhood deceases. Thus, parameter σ is decreased to improve convergence.

The learning process described in **Steps 2-5** is repeated until a specific convergence criterion is met. Typically, training is terminated when the average weight change for an iteration drops below a predefined value.

After convergence, the number of times each neuron *j* was selected as a best matching unit (BMU) is stored as $N_{BMU,j}$.

$$\sum_{j=1}^{J} N_{BMU,j} = C \quad (6)$$

where *J* is the number of neurons and *C* is the total number of data points.

Furthermore, for labeled data, the number of times each neuron *j* was selected as a best matching unit (BMU) for each class is stored as $N_{BMU,j,f}$.

$$\sum_{j=1}^{J} \sum_{f=1}^{F} N_{BMU,j,f} = C \quad (7)$$

where *f* is the class label and *F* is the number of classes in the dataset

III. SOM Based Thought Pattern Recognition for Mobile Robot Control

This paper presents a methodology that benefits from a combination of, unsupervised learning capability of SOM and the non-linear classification capability of ANN to perform thought pattern recognition. The thought pattern recognition methodology presented in this paper can be divided into 4 steps:

Step 1 - Data Acquisition: EEG data acquisition for different actions from an individual.

Step 2 - Data pre-processing: Converting the EEG data in the time domain to the frequency domain. Then segmenting the frequency data into the frequency bands that exist in brain signals.

Step 3 - SOM based clustering: Clustering the thought patterns using the frequency data obtained in **Step 2** as inputs.

TABLE I. Frequency Bands and Their Notation [8]

Frequency Band	Notation	Frequency Range (Hz)
Delta	δ	<4
Theta	θ	4 - 8
Alpha	α	8 - 13
Beta	β	13 - 25
Gamma	γ	>25

Step 4 - ANN based classification: Classifying the thought patterns using the clusters obtained in **Step 3**.

Each step of the process is explained in detail below.

A. Step1: Data Acquisition

EEG data for *T* number of actions are acquired from an individual using a non invasive EEG measurement device, which includes several sensors. Therefore, if the measurement device contains *M* number of sensors, a single data record consists of *M* dimensions. A data record acquired at time *t*, from a EEG measurement device with *M* sensors, can be expressed as,

$$d_t = \{S_1^t, S_2^t, ..., S_M^t\} \quad (8)$$

where S_m^t is the value of the m^{th} sensor at time *t*.

For real-time application, and reduced noise in the input data, data processing performed for a window of *n* data records at a time. The data window is designed to move through the data set, moving one data record at a time. Thus, two adjacent data windows; W_k and W_{k+1} , can be expressed as,

$$W_k = \{d_t, d_{t+1}, ..., d_{t+n}\} \quad (9)$$

$$W_{k+1} = \{d_{t+1}, d_{t+2}, ..., d_{t+n+1}\} \quad (10)$$

where, d_t is the *M* dimensional data record acquired at time *t*.

B. Step2: Data Pre-Processing

Once the window W_k is acquired, the raw data is converted into the frequency domain using Discrete Fourier Transformation (DFT) method. The DFT method converts the data in the time domain to the frequency domain enabling segmentation of data with respect to frequency bands that exist in EEG signals.

DFT is applied to each sensor separately to obtain the frequency values for each sensor independently. Thus, for window W_k , DFT is applied *M* times. The DFT conversion process can be expressed as,

$$\hat{W}_k^m = \frac{1}{n} \sum_{t=0}^{n-1} S_m^t e^{-2\pi i \frac{tq}{n}}, q = 0, ... n-1 \quad (13)$$

where $\hat{W}_k^m$ is the output of the DFT process for the k^{th} window for sensor *m* sensor and S_m^t is the raw EEG value of sensor *m* at time *t* data record

The obtained frequency domain data is then segmented into the five frequency bands that exist in brain signals. The frequency bands are shown in Table I. Once the segmented bands are obtained, the average power of each of the frequency band for each sensor is calculated. For instance:

$$P(\alpha_m^k) = \frac{1}{n}\sum_{i=0}^{n-1} p(\alpha_m^i) \tag{14}$$

where $P(\alpha_m^k)$ is the average power of the frequency band *Alpha* for the k^{th} window and m^{th} sensor and $p(\alpha_m^i)$ is the power of *Alpha* for record *i* and sensor *m* for the k^{th} window. Similarly for all the other frequency bands the average powers are calculated. Therefore, the set of average powers for are $R_m^k = \{P(\alpha_m^k), P(\beta_m^k), P(\gamma_m^k), P(\delta_m^k), P(\theta_m^k)\}$, for window W_k for sensor *m*.

Further, each of the *M* sensor value for each window is averaged to produce:

$$\bar{d}_k = \{\bar{S}_1^k, \bar{S}_2^k, ..., \bar{S}_M^k\} \tag{11}$$

where $\bar{d}_k$ is the averaged set of sensor values for window *k* and:

$$\bar{S}_m^k = \frac{\sum_{i=t}^{t+n} S_m^i}{n} \tag{12}$$

Using the power of the frequency ranges and the averaged sensor values, the input vector U_k for the SOM is generated:

$$U_k = \{\bar{d}_k, R_1^k, R_2^k, ..., R_M^k\} \tag{15}$$

C. Step3: Unsupervised Clustering using SOM

Thus, for a given window *k* the input vector U_k consist of *5M + M* elements, making up a *6M* dimensional input vector. Further, for training, the action label assigned in data collection is added to the window. This will act as the class label for the method.

As mentioned in Section II, the SOM finds the BMU for each input pattern and for each neuron and saves the number of times which a neuron was selected as the BMU for the respective class ($N_{BMU,j}$ from (7)). The labeled training data is sent to the SOM and once the specified convergence criterion is met and the training process is completed, each neuron in the SOM is assigned a class label *l*. This class label is chosen as the largest of the $N_{BMU,j,f}$ values of the neuron.

Then for a given, unlabeled input U_k, the cluster can be extracted as the class label *l* of the neuron that was selected as the BMU for U_k.

Fig. 2 Emotiv EPOC Neuroheadset [1]

D. Step4: Classifcation of Thought Pattern using ANN

Once the clusters are extracted from the SOM for the training data, an ANN is trained for each of the clusters in the SOM. This is done by first extracting the cluster label for each of the input patterns in the training data, then using each cluster to train a separate ANN. Each ANN will classify a given input pattern into one of the *T* actions that the system identifies.

After each ANN is trained, a given input pattern can be classified. Once a given input pattern is pre-processed using Steps 1 and 2, it is fed into the trained SOM in Step 3. The SOM assigns a label to the input patter according the cluster. Then the ANN assigned to that cluster is used to classify the input patter. Thus, for a given input patter only one ANN will be used for classification. However, since the ANN is trained on a clustered sub-set of data, a localized classification is performed, thereby improving the classification accuracy.

IV. Implementation

This section details the specifics of the implementation of the presented SOM based thought pattern identification methodology in this paper.

A. Data Acquisition

In this paper, EEG data acquisition was carried out using a commercial-off-the-shelf, low cost, non invasive, BCI device, Emotive EPOC Neuroheadset [16] (See Fig. 2). The Emotive EPOC Neuroheadset was chosen because it has been shown that it compares well with high grade research level equipment and the information retrieved is reliable and sufficient for most applications [26], [27], and its price and availability as a consumer product.

The Emotive EPOC measures the brain activity of the wearer by utilizing 14 sensors placed on the scalp, which sensors are placed according to the international 10-20 system

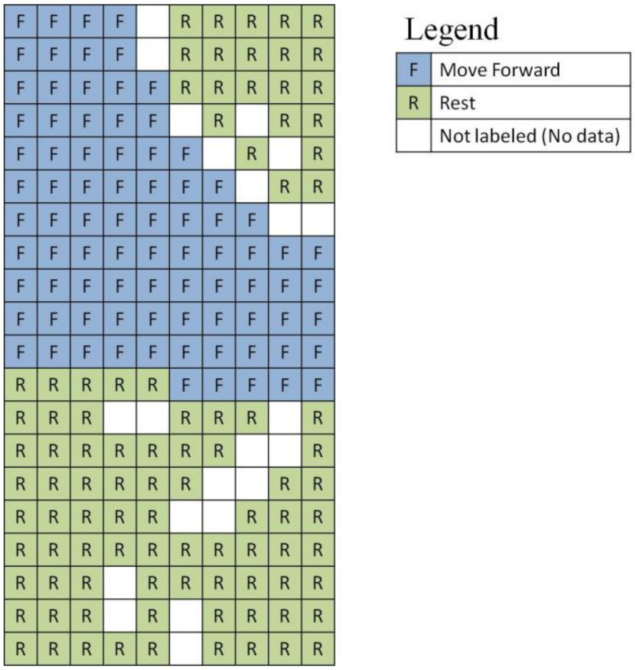

Fig. 3 Labels of the trained SOM for User 4

[27]. Since the Emotive EPOC headset was used for data acquisition, M in (8) was equal to 14.

EEG data acquisition process was assisted by a Graphical User Interface (GUI). The GUI provided an interactive 3D object that acted as a visual stimulus in the data collecting process. Alongside the values of the 14 sensors, an action label was recorded for training and validating purposes.

B. *Implementation of Thought Pattern Recognition*

The size of the moving data window n described in Section III was set to 100. Data pre-processing Step 2 (see Section III) was applied to this window. Since data from 14 sensors were recorded, the dimensionality of the input vector to the SOM was 84.

The SOM was implemented as a 2D lattice which consisted of 200 neurons arranged in a 20×10 matrix. Each of the neural networks trained contained 1 input layer consisting of 84 neurons, 2 hidden layers consisting of 10 and 5 neurons each and an output layer consisting of one neuron.

500 data points (windows with size 100) was used for training the SOM and the neural networks, and 300 data points were used for testing.

V. Experimental Results

The presented methodology was applied to EEG data collected from 5 individuals for two thought patterns, “move forward” and “rest”. Specific implementation details given in Section IV were used.

Fig. 3 shows the 2D lattice of the trained SOM for user 4, along with class labels for each neuron.

The presented thought pattern recognition method was compared to a typical thought pattern identification methodology using only ANN without the unsupervised learning capability of SOM. Same EEG data were used for both methods, while for the ANN only method, only Steps 1 and 2 were used for pre-processing. Furthermore, the same ANN architecture was sued for both methods. The performance of each method was measured by utilizing the classification accuracy and true positive and true negative rates (See Table II).The input patterns which were classified correctly as "Move Forward" were considered to be true positive and input patterns which were correctly classified as "Rest" were considered to be true negatives. False positives and false negatives were the patterns which were incorrectly classified for the above patterns respectively. The classification accuracy was obtained by calculating the percentage of correctly classified instances out of all instances.

Table III shows classification accuracy achieved by each method for each user, while Table IV lists the average true positive, true negative, false positive and false negative rates for each method. The presented method was shown to have a higher classification accuracy in all cases while the overall percentage improvement was 8% for the testing data.

TABLE II. CONFUSION MATRIX

		Classified as	
		“Move Forward”	“Rest”
Actual Class	“Move Forward”	True Positives (TP)	False Negatives (FN)
	“Rest”	False Positives (FP)	True Negatives (TN)

TABLE III
COMPARISON OF RESULTS OBTAINED BY SOM BASED ANN METHOD AND ONLY ANN BASED METHOD

Users	Presented SOM based ANN		ANN	
	Training Accuracy	Testing Accuracy	Training Accuracy	Testing Accuracy
1	98.60%	95.33%	97.80%	89.67%
2	98.80%	96.00%	96.80%	88.00%
3	98.20%	97.00%	95.60%	86.00%
4	99.40%	98.33%	97.60%	91.33%
5	98.40%	96.33%	96.80%	87.00%
Average	**98.68%**	**96.60%**	**96.92%**	**88.40%**

TABLE IV. AVERAGE CLASSIFICATION RESULTS FOR ALL USERS

Method	Train/Test	TP	TN	FP	FN
SOM - ANN	Training	98.96%	98.40%	1.60%	1.04%
	Testing	96.93%	96.27%	3.73%	3.07%
ANN	Training	97.12%	96.72%	3.28%	2.88%
	Testing	89.60%	87.20%	12.80%	10.40%

VI. CONCLUSION

This paper presented a methodology for identifying thought patterns for brain activity based mobile robot control. The presented method utilizes the unsupervised learning capability of Self-Organizing Maps (SOM) and the classification capabilities of Artificial Neural Networks (ANN) to highly accurate achieve thought pattern recognition.

The presented method was implemented using a low-cost commercial-consumer grade EEG device and was tested on 5 different individuals for identifying two thought patterns related to mobile robot control. Furthermore, the presented method was compared to a typical thought pattern recognition method that utilizes ANN. The experimental results showed an improvement of 8% over ANN based classification for testing data.

As future work, the presented method will be tested on a larger set of thought patterns collected from larger number of individuals. The presented method will also be tested on real world scenarios of controlling a mobile robot in an environment with obstacles.

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