Brain Based Control of Wheelchair

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Abstract - *This paper presents a brain based control of the wheelchair for physically impaired users. The design of the system is focused on receiving electroencephalographic (EEG) signals from the brain, processing and turning the system and then performing control of the wheelchair. The number of experimental measurements of brain activity has been obtained using human control commands of the wheelchair. The obtained data including EEG signals and control commands are used to design brain based control mechanism in training mode. The classification of brain signals has been done using a Support Vector Machine (SVM) and neural networks. The training data is used before using the system under real conditions. Then test data is applied to measure the accuracy of the control. The system designed in this paper is adjusted to control a wheelchair with five commands: move forward, move backward, stop, turn left and turn right in real conditions. The provided approach allows reducing the probability of misclassification and improving control accuracy of the wheelchair.*

Keywords: Brain Based Control, Brain–Computer Interface, Wheelchair Control, SVM, neural networks.

1 Introduction

The use of human brain signals to control devices and software in order to interact with the world is an important problem in bioengineering. The solution to this problem includes two stages. The first stage is the development of the interface between the brain and computer. The second stage is the design of brain based control of devices. The basic aim of the BCI is related to the design of communication channel for disabled people. A BCI system provides communication between computer and mind of pupils. This communication can be based on muscular movements during brain activity or the changes of the rhythms of brain signals. These brain activities can be estimated with electroencephalographic (EEG) signals. Since the brain signals are very weak we need to apply some spatial and spectral filters and amplifiers to the EEG to extract characteristic features of signals. Several EEG signals can be detected, resulting in different types of BCI. These signals are based on change of frequencies, change of amplitudes. For example during voluntary thoughts the frequencies of signals are modified, during movement a synchronization/ desynchronization of brain activity which involves μ rhythm amplitude change. This relevant characteristic makes rhythm based BCI suitable to be used.

Recently some research works have been done to develop many applications of BCI for wheel chairs. BCI is a control interface that translates human intentions into appropriate motion commands for the wheelchairs, robots, devices, etc. BCI allows improving the life quality of disabled patients and letting them interact with their environment. [3] considers the application of BCI and control of wheelchair in an experimental situation. The research considers the driving of a simulated wheelchair in a virtual environment (VE) before using BCI in a real situation. The virtual reality (VR) decreases the number dangerous situations by using train and test applications. [4,5] describe a BCI system which control the wheelchair that moves in only one direction- move forward. In [6] a simulated robot is designed that performs two actions- ‘turn left then move forward’, or ‘turn right then move forward’. [7,8] uses three possible commands turn left, turn right and move forward. In [9] BCI is designed using EEG signal captured by eight electrodes. Wavelet transform was used for feature extraction and the radial basis networks was used to classify the predefined movements. In [10] controller based on the brain-emotional-learning algorithm is used to control the omnidirectional robot. [11] presents the design of an asynchronous BCI based control system for humanoid robot navigation using an EEG. [12] apply BCI to robot control. [13] considers a non-invasive EEG-based Brain Computer Interface (BCI) system to achieve stable control of a low speed unmanned aerial vehicle for indoor target searching. [14-17] consider the design of brain controlled wheelchair. The constriction of viable brain–actuated wheelchair that combines brain computer interface with a commercial wheelchair, via a control layer is considered. Combining the BCI with a shared control architecture [13] allows to dynamically produce intuitive and smooth trajectories.

Another problem in brain based control is the obtaining of high classification accuracy. In brain based wheelchair control, a classification error (a wrong command) can cause dangerous situations, so it is crucial to guarantee a minimum error rate to keep the users safe. In this paper, the design of BCI and efficient brain based control of wheelchair is presented.

2 BCI system architecture

Figure 1 depicts BCI based control of the wheelchair. BCI system consists of an Emotiv headset connected to a computer where classification algorithms are run which is connected to a microcontroller that controls the movement of motors. A BCI based control system is usually composed of four main units: signal acquisition unit, signal preprocessing unit, classification unit and action unit. Figure 2 presents the structure of the system. The brain signals are measured by emotive sensors using 14 different channels. These input signals are sent to the signal processing unit. The signals after preprocessing are entered to the classification system. The output signals of the classification block are motor signals (clusters) that are sent to the wheelchair.

Figure 1. The computer brain–actuated wheelchair

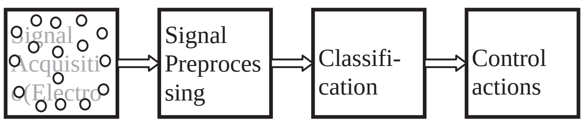

Figure 2. Structure of BCI.

In signal acquisition block the EEG signals are captured using the Emotiv headset. Emotiv EPOC is an EEG Headset which supplies 14 channels EEG data (Figure 3) and 2 gyros for 2 dimensional controls. Its features are adequate for a useful BCI in case of resolution and bandwidth. Our system uses upper face gestures for actuation commands since most Emotiv sensors are located in the frontal cortex they are the most reliable signals to detect.

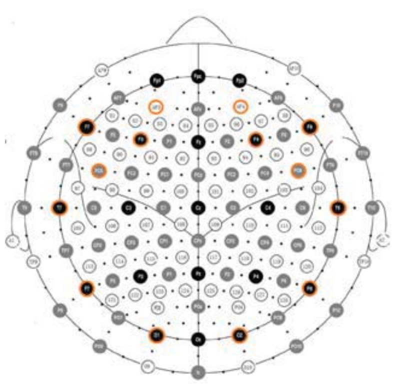

Figure 3. Emotiv's sensor Layout compared to standard 72 sensors layout. The distribution of EEG electrodes. Fourteen channels are marked for data acquisition.

Two different approaches can used for processing of the input sensor signals: Fast Fourier Transform (FFT) and without FFT. In this paper FFT approach is used to process input signal. The use of FFT allow to decrease the size of the input data. Here the input signal received from the headset is divided into windows having 2 sec. time interval with 50% overlap (Figure 4). The use of overlapping windows allows us to increase the accuracy of the classification. Each two seconds window corresponds to 256 samples of data. Each second corresponds to 128 data samples. The obtained signals from the channels, stored as windows, are then sent to normalization block. Each channel is normalized in order to center each channel on zero by calculating the mean value of each channel for the window, then subtracting it from each of the data points in the channel. After normalization, Hamming window is applied to each channel in the window. EEG signals do not generally repeat exactly, over any given time interval, but the math of the Fourier transform assumes that the signal is periodic over the time interval. This mismatch leads to errors in the transform called spectral leakage. Hamming window is used to mitigate this problem. Then fast Fourier transform (FFT) is applied to each channel in the window to find out the frequency components of the signal. Each frequency component is used as a feature, which results in 64x14 features. In order to increase the performance of the classification, the features are ranked by evaluating the worth of a frequency by measuring the information gain with respect to the class.

InfoGain(Class,Frequency)=H(Class) -H(Class | Frequency)

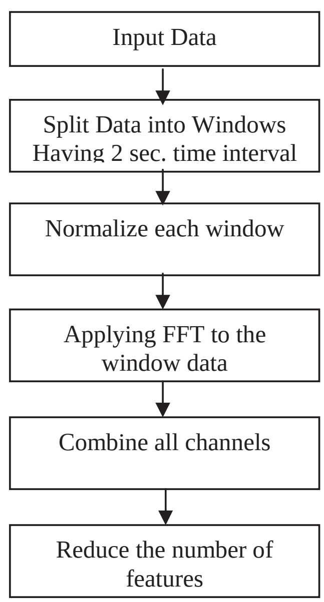

Fig.4. Signal Preprocessing unit.

After frequency representation, the combination of all channel signals is performed. The filtering operation is applied in order to select important features of the brain signals. These features are used for classification purpose. The whole signal preprocessing stages are shown in Figure 4. In the second approach the acquired brain signal after windowing, normalization and combining operations are used for classification purpose.

These signals are input for classification block. The signals are processed and classified. Output of classification system is used to activate the wheelchair. Even though during training system reports 100% success rate in real world conditions it does misclassify, a state machine is used to further increase safety and reduce misclassification. As an example the system won't transition from forward motion to backward motion without stopping in neutral. Output of the state machine drives the microcontoller which controls the motors on the wheelchair. The number of classes is equal to the number of control actions.

3 Classification

3.1 Support Vector Machines

The features extracted from the EEG signals are used for classification and determining control action. For this purpose in the paper classification techniques, such as SVM and neural networks are applied. The SVM method was invented by Vapnik, and the current standard improvement was proposed by Cortes and Vapnik [18].

Support vector machine tries to find out a hyperplane that has best separation which can be achieved by largest distance to the nearest training data point of any class. Let assume a binary classification have a data points (x_i,y_i), where $x_i \in R^p$ data points, $y_i \in \{-1,1\}$ classes. Each (x_i) is a vector. It needs to find the maximum-margin hyperplane that divides the points into two class. It can be described as:

$w.x + b = 1$ and $w.x + b = -1$.

where w is the normal vector to the hyperplane. It needs to minimize $\|w\|$ to prevent data points from falling into the margin, it needs to add the following constraint: for each i either $w.\ x_i - b \geq 1$ for x_i of the first class or $w.\ x_i - b \leq -1$ for x_i of the second class. As a result, it can be written as $y_i\ (w.\ x_i - b) \geq 1,\quad 1 \leq i \leq n$. The samples along the hyperplanes are called Support Vectors (SVs) and separating hyperplane with largest margin can be defined by $M=\dfrac{2}{\|w\|}$ that specifies support vectors means training data points closets to it. Taking into account the mentioned we can obtain the optimization quadratic problem:

$$\text{Minimize } \|w\| \qquad \text{Subject to: } y_i\ (w.\ x_i - b) \geq 1, \text{ for any } i=1,\ldots,n. \tag{1}$$

The main goal in SVM is the maximization of the margine of separation and minimization of training error. The above problem can be transformed into Lagarange formulation.

$$\max imize \quad L(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i,j=1}^{n} y_i y_j \alpha_i \alpha_j K(x_i, x_j)$$

$$subject\ to \quad \sum_{i=1}^{n} y_i \alpha_i = 0 \tag{2}$$

$$\alpha_i \geq 0, \quad i = 1, \ldots, n.$$

where $K(x_i, x_j) = \langle \varphi(x_i), \varphi(x_j) \rangle$ is a kernel function that satisfies Mercer theorem. Based on Karush-KuhnTucker(KKT) complementarity conditions the optimal solutions α∗ ,w∗ ,b∗ must satisfy the following condition.

$$\alpha_i^*[y(w^*\varphi(x_i) + b^*) - 1] = 0, \quad i = 1, \ldots, n.$$

where the α_i^* are the solutions of the dual problem. The resulting SVM for function estimation becomes

$$f(x) = \text{sgn}(\sum_{i=1}^{m} \alpha_i^* y_i K(x_i, x_i^*) + b) \tag{3}$$

where m is the number of support vectors. SVM technique is a powerful widely used technique for solving supervised classification problems due to its generalization ability. In essence, SVM classifiers maximize the margin between training data and the decision boundary (optimal separating hyperplane), which can be formulated as a quadratic optimization problem in a feature space.

3.2 Neural Network

Feed-forward neural network is applied for classification of brain signals. The used NN include input, hidden, and output layers. The sigmoid activation function is used in the neurons of hidden and output layers. Once the neurons for the hidden layer are computed, their activations are then fed to the next layer until all the activations finally reach the output layer. Each output layer neuron is associated with a specific classification category. In a multilayer feed-forward network (Figure 5), each neuron of previous layers is connected the neurons of next layers by using weight coefficients. In computing the value of each neuron in the hidden and output layers one must first take the sum of the weighted sums and the bias and then apply activation function f(sum) (the sigmoid function) to calculate the neuron's activation [19].

The extracted features of the anthemia diseases are inputs of neural networks. In this structure, $x_1, x_2, \ldots, x_m$ are input features that characterize the anthemia diseases. The j-th output of two layer neural networks is determined by the formula

$$y_j = f_k\left(\sum_{j=1}^{h} v_{jk} \cdot f_j\left(\sum_{i=1}^{m} w_{ij} x_i\right)\right)$$
$$where \quad f(\Sigma) = \frac{1}{1+e^{-\Sigma}} \tag{4}$$

where w_{ij} are weights between the input and hidden layers of network, v_{jk} are weights between the hidden and output layers, f is the sigmoid activation function that is used in neurons, x_i is input signal. Here k=1,..,n, j=1,..,h, i=1,..,m, m, h and n are the numbers of neurons in input, hidden and output layers, correspondingly.

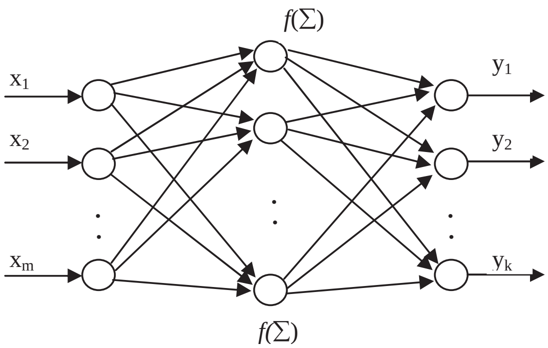

Figure 5. Multilayer feed-forward network

After activation of neural network, the training of the parameters of NN starts. NN is trained using anthemia data set taken from UCI library. During learning the 10-fold cross validation is used for evaluation of classification accuracy. There should be set of experiments in order to achieve required accuracy in the NN output. The simulation is performed using different number of neurons in hidden layer. The number of output neurons was 8 which was equal to the number of classes. The backpropagation algorithm is applied for training of NN. Neural network training consists of minimizing the usual least-squares cost function:

$$E = \frac{1}{2}\sum_{p=1}^{O} (y^d - y)^2 \tag{5}$$

where O is the number of training samples for each class, y^d and y is the desired and current outputs of the p input vector.

The training of the NN parameters has been carried out in order to generate a proper NNs model. The parameters w_{ij}, v_{jk} *(i=1,...,m , j=1,...,h, k=1,…,n)* of NNs are adjusted using the following formulas.

$$w_{ij}(t+1) = w_{ij}(t) + \gamma \frac{\partial E}{\partial w_{ij}}; \quad v_{jk}(t+1) = v_{jk}(t) + \gamma \frac{\partial E}{\partial v_{jk}} \tag{6}$$

where, γ is the learning rate, *i=1,...m; j=1,...h; k=1,…,n; m, h, n* are the number of inputs, hidden and output neurons of the network.

The whole process includes the following steps:

1) In the first step, the weights of neurons are initialized in the interval of [0-1].
2) Input data are fed to NN input (forward propagation).
3) Outputs of neurons of hidden layer are computed (Feedforward process)
4) The outputs of the hidden layer are fed to the inputs of output layer of NN and the outputs of NN are computed.
5) The error between current outputs and desired outputs (target) is computed.
6) Error is propagated back to the previous layer in order to update the weight coefficients of the neurons of the network. The back propagation of error signal is continued until the update of all weight coefficients in the layers is performed.
7) Repeating the steps 2 to 6 until the error becomes an acceptable small value.

4 Experiments and Results

The BCI system is simulated and used in real life application. The EEG signals are measured with Signal acquisition unit- the Emotiv EPOC headset. In the experiments, we have used 14 channels for measuring EEG signals. The measured EEG signals have different rhythms within the frequency band. The experiments show that measuring brain signals is difficult so we have tested our system using brain muscle signals. The signals obtained from 5 sample channels are shown in Figure 6. Figure 6(a) depicts a neural pose, patient relax not doing anything. Figure 6(b) depicts a positive gesture. As shown in figures, the EEG signals with positive gesture pose are changing more frequently than neutral pose. After preprocessing the important features of these signals are extracted and used for classification purpose.

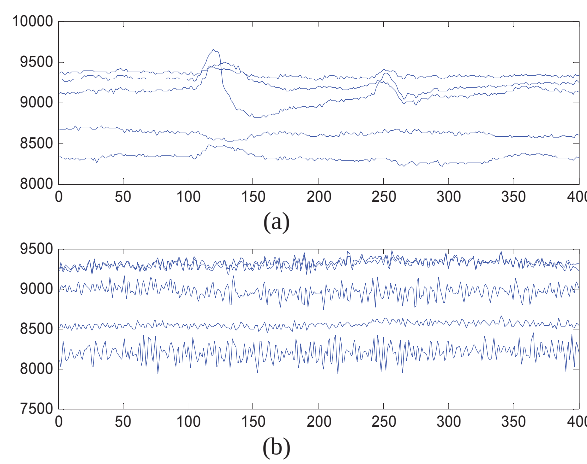

Figure 6. EEG signals for five channels: a) neutral pose, b) positive gesture pose

Five clusters are used in the experiment: Move Backward, Move Forward, Stop, Turn Left, and Turn Right. For each cluster, the system recorded 10 seconds of data. The classification of the signals is performed using SVM with the polynomial kernel and neural networks. 10 fold cross validation is used for separation the data into training and testing set. For comparison purpose we test the system using different classification techniques. In the result of classification the following results are obtained (Table 1).

Table 1. Classification results

Method	Correctly Classified Instances	Incorrectly Classified Instances	Mean absolute error	Root mean squared error
SVM	50 / 100%	0	0.24	0.3162
MLP (NN)	50 / 100%	0	0.0309	0.0884
Bayesian	47 / 94%	3 / 6%	0.024	0.1549
Random tree	37 / 74%	13 / 26%	0.104	0.3225

As shown using SVM and Neural networks the classification rate is achieved as 100%. These clusters activate the corresponding control signal which is then used to actuate the motors of the wheel chair.

5 Conclusion

The paper presents design of brain based control system for the wheelchair. The emotional and muscular states of the user are evaluated for classification and control purpose. The design of BCI has been done to drive brain controlled wheelchair using five mental activities of the user: Move Backward, Move Forward, Stop, Turn Left and Turn Right. For classification of EEG signals, SVM and neural networks with 10 fold cross validation data set are used. The obtained 100% classification results prove that the used techniques are a potential candidate for the classification of the EEG signals in the design of brain based control system. In the future, we are going to improve the number of commands for control wheelchair and decrease detection time of the EEG signal used for measuring brain activities and design efficient brain controlled wheelchair.

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