Clinical Epidemiology and Global Health 7 (2019) 274–278

Contents lists available at ScienceDirect

Clinical Epidemiology and Global Health

journal homepage: www.elsevier.com/locate/cegh

Brain-Computer Interface for wheelchair control operations: An approach based on Fast Fourier Transform and On-Line Sequential Extreme Learning Machine

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ARTICLE INFO

Keywords:
EEG
BCI
Fourier transform
Extreme learning machine
OS-ELM

ABSTRACT

Objective: The paper aims to control an electric wheel chair with a Brain-Computer Interface (BCI) headset. This wheel chair would be helpful for disabled people who cannot move their hands and legs or basically suffering from cerebromedullospinal disconnection. The main objective is to map different facial expression to the movement of the wheelchair.
Methods: The headset used for this purpose comprises of an EEG cap which has a total of 16 electrodes connected out of which 14 electrodes are used for acquiring data and the rest 2 are used as ground and reference. To operate the wheelchair the subject has to place the cap on his/her head and different facial expressions (clench, smile, blink, etc.) are performed. The movement of muscles around the face due to facial expressions can be observed from the EEG signals being recorded. Each expression is linked to movement of the wheelchair. Signal is preprocessed to remove the artifacts and then features are extracted using Fast Fourier Transform. In this paper, for classification we have used state-of-the-art machine learning technique which is a slight variation of Extreme Learning Machine called as Online Sequential Extreme Learning Machine abbreviated as OS-ELM.
Results: An overall accuracy of 97.62% was obtained using 10-fold cross validation.
Conclusion: The proposed framework attains better classification accuracy compared to various other classifiers.

1. Introduction

Brain-Computer Interface (BCI) is a connection between a computing device and brain that allows signals generating from the brain to regulate some external activity, such as control of a wheelchair or a synthesized limb. The interface regulates direct communication between the brain and the entity to be controlled. Unlike the typical computer input devices like mouse or keyboard, the BCI records the signals generated from brain at different channels on scalp of the head, generates necessary control signals which are used for operating the connected computers.

According to the survey, in past these issues can be solved by a plethora of techniques. Band Pass Filtering (BPF) is primarily used for noise reduction. On-Line Sequential Extreme Learning Machine (OS-ELM) is used to simplify the classification and Fast Fourier Transform (FFT) is used for characterizing features of the corresponding signals.[22] Fig. 1 depicts BCI architecture which shows four major steps involved in any BCI operation namely Data Acquisition, Pre-processing, Feature Extraction and Feature Classification. BCI has a plethora of applications among which medical application is ruling the industry.

Our main focus of this work is to restore and rehabilitate a part in medical application which targets to provide support to disabled people by making them independent. Other BCI applications include domain of security, education, games, etc.

This paper focuses on the restoration of the disabled people by implementing the methods discussed above[8,19]. The main aim is to uniquely distinguish the ornamentation of each facial expression because same ornamentation among 2 expressions would confuse the wheelchair and it will start disfunctioning later. After performing efficient classification of the expressions, using compatible processor the expressions can be mapped to movements of the wheel chair. The microprocessor operates the wheelchair using an electric motor. Thus, the overall procedure makes a system that maps the facial expressions to wheelchair movements online[9].

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https://doi.org/10.1016/j.cegh.2018.10.007
Received 25 June 2018; Received in revised form 7 October 2018; Accepted 30 October 2018
Available online 01 November 2018

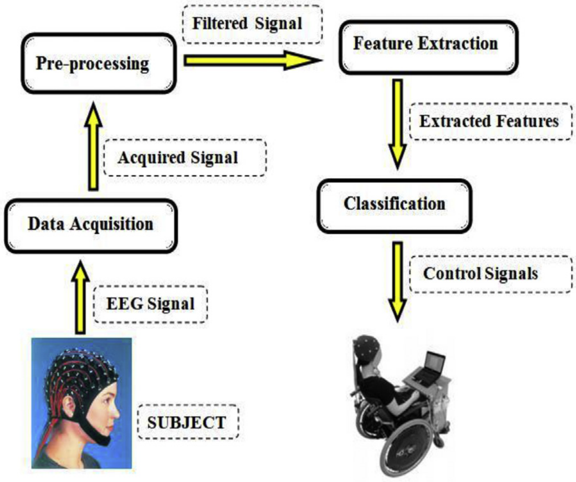

Fig. 1. BCI architecture.

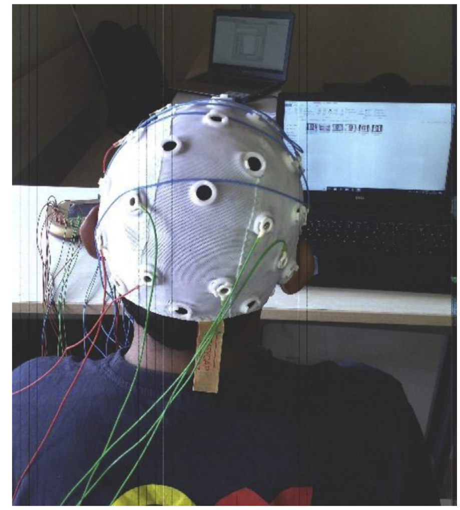

Fig. 2. Experimental setup.

2. Data acquisition

2.1. Subjects

The data collection apparatus consists of three components namely the easy cap, amplifier and electrodes for setting up connection. 10/20 International system was followed for placing the electrodes.[21] The subjects chosen were between ages 18–25 years. It was made sure that the chosen subjects did not have any past brain injury or any brain disorders. A formal no objection certificate consent was taken from each subject before the data was collected from them. Each subject was instructed properly about the entire experiment to avoid any problem during the experiment. Also we made sure that no disturbance occurs there during data collection hence fans and AC's were kept off.

2.2. Experimental setup

During the experiment the subjects were asked to be still as any movement made during the process resulted in variation of the signal from the normal wave pattern. The signals were absolutely parallel when the subject was sitting without any movement. The subject had to wear the EEG cap on his/her head. A total of sixteen electrodes were used for the experiment. Out of 16, 14 electrodes were used for data acquisition whereas 2 were used as ground and reference. The 14 electrodes for data acquisition were FP1, FP2, O1, O2, F7, F3, FC5, T7, P7, P8, T8, FC6, F4 and F8. The two electrodes used for ground and reference were P3 and P4 respectively. All the above mentioned electrodes were attached to the EEG cap in their correct position and abrasive electrolyte gel was applied to intensify the signals and to make sure the connection is strong. The electrode was connected between the head and an amplifier which amplified the signals and it was then connected to the computer system having a minimum RAM of 1 GB and core i3 processor. Fig. 2 represents the entire experimental setup. Two softwares were used such as, BrainVision Recorder which was used for recording of the signals and BrainVision Analyzer which was used for signal analysis which includes artifact removal or pre-processing.

2.3. Experiment

Five facial expressions were chosen for the experiment namely blink, clench, eyebrow raise, headshake and smile. Five different videos were made for five facial expressions. Each video consisted of 3 segments each of which was repeated four times. Each segment started with “Relax” written on the screen for 4 s followed by “Prepare” for 4 s and ended with “Perform” for 2 s. Fig. 3 illustrates the duration chart of

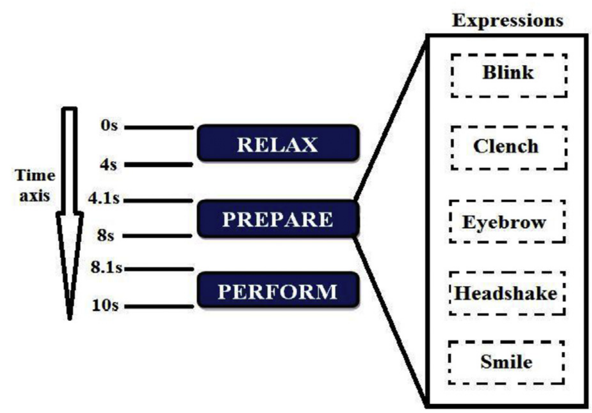

Fig. 3. Duration Chart with all expressions.

the experiment and shows all the expressions. When relax was displayed on the screen for 4 s the subject was asked to relax and just sit doing nothing. While “Prepare” was displayed on the screen for 4 s, the subject was asked to think in his/her mind about the expression to perform while a sample image of the expression was shown. In the “Perform” part which was for 2 s a star image was shown on the screen and the subject was asked to perform the expression here intensely. Since each segment was repeated 4 times hence a single video comprised of 40 s. As each video again was repeated 4 times hence, a single expression was recorded 16 times having a duration of 160 s. Short break was given between any two videos.

2.4. Data analysis

The EEG data was collected for five different facial expressions as discussed in above sub-sections. Before doing any analysis on EEG data, it is important to understand different types of EEG signals and also different types of channels on the scalp of the head based on 10/20 international system. There are billions of neurons in the human brain which are interconnected in a very complex fashion. The neural activity or oscillation measurable by EEG can be seen even if the signal is unprocessed, that is the signal has not undergone any kind of sampling or filtering. But, the signal is always a combination of different kinds of frequencies which basically shows certain experimental, non-cognitive or representational data. Since these frequencies vary on various factors experimentations classified these frequencies based on frequency bands. The classification yields five different frequency bands.[16]

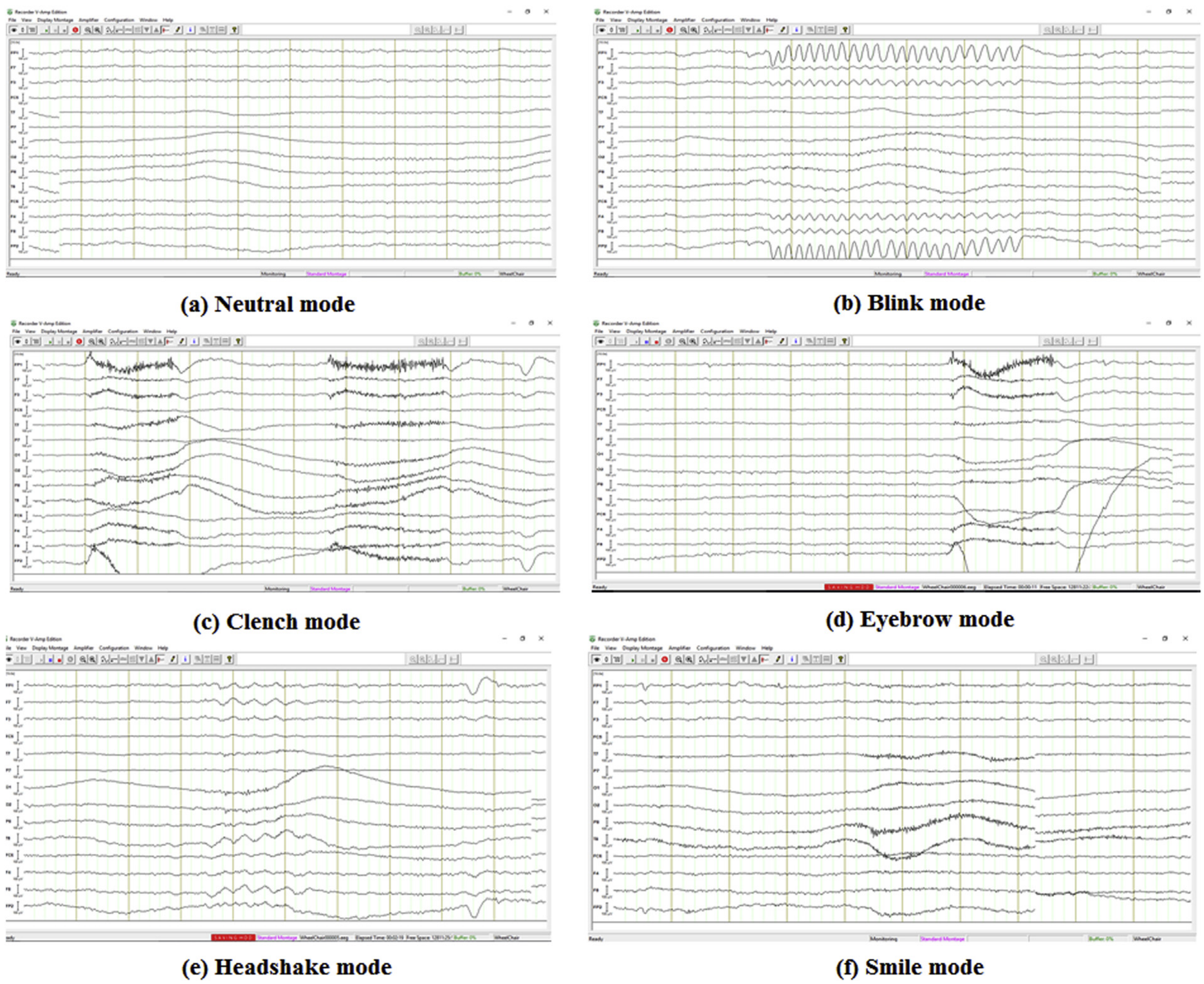

Fig. 4. Recorded EEG signals of all modes.

Table 1
Wheelchair direction appendix.

Facial Expression	Wheelchair Movement
Blink	FRONT MOVEMENT
Eyebrow Raise	RIGHT MOVEMENT
Headshake	LEFT MOVEMENT
Smile	REVERSE MOVEMENT
Clench	STOP

Actual \ Predicted	Blink	Clench	Eyebrow Raise	Headshake	Smile
Blink	100%	0	0	0	0
Clench	0	100%	0	0	0
Eyebrow Raise	0	0	96.8%	3.2%	0
Headshake	0.4%	0	0	99.6%	0
Smile	0	0	0	0	100%

Fig. 5. Confusion matrix.

Table 2
Comparison of performance measures in different classifiers.

Classifier	Accuracy	Sensitivity	Specificity
SVM	90.69	85.68	88.23
Random Forest	79.85	83.85	77.68
ELM	94.32	95.28	98.54
OS-ELM	**97.62**	**97.55**	**99.00**
K Nearest Neighbor	88.24	92.61	93.22
Decision Tree	86.15	88.46	85.28
Multilayer Perceptron	74.38	76.54	71.09

Bold indicates that these values are obtained from "Proposed framework based on OS-ELM".

Starting with the least frequency, the Delta band which is the slowest and have frequency in the range of 1–4 Hz. The next band is the theta band which is between 4 and 8 Hz. Alpha band ranges from 8 to 12 Hz, beta band ranges from 12 to 25 Hz and Gamma which is above 25 Hz. As stated in experimental setup section, total 14 channels were used for data collection and 2 were used as ground and reference. The analysis of the recorded signals is given below:

Fig. 4(a) depicts the EEG recording of the subject when he/she was in neutral mode that is the subject was asked to sit at ease and do nothing. It can be observed from figure that the signals in different channels are absolutely parallel, however channels O1, O2, P8 and T8 shows negligible variations due to some noise which was removed in the preprocessing step.

Fig. 4(b) depicts the signals generated when the subject was performing the expression “blink”. It can be observed that Major variations in the amplitude were seen in the channel FP1 and FP2. Channels F3, F4, F7 and F8 showed minor variations whereas rest channels showed negligible variations. Hence, channels FP1 and FP2 were crucially considered while classification.[17,18]

Fig. 4(c) shows EEG signals when the subject was per-forming “Clench” expression. It can be analyzed that there was a significant increment in the frequencies of nearly all the channels however the change in the amplitudes were not that significant as compared to blink.

Fig. 4(d) depicts EEG signals when the subject was raising his/her eyebrow i.e. he/she was performing “Eyebrow Raise” expression. In this mode, the frequency change in FP1 was the most significant. There was a significant drop in the amplitudes of T8 and O1 and minor increment in the amplitudes of F3, F4, F7 and F8.

Fig. 4(e) shows the EEG signals when the subject was asked to shake his/her head that is perform “Headshake” expression. The frequencies of O1 and O2 showed a significant increment whereas the frequencies of other channels were less in number and equal.

The last expression shown in Fig. 4(f) is the “Smile” expression. The observation of smile expression appears similar to the neutral expression in the time domain.

3. Proposed work

3.1. Overview

In the proposed approach, classification of five chosen facial expressions’[6] EEG signals is performed and then these expressions are mapped to the movements of the wheelchair. The four expressions are considered for 4 primary directions i.e. left, right, front and back respectively. However, the last expression is to stop the wheelchair. As mentioned in the above section, there are four major phases in this work, namely, Data Acquisition, Data Preprocessing, Feature Extraction and Feature Classification. In the Data Acquisition phase, the raw EEG signals are acquired from the subjects. In our work, we have used Easy cap to collect the EEG data and a BrainAmp for signal amplification. In the next phase, Data Preprocessing which involves re-moving of artifacts from the raw signals for better classification performance. This phase starts with signal sampling followed by signal filtering. The filtered signal (artifact free data) is then passed for feature extraction where only the relevant features are extracted without the loss of information from the original signal. The extracted features are provided for classification task.

3.2. Preprocessing

As discussed above, the preprocessing step starts with sampling of the input signal. As the data being collected is a continuous EEG signal, it needs to be discretized for computation purpose. Hence, the input signal was being sampled and sampling frequency was set to 256 Hz. In our work, after sampling we carried out noise reduction using a bandpass filter. A band-pass filter allows only a specific range of frequencies. In our work, we had set the frequency from 0.3 Hz to 30 Hz. Signal below 0.3 Hz was feeble signal and was neglected. Signal above 30 Hz constituted noise or gamma signals hence were neglected.

3.3. Feature extraction

In this paper, we have used Fast Fourier Transform (FFT)[1] to extract features from delta, theta, alpha and beta waves constituting entire wave.[10] Gamma waves are rejected as they are mostly noise. In our work, we had an input matrix of 14 × 40500 for a single expression of a subject. For a particular expression say smile, input matrix was for all the 19 subjects with 57 trials each. Hence the input matrix for a single expression was of dimension 798 × 40500. Considering all the five expressions the total input matrix was of 3990 × 40500. The resultant matrix was obtained after applying FFT to the input matrix. The elements of resultant matrix are nothing but the frequency components of the input signals which had been discretized to carry out computations. Statistical features were applied on this matrix column wise i.e. each column of the matrix acted as one set of data or variables on which statistical features were applied. In our work, we had used mean, standard deviation and entropy features and concatenated all the features horizon-tally. The equations of these features are shown in Equations (1)–(3) respectively.[1] The final matrix was then provided as an input for the classification task.

$$Mean,\ \bar{x} = \frac{\sum_{i=1}^{N} x_i}{N} \tag{1}$$

$$Standard\ Deviation,\ s = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N-1}} \tag{2}$$

$$Entropy = -\sum_{x} p_x \log p_x \tag{3}$$

Here, x_i‘s are the data values, N is the total number of values and p_x in the entropy calculation is the probability of the distribution for each x.

3.4. Classification

This section will focus on the working of ELM[5,7] and the modification of ELM to produce OS-ELM,[2] which has been used for multi-class classification in our work. Let us assume we have N different samples (y_i, t_i), where $y_i = [y_{i1}, y_{i2},\ldots,y_{in}]^T \in R^n$ and $t_i = [t_{i1}, t_{i2},\ldots, t_{im}]^T \in R^m$, single layer feed forward neural network with N_h hidden neurons and $f(x)$ activation function, we can approximate the total number of samples with zero error means such that there exists β_i, w_i, b_i which satisfies the below mentioned Equation (4) [2]:

$$\sum_{i=1}^{N_h} \beta_i f(w_i \cdot y_j + b_i) = t_j, \quad j = 1, \ldots, N \tag{4}$$

where $w_i = [w_{i1}, w_{i2},\ldots,w_{in}]^T$ is the weight vector which constitutes the connection between input neurons and hidden neurons and $\beta_i = [\beta_{i1}, \beta_{i2},\ldots, \beta_{im}]^T$ is the weight vector which constitutes the connection between the hidden layers and output layers.

The above N equations (equation (4)) can be compacted and written in the form of equation (5) as shown below:

$$H\beta = T \tag{5}$$

Since number of hidden neurons in hidden layer is less than the number of training examples, the matrix H becomes an overdetermined matrix i.e. more rows than columns. Hence, Equation (5) has a unique solution for a particular H matrix. According to the proof of some previous works[17,19] we don't need to adjust the weights w_i and the biases b_i of hidden neurons during training. We can instead simply assign values to them randomly and then the output weights β can be estimated using the concept of pseudoinverse which has been shown below in Equation (6) [2]:

$$\hat{\beta} = H^{+}T \tag{6}$$

where H+ is the psuedoinverse which can be calculated by various methods. However, in our work Moore-Penrose gene-alised inverse method has been used which is depicted in Equation (6). As mentioned in preceding sections, the main focus is given to the matrix H. Since N_h is the number of neurons in hidden layer and N represents the number of training examples then $H \in R^{N \times N_h}$ and $N > N_h$. Also, it can be noted that rank of matrix H i.e. rank(H) = N_h. Under this criteria left pseudo inverse of the specific matrix is calculated which is denoted as H^{+}[2] (Moore-Penrose generalized inverse of matrix H).

$$H^{+} = (H^{T}H)^{-1}H^{T} \quad (7)$$

Hence, the least square solution $\hat{\beta} = H^{+} = (H^{T}H)^{-1}H^{T}$. The sequential implementation of this least square solution $\hat{\beta}$ can be termed as recursive least square (RLS) algorithm.

In our work, we have used two phases in the classification using OS-ELM. The first phase used was the boosting phase where some batch of data was used to train the neural network in the initialization stage and these data were discarded once the boosting phase was completed. The main phase was the second phase which was the sequential learning phase. In this phase, RLS algorithm was used to update the output weight using the concept of recursion. Now, suppose we receive a new sample data (x_p, t_p) then the hidden layer output matrix H_p is computed and then the output weights are updated using the below mentioned recursive equations[3]:

$$L_{p-1} = L_{p-2} - \frac{L_{p-2}h_{p-1}^{\mathrm{T}}h_{p-1}L_{p-2}}{1 + h_{p-1}L_{p-2}h_{p-1}^{\mathrm{T}}} \quad (8)$$

$$\beta_{p-1} = \beta_{p-2} + L_{p-1}h_{p-1}^{\mathrm{T}}(t_{p-1} - h_{p-1}\beta_{p-2}) \quad (9)$$

We have used one-by-one OS-ELM algorithm instead of chunk-by-chunk type. The algorithm was used to classify the dataset into five different classes for five different facial expressions. The below mentioned Table 1 shows different mapping of expression to the wheelchair movements.

4. Results and discussion

After feature extraction the result obtained is provided as an input to OS-ELM for feature classification. In our work, we had partitioned the dataset into 85% and 15%. 85% of the dataset was utilized for training while rest 15% was utilized for testing. Several iterations were performed and method of cross validation was used to find out the final accuracy. An accuracy of 97.62% was obtained. Precision obtained was 97.84%, sensitivity was 97.55% and specificity obtained was 99.00%. The above parameters were computed using below mentioned equations.[4]

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (10)$$

$$Precision = \frac{TP}{TP + FP} \quad (11)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (12)$$

$$Specificity = \frac{TN}{TN + FP} \quad (13)$$

The obtained confusion matrix for multi class classification is illustrated in Fig. 5.

The dataset was trained and tested on various classifiers and a comparison has been made using the performance measures such as accuracy, sensitivity, and specificity. It has been observed that OS-ELM performed better than the rest of the classifiers. The comparison table is shown below in Table 2:

5. Conclusion

The entire experiment being conducted resulted in a simulation of BCI controlled wheelchair which has been created by doing a multi-class classification using Online Sequential Extreme Learning Machine on the features obtained using Fast Fourier Transform[12]. The data acquisition process was done using an Easy cap and by setting up Electroencephalography setup. A video was made for each expression/movement, namely, neutral, clench, smile, headshake, blink and eyebrow raise. The dataset obtained was analyzed and unnecessary artifacts were removed to filter the signals. The features of the preprocessed signals were obtained using FFT. Classification was performed using Online Sequential Extreme Learning Machine. The classified expressions can be mapped to different movements of the wheelchair and can be connected to a compatible processor to generate necessary control signals for wheelchair control operations.

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Further reading

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