P300 Evoked Potentials Data Classification Using Feed Forward Neural Network.

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ABSTRACT
In this paper six-choice P300 evoked potentials data classification is tested using a population of four disabled and four able-bodied subjects. The P300 is a positive deflection in the human EEG, appearing approximately 300 ms after the presentation of rare or surprising, task-relevant stimuli. Four different electrode sets were tested. Feed forward neural network with back propagation learning was used for classification. For able-bodied subjects data sets, 100% end-run accuracy is obtained with all electrode sets, for disabled subjects data sets 100% end-run accuracy is obtained for electrode Set 16 and Set 32. Highest obtained target trial recognition accuracy in runs for able-bodied subjects data was 93% and for disabled subjects data was 77%. The bitrates obtained for the disabled subjects range between 6 and 31 bits/min and for able-bodied subjects range 9 and 51 bits/min. The effect of different electrode configurations was tested.

KEYWORDS: P300, feed forward neural network, back propagation, offline analysis, classification, brain computer interface

1 INTRODUCTION

A Brain-computer interface (BCI) is a communication pathway between a human brain activity and an external device (Cecotti and Graser, 2011). Such systems allow people to communicate through direct measurements of brain activity (Allison et al, 2007, Birbaumer and Cohen, 2007, Kostov and Polak, 2000).

For people who are unable to communicate by standard means because of severe motor disabilities, BCI may be the only way of communication possible (Birbaumer and Cohen, 2007). EEG (electroencephalography) techniques are the common solution for non-invasive BCIs.

The P300 is a positive deflection in the human EEG, appearing approximately 300 ms after the presentation of rare or surprising, task-relevant stimuli. In P300 based BCI a matrix of possible choices is presented on a screen and scalp EEG is recorded over the centroparietal area while these choices flash in succession. Only the choice desired by the user evokes a large P300 potential (i.e. a positive potential about 300 ms after the flash).

Target of our work is to build up machine learning algorithm for multichannel signals, based on artificial neural network. This paper works with data recorded from P300 based BCI research and as a classification method is chose artificial feed forward neural network with back propagation learning. Signal processing and machine learning algorithms were implemented with MATLAB.

This paper uses data acquired by Multimedia Signal Processing Group on École Polytechnique Fédérale de Lausanne (EPFL) with their P300 based BCI (Hoffmann et al, 2008).

2 MATERIALS AND METHODS

2.1 DATASETS DESCRIPTION

In (Hoffmann et al, 2008) authors made available raw datasets to be downloaded from EPFL BCI group web page (http://bci.epfl.ch/p300), to stimulate further research on data analysis techniques for P300-based BCI systems. Experiments in our paper were performed on abovementioned data. Here is basic information about experimental setup (Hoffmann et al, 2008): "Users were facing a laptop screen on which six images were displayed. The images showed a television, a telephone, a lamp, a door, a window, and a radio. The images were selected according to an application scenario in which users can control electrical appliances via a BCI system. The application scenario served however only as an example and was not pursued in further detail. The images were flashed in random sequences, one image at a time. Each flash of an image lasted for 100 ms and during the following 300 ms none of the images was flashed, i.e. the ISI was 400 ms. The EEG was recorded at 2048 Hz sampling rate from 32 electrodes placed at the standard positions of the 10-20 international system.

Given data contained 8 subjects (4 disabled and 4 able-bodied) measurements with 4 sessions for each subject, each session with 6 runs with over 130 trials per run. Single trial means 1 flash of random picture, each 6 trials contain each picture flash in random order. Data also contained results and order of flashing picture. Further information about experimental setup, subjects or experimental schedule can be acquired also in (Hoffmann et al, 2008).

2.2 DATA PREPROCESSING

Before the use of classification algorithm, preprocessing routines were implicated on data to prepare them to classification ready state. The average signal from the two mastoid electrodes was used for referencing. A sixth order forward-backward Butterworth bandpass filter was used to filter the data. Cut-off frequencies were set to 1.0 Hz and 12.0 Hz. The EEG was downsampled from 2048 Hz to 32 Hz by selecting each 64th sample from the bandpass-filtered data. Single trials of duration 1000 ms were extracted from the data. Single trials started at stimulus onset, i.e. at the beginning of the intensification of an image, and ended 1000 ms after stimulus onset. The samples from each electrode were scaled to the interval [-1, 1]. Difference between (Hoffmann et al, 2008) preprocessing is that data in this work were not windsorized (there was just optical checking of data) and from 1000ms single trials were extracted 200-600ms windows used to construct feature vectors.

2.3 MACHINE LEARNING AND CLASSIFICATION

Feed forward neural network with back propagation learning was used for classification. Neural networks are commonly used for EEG signal processing (Allison et al, 2007). Network parameters were aquired experimentaly. Result for each single trial was computed and compared with target. End-run accuracy was computed as a probability of selecting right target at the end of runs, based on percent occurrence.

Back-propagation learning was implemented in batch mode where adjustments are made to the free parameters of the network on an epoch by-epoch basis, where each epoch consists of the entire set of training examples. To determine when it is best to stop the training session a cross-validation was used. Parameter dividerand was used to separate input and target vectors into three sets: training, validation, and testing. Training subset was used for training of the model. Validation subset was used for evaluating the model performance. The network was finally tuned by using the entire set of training examples and then tested on test data not seen before.

Number of neurons in input layer used for classification was N_e*N_t, where N_e denote number of electrodes 4, 8, 16, 32, N_t denote number of samples per electrode in trial was 15 (from 6th to 20th sample equal to window 200ms to 600ms), so the network has 60, 120, 240 or 480 input neurons depends from number of electrodes used in test. Number of neurons in hidden layer was 2, 10 or 20 with hyperbolic tangent sigmoid transfer function. Number of neurons in output layer was 2 with hyperbolic tangent sigmoid transfer function. Training function was gradient descent with momentum backpropagation.

Sessions 1, 2 and 4 was used for training neural network and session 3 was used for final testing. There were constructed training input and training output vectors from training sessions and test input and test output vectors from testing session. Dimension of train vectors was $(N_e*N_t)x(20*6*6*3)$ for input and $2x(20*6*6*3)$ for output. Dimension of test vectors was $(N_e*N_t)x(20*6*6)$ for input and $2x(20*6*6)$ output. N_e denotes number of electrode in testing set and N_t number of samples per electrode in trial.

Four electrode configurations with different numbers of electrodes were tested. The electrode configurations are shown in figure 1.

3 RESULTS

Accuracy of recognition subject's intent in single trial 41% to 77% for disable subjects and 47% to 93% for able-bodied subjects was acquired. As we can see in figure 2 increasing number of electrodes result in higher target trial recognition accuracy. A 100% end-run accuracy of recognition subject's intent for electrodes Set 16 and Set 32 was acquired thanks to high percent occurrence of target image versus other non-target images for all test subjects. For Set 4 and Set 8 this number was 91%. The bitrates obtained for the disabled subjects range between 6 and 31 bits/min and for able-bodied subjects range 9 and 51 bits/min. Number of neurons in hidden layer in range 2, 10, or 20 doesn't seem to have impact on classification accuracy in this setup.

4 CONCLUSION

We have presented part of offline classification system for P300 based brain computer interface. This is far from being final version of classification system and there is still lot of improve. In the future experiment our aim will be on input data preprocessing, locale reason of high fluctuation between maximum and minimum trial accuracy, deep comparison of able-bodied subjects versus disabled subjects with average waveform, other neural network architectures could be tested (e.g. pulse coupled neural network) (Sevcik, 2009) and not in last order online tests should be applied.

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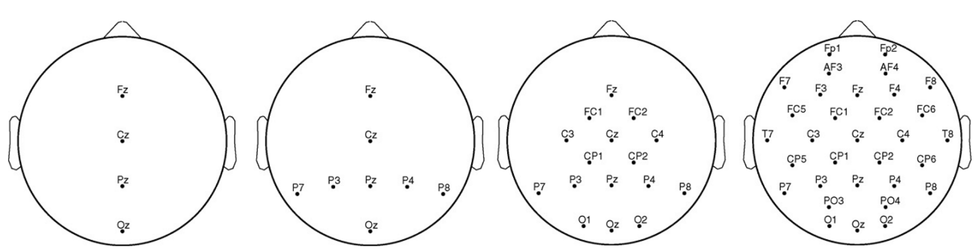

Figure 1: Four placement configurations with different numbers of electrodes. Electrodes placement Set 4, Set 8, Set 16 and Set 32.

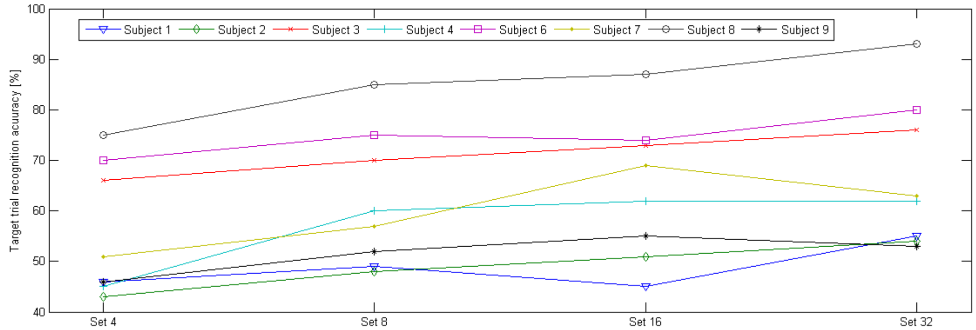

Figure 2: Disabled subjects 1-4 and able-bodied subjects 6-9. Increasing number of electrodes result in higher target trial recognition accuracy.