Application of BCI Technology for Color Prediction Using Brainwaves

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Abstract. In this paper we present the results of the research regarding color recognition using brain-waves read from a consumer grade non-intrusive Brain Computer Interface device. The brainwaves obtained from the device are pre-processed and filtered using different algorithms and then several machine learning techniques are applied for prediction of three colors. At the end, the obtained results are presented and discussed.

Keywords: brain computer interface, brainwaves, color prediction

1 Introduction

At the beginning of the computer era people did not pay much attention on easy interaction to computer systems with humans. It was assumed that they will only be used from highly qualified users. However, computers are nowadays wide-spread and used in every aspect of people's lives. One of the many ways to communicate with a computer that is still under development is the computer interface with brain waves. Brain computer interface (BCI) is a system that interprets the thoughts of man to make commands that control a computer or other device. Human-computer interaction is bidirectional: many systems adapt to the user, which in turn should constantly adapt to new solutions of the system. The task of this feedback loop adaptation between system and user is important in BCI systems that seek to approximate the neuronal function [2].

There are several techniques for reading the electrical signals produced by the brain in humans. BCI can be divided the 3 groups: totally invasive, partially invasive and noninvasive. The first two demand complex procedures for setting up on the human body, while the third one is simpler for set-up, but is significantly more inaccurate. Obviously, the consumer grade BCI hardware belongs to the third group.

Much research is done with more complex noninvasive hardware (fMRI, MEG, EEG etc.) and many promising results are obtained in this area [1]. Consumer grade hardware however is rarely researched and its capabilities are limited to the manufacturers' software products that are usually limited to different kinds of games.

In this paper we are using a consumer grade BCI device that is easy to obtain and has a low price. The goal of this paper is to detect the capabilities of the device to be used as a control device for the color selection task. The basic idea is to train a decision making model using several machine learning algorithms on real data. After the model is obtained, the model would be used to detect what the user is thinking about. For the purposes of this paper, the training data is obtained by measuring the brainwave activity while the user watches a certain color and then the trained model is used by the user for color selection. The bidirectional training of the BCI devices is not taken into consideration in this paper. Only the computer model of the way the human thought is generated. The human is not trained for recognizing colors with the device.

2 System Architecture

For the purposes of the experiment, we used a cheap and widely available device. The device used in this experiment is Mindwave from the company Neurosky [3]. This device measures the standardized EEG brain waves but it gives special measurements for blink detection, attention and meditation levels of the user. Although it is relatively new, there are already lot of programs and games that mostly use the specialized readings, and much less applications that use the whole spectrum of EEG waves. Most of the applications are games, but there are several that allow visual display of the readings from the device. The device is one of the best selling commercial EEG devices and is financially much more accessible than other devices on the market. Some primary schools in the United States have implemented it for various purposes. A lot of the pupils that used this device while studying and problem solving have shown better results by learning how to increase their concentration and attention. The Mindwave is also used in training for sports that need calmness and concentration like archery and billiard. There are several applications for educational purposes from which the ones that help with math and problem solving are used the most.

Despite the above mentioned advantages, this device has also some disadvantages. Its biggest disadvantage, that is also common with a lot of other consumer based BCI devices, is that because of not using conductive gel there is a significant amount of noise. Furthermore, this device has only 2 sensors for measuring brainwaves.

For the purposes of this experiment the Neurosky Mindwave SDK package is used [4]. With the help of this software development kit a program in Java was developed for connecting with the device, showing colors to the user and collecting the data from the Mindwave. The software developed had additional functionalities that are not in the scope of this paper. Fugure 1 shows the Mindwave device used for the purposes of our experiments.

Fig.1. Mindwave device

The used SDK provides access to the Mindwave sensor measurements as numeric values and several aggregated values. These values are high and low Alpha, Beta and Gamma waves, Delta, Theta, Attention and Meditation, in addition there is the blinking strength. The values are obtained with frequency of 1 Hz. This means that a new measurement is available every second. Figure 2 shows the process for obtaining the model for color recognition in this paper.

Fig.2. Model training workflow

The device is used for obtaining the data for each color. The data is obtained from the brainwaves of a person that looks at a certain color. For this experiment we used three colors – Red, Blue and Yellow. During the training phase the raw data is stored in a file. Afterwards with the addition of the header it is converted in the .ariff file format and inserted into the WEKA program [5]. WEKA (Waikato Environment for Knowledge Analysis) is popular program for machine learning written in Java developed by the University of Waikato. The data that is inserted in the system consists of several parameters: Attention, Meditation, Delta, Theta, Low Alpha, High Alpha, Low Beta, High Beta, Low Gama and High Gama. The colors used were Red, Blue and Yellow. WEKA software is used in both the preprocessing and the model training phase.

For the preprocessing phase, the attribute selection and the wavelet transformation were used as provided by WEKA. After that, models were built by several machine learning algorithms:

- Bayes Network
- Multilayer perceptron
- Decision trees
    - J48 (pruned and unpruned)
    - Random Forest

- Hybrid Algorithm: Rotation Forest.

The models can be used in the decision making process as described in the workflow on Figure 3:

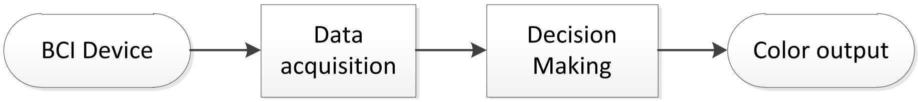

Fig.3. Using BCI for color selection

The built models can be used for selecting colors trough the BCI device or for other tasks (provided that a model is built for each specific task that the BCI device is intended for). As stated before, all of these algorithms were implemented in the WEKA software.

3 Experimental Results

The comparison of each approach was done by comparing the performance of the trained models with 10 fold cross validation.

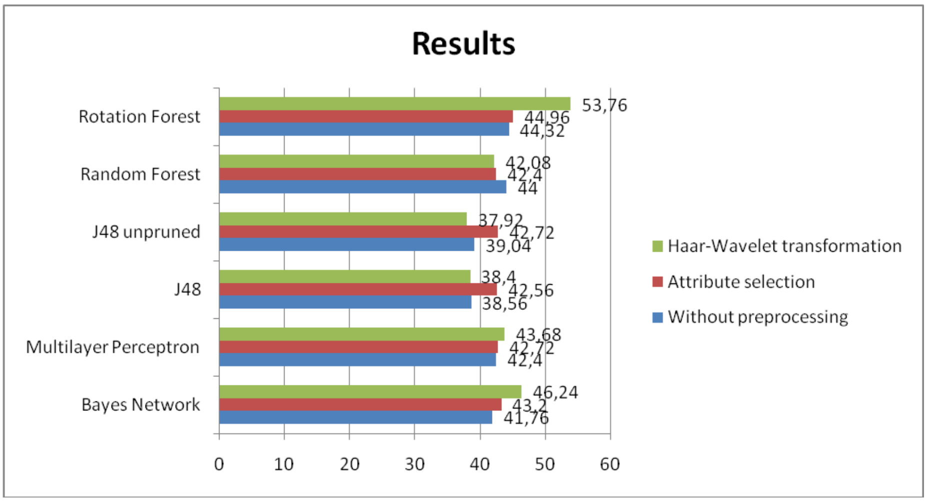

Fig.4. Precision results in %

The training was done with total of 675 samples. The obtained results for different preprocessing methods are given on Figure 4.

While building of the models the Multilayer perceptron requires noticeably more time for training then the other classifiers and gives almost the same results. The best result for the Multilayer perceptron is the precision of 43,68% with preprocessing of the data with Wavelet function.

With the training of the Bayes classifier gives better precision than the multilayer perceptron when the data is preprocessed. The best result was obtained with wavelet filtering of the data with a precision of 46,24%. This classifier gave good classification precision for the yellow and red color. The precision for the blue color classification was much worse and contributed towards the lower total performance.

The worst results for the decision tree algorithms were obtained with the J48 classifier although they gave the fastest training time. Un pruned J48 tree with attribute selection showed a precision of 42,72% which is almost as good as the neural network, with the difference that the Decision tree is trained and executed much faster than the Multilayer perceptron.

The Random forest, gives a precision of 44% for the whole data set. Here the success rate with the red color is only 28% while with the other 2 colors it is substantially bigger.

The best precision with all learning algorithms is achieved with the Rotation forest. The best precision obtained with this algorithm was 53,76%. The algorithm is described in [6].

From the collected results it can be seen that the best classifier for our data set from the selected classifiers is the Rotational forest. The analysis showed that this algorithm also gave the best performance in terms of the ROC area. The ROC area results for each algorithm with each preprocessing are given in Figure 5.

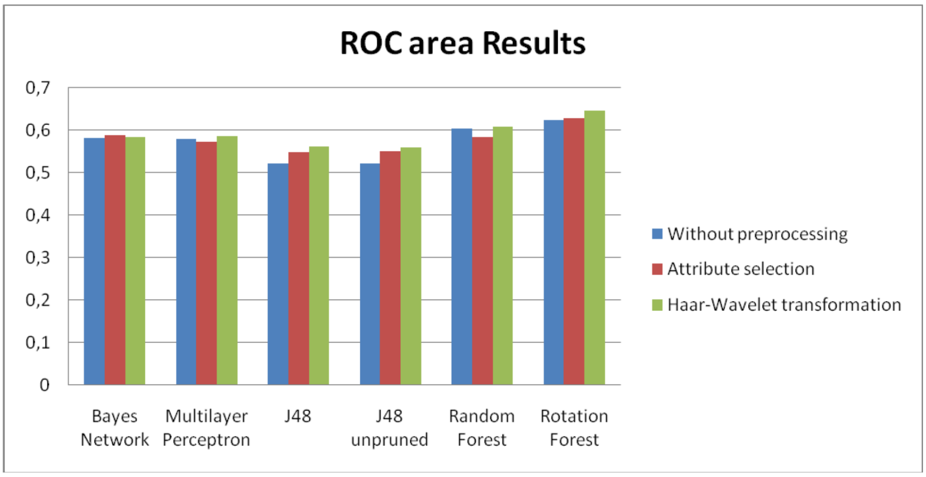

Fig.5. Results given in ROC area for each training algorithm

As it can be seen in both Figure 4 and Figure 5, the best results are obtained with the use of the Haar-Wavelet transformation of the dataset which is expected since the dataset is consisted of series of data. We must note that the results are influenced by the significant noise that the used device introduces in its measurements. The Mindwave is reported to have some noise canceling techniques but due to the sensitivity of the sensor it is hard to implement a more successful method to cancel out the noise coming mostly from muscle movements and electronic devices in the vicinity.

4 Conclusion and Future Work

BCI has great potential, both in science and medicine and in the entertainment industry. Despite the current shortcomings of commercially available BCI devices, they can be used for entertainment and research purposes. It is expected in the future this technology would become greatly advanced and enable more reliable reading of brain waves.

For this paper a computer program was implemented for reading brain waves when visual stimuli were shown. As already mentioned, our main goal was to use the same training process with minimal modifications with other stimulus, like paintings or music. Also small modifications are needed if we want to use another similar BCI device, or want to process data using statistical and other classification techniques “on the fly”.

The research on the same set of data gave best results using a Rotational Forest where the data were previously processed by wavelet transformation. The obtained results have shown a precision of around 40% with the best accuracy of about 53%. This precision is a promising result, because it is a lot better than randomly guessing the color – 33% accuracy, but is far from any practical applications.

In future the research could lead in two directions. The first is the use of other techniques like transformations of attributes and their classification, use of time series, temporal analysis, Fourier transformation and some of the newer algorithms for classification to obtain other parameters and information on the measurements.

The second direction is to use more advanced but more expensive equipment for which would have more sensors and less noise. As it is shown in the results, the used algorithms didn’t differ much in performance, thus we can expect a better result from less noisy equipment.

We must point out, however, that brain wave interface devices also require some learning on the side of the user. So in future research we plan to include models that would learn from both the data obtained from the device and the feedback from the human. In our research case the human was just seeing the color which doesn’t guarantee that the brainwaves are related solely to that visual stimulus. Other distractions must be taken into consideration and somehow included in the model.

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