Comparison of EEG Devices for Eye State Classification

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***Abstract*—In this paper, we investigate whether the price of an EEG device is directly correlated with the quality of the obtained data when applied to a simple classification task. The data of three different devices (one medical and two consumer) was used to determine the eye state (open or closed). For classification, 83 machine learning algorithms were used on the raw EEG data. While the cheapest device performed extremly poor with only one classifier better than the majority vote the other two devices achieved high accuracy. The lowest error rate for a more expensive consumer EEG was 1.38% and produced by KStar. For the medical device the best performing classifier was IBk which achieved an error rate of 1.63%. Except for KStar, the classifiers achieved a lower error rate by the medical EEG measurement system than the consumer EEG system.**

I. Introduction

There are many possible applications which could use brain activity measured by electroencephalography (EEG) as an input mode. For instance, the use of brain waves to control computer games [1], track emotions [2], provide handicapped people with an alternative input mode [3] and for different military scenarios. [4]
There are several important points that have to be taken into consideration when thinking about the use of EEG signals to control applications:

1) the accuracy for the detection of a certain state from which the control commands are generated
2) the speed of the detection algorithm
3) the cost of the EEG measurement device
4) the usability which includes preparation time and restrictions for the user during the use of the device.

One possible input for binary control tasks could be the state of the eyes that is whether they are open or closed. In a previous study [5], it was shown that the eye state can be predicted with a consumer EEG with high accuracy of 97.3%. The advantage of a consumer EEG system in comparison to a medical EEG would be the lower price and the higher usability. Most of the consumer EEGs can be easily set up and do not restrict the movement of the user by a wired connection to amplifiers.

Yet, although the results were promising, there were several problems. First of all, the study[5] was conducted with only one participant. Thus, it was not clear whether the results were statistically significant. Second, there was no comparison to the accuracy achieved when using a medically approved EEG. Despite of the fact that an error rate of 2.7% can still be too high for less fault-tolerant applications, the problem with the best classification algorithm is, as already pointed out in Roesler's study, the slow classification speed. The slow classification is caused by the fact that KStar is an instance based learner [6]. This means that the algorithm classifies a new instance by comparing it to a database of previously classified instances which makes the classifier unusable for online classification and thus for the use in any real-time application.

Thus, even if a professional EEG device would only increase the performance of other classifiers, it could be a necessary investment when the goal is to use the EEG signal as an input signal for real-time applications .

The paper is structured as follows: Section II provides the detailed information about the conducted experiment, the EEG devices and the obtained corpora. In Section III the machine learning algorithms used for classification are described. Then, the classification results for each device are described. Finally, Section V draws conclusions and outlines possibilities for future work.

II. Materials and Methods

A. Stimuli and participants

The experiments were done in the same way as described in [5]. All experiments were conducted in a quiet room. During the experiment, the face of the participants was recorded. The experimental procedure was specified as follows:

1) After placing the electrodes on the scalp the participants were told to sit relaxed, face the camera and change the eye state at free will after clicking the start button.
2) The task was repeated one to two times after a resting period of one minute.

Additional constraints given to the participants were that the individual eye state intervals should vary in length and the duration of both eye states should be about the same when accumulated over the entire session. The participants were not aware of the fact that the first 20 seconds of the measurement were not recorded. This was done to prevent artifacts due to the clicking on the start button and initial movement to face the camera.

B. EEG Measurements

The duration of the measurement was 140 seconds. Yet, as described in the previous section the initial 20 seconds were discarded to prevent artifacts. Most of the eye states were automatically annotated during the measurement by the video

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recording program. Only frames which the program could not classify due to bad lighting conditions where later annotated by hand. The used camera was a simple webcam.

C. EEG devices

Three different EEG devices were used for the measurements. Due to the high accuracy achieved with the Epoc in [5] the MindWave[1] from *NeuroSky* was selected to see whether a similar accuracy can be achieved with an even simpler and cheaper device. Secondly, the Epoc[2] from *Emotiv* was used to verify the generalizability of the results and to represent a more expensive consumer EEG. And finally, the BrainAmp Standard[3] from *Brainproducts* was investigated which is a medical EEG and needs specific training to be set up.
Table I shows a comparison of some of the specifications of the individual devices.

Device	MindWave[7]	Epoc[8]	BrainAmp Standard[9]
available channels	1	14	32
used channels	1	14	12
sampling rate	512Hz	128Hz	1kHz
price	80$	700$	60,000€

TABLE I: EEG device comparison

Due to the fact that the MindWave and the Epoc have different fixed electrode positions a direct comparison of the quality of a single electrode is not possible. Therefore, the difference in the number and position of the electrodes was not specifically assessed when evaluating the experimental performance. Thus, the number of electrodes of the BrainAmp Standard was constrained to 12 of the 32 possible electrodes to reduce the setup time and size of the corpora. The 12 electrodes were placed at the frontal, central and temporal positions of the 10-20 system. [10] This was done because most electrodes of the Epoc are frontal and the MindWave has only one frontal electrode. A detailed overview of the electrode positions is given in Figure 1

D. Corpora

Six copora were recorded for each device. The copora were from up to four different probands (see Table II). All corpora consist of as many attributes as the number of electrodes of the corresponding EEG device plus the binary class attribute. How many instances correspond to one class varies between the corpora because the probands decided how long they opened or closed their eyes. The percentage of instances belonging to the eye open state varied between 18% and 63%. On average 44.7% of the instances in the MindWave, 39.3% of the instances in the Epoc and 44.4% of the instances in the BrainAmp Standard datasets belonged to the eye open state.

[1]http://store.neurosky.com/products/mindwave-1
[2]http://www.emotiv.com/epoc.php
[3]http://www.brainproducts.com/productdetails.php?id=1

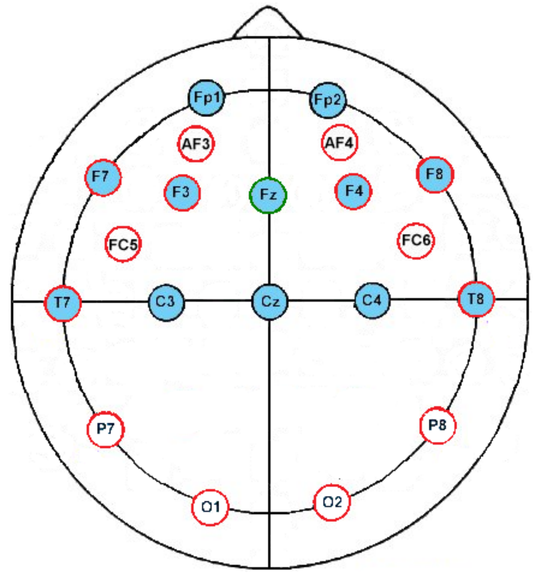

Fig. 1: Electrode positions. Blue circles indicate BrainAmp Standard, red bordered the Epoch and green bordered the MindWave.

device	corpora	participants	attributes	instances eye open
MindWave	6	4	2	44.7%
Epoc	6	3	15	39.3&
BrainAmp	6	2	13	44.4%

TABLE II: Overview of the used corpora

III. Machine learning algorithms

For classifier testing, the Weka toolkit [11] version 3-6-11 was used. Ten-fold cross-validation was carried out for all 83 standard classifiers of the toolkit with default settings. Yet, only 50 were running without an error on the datasets from all devices. Some classifiers were not suitable for cross-validation while others had problem with negative attribute values of the BrainAmp Standard datasets. Although, it would have been possible to preprocess the data to avoid the errors. The goal was to evaluate the performance on the unprocessed raw data and the remaining 50 classifiers were still sufficient to provide a general picture about the quality of the obtained EEG data. All classifiers were applied to each corpus separately. The mean error rate was then calculated across all copora of a device.

IV. Classification results

A. MindWave

For the MindWave the overall number of classifiers which made a majority vote was 20. 29 of the remaining 30 classifiers were performing worse than majority vote and only one classifier (Conjunctive Rule) achieved an accuracy of 43.52% which was slightly better than majority vote of 43.66%.

These results clearly show that the MindWave headset is not suitable for even a simple task as the classification of the eye state. However, this is not necessarily due to the fact that it has only one sensor. The Epoc headset still gets less than half the error rate when the classifiers are only trained with the values of electrode F4. Thus, the bad accuracy is also due to the quality of the electrode. To sum up, the MindWave does not seem to be useful for serious EEG experiments or to control an application.

B. Epoc

The results for the Epoc in [5] were already quite promising. Yet, the results on the six corpora have shown an even lower error rate for most classifiers. KStar [6] is again the best performing classifier with a mean error rate of 1.38%. This is a relative reduction over the result reported in [5] for KStar with default settings of 56%. IBk [12] achieved with 2.66% the second lowest error rate. Thus, the results are consistent with [5] in that instance based learners achieved the lowest error rates.

Close to them is RandomForest [13, p.407] with an error rate of 3.83%. In contrast to the instance based learners, RandomForest could be suitable for online classification. All other classifiers which achieved an error rate below 10% were mostly decision tree algorithms like FT, J48 or REPTree. These algorithms could also be suitable for online classification if the error rate can be decreased with the help of parameter tuning.

The average error rate over all classifiers (excluding classifiers which only achieved majority vote) was 16.5%.

C. BrainAmp Standard

For all classifiers except one the BrainAmp Standard achieved a lower error rate than the Epoc headset. In contrast to the Epoc headset the instance based learner IBk achieved the lowest error rate with 1.63%, followed by an error rate of 1.72% achieved by KStar. As previously mentioned, instance based learners are in general not suitable for online classification due to their slow classification speed. KStar took nearly two weeks for ten-fold cross-validation on one dataset from the BrainAmp Standard on a system with Ubuntu 12.04.1 LTS, QEMU Virtual CPU version 0.15.1, quadro core with 2GHz each and 32GB RAM.

KStar and IBk were followed by FT [14] which is a decision tree algorithm and which was also the third best classifier for the Epoc device. However, the fourth place was taken by the MultilayerPerceptron [15] algorithm which achieved a more than five times lower error rate for the BrainAmp Standard. Also the second neural network algorithm, VotedPerceptron, performed nearly three times as good on the BrainAmp Standard data. This clearly shows that most of the algorithms which require extensive training but provide fast classification were performing better on the BrainAmp than the Epoc data.

The average error rate over all classifiers (excluding classifiers which only achieved majority vote) was 11.1% and therefore 5.4% lower than the average error rate of the Epoc headset. Which is a relative reduction of the error rate of 33%.

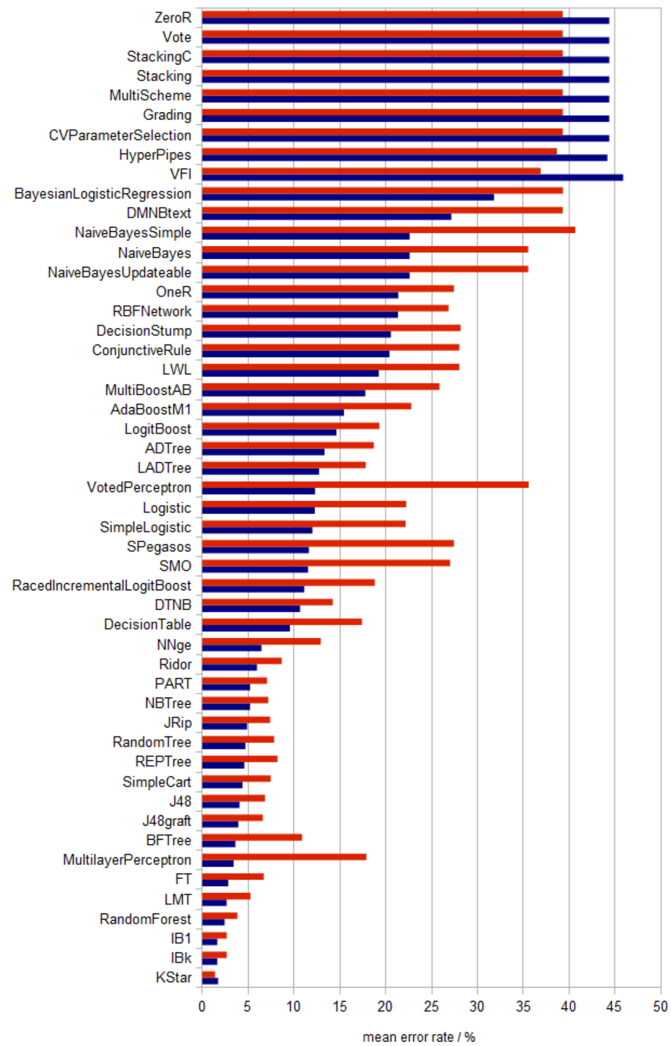

Fig. 2: Mean error rate of the error rates of all corpora for BrainAmp Standard (blue) and Epoc (orange)

V. Conclusions and Future work

The results of the experiments with the three different EEG devices have shown that the MindWave equipped with only one sensor cannot be used for eye state prediction. Yet, the more expensive consumer EEG device the Epoch headset shows very high performance for eye state predicition. Nevertheless, the quality of the data of a professional EEG like the BrainAmp Standard is still higher than the Epoch indicated by the lower average error rate. This can make a significant difference when using the device for online classification since several fast classifiers had a much lower error rate on the data from the BrainAmp than for the Epoc data. Additionally, a professional device offers the possibility to freely choose the number and positions of the used electrodes. This could also improve the performance due to the selection of electrodes close to more influential brain regions for the task of eye state prediction. Yet, the advantages of the Epoc in comparison to the BrainAmp Standard are the significantly lower price and the higher usability due to a wireless connection and a faster and easier setup.

Due to the fact that the Epoch and the BrainAmp Standard performed quite similar on the investigated task, further work will focus on more complicated tasks to see whether the difference in price will then be more obviously represented in the classification performance. Another step will also be to classify the eye state in real time and while the participant is carrying out other activities like moving around. This would show whether an EEG can be used successfully to determine the eye state in a real enviroment in which the participant will most of the time not be able to sit relaxed on a chair without moving. And further investigations will also explore whether some electrode positions are more important than others for eye state prediction in which case the number of sensors could be decreased which would simplify the set up and could lead to the development of a high quality EEG device with only a few electrodes and a wireless connection to a computer to evaluate the data in real-time.

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