A First Step towards Eye State Prediction Using EEG

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***Abstract*—In this paper, we investigate how the eye state (open or closed) can be predicted by measuring brain waves with an EEG. To this end, we recorded a corpus containing the activation strength of the fourteen electrodes of a commercial EEG headset as well as the manually annotated eye state corresponding to the recorded data. We tested 42 different machine learning algorithms on their performance to predict the eye state after training with the corpus. The best-performing classifier, KStar, produced a classification error rate of only 2.7% which is a 94% relative reduction over the majority vote of 44.9% classification error.**

I. Introduction

For many applications requiring human input, measuring brain activity by way of electroencephalography (EEG) can be of substantial benefit. For instance, brain stimuli have been used as input mode for computer games [1], to track emotions [2], for handicapped persons to control devices [3], or for military scenarios [4]. Especially the latter two examples require accurate detection of the stimuli in question to avoid false alarms. It is therefore of utter importance to determine which specific stimuli can be detected with sufficient accuracy.

Several papers investigated the differences between the two eye states (that is, whether eyes are open or closed). [5] came to the conclusion that the "greatest difference between two states was that the power in the eye closed state was much higher than that in the eye open state." However, the authors did not pursue this finding any further in an attempt to use power as a feature for predicting the eye state. [6] investigated how to track eye blinking (the change of the eye state) based on EEG input. This study was limited to a single classification algorithm (artificial neural networks—ANNs) producing a very poor performance. Furthermore, eye blinking and eye state are intrinsically different properties in that the former is an event of a short duration whereas the latter can vary largely in duration (see also Figure 1).

To sum up, none of the papers discussed above tried to predict the eye state based on a given set of EEG sensor values. Even though [7] mentions the "potential to be used as a switching mechanism for assistive technologies", the authors do not go so far as to implement an algorithm performing said classification, not to speak of measuring its performance on a collected corpus.

To render our research as useful as possible for the scientific and technological community, we decided not to use a medical EEG but the Emotiv EPOC headset[1]. Compared to a medical EEG, the EPOC headset is much more affordable, and it can be set up quickly and without the help of another person. Furthermore, we used the open-source software Weka[2] for our classification experiments making results easily reproducible by other researchers. To this end, we also released the corpus we created for the present work to the public domain (see Section II-C for details).

After running extensive experiments with up to 42 different classifiers and multiple settings of tuning parameters, we were able to achieve a classification error rate of less than 3% using the instance-based learner KStar [8]. This result indicates that eye state prediction has the potential to be used as accurate binary input channel.

The rest of the paper is structured as follows: Section II gives more details about the technical details of the EEG measurement we performed and the corpus we established. After giving a brief overview about the performance of all classifiers we compared, Section III describes the tests with KStar together with an analysis of the results. Finally, Section IV draws conclusions and outlines future perspectives of the present work.

II. Materials and Methods

A. Stimuli and Probands

The experiment was carried out in a quiet room. During the experiment, the proband was being videotaped. To prevent artifacts, the proband was not aware of the exact start time of the measurement. Instead, he was told to sit relaxed, look straight to the camera, and change the eye state at free will. Only additional constraint was that, accumulated over the entire session, the duration of both eye states should be about the same and that the individual intervals should vary greatly in length (from eye blinking to longer stretches), see Figure 1.

B. EEG Measurement

The duration of the measurement was 117 seconds. The sampling rate of the EEG headset A/D converter was four times the frame rate of the video camera. The eye state was manually annotated by analyzing the video recordings aligned with the EEG data. Both, open or partially open eyes

[1]http://www.emotiv.com
[2]http://www.cs.waikato.ac.nz/ml/weka

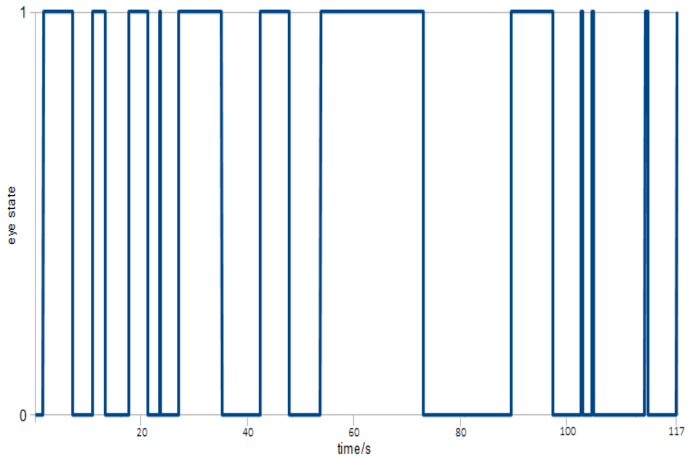

Fig. 1. Distribution of eye states during the two minutes. 0 represents eye open and 1 eye closed.

were categorized as open; only completely closed eyes were categorized as closed. Three instances (out of almost 15k) were removed from the corpus because of obvious transmission errors.

C. The corpus

The corpus consists of 14977 instances with 15 attributes each (14 attributes representing the values of the electrodes and the eye state). The instances are stored in the corpus in chronological order to be able to analyze temporal dependencies. 8255 (55.12%) instances of the corpus correspond to the eye open and 6722 (44.88%) instances to the eye closed state.

Table I shows the value ranges of the 14 sensors in the corpus. There is an obvious difference in amplitude of certain sensors when comparing the range of values for different eye states. On the one hand, for the sensors F7, F3, O2, P8, T8, FC6, and F4, the maximum values for the eye open state are higher than the maximum values of the eye closed state while the minimum values are nearly the same. On the other hand, for the sensors AF3, FC5, T7, P7, O1, F8, and AF4, the minimum values for the eye open state are lower than for the eye closed state while the maximum values are about the same. All sensors have in common that open eye state comes along with a higher value range than the eye closed state while the mean stays nearly the same. Accordingly, also the standard deviation increases.

As motivated above, sensors could be split into two groups. In the first group, the maximum increases when eyes open while, in the other group, the minimum decreases in the same event. Most sensors of the first group happen to be located on the right hemisphere while most of the second group are on the left hemisphere of the brain, as displayed in Figure 2.

To encourage the research community to further explore the task of eye state prediction and allow the interested reader to reproduce the results reported in this paper, we released our corpus to the public domain. It can be downloaded from

http://suendermann.com/corpus/EEG_Eyes.arff.gz.

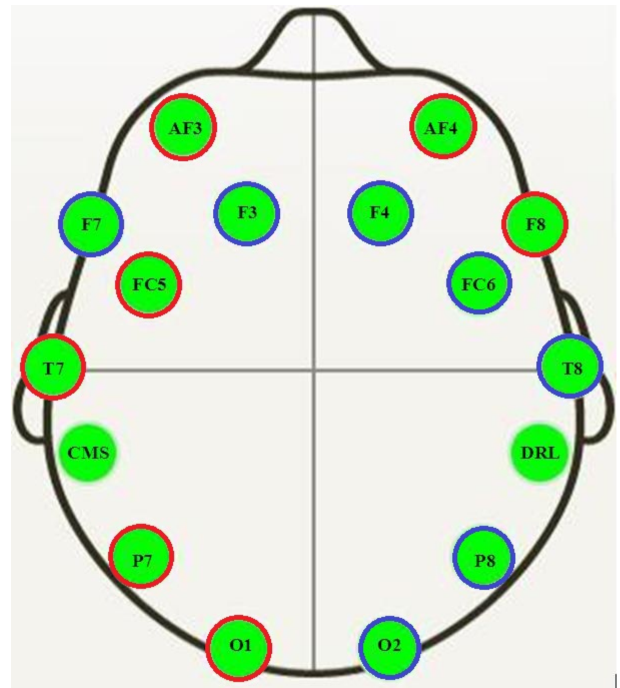

Fig. 2. Overview of the sensor position and the corresponding behavior group. Blue corresponds to a maximum increase and red to a minimum decrease when opening eyes.

TABLE I
RANGES AND MEANS OF THE SENSOR VALUES FOR THE EYE STATES

Eye State	closed min	closed mean	closed max	open min	open mean	open max
AF3	4198	4305	4445	1030	4297	4504
F7	3905	4005	4138	3924	4013	7804
F3	4212	4265	4367	4197	4263	5762
FC5	4058	4121	4214	2453	4123	4250
T7	4309	4341	4435	2089	4341	4463
P7	4574	4618	4708	2768	4620	4756
O1	4026	4073	4167	3581	4071	4178
O2	4567	4616	4695	4567	4615	7264
P8	4147	4202	4287	4152	4200	4586
T8	4174	4233	4323	4152	4229	6674
FC6	4130	4204	4319	4100	4200	5170
F4	4225	4281	4368	4201	4277	7002
F8	4510	4610	4811	86	4601	4833
AF4	4246	4367	4552	1366	4356	4573

III. MACHINE LEARNING ALGORITHMS

A. General testing

For our classification experiments, we used the Weka toolkit [9]. At the beginning, ten-fold cross-validation was carried out for all suitable classifiers in Weka with their default parameter settings to get a general overview. Results of this experiment are shown in Figure 3.

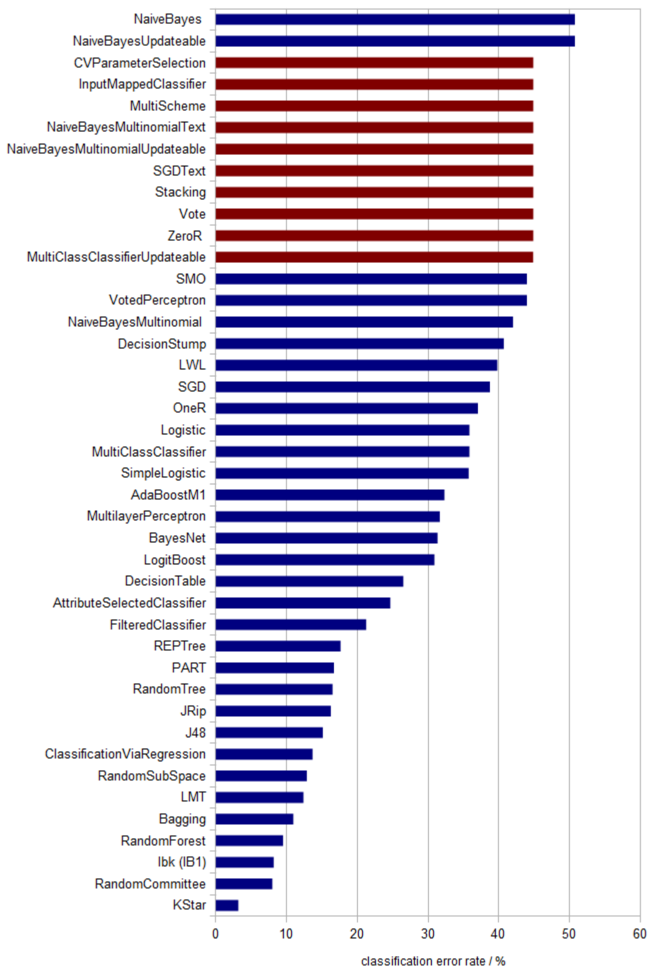

Fig. 3. Performance of all classifiers with default settings. Baseline performance (i.e. majority vote) is shown in red.

Surprisingly, standard classifiers such as naïve Bayes [10], SMO [11], logistic regression [12], or ANNs [13] with a proven track of high classification performance produced rather poor results on this task (over 30% classification error). Decision tree algorithms such as JRip [14] or J48 [15] performed much better (about 15%). However, instance-based learners such as IB1 [16] and KStar [8] outperformed decision trees yet again substantially. The latter achieved the clearly best performance with a classification error rate of merely 3.2%.

B. KStar

Being an instance-based learning algorithm, KStar classifies an instance by comparing it to a database of pre-classified instances. In this comparison, a parameter (the global blend b) influences to which extent neighbors of the instance to be classified are taken into account. By definition, the global blend can vary between 0 (just the closest neighbor is considered) and 100 (all instances in the corpus are equally considered).

We ran an experiment to find which global blend is most beneficial and found that $b \approx 40$ is a good choice for the present corpus. The error rate decreased to 2.7% which is a relative reduction of 15% compared to the error rate when using the default setting $b = 20$ (see Figures 4 and 5). The relative error rate improvement over the majority vote baseline of 44.9% was 94%.

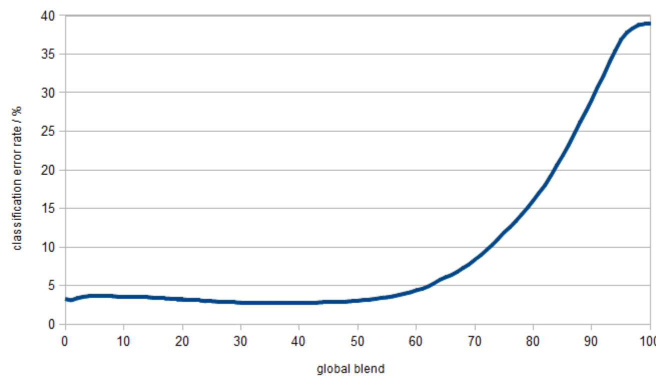

Fig. 4. Performance of KStar for all possible values of global blending.

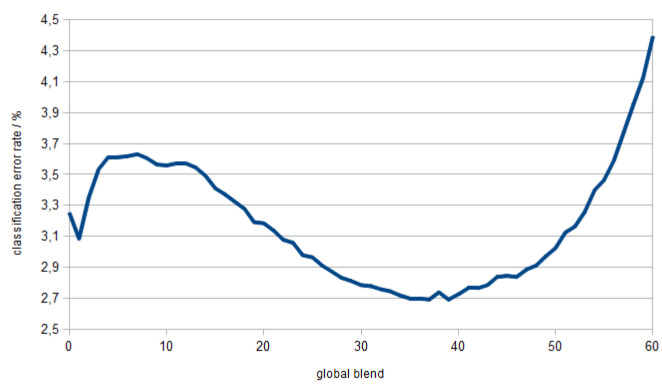

Fig. 5. Performance of KStar for the best values. Different scaling of Fig. 4 to see the minimum of the classification error rate.

In order to informally investigate the robustness of KStar w.r.t. to the transmission errors mentioned in Section II-B, we also tested its performance when inserting instances with unrealistic values (significantly higher than the usual sensor maxima). KStar exhibited nearly no performance degradation as opposed to multiple other classifiers (like naïve Bayes and ANNs). Intuitively, the use of a global blend $b < 100$ makes sure that extreme outliers get filtered out of the instance sets under consideration, so, their impact is negligible. In contrast, probabilistic classifiers and many others draw conclusion based on the entire body of available training data. Hence, extreme outliers may significantly skew distributions and thereby negatively affect performance.

Drawback of KStar and other instance-based classifiers is their runtime behavior. To execute a test over the entire described corpus took over 38 minutes on a system with Ubuntu 12.04.1 LTS, QEMU Virtual CPU version 0.15.1, dual core with 2.4GHz each and 32GB RAM, corresponding to a real time factor of about 20. This observation will have to be taken into account when attempting to track eye state in real-world systems.

IV. Conclusions and Future work

This paper demonstrated that it is possible to predict eye state using EEG sensor input with an accuracy of more than 97%. The high accuracy and the fact that no special training is required suggest the use of eye state inferred from EEG signals for controlling tasks. However, the present study involved only a single subject which raises the question whether results are generalizable. We are currently investigating the presented technique's behavior across multiple probands including user-independent training. Preliminary results of these experiments look very encouraging. To allow for applying the presented technology securely and effectively, the dependence of eye state prediction accuracy on other activities carried out by the subjects will have to be explored. Furthermore, it would be interesting to see whether the number of sensors can be decreased by means of feature selection [17] without compromising performance. Also other techniques for dimensionality reduction such as linear discriminant analysis [18] could be useful to look at. Less sensors would reduce production cost of required EEG devices and also speed up instance-based classification.

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