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AN ALGORITHM FOR DETECTION OF MULTIPLE BLINKS OF SINGLE AND BOTH EYES FROM EOG SIGNAL

I. Rejer[1], Ł. Cieszyński[1]

[1] Faculty of Computer Science and Information Technology, West Pomeranian University of Technology, Szczecin, Poland

E-mail: irejer@wi.zut.edu.pl

ABSTRACT: The paper presents an algorithm for blinks detection from an EOG (electrooculographic) signal. The algorithm is based on the analysis of time waveforms recorded from Fp1 and Fp2 and is capable to work as well in a fix trial length mode as in a free user mode. The paper covers the description of the algorithm and its verification via an experiment conducted with ten healthy subjects. During the experiment the recognition of nine blinking schemes was tested: single, double and triple blinks with left, right, and both eyes. The recognition rate calculated over nine blinking schemes and ten subjects was equal to 92%. When analyzing the results across different blinking schemes we found that: 1) it was much easier to recognize left-right blinks (96%) than both eyes blinks (83%); 2) the detection accuracy dropped with the increasing number of blinks (98% - single, 91% - double, 87% - triple blinks) but it was sufficiently high even for triple blinks.

INTRODUCTION

Eye blinks have all the features needed to establish a successful communication channel. They can be precisely characterized for an individual, easily modulated or translated to express the intention, and can be detected and tracked consistently and reliably [1]. Of course, they need some motor control from the user but if such control is possible, they constitute a fairly stable channel. Comparing to control signals used in nowadays BCIs (Brain-Computer Interfaces), the eye blinks provide more comfortable communication that SSVEP-BCI (Steady State Visually Evoked BCIs) and P300-BCI (BCI based on P300 component). First of all, they do not need any external device that would provide stimulations evoking the required brain response. That also means that nor flickering light or highlighting objects are constantly present at a user visual field. Moreover, since the different styles of eye blinks are evoked only at a user will, the user can decide when he wants to switch the interface from an 'off' to 'on' state. On the other hand, comparing EB-interface (Eye Blink) to MI-BCI (Motor Imagery BCI), the first one is much more stable and does not require any user training. At this moment both types of interfaces provide a comparable number of control states (usually no more than 2-4) but this can be easily changed with the algorithm described further in this paper.

The papers on eye blink detection usually describe recognition systems providing a rather limited number of control states, often only 1-4 states, [1-3]. This paper aims to propose a recognition algorithm that significantly increases this number. The proposed algorithm enables the recognition of succeeding blinks of left, right and both eyes. Since the algorithm allows to detect different number of blinks, the number of control states provided by the interface using this algorithm is adaptable. It starts from two states, corresponding to single blinks of left and right eye but can easily be extended to three, six, nine or more by using double, triple, and more blinks. Of course, since a single simultaneous blink with both eyes is a spontaneous physiological activity, it is usually excluded from the set of control states.

The algorithm is based on the EOG time waveforms recorded from two prefrontal contralateral channels. We do not use the EOG signal recorded from the standard positions, it is from the electrodes located around the eyes because we want to ensure the maximum comfort of the user using the EB-interface. In the experiment testing the algorithm accuracy, all the electrodes were incorporated into a forehead band and the users found it a more convenient solution than when the electrodes were placed around the eyes.

The paper covers both, the detailed description of the algorithm and its experimental verification. The experiment described in the paper was conducted with ten healthy subjects whose task was to blink according to the blinking schemes presented in the computer screen. During the experiment the recognition of nine blinking schemes was tested: single, double and triple blinks with left, right, and both eyes.

RELATED WORK

The eye blinks related signals are predominant in the frontal and prefrontal sites on the scalp. Peaks appearing in the signal waveform recorded from these areas inform that an eye open (negative peak) or eye close (positive peak) event took place. Hence, an eye blink event can be detected when the positive peak followed by a negative deflection in a signal waveform is formed. The algorithms on eye blink detection directly or indirectly utilize these features. For example, in [4] the kurtosis, a statistical coefficient that describes the relative flatness of the data distribution, was used to detect the eye blink

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episodes. The kurtosis is a quite good indicator for eye blink episodes because it is positive for peaked data distribution (typical for eye blink) and negative for flat distribution (typical for noise). As the authors report in the paper, they were able to detect single, double and triple eye blinks only with kurtosis coefficient calculated from the data recorded with one bipolar EEG channel. However, the speed of the interface presented in the paper was somewhat limited because with these three choices one character per minute was selected from a 27-letters keyboard. The information on the accuracy of the proposed solution was not provided.

The kurtosis concept was also used in [5], where the kurtosis coefficient was applied in the RBF classifier. The classifiers inputs (calculated from a one-second window) were: maximum amplitude, minimum amplitude, kurtosis of the present window, kurtosis of the previous window, and kurtosis of the next window. The authors reported 76% accuracy over the test data. A neural classifier was also used in [3], where four control states corresponded to left wink, right wink, single blink, and double blink were applied to control the wheelchair movements. The classifier's inputs were DWT (Discrete Wavelet Transform) coefficients extracted from F7 and F8 channels and its sensitivity and specificity were equal to 80% and 75%, respectively.

Much more algorithms on eye blink detection and recognition can be found in the papers on eye blink artifacts correction [6,7]. However, these algorithms usually either deal with the signal in an offline mode, it is after the recording was completed, or correct the parts of the signal of the given characteristics. While the former often need long segments of signal acquired from a dense matrix of channels to work correctly (e.g. algorithms based on sources detection or trends recognition), the latter are not sensitive enough to distinguish between succeeding blinks.

All the papers mentioned so far extracted information about the blinking pattern directly from the EOG signal. However, this is not the only possibility. Another approach is based on visual detection of gaze direction and blinking episodes. For example, in [8] a 4-steps detection system based on methods for image recognition was proposed. The system first detects a face region (with Haar-like features), then extracts and eye region (via analyzing geometrical dependencies), and finally detects and classifies the eye-blinks as spontaneous (shorter than 200ms) or voluntary (longer than 200ms). Voluntary blinks are further classified as long or short and hence the algorithm provides two control signals that can be used for selecting letters from a virtual keyboard or controlling cursor movements on the screen. The authors reported the results of the experiment with 49 subjects where the average time of entering a single sign was equal to 16.8 s before the training session and 11.7 s after the training session and the accuracy of detecting control eye-blinks was equal to 99%.

RECOGNITION ALGORITHM

The EOG activity is a result of the difference in charge between the cornea and the bottom of the eye. If this activity is recorded from the forehead electrodes, it is positive when the eyeballs go up and negative when they go down. Because of the so-called Bell effect (eyeballs go in the opposite direction to the eyelids) the eyes closure induces positive potential and eyes opening – negative potential.

The eye-blink episode builds upon the phenomenon described above and hence has a very specific time pattern (Fig. 1a). It starts from a rapid and narrow positive peak that is followed by a slightly wider but also very deep negative trough. Exactly after the blink episode, two more components are formed, first – a significantly lower and wider positive component and second - a very small and wide negative come-back. When two or more blinks are followed one after another, the blinking scheme remains the same (one sharp positive peak followed by a negative trough) for each blink and the two after-blinking components at the end (Fig. 1b).

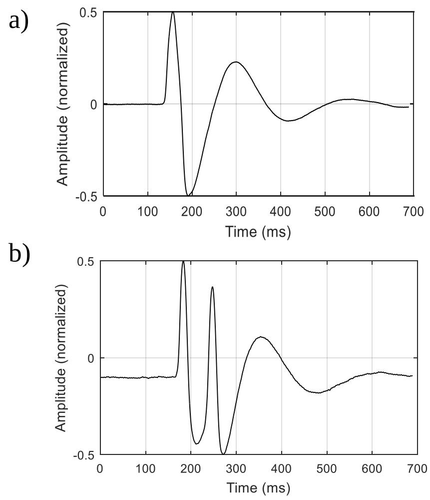

Figure 1: EOG signal from Fp1 during left eye blink event; a) single blink; b) double blink; non-filtered single-trial signals.

The height and width of the peak formed in the time course of EOG signal recorded from a single channel (preferably located at Fpz position) are the two characteristics that can be used to take a decision whether the blinking episode occurred or not and to distinguish between one, two or more consecutive blinks of one/both eyes. However, the algorithm based exclusively on counting the number of blinks provides a highly limited number of possible control states. This number can be increased (by a factor of three) if not only the number of blinks but also a blinking eye is detected from the signal. Of course, since the blinking scheme is the same for both eyes, it would be extremally difficult to distinguish the blinking eye from the signal recorded from an electrode located between both eyes (Fig. 2). This task is much easier when instead of one, two EOG channels are used.

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Figure 3 presents the EOG signal recorded from two prefrontal electrodes (Fp1 and Fp2) during a double blink of the left eye. As it can be noticed in this figure the involuntarily blink of the non-intended right eye is characterized by a much smaller amplitude at Fp2 (solid line) than the intended blink of the left eye (dashed line).

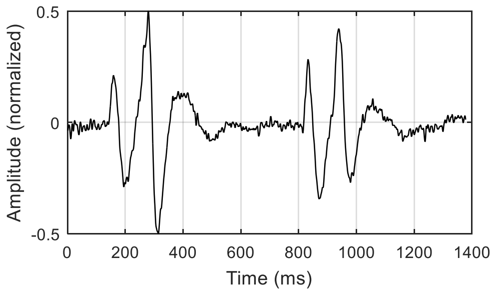

Figure 2: EOG signal from Fpz during double left eye blink (signal between 0-700ms) and double right eye blink (signal between 700-1400ms); non-filtered single-trial signal.

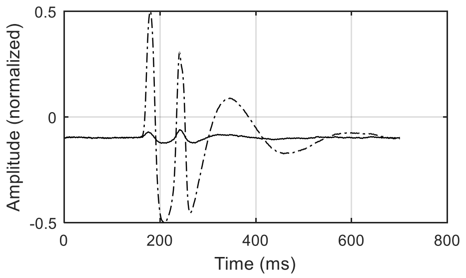

Figure 3: EOG signal from Fp1 (dashed line) and Fp2 (solid line) during double left eye blink; non-filtered single trial signal.

The last figure from this section (Fig. 4) presents the waveforms recorded from Fp1 and Fp2 during simultaneous blinks of both eyes. As it can be noticed this time peaks of both waveforms have the amplitude significantly greater than the rest of the signal. Usually, the amplitude of both peaks is not equal (because of small shifts in electrodes montage and also because of physiological differences between eyes), however, it is always well beyond the ongoing EEG activity.

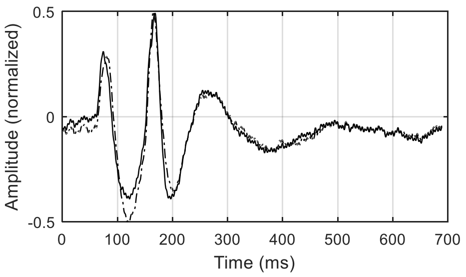

Figure 4: EOG signal from Fp1 (dashed line) and Fp2 (solid line) during double both eyes blink; non-filtered single-trial signal.

The algorithm that we propose to use for recognizing different eye blinking patterns from the EOG signal starts from the calibration session. The calibration session is necessary not only because of the subjects' differences in blink characteristics but also because these characteristics can be quite different even for the same subject in two succeeding experiments. Of course, the core of the blinking pattern does not change, the eye-close event evokes the positive peak and the eye-open event – a negative peak. However, the amplitude of the peaks in both channels can differ significantly. This what evokes this change are small shifts in the electrodes montage. Even slight differences in the electrodes' localization on the skull can highly suppress or enhance the peaks formed for left, right or both eyes. The task of the calibration session is to prevent the influence of these shifts on the algorithm accuracy. Therefore, the calibration session should be performed anytime when the user starts his/her work with the interface applying the proposed algorithm.

During the calibration session, the user is asked to blink once and twice with each eye individually and with both eyes together. Between both series, the user is asked not to blink at all. Hence, the calibration session is divided into seven segments, following one after another:

- S1, S2, S3 - single blink with left, right, and both eyes, respectively;
- S4 – no blinking period;
- S5, S6, S7 – double blink with left, right, and both eyes, respectively.

Assuming that three seconds are allocated to each condition, the whole calibration session lasts no more than 30 s. The signal acquired during the calibration session is used to calculate six parameters that are later used as thresholds in the recognition process. The description of parameters is presented in Tab. 1. All six parameters are calculated as the mean value from the two corresponding segments of the calibration session mentioned in the table.

Table 1: Parameters calculated from the calibration session

Name	Description	Segment
T1a_c	Hight of Fp1 peak corresponding to the left eye blink	S1, S5
T1b_c	Hight of Fp2 peak corresponding to the right eye blink	S2, S6
T1c_c	Hight of Fp1 peak corresponding to both eyes blink	S3, S7
T1d_c	Hight of Fp2 peak corresponding to both eyes blink	S3, S7
T2_c	Distance between peak and the consecutive zero crossing point (in samples)	S1, S2
T3_c	Distance between two succeeding peaks (in samples)	S5, S6

The parameters calculated over the calibration session are not directly used in the recognition process but first are modified to make them far less restrictive. The

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modification rules are as follows:

- all four *T1_c* parameters are modified by a factor 0.5 (*T1=0.5T1_c)*;
- *T2_c* parameter is modified by a factor of 2.0 (*T2=2T2_c*);
- *T3* parameter is modified by a factor 2.0 (*T3=2T3*_c).

The algorithm is very flexible to the levels of these modification factors. It works correctly even if they are changed significantly. So far, we tested the algorithm for the levels: 0.4-0.6 (for T1s), 1.5-3 (for T2), and 1.5-3 (for T3).

The core part of the algorithm is composed of nine steps:

1. Find the first sample exceeding *min(T1a, T1c)* in Fp1 channel and/or *min(T1b, T1d)* in Fp2 channel.
2. Record the following samples (starting from the sample found in 1 until the signal crosses zero in both channels.
3. Find *max(Fp1)* and *max(Fp2)* and the distance between the sample of maximum value and the last sample from the recorded signal (*D1* – distance calculated over *Fp1*, *D2* - distance calculated over *Fp2*).
4. Decide on the eye (*left*, *right*, *both*) and the channel (*Fp1*, *Fp2*) that will be used in the process of searching for succeeding peaks. The decision on the eye (*left*, *right*, or *both*) and channel (*chosenChannel*) is taken according to one of two rules. Rule 1 is triggered when *T1a+T1b* > *T1c+T1d* and is defined as follows:
   a) if max(Fp1)>T1a & D1<T2 -> *left, Fp1, T1=T1a*
   b) if max(Fp2)>T1b & D2<T2 -> *right, Fp2, T1=T1b*
   c) *both*: if max(Fp1)>T1c & D1<T2 & max(Fp2)>T1d & D2<T2
      - if max(Fp1)>=max(Fp2) -> *Fp1, T1=T1c*
      - if max(Fp1)<max(Fp2) -> *Fp2, T1=T1d*

   Rule 2 is triggered when *T1a+T1b* < *T1c+T1d.* This rule is almost identical to Rule 1. The only difference is that condition *c* is tested before conditions *a* and *b*. The split into two rules is necessary because there are two blinking schemes across the subjects. While most subjects blink stronger when using both eyes simultaneously, there are also subjects who blink stronger when only one eye is used.
5. If none of the conditions given in 4 is fulfilled, discard all the recorded samples and start from 1. In the other case set *n=1* (*n* – number of peaks found in the signal), discard all the recorded samples and start looking for the next peak in the chosen channel (go to 6).
6. Find the first sample exceeding *T1* and record the following samples (starting from the this 'exceeding' sample) until the signal crosses zero.
7. Find *max(chosenChannel)* and the distance between the sample of maximum value and the last sample from the recorded signal (*D*).
8. If *max(chosenChannel)>=T1 & D<=T2* set *n=n+1,* discard all the recorded samples and start looking for the next peak in the chosen channel (go to 6).
9. If rule given in 8 is not fulfilled or the length of the recorded signal exceeds *T3* (in a free user mode) or exceeds the trial length (in a fixed trial length mode) return the number of peaks *n* and the chosen eye (*left*, *right*, or *both*) and start from 1.

MATERIALS AND METHODS

To test the algorithm described in the previous section, an experiment with ten healthy subjects (seven men and three women) was performed. All the subjects were right-handed, had normal vision and did not report any mental disorders. The experiment was conducted according to the Helsinki declaration on proper treatments of human subjects. Written consent was obtained from the subject before the experiment.

The detailed scheme of the experiment with one subject was as follows. The subject was placed in a comfortable chair and the electrodes were applied on his head. In front of the subject in an approximate distance of one meter an LCD monitor was located. A short sound signal announced the start of the experiment. Two seconds later the calibration session started. This session was performed two times: 1st - to make the subject familiar with the sequence of segments; 2nd - to calculate the algorithm parameters.

During the calibration session a sequence of pictures informing the subject of what was his/her task in the given segment was displayed (Fig. 5). Each picture was present on the screen for three seconds.

Figure 5: One of the pictures displayed during the calibration session (single blink of the left eye).

When the first calibration session ended, a picture presenting the EOG signal recorded during subject actions was displayed on the screen (Fig. 6). The experimenter discussed the subject's mistakes (wrong eye or wrong number of blinks) and explained once again what was the subject's task in each segment. Right then the real calibration session started.

Ten seconds after the calibration session the actual experiment started. During the whole experiment, a picture with nine texts informing the subject about his/her task was displayed on the screen (Fig. 7). Every three seconds a frame was displayed around one of the nine texts. The subject's task was to blink once, twice or three times with left, right or both eyes just as was indicated by the text surrounded by the frame. The experiment consisted of 36 trials, four trials per each blinking scheme.

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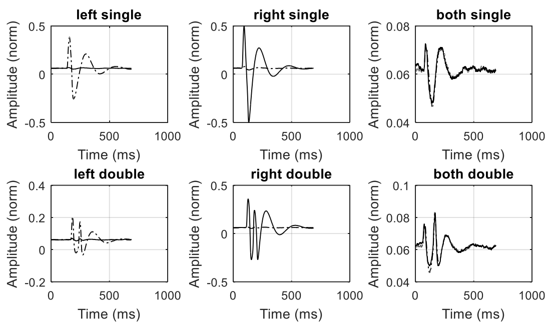

Figure 6: EOG signals recorded during the first calibration session with one of the subjects (Fp1 - dashed line, Fp2 - solid line).

EOG data was recorded from two monopolar channels at a sampling frequency of 250 Hz. Four passive gold cup electrodes were used in the experiments. Two of them were attached to the subject's skull at Fp1, and Fp2 positions according to the International 10-20 system [9]. The reference and ground electrodes were located at the left and right mastoid, respectively. The impedance of the electrodes was kept below 5 kΩ. The EOG signal was acquired with OpenBCI amplifier and recorded with OpenVibe Software [10]. The whole experiment, covering the preparation part, electrodes application, 2 calibration sessions, the actual experiment, and the after-cleaning lasted about 20 minutes with one subject.

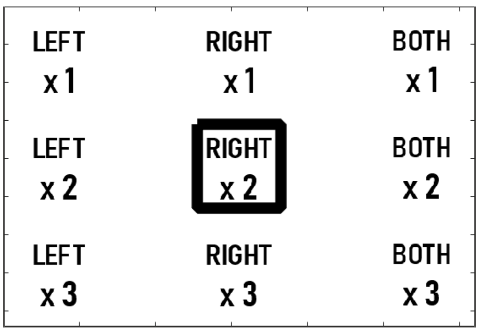

Figure 7: The tasks' panel.

RESULTS AND DISCUSSION

The classification accuracy calculated from all 36 trials for each subject is presented in Fig. 8 and the last column of Tab. 3. As it can be noticed, the accuracy was quite high for most of the subjects. For S1, S7, S8, and S9 it was even higher than 97%. However, there were also some subjects (most of all S6 and S2) that achieved much lower accuracy (S6 - 78%, S2 – 83%). Of course, having in mind that this accuracy was obtained for 9-classes classification, it was still a very good result. To find out whether these differences in the classification precision were caused by a systematic algorithm error or rather a subject specificity, we decomposed the results into 6 schemes. The three first schemes corresponded to a different blinking eye (left, right or both), the next three schemes - to a different number of blinks (1x - single, 2x - double, or 3x - triple). Each scheme covered 12 of the trials from our 36-trial experiment.

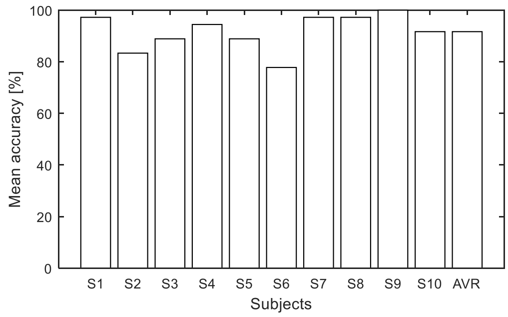

Figure 8: Classification accuracy for each subject calculated over all 9 blinking schemes.

Figures 9-10 and Tab. 2 present classification accuracy obtained for each subject under different blinking eye schemes (Fig. 9) and different number of blinks (Fig. 10). The first conclusion that should be made here is that regardless of the number of blinks, it was much easier to recognize left-right blink than both eyes blink. While the single eye recognition rate (averaged over different number of blinks) was equal to almost 96% (for both: right eye and left eye), it was significantly smaller (83%) for both eyes (according to paired sample *t*-student test with p=0.05).

The second observation that can be deduced from Tab. 2 and Fig. 10 is that the accuracy dropped with the increasing number of blinks from 98% (for single blinks) to 91% (for double blinks) and 87% (for triple blinks). While this drop was significant when comparing single to triple blinks (according to paired sample *t*-student test with p=0.05), it was incidental for single and double or double and triple blinks.

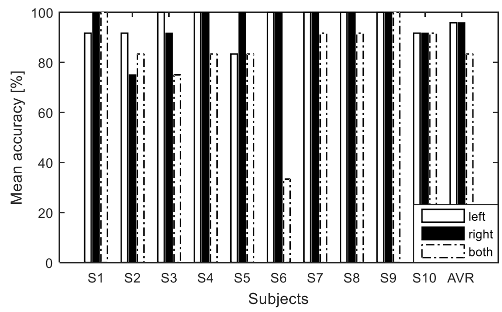

Figure 9: Classification accuracy for each subject calculated separately for left, right, and both eyes condition.

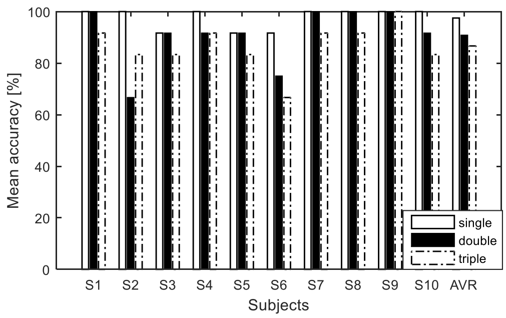

Figure 10: Classification accuracy for each subject calculated separately for single, double, and triple blinks.

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Table 2: Classification accuracy for each subject across analyzed number of blinks and blinking eyes (1x, 2x, 3x – single, double, and triple blinks; L, R, B – left, right, and both eyes).

	L	**R**	**B**	**1x**	**2x**	**3x**	**All**
S1	91.7	100.0	100.0	100.0	100.0	91.7	**97.2**
S2	91.7	75.0	83.3	100.0	66.7	83.3	**83.3**
S3	100.0	91.7	75.0	91.7	91.7	83.3	**88.9**
S4	100.0	100.0	83.3	100.0	91.7	91.7	**94.4**
S5	83.3	100.0	83.3	91.7	91.7	83.3	**88.9**
S6	100.0	100.0	33.3	91.7	75.0	66.7	**77.8**
S7	100.0	100.0	91.7	100.0	100.0	91.7	**97.2**
S8	100.0	100.0	91.7	100.0	100.0	91.7	**97.2**
S9	100.0	100.0	100.0	100.0	100.0	100.0	**100.0**
S10	91.7	91.7	91.7	100.0	91.7	83.3	**91.7**
Mean	**95.8**	**95.8**	**83.3**	**97.5**	**90.8**	**86.7**	**91.7**

Finally, we aggregated the results obtained from different subjects to find out which of our 9 classification schemes was correctly recognized in most cases. The aggregated results are presented in Tab. 3. As it can be noticed in the table the best detection rate was obtained for single right eye blink (100%), then for single and double left eye blink (98%), and next for double right and single both eyes blink (95%). If instead of the nine blinking schemes, only the first four were used (excluding single blink with both eyes as spontaneous physiological activity), the average accuracy would reach exactly 97.5%.

Table 3: The mean classification accuracy for each of the nine blinking schemes; results aggregated over all subjects.

	Left	Right	Both	Mean
1 x	**97.50**	**100.00**	95.00	97.50
2 x	**97.50**	**95.00**	80.00	90.83
3 x	92.50	92.50	75.00	86.67
Mean	95.83	95.83	83.33	

CONCLUSION

As it was shown in the paper, the proposed detection algorithm can recognize a quite high number of control states with a high detection rate, without any external stimulations and with use of a very short (30 s) calibration. Therefore, for the users that can still control their eyelids muscles, it can provide a good alternative to the brain-computer interfaces.

The main outcomes from the experiment described in the paper are: 1) the overall detection rate calculated over nine blinking schemes and ten subjects was equal to 92%; 2) the detection rate calculated over four best blinking schemes was equal to 98%; 3) it was much easier to recognize left-right blinks (96% - right eye and 96% - left eye) than both eyes blinks (83%); 4) the detection accuracy dropped with the increasing number of blinks (98% - single, 91% - double, 87% - triple blinks).

We believe that the algorithm described in this paper might be further improved by enhancing the recognition of both eyes' blinks. Moreover, to formulate more valid conclusions we plan to conduct experiments with more subjects and a greater number of blinks.

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