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The EOG event recognition method in an EEG signal towards SSVEP BCI improvement

Abstract

This paper presents a method of recognizing EOG artifacts in an EEG signal. Moreover, it shows the possibility of determining the direction of eye movement. The idea behind this method is to develop a hybrid brain-computer interface relying on SSVEP phenomena and EOG artifacts acquired from the EEG signal. Recognition of an EOG event and its direction can be used to improve the SSVEP detection accuracy, overall system responsiveness, and increase the information transfer rate (ITR). Eye movement direction is recognized using a decision tree and histogram-based features calculated from EEG signals recorded in Fp1-O1 and Fp2-O2 points. The accuracy of 75% was achieved for a group of 8 subjects, while the average precision of detecting movement direction in horizontal plane was 78%.

Keywords: Hybrid BCI, EEG, EOG artifact, SSVEP, tree classifier.

1. The EOG event recognition method in an EEG signal towards SSVEP BCI improvement

Human-Machine Interfaces based on biological signals give the user a feeling of interface transparency and should create a very thin barrier between the first encounter and fluent usage. Bio-signal based interfaces include BCIs (Brain-Computer Interfaces) utilizing person's brain activity. Electro-encephalography (EEG) interfaces are the most popular, as they are a non-invasive, moderately easy and cheap way of measuring the brain activity.

One of the most widely researched methods of creating a BCI are steady-state visually evoked potentials (SSVEP) phenomena. SSVEP is a method of stimulating a subject's retina with light stimuli of specific frequency. Then a trace of flickering frequency and its harmonics can be found in the EEG signal. Introducing multiple visual markers with various frequencies, SSVEP phenomena can serve as an approach to human-machine interface development.

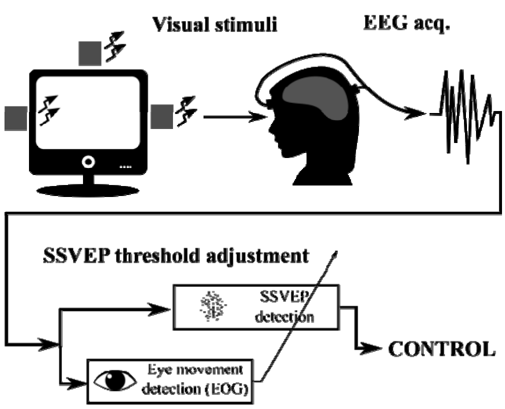

Fig. 1. Schematic idea of the hybrid SSVEP-EOG brain-computer interface

The easiest way of BCI quality evaluation is to measure its accuracy and Information Transfer Rate (ITR). Our goal is to improve these parameters of the SSVEP-based interface by introducing electrooculography (EOG) measurement as a way of detecting user intention of changing focus between visual markers. EOG is a method of evaluating eye movement based on the assessment of cornea-retinal standing potential normally acquired by facial electrodes placed in eye proximity. EOG eye movement artifacts can be not only measured near the eye, but they also appear in EEG signals. Our system takes benefit of these two phenomena by measuring both with one EEG acquisition system. Fig. 1 shows the basic idea of a hybrid SSVEP-EOG setup.

In order to trigger a control command in a SSVEP-based interface, the user must transfer eyesight to a selected visual marker, which results in the eye movement. This is the stage where a hybrid SSVEP-EOG system can benefit, by detecting EOG artifacts in the EEG signal. If properly recognized, an EOG event will lower the steady-state potentials detection threshold and thereby lower systems command latency and provide the higher ITR. This paper focuses on EOG event recognition in an EEG signal and determining the possibility of eye movement direction identification.

2. Related Work

Hybrid BCI is not a novel idea, as described by Pfurtscheller et al. [1] and Amiri et al. [2] it has been picked up by variety of researchers since 90's. Combinations of SSVEP, P300 evoked potentials, event-related (de)synchronization (ERD, ERS) or even heart rate measurement have been successfully implemented in order to provide faster and more responsive BCI systems. Incorporating EOG measurement into BCI also has been taken under account. However, unlike our approach, most of the researchers use separate systems for EOG and EEG acquisition [3], or mainly use them to detect separate, completely independent commands [4].

In most research cases, EOG is treated as contamination of EEG signal. There are many studies which focus on EOG artifacts detection and its suppression in the EEG signal. In [5] two algorithms, Recursive Least Square (RLS) and Blind Source Separation (BSS), they are compared as methods of EOG artifacts removal. Moretti et al. [6] show a method of EOG artifacts detection, with accuracy of 95%, and its further correction.

3. Experiment

3.1. Setup and test group

The experimental setup interface consisted of a 2-channel differential, portable Olimex SMT EEG amplifier together with a cap with reusable Ag/AgCl gel cup electrodes. For this test 3 visual markers (placed around the computer screen) were used as points of focus, in order to unify subjects' eye movements. Fp1-O1 and Fp2-O2 pairs were chosen as differential measurement points. A DRL electrode was placed at CZ point. The placement of acquisition electrodes is shown in Fig. 2.

Data for 7 male and 1 female participants aged between 19-35 was recorded. During the test, the subjects were given voice commands directing their focus to a specific marker. An observation period of an individual marker was 4 seconds. As recognition of the eye movement direction is the main focus of this paper, the test was designed to capture all possible transitions between the markers and the center of the computer screen.

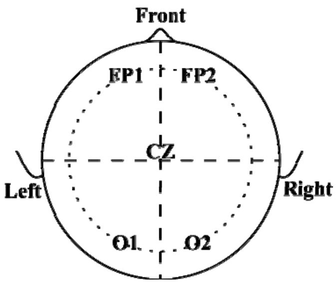

Fig. 2. EEG electrode placement during the experiment

A single sequence consisted of transitions between the center of the screen and each marker, and transitions between the markers. The transitions were labeled as it is presented in Fig. 3. The transitions with primarily horizontal eye movement were labeled as 'Left' or 'Right'. The transitions between idle state and M1 marker, where mostly vertical movement should occur, were labeled as 'other'. The periods when a state change is not expected were labeled as 'stay'. Transition sequences occurred in both clockwise and anti-clockwise directions and included a total of 64 transitions per sequence. The sequence was repeated 4 times for each person.

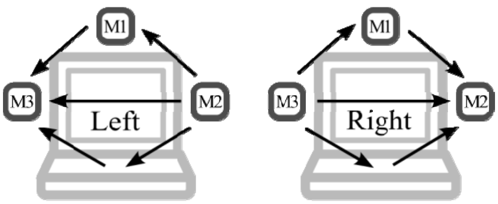

Fig. 3. Transition classes: 'Left' and 'Right'

3.2. Signal processing

A 2-channel EEG signal was recorded at 256 Hz sampling rate and synchronized with computer-generated voice prompts by a dedicated PC application. A bandpass, 0.5 Hz to 40 Hz, Butterworth filter was used.

Besides EOG artifacts occurring during eye movements, EEG also includes strong artifacts generated during blinking. Labeling of blinking artifacts was performed by thresholding EEG signal. The threshold level was set at 3σ where σ is the standard deviation calculated from the period of EEG signal when no blink artifact occurred.

Eye movements are expected shortly after a focus transition command. As the user reaction time is not constant, the artifact start time is variable. An eye tracking system was not used, so the evidence related to the exact artifact time was not accessible. Therefore for detection of eye movements, a features set based on the EEG signal histogram was used. The histogram consisted of 6 bins per channel, uniformly distributed in the range between -40 to 40 μV. It resulted in a 12-element feature vector. The samples of higher amplitudes (generated by eye blinking) were accumulated in the lowest and the highest bins. The histogram was calculated over a 0.78 s window moving with a 0.125 s step. It gave the classifier a sampling rate of 8 Hz. The training and validation set consisted of the elements representing both periods with transition expected in 'left', 'right' and 'other' directions, and steady state of marker observation in which eye movement was not expected (labeled as 'stay'). According to the pilot study, the reaction time for voice prompt was lower than 0.6 s and eye movement-related artifact duration was ca 0.6 s, thus label samples representing transitions were extracted from the period between 0.2 s and 1.3 s following the transition command. The elements labeled as 'stay', for which eye movement was not expected were extracted from the 2 s period preceding each transition command. The periods in which blinking artifact occurred were excluded from training and validation sets. The number of elements labeled as 'stay' was ca 6 time larger than the size of other sets. To keep similar number of elements in each class, 'stay' set was uniformly decimated by 6.

For classification purposes, a decision tree was used. The input was a 12-element vector set. The calculations were performed using MATLAB environment and Machine Learning Toolbox. For validation purposes, 4-fold validation was applied where 3 sequences were used as a training set for the classification tree and 1 was used as the validation set.

4. Results

The EEG signal probability distribution functions (PDF) from O1-Fp1 measurement pair estimated separately for each transition are presented in Fig. 4. The rows correspond to the initial state and the columns to the target state. The figures located on the diagonal represent 'stay' class where eye movement is not expected and the subject focuses on a certain marker. It can be seen that for 'stay' class all density functions have similar profiles. The figures outside the diagonal represent transitions of eye focus from one marker into another where the eye movements are expected. For majority of transitions the estimated PDF profiles differ from 'stay' which shows the possibility of distinguishing the transition type.

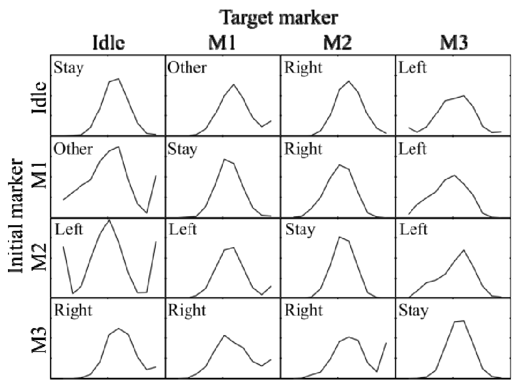

Fig. 4. Estimates of the probability density function of the Fp1-O1 EEG signal for all possible transitions in the 3-command SSVEP system

The overall results for recognition by means of the tree classifier are shown in Fig. 5. The green cells present the number of true position detection of a particular class, while the red correspond to the number of confusions between the expected and target class.

Output class \ Expected class	Stay	Other	Left	Right	Precision
Stay	562	57	57	57	76.3%
Other	58	342	64	64	64.8%
Left	61	54	572	38	78.9%
Right	63	67	34	570	77.7%
Recall	75.5%	65.8%	78.4%	78.1%	Accuracy **75.1%**

Fig. 5. Confusion matrix of the tree classifier for eye-movement direction recognition

The bottom row contains recall values for particular class and the right column presents the precision calculated separately for each case. In the tested group, the average accuracy of 75% ± 6%

is achieved. The mean precision for the left and right direction detection is 78.9% ± 8% and 77.7% ± 12%, respectively. The precision for the 'stay' class is similar to that for the left and right class (76.3% ± 9.7%), while for the 'other' class there is the lowest accuracy (64.8% ± 9.3). The confusions between the 'left' and 'right' classes are ca. 1.5 times rarer (23% of all confusions) than the confusions with the 'other' or 'stay' classes (35% and 40% of all confusions). In the case of 'other' and 'stay' classes, the number of confusions is similar for all the classes.

5. Conclusions

In this paper, a method enabling detection of eye movement direction (left or right) has been proposed. The feature vector extracted from the EEG signal histogram allowed for proper classifier training even when the exact time of the eye movement was not available. The histogram-based features are invariant with respect to translation, thus the reaction time variation does not strongly influence the histogram shape. Nevertheless, the histogram-based features partially ignore the signal profile, its time and frequency relation. Thus, the system accuracy is the highest for horizontal eye movements where the potential variation generated by rotation of cornea-retinal dipole is strong. Using time and frequency features might increase the recognition accuracy however it requires using an eye tracking system in order to select the most discriminating feature set. The lower accuracy of the 'other' class detection rate can be partially explained by the fact that during transitions between the M1 marker and display, a horizontal eye movement might also occur. The essential factor influencing the resulting accuracy could be a subject's failure or incorrect execution of a command.

The developed method is not dedicated to recognition of the observed marker, as this task is performed by the SSVEP analysis. However, if a movement direction is recognized, the probability of transition between stimuli markers increases. Moreover, the probability of selecting a command in the movement direction also increases, while the probability of 'stay' or markers located in the opposite direction decreases. As the eye movement artifacts occur prior to the SSVEP-related response, it can be combined with a SSVEP classifier into the Bayes classifier or the HMM model to increase the system responsiveness and accuracy.

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