Extracting Blink Rate Variability Based on EEG Signals

Temesgen Gebrehiwot, Rafal Paprocki , Artem Lenskiy*

***Abstract*—** Most of the researches on EEG signal treat a blink on equal terms with artifacts and noise, and attempt to eliminate it from an eligible signal. Prior works in brain performance have implicated relationship between blinks and inner mental states. Further study on this topic may be supported by idea of blink extraction from EEG signal. The aim of presented study is to propose a blink detection method and discuss it application to extraction of blink rate variability.

***Index Terms*—**blink rate variability, inter blink interval dynamics, EEG artifacts.

I. Introduction

Blinking is a semi-autonomic closing of the eye lids. Every time we blink, our eyelids spread a cocktail of oils and mucous secretions across the surface of the eye to keep your globes from drying out. Blink also keeps eyes protected against potentially damaging stimuli, such as bright lights and foreign bodies like dust. So why don't we notice the world plunging into darkness every two to ten seconds? The sudden changes in an image due to saccades or blinks, do not interfere with our subjective experience of continuity [1], the very act of blinking suppresses an activity in several areas of the brain responsible for detecting environmental changes, so that you experience the world as continuous. Researches have shown the synchronous behavior in blinking between listener and speaker in face-to-face conversation [2]. Each blink spreads the tears on the eye cornea to moisture and disinfects the eye. Reduced blink rate causes eye redness and dryness also known as Dry Eye, which belongs to the major symptoms of the Computer Vision Syndrome [3].

The blinks have been known to be linked to interior brain activities. Increasing the accuracy of blink detection is of high importance as humans look for an easier method of collecting internal brain activity information. The detection of the eye blinks had a huge impact in various fields in some Brain Computer Interface (BCI) they detected eye blinks and determined the pattern with the duration after collecting this analysis, they used it in as an input to a computer in similar manners that we use our mouse. This implementation of the use of blinks has opened a wide door to new possibilities for disabled people [4]. Another area where blinks play an important role is prevention of car accidents. World Health Organization (WHO) has announced that the ninth cause of death globally are car accidents. National Motor Vehicle Crash Causation Survey (NMVCCS) has found that 30% of car accidents are made happen by the drowsiness of drivers [5]. It is noted that workload increase blink rate and blink rate are known to decrease in monotonous and drowsy conditions [6]. Blink rate (BR) is inversely correlated with the increase of workload so blinks can be used to detect drowsiness before it creates damage [6]. Researchers have shown that blinks can play a significant role in detecting many different brain disorder and brain activities. Spontaneous BR has been studied in many neurological diseases like Parkinson's disease and Tourette syndrome[7][8][9]. The use of blink detection does not stop there. Researchers have found that blink rates can be used as a source of data in detecting psychiatric disorders like schizophrenia and attention hyperactivity all this is because blinks are regarded as a non-invasive peripheral markers of the central dopamine activity which makes their accurate detection more important [10-15]. Researchers have studied the synchronousness of the eye blinks in audience, who experienced the same transportation of storytelling. The eye blink synchronization among audiences is driven by attention cycles, which are in turn driven by emotional processing [16-18]

Blinks are not always the most desired signals when it comes to non-invasive brain signal measuring as many electroencephalographs (EEG) remove them to acquire brain data. Eye blink is one of the main artifacts in the EEG signals [19]. Researchers are focusing on removing these parts of the signals to obtain clean brain signal values.

To analyze blinks and variation of inter-blink intervals it is important to accurately detect blinks. We propose use a proposed blink detection algorithm to construct a series of inter-blink intervals that we coin blink rate variability (BRV). We construct BRV for subjects taking memory test and estimate. We further compare the numbers of detected blinks by the algorithm and by manually counting.

II. Experimental

A. Data Acquisition

The video stream was captured with a Pointgrey Flea3 USB camera. Video stream was stored on a disk drive to be processed in the future. Simultaneously, EEG signals were recorded. For the recording of EEG signals, we employed Mitsar-EEG 201 amplifier and accompanying WinEEG software. The electrodes were placed according to the international “10-20 system” [20]. Electro-gel has been injected into electrodes hollow in order to decrease the electrode-skin resistance. Currently, the EEG signals were recorded for the purpose of eye blink detection. In the future we are planning to analyze EEG to detect various types of brain activity. The experimental setup is shown in the figure 1.

Fig. 1 Experimental setup

Temesgen Gebrehiwot, Rafal Paprocki and Artem Lenskiy are with the Korea University Technology, 1600, Chungjeol-ro, Byeongcheon-myeon, Dongnam-gu, Cheonan-si, Chungcheongnam-do, 31253 Republic of Korea (e-mail: lensky@koreatech.ac.kr).

B. *Testing Procedures*

The recording session consisted of five stages: (a) resting, (b) the IQ test, (c) resting, (d) reading, and (e) the memory test. The testing software was developed in Java in such a way that it does not require any interventions. The whole testing session took 30 minutes, 5 minutes resting before the IQ, 10 minutes the IQ test, 5 minutes resting stage, 5 minutes reading and 5 minutes the memory test. Before the memory test a resting stage and passage about Ethiopia was given. After reading the passage user was presented questions one by one.

In this paper we focus on detecting blink while subjects reading the passage and answering question about the passage. Over all 18 people participated in the experiment among them 4 subjects were dropped due to falling a sleep, adjusting the cap or constant head movements.

III. Eye Blink Detection Procedure

Electrodes are applied to the head according to 10-20 system. We used bipolar montage, which means we determine the potential between Fp1 and Fp3, also Fp2 and Fp4. Figure 2 presents EEG signals for both pairs.

EEG signals were recorded while participants were taking the tests and imported in form of CSV files to Matlab for further analysis. The process of blink detection can be divided into two stages: preprocessing and blink detections. The preprocessing stage consists of the following steps: (a) bandpass filtering (b) independent component analysis (c) selection of the independent component with eye blinks. The blink detection stage consists of (d) signal thresholding, (e) candidate extraction, (f) polynomial fitting with finding maximum in the polynomial function, and (g) finally calculating blink rate variability.

The first step in the process of blink detection is band-pass filtering. We applied bandpass filter with finite impulse response. For the filter's windowing function we chose Hamming window of degree 128. In figure 3 the EEG signals after bandpass filtering and normalization are presented. It can be observed that the signals became smoother and the lower frequency components responsible for trends in the signals disappeared.

The next step is to combine two signals in a way that lead to a cleaner signal.

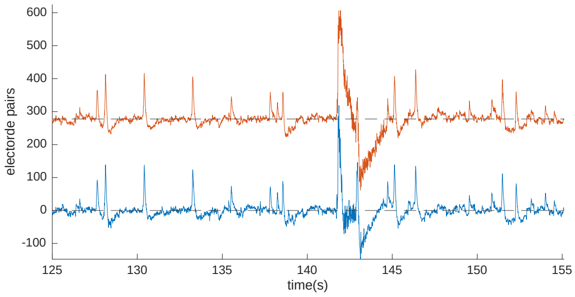

Fig. 2 Fp1-Fp3 and Fp2-Fp4 electrode pairs

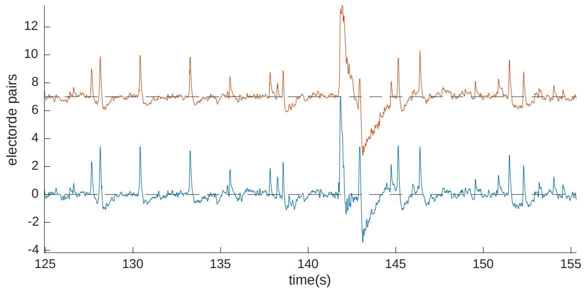

Figure 3 After band-pass filtering

Usually, we want to get rid of ocular artifacts from EEG signals, as the eye blink is an artifact and leads to interpretation problems [21]. However, our goal is on contrary in extracting blinks from EEG. We employ fastICA[22] algorithm for solving Blind Source Separation (BSS)[23], which allows us to separate neural activity from muscle and blinks[24]. Independent component analysis (ICA) consists of two stages. The first is responsible for decorrelation or whitening, when correlations in the data are removed. The second stage is responsible for separation, which is orthogonal transformation of whitened signals (rotation of the joint density). The task is to find an orthogonal matrix U such that the projects on the orthogonal axis are non-Gaussian [22]. One by one we are looking for the rows of the matrix $U = (u_1, u_2)^T$ so a measure of non-Gaussianity $|E(G(u_k^T x_{st}))|$ is maximized by such u_k that the length of u_k is one and orthogonal to rows(u_1, u_2). The function G can be any nonquadratic function, which is twice continuously differentiable with $G(0) = 0$. We tested a number of nonlinearity functions and the one that results in a better component separation is the $g(z) = z^2$ skewness measure. The $g(z) = z^2$ $(skew)$ nonlinearity finds skew sources but in the case of symmetric sources is not efficient. In our data the skew measure shows best results due to the fact that the waveforms corresponding to blinks are asymmetrical (fig. 4).

To distinguish which of the components corresponds to the blink component $\boldsymbol{c}$, we select the component based on the following rule

$$\boldsymbol{c} = \begin{cases} \sum H(|s_i^{I}| - 3\sigma(s_i^{I})) > \sum H(|s_i^{II}| - 3\sigma(s_i^{II})), & 1st \\ otherwise, & 2nd \end{cases}$$

where H is the Heaviside function.

At the next step we set to zero to all samples that are less than the standard deviation of the signal. All samples below the threshold are zeroed. All the reaming contiguous segments we treat as candidates (fig. 4 top). Finally, a polynomial function is fitted to the samples within each segment. If the arc length of the polynomial function is less than a predefined threshold, the region is rejected (fig. 5). We also reject regions with a slop of the front and the end transitions having an angle less than 80 degrees for the front and having greater than 100 degrees for the end transition. The slop is calculated as an angle of line connecting end points of the fitting polynomial and its maximum.

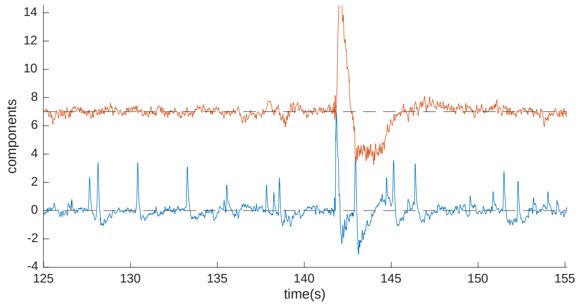

Fig 4. Independent components

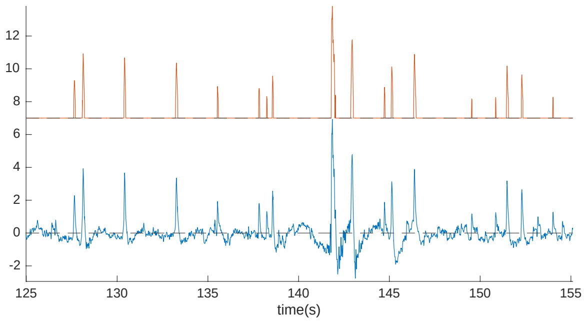

Fig 5. The top graph shows the threshold signal

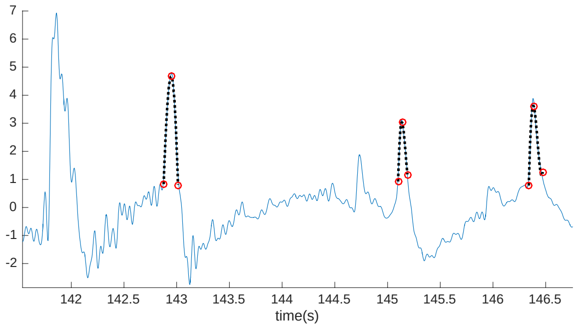

Fig 6. Zoomed version of the previous figure

To construct blink rate variability, the time of occurrences of consecutive blinks are subtracted. The interval between blinks is stack-up into a series that constitutes blink rate variability. (fig. 7).

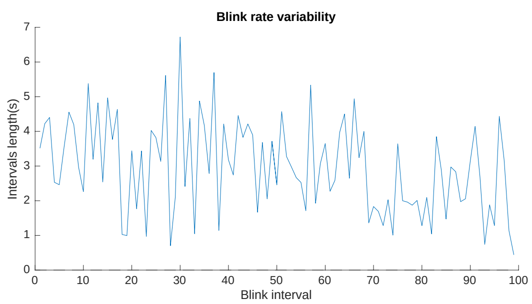

Figure 7 Extracted blink rate variability

IV. RESULTS AND DISCUSSION

Figure 8 compares BRV for all the subjects during the memory test. The X-axis is the blink interval where Y-axis presents interval lengths per each subject.

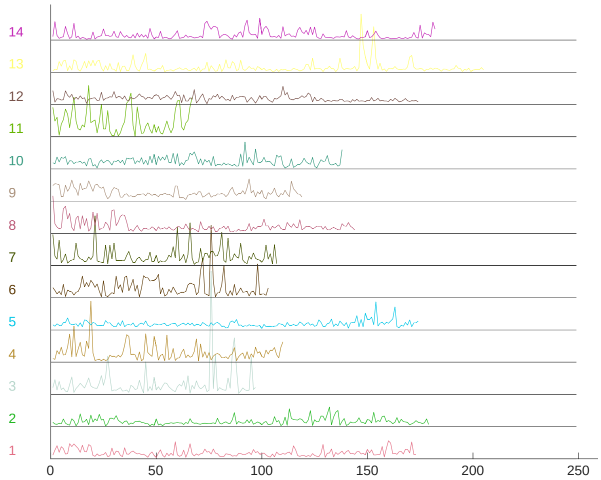

Fig. 8 Extracted blink rate variability for each subject

TABLE I: COMPARISON OF AUTOMATIC AND MANUAL BLINK DETECTION

Subj.	Passage auto.	Passage fp1_fp3	Passage fp2_fp4	Test auto.	Test fp1/fp3	Test fp2/fp4
1	106	87	98	159	159	182
2	177	180	174	183	179	205
3	25	23	23	10	13	15
4	29	35	39	43	50	92
5	93	92	65	175	176	185
6	35	26	55	85	86	95
7	45	38	33	53	84	89
8	58	58	54	144	127	140
9	90	57	86	122	120	119
10	126	123	123	137	143	134
11	25	43	46	66	62	55
12	144	146	139	179	178	188
13	127	128	122	122	200	205
14	120	101	91	185	185	190

V. CONCLUSION

Blinking is natural, biological, semiautomatic process. It is linked to interior brain activity and relationships between blinks and performing task or brain disorders has been shown. The blink rate variability finds application in variety of fields, like car safety, psychology or BCI. However blink detection procedures have to be examined more deeply. Due to need of extracting blinks from EEG signal, we discuss an algorithm for detecting blink rate variability. We apply fastICA algorithm to obtain independent components. Then after tresholding, we analyze polynomial for each candidate blink and reject some candidates based on the length.

Presented comparison of the manual blink detection and automatic blink detection shows that the proposed algorithm is suitable for blink rate variability extraction.

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Temesgen Gebrehowt
was born in Addis Ababa Ethiopia in 1988 December 19th. He went to Hilcoe School of computer science and graduated in Bachelors of science in 2011.Currently I am on my last semester to get my second Bachelors in Korea university of Technology and Education

Rafal Paprocki
born in 1st June 1987 in Reszel, Poland. Brother of beautiful sister, son of
lovely parents. Engineer and master finished in Military University of Technology in Warsaw, included with one master semester scholarship in Italy. Used to work as IT project coordinator, then web developer, handling own projects in parallel. Currently Ph.D. student in Korea university of Technology and Education in Cheonan, South Korea.

Artem Lenskiy
Received BSc and MSc degrees in computer science form Novosibirsk State Technical University, Russian in 2002 and 2004, respectively. After teaching at the same university for a year, he joined doctor course at the University of Ulsan, Korea. He was awarded the Ph.D. in 2010 from the same university. After conducting research as a postdoc fellow at the Ulsan University, he joined Korea University of Technology and Education as an assistant professor in 2011.
His research interests include machine learning and self-similar processing applied to various research and engineering fields including financial time series analysis, telecommunication and physiological signal analysis.