Eye-Blinking Artefacts' Duration Analysis

Plamen Manoilov

Abstract – **The artefacts impede the analysis of the electroencephalogram's (EEG) signal and should be handled properly. The most common and characteristic kinds of artefacts are the electrooculographic (EOG) ones, especially subject's eye blinks. In this paper an analysis of the duration of the EEG section, polluted by eye blinking artefacts is described with a connection of using the EEG for brain-computer interface (BCI), working with α- and μ-rhythms (range 8-13 Hz) brain potentials.**

Keywords – **BCI, blink artefact, EEG analysis, EOG, power spectrum**

I. Introduction

A direct Brain Computer Interface (BCI) is an assistive device that accepts commands directly from the human brain without requiring any physical movement. The ultimate goal of such an interface is to provide effective communication without using the normal neuromuscular output pathways of the brain, but by accepting commands directly encoded in the neurophysiological signals. BCI should be able to detect user's wishes and commands while the user remains silent and immobilized.

For people who are locked-in after having lost all voluntary muscle control due to advanced amyotrophic lateral sclerosis, brainstem stroke or muscular dystrophy, BCI may be their only means of communication with the environment. Obviously, brain-computer communication is vital for people with such severe motor disabilities to increase their quality of life.

BCI may be as useful for people without any disabilityes too. In the Alternative Control Technology (ACT) program of the US Air Force Research Laboratory [11] they use EEG to achieve hands free control by US military pilots.

To be as effective as possible, an ideal BCI should allow the user to determine when a command is to be initiated, provide multiple independently controllable channels, and support high information transfer rates. It is unlikely that an ideal BCI will be available in the near future, but a simple reliable interface providing single switch control would also be beneficial for locked-in patients.

The majority of research on human brain-computer communication has been performed using electroencephalographic [1, 5, 6] (EEG) recordings which are well studied, easily available, and noninvasive. The less widely used electrocorticogram (ECoG) [4] is only available if subjects require electrode implantation on the cortical surface for clinical treatment or evaluation, and research access could be scheduled around clinical activities. Compared to EEG, ECoG recordings have less vulnerability to artefacts, superior spatial resolution, giving ECoG the potential to allow brain-computer communication with greater functionality, although a surgical risk exists at every time.

Designing a BCI system one can choose from a variety of features that may be useful for classifying brain activity, recorded during mental tasks performance. The EEG is measured, sampled, and next used for a communication. Depending on the BCI, particular preprocessing and feature extraction methods are applied to the EEG sample(s) 1-1.5 s of length. It is then possible to detect the task-specific EEG signals or patterns from the EEG samples, with a certain level of accuracy. A classifier that could be Statistical Model Neural Network (SMNN), Hidden Markov Models (HMM) or variations of Linear Discriminant Analysis (LDA) then classifies these features.

EOG stands for electro-oculographic artefacts, which appear in the EEG as a result of subject's eyes moving and blinking. Eye blink artefacts are easy to distinguish. In time domain they show enormous high amplitude relative to the other EEG signal and supposed could have an influence on the control.

II. Problem Statement and Study Description

This study is done during a work on a project for creating a BCI, started in Delft University of Technology, The Netherlands in 2004. Professor drs dr Leon Rothkrantz, head of Man-Machine Interaction research group, Faculty of Electrical Engineering, Mathematics and Computer Science supervised the project.

During the experiments the subjects performed different mental tasks, among them mental rotation, motor imaginary, mathematical calculations, visual presentations etc., issuing different patterns in mu (μ) and alpha (α) rhythmic brain activity frequency ranges, which after a successful classification could be used for building a BCI.

In a result of the experiments a database, which contains 40 sessions EEG data, around 20 minutes each, recorded from two subjects (male, 25 and 30) was prepared for use together with a tool for a statistical analysis ("R", "MATLAB"). Second stage was processing the EEG from the database and

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finding (if possible) a specific pattern for every mental task. After classifying the tasks, some of them with more clear and well-expressed pattern could be chosen for using for BCIs control. One of the questions to be solved was how to deal with the subject's eyes' blinks caused EOG artefacts.

Sources exist [1], where the researches process the data, containing eye-blinks. From other side, other sources exist [6, 7], where is stated, that eye-blinks could lead to errors in BCIs research and work. The decision was taken to study the power spectrum of the EOG artefacts and define their influence on EEG in connection with the chosen working frequency range.

After this study was done [9], the conclusion was made that the EOG artefacts influence on EEG range 8-13 Hz is significant and they should be eliminated from the data before the feature extraction. For further data processing a decision was taken first to cut the blinks and only after that process the data. Even doing this action by hand, the question about the length of the polluted by the eye-blink segments of data arises.

Some authors [3] simply omit the trials where they discover eye blinks. They achieve this automatically by linearly detrending and removing those time series whose maximum, rectified EOG amplitude, exceeded a threshold. If the blink appears at the end of a trial, its influence could contaminate the next trial. Segments for processing are 1-1.5 s long. Blink influence could last longer. From other side, cutting blindly long segments with blinks will discard useful parts of EEG and slow down BCIs work.

Other author [2], Fig. 1, recognizes and marks the blinks by using parameters of the EEG waveform where it has the highest amplitude. Later the marked EEGs are intended to be used by medical doctors. Study about the length of the polluted by blinks segments is not reported.

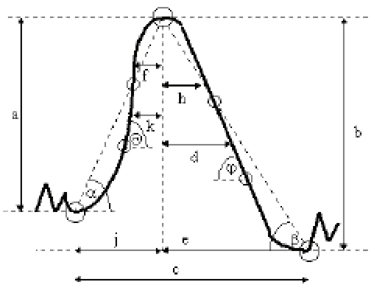


Fig. 1. Parameters, used in [2] to recognize eye blinks

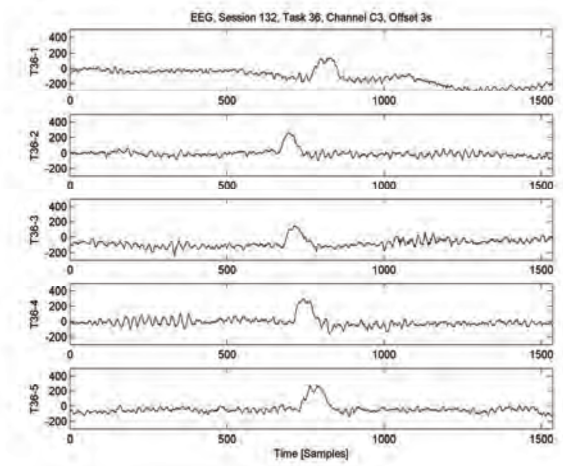
Blinks, recorded during different sessions and tasks are shown in Fig. 2. Except their high amplitude in the low frequency range they do not have any specific and repeated forms. The length of some of them exceeds 1s (256 samples). The duration of their visible part in the time domain is different and subject-dependent. In fact they depend on the subject's emotional stress, fatigue, eye dampness, etc.

The study described in this paper continues the work in [10]. To find the duration of the influence of the blink to the EEG, Gabor transform is used, according to (1)

$$P(k,t) = G_N(k,t)G_N^*(k,t) \text{, where} \qquad (1)$$

$$G_N(k,t) = \sum_{n=0}^{N-1} x(n,t)H(n)e^{-i2\pi kn/N} \text{ ,} \qquad (2)$$

$G_N^*(k,t)$ - complex conjugate,



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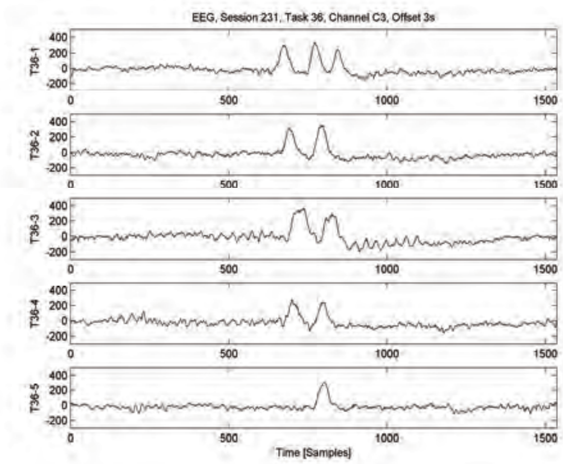


b)

Fig. 2. Blinks with different forms and durations in time domain

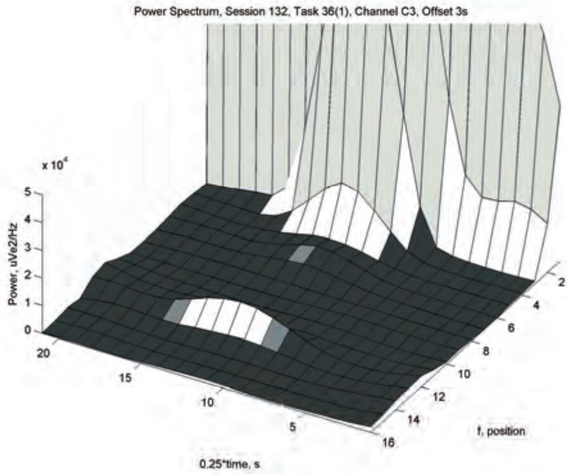
N - number of samples for the analysis,

$H(n)$ - n^{th} sample of Hamming window with length N ,

$x(n,t)$ - n^{th} sample of the current segment, with offset t from the beginning of the EEG.

The study uses 6-seconds EEG sections with blinks, to envelop parts before and after the blink. The blink is centered. Every section is divided to segments 1 s each with 0.25 s overlapping. Moving average filter is used along to equal frequencies in neighbour segments after Fourier analysis is done. The results are given as 3D plots in Figs. 3 and 4.

First a similar to Fig. 1 blink's form is chosen - Fig. 2a, session 132, task 36, run 1. The position axis marks in Fig. 3 correspond to the real frequency as (position –1)=frequency, Hz. The distance between the tick marks in time scale is 0.25 s. In all channels amplitude variations of some frequency components in the range of 8–13 Hz are noticed synchronously with 2 Hz-low frequency component, caused by the blink (in C3, Fig. 3a, and P3, Fig. 3b, at 11 Hz, and in O1, Fig. 3c, at 10 and 11 Hz). No matter that the white noise is slightly filtered, each time in α-range exists a frequency component(s) which amplitude follows caused by the eyelids



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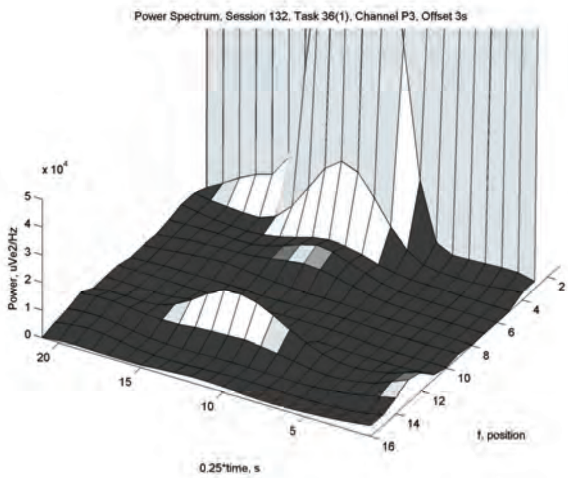

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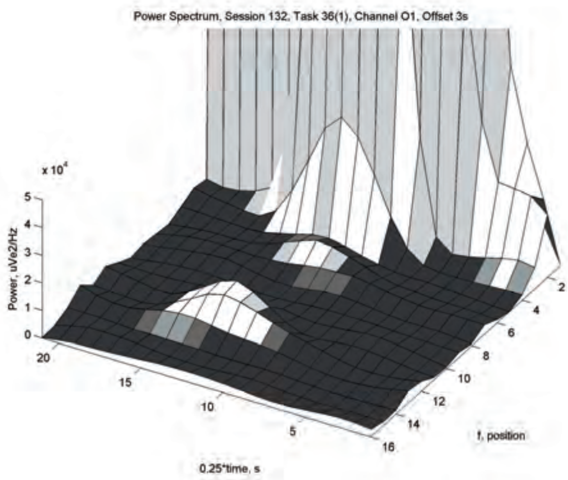
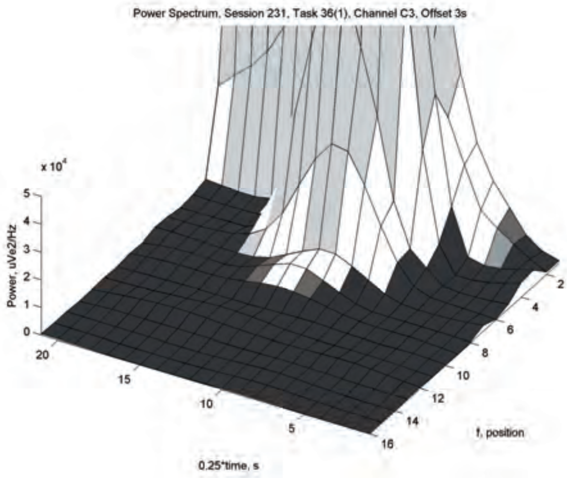


c)

Fig. 3. Spectrogram for C3, P3, O1, session 132

low frequency. The visible part of the eye blink in the time domain, Fig. 2a, is around 128 samples - 0.5 s. Following the 2 Hz component amplitude, the duration where it is rising



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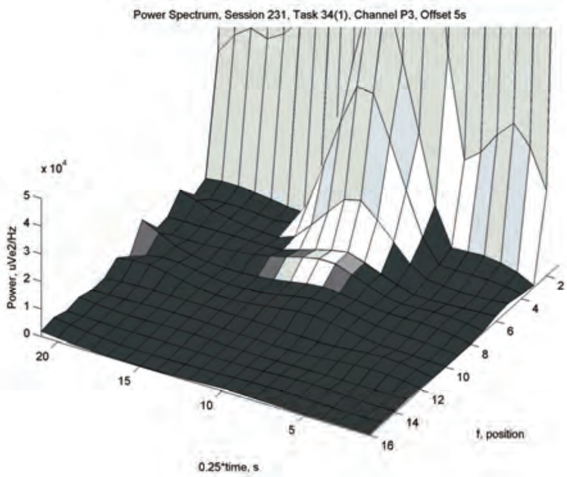

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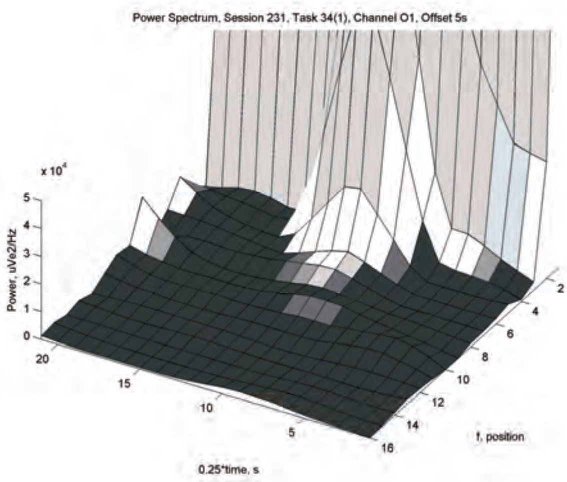

c)

Fig. 4. Spectrogram of a “longlasting” blink, C3, P3, O1, session 231

(comparable to its steady state) is 12*0,25=3 s. The changes of 11 Hz frequency amplitude are similar.

The spectrograms of more complex and long lasting blink from Fig. 2b, session 231, task 36, run 1, are shown in Fig. 4. Although three visible periods of the low frequency could be seen there, this is one blink. The visible part in the time domain lasts above 1 s (more than 256 samples). The power is higher in the low frequency part of the range. The 8 Hz part is most affected. Similar to the previous case, the eye blink influence lasts in average 3 s.

The analysis of blinks with different forms and durations in the time domain results in almost equal length of 3 s of the affected section.

Unlike [12], where is stated that average blink duration is 100 ms in our EEG records in the time domain the visible part of the blinks are from 200 to 1100 ms long. Most of them last around 500 ms.

By reason of the different forms (subject-dependent) it is impossible to define eye blinks duration in the time domain. More important characteristic of the blinks is their influence over α-range frequencies. Blinks with different forms in the time domain affect different frequencies between 8 and 13 Hz. These frequencies appear synchronously with the 2 Hz frequency component.

III. Conclusions

In all channels the blinks amplitude is more than 5 times higher than the amplitude of the blink-free EEG data.

The power of the eye blinks is concentrated up to 3 Hz range.

Eye blinks could be recognized in the time domain by controlling the amplitude of the raw EEG or in the frequency domain by controlling the 2-3 Hz power.

In the range 8-13 Hz in segments, which contain blinks, the power of frequency components is more than 50% more in comparison to blinks-free EEG parts.

When the analyzed segment contains a blink, the power in all channels varies, which lowers the probability of a correct classification of the mental tasks' patterns.

It was decided to omit the EEG segments, which contain eye blinks.

The power of work frequencies (8-13 Hz) could be followed from the spectrograms of all the channels. Depending on the blinks form in the time domain different frequency components change sinchronously with the 2 Hz frequency, where the blinks power is concentrated.

According to the study, rejecting 3 s section is quite enough to have blinks free neighbor parts.

References

[1] Blankertz B., G. Curio, K.-R. Müller, Classifying single trial EEG: Towards brain computer interfacing. In T. G. Diettrich, S. Becker, Z. Ghahramani, editors, Advances in Neural Information Processing Systems (NIPS 01), volume 14, 2002, pp. 157-164, http://ida.first.fhg.de/publications/BlaCurMue02.pdf.

[2] Bogacz R., Blinking Artefact Recognition in EEG Signal Using Artificial Neural Network, Master thesis, Politechnika Wroclaw, Department of Informatics, Wroclaw, 1998 http://www.ci.pwr.wroc.pl/~bogacz/artefact (in Polish).

[3] Burke D. P., S. P. Kelly, P. Chazal, R. B. Reilly, C. Finucane, A Parametric Feature Extraction and Classification Strategy for Brain–Computer Interfacing, IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 13, No. 1, March 2005.

[4] Freemen W. J., L. J. Rogers, M. D. Holmes, D. L. Silbergeld, Spatial Spectral Analysis of Human Electrocorticograms, Including the Alpha and Gamma Bands, Journal of Neuroscience, 95, 200, pp. 111-121.

[5] Hjorth B., An on-line transformation of EEG scalp potentials into orthogonal source derivations, Electroencephalography and Clinical Neurophysiology, vol. 39, 1975, pp. 526–530.

[6] Lauer R. T., P. H. Peckham, K. L. Kilgore, EEG-Based Control of a Hand Grasp Neuroprothesis, Neuro-Report , vol. 10, 1999, pp. 1767–1771.

[7] Lauer R.T., P. H. Peckham, K. L. Kilgore, W. J. Heetderks, Applications of Cortical Signals to Neuroprosthetic Control: A Critical Review, IEEE Transactions on Rehabilitation Engineering, vol. 8, 2000, pp. 205–208.

[8] Malmivuo J., R. Plonsey, Bioelectromagnetism, Principles and Applications of Bioelectrical and Biomagnetic Fields, New York, Oxford, Oxford University Press, 1995, http://www.tut.fi/~malmivuo/bem/bembook/bembook.zip.

[9] Manoilov P. K., EEG Eye-Blinking Artefacts Power Spectrum Analysis, Proceedings of the International Conference on Computer Systems and Technologies CompSysTech'06, V.Tarnovo, Bulgaria, 15-16 June, 2006, pp. IIIA.3-1—IIIA.3-5.

[10] Manoilov P. K., Electroencephalogram eelctrooculographic artefacts analysis, Proceedings of the National conference with an International participation, ELECTRONICS'2006, 1-2 JUNE, 2006 pp. 156-161 (in Bulgarian).

[11] Middendorf M., G. McMillan, G. Calhoun, K. S. Jones, Brain–Computer Interfaces Based on the Steady-State Visual-Evoked Response, IEEE Transactions On Rehabilitation Engineering, vol. 8(2), 2000, pp. 211–214.

[12] Parra L. C., C. D. Spence, A. D. Gerson, P. Sajda, Response Error Correction—A Demonstration of Improved Human-Machine Performance Using Real-Time EEG Monitoring, IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 11, 2003, pp. 173-177.