EOG ARTEFACTS' DURATION ANALYSIS

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Artefacts are noises introduced to the electroencephalogram's (EEG) signal by not intended central nervous system (CNS) signals or sources of electric fields inside and outside subject's body. The artefacts impede the analysis of the signal and should be handled properly. The most common and characteristic kinds of artefacts are the electrooculographic (EOG) ones, especially subject's eye blinks artefacts. In this paper an analysis of the power spectrum of eye blinks artefacts is described with a connection of using the EEG for brain-computer interface (BCI), working with α- and μ-rhythm (range 8-13 Hz) brain potentials.

Keywords: BCI, blink artefact, EEG analysis, EOG, power spectrum

1. INTRODUCTION

A direct Brain Computer Interface (BCI) is an assistive device that accepts commands directly from the brain without requiring 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 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 a BCI may be their only means of communication with their environment. Obviously, brain-computer communication is vital for people with such severe motor disabilities to increase their quality of life. 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 (EEG) recordings which are well studied, easily available, and noninvasive. The less widely used electrocorticogram (ECoG) 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 artifacts, superior spatial resolution, giving ECoG the potential to allow brain-computer communication with greater functionality, although a surgical risk exists.

The EEG is measured and sampled, while the subject performs some mental activity. The EEG data is used for communication by classifying the activity to different tasks, which correspond to functions in the used application, for instance, pressing a key or moving a mouse. Depending on the BCI, particular preprocessing and feature extraction methods are applied to the EEG sample(s) of certain 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 Networks (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.

The role of wavelet analysis and synthesis as a pattern classification and analysis technique is well established. Wavelet transform translates the original signal in the time-frequency domain in such a way that the high localization properties of the signal are retained. Wavelets divide data into different frequency components, whereby each component may be studied at a resolution matched to its scale. In this sense, wavelet transform have the important and useful abilities of detecting and recognizing stationary, nonstationary or transitory characteristics of the signal including abrupt change, spikes, drifts, and trends. In this paper a study of the polluted by eye-blinks EOG artefacts segments using discrete wavelet transform (DWT) is described.

2. Problem Statement and Study Description

The study was done during a work on a project for creating a BCI, started in Delft University of Technology, Delft, The Netherlands in 2004. Professor DSc 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.

First 10 months preparation for measurements and the measurements themselves were done and a database, that contains 40 sessions EEG data, around 40 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 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 solve was how to deal with the subject's eyes' blinks EOG artefacts.

Sources exist [3], where the researches process the data, containing eye-blinks. From other side, other sources exist, where is stated, that eye-blinks could lead to mistakes in BCIs research and work [6, 7]. 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 that the EOG artefacts influence on EEG 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 simply discard the samples where they discover an eye blink (samples here means the parts of the EEG which they use for a processing). According to authors it is not the proper way, because if the blink appears at the end of a sample, its influence could contaminate next sample. From other side, cutting blindly long segments with blinks will discard useful parts of EEG and slow down BCIs work.

Based on [9], as an index for the eye blink's existence, the power of 3 Hz was taken. The goal was to follow the 3 Hz power along the time. Using Short Time Fourier Transform (STFT) the next study was done [1]. Overlapping 0.5 s each other segments with 1 second length were chosen and results about the polluted segment length were yielded.

The STFT represents a sort of compromise between the time- and frequency-based views of a signal. It provides information about when and at what frequencies changes in the signal occurs. However, it is possible to obtain this information with limited precision, determined by the size of the window. The drawback is that once a particular size for the time window is chosen, that window is the same for all frequencies. EEG is a complex signal which requires a more flexible approach – one, where we can vary the window size to determine more accurately either time or frequency. To improve the precision, the same study was made, using wavelets.

For reliable results, it was important to choose the mother wavelet, which was suitable for the signal of interest. It is known [8] that alpha and mu rhythms (8–13 Hz) are sinusoidal-like EEG signals. For this purpose an artificial EEG data sets was generated and processed, containing pure sinusoidal delta, theta and alpha rhythms. Discrete wavelet transform (DWT) was performed in MATLAB. The signal was decomposed into wavelet components of specific frequency ranges. Meyer's wavelet dmey was used. Other wavelets of type daubechies (db4-db8), symlets (sym6-sym8) and coiflets (coif3-coif5), where the ciphers are the numbers of vanishing moments in mother wavelet function Psi (Ψ), were investigated as well, but best results were achieved with the dmey mother wavelet. In order to extract the needed information each EEG channel of interest was decomposed up to level 5 and every node from the wavelet tree - reconstructed from wavelet to time domain. The distribution of frequencies is in table 1. Next, real EEG data, containing eye blinks with different forms, fig. 1 were decomposed and studied.

Table 1

Approximation /detail	Best expressed frequencies	Brain rhythm
a5	Up to 3 Hz	Delta (0.5-4 Hz)
d5	From 5 to 6 Hz	Theta (4-8 Hz)
d4	From 8 to 14 Hz	Mu (9-11), Alpha (8-13 Hz)
d3	From 18 to 32 Hz	Beta (13-30 Hz)
d2	From 34 to 54 Hz	-
d1	Above 64 Hz	-

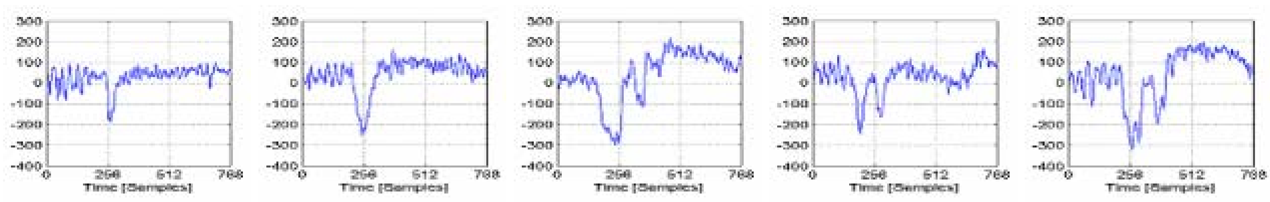
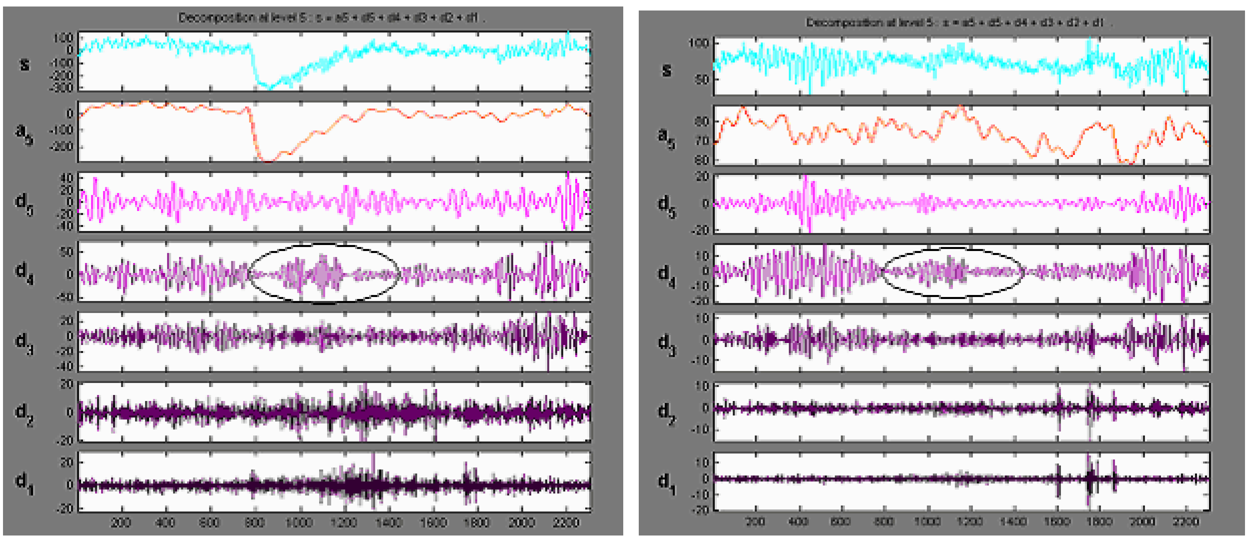


Fig. 1. Blinks with different forms in 3 s intervals (768 samples). Contrariwise to [10] where is stated that: "Eye blinks last for approximately 100 ms", typical duration of an eye-blink for both subjects in our records was 500 ms.

First DWT was performed on a raw data, fig. 2a. The low frequency components appear in the approximation. A noticeable reduction was noticed in d4 during the eye blink (changes in mu and alpha rhythms).



a) b)

Fig. 2. DWT of an eye-blink before (a) and after (b) filtering

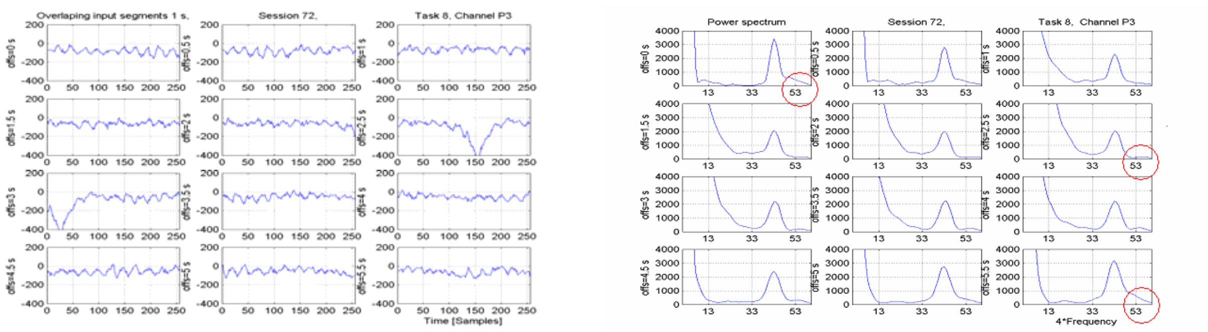
Scalp recorded EEG, however, represents a noisy spatial overlapping of activities arising from very diverse brain regions. Spatial filter techniques attempt to accentuate localized activity and reduce diffusion in multichannel EEG. The surface Laplacian method, which derives the second spatial derivative of the instantaneous spatial potential distribution was used for a high-pass spatial filtering purpose. Assuming that the distances from a given electrode to its four directional neighboring electrodes are approximately equal, the surface Laplacian was approximated by subtracting the average value of the neighboring channels from the channel of interest [4], according to equation 1,

$$M_j^{Lap} = M_j - \frac{1}{4}\sum_{k \in S_j} M_k \,, \qquad (1)$$

where M_j is the scalp potential EEG of the channel (P3), and S_j is an index set of the four neighboring channels (C3, T5, O1, Pz). DWT approximation and details after performing Laplacian spatial filtering are on fig. 2b.

3. Analysis and Conclusions

Before doing any discussion, it is worth to reveal the nature of the eye blinks. Under "eye blinks in the EEG" researchers usually mean spikes, having amplitude 3-5 times higher than the signal before the blink, which appear in EEG when the subject blinks. There are sources [5], where the eye blinks are eliminated from the EEG by independent component analysis (ICA), by taking data from additional electromyographic (EMG) channels, which electrodes are connected near the eyes, or from closest Fp1 and Fp2. This way the researchers assume that eye blink artefacts are only as a result of diffusion of stronger EMG signal to EEG electrodes. Hence, the activity of the brain, issuing a signal to control the eyelids stays in shadow. It is not known the CNS-dependent part of eye blink artefact to be studied till now.



a) b)

Fig. 3. Eye blink and segments' power spectrum (copy from [1])

The signal on fig. 2 is denoted by '**s**'. Laplacian filtering eliminates the low frequency parts of the blinks. Their source is away from the selected electrode P3 and they do not appear on fig. 2b. However, during the blink detail d4 still has changes. Let have a look back to [1]. Fig. 3a shows 1 s overlapping segments, containing an eye blink, fig. 3b - the power spectrum of every segment. One can notice the reduction / fluctuations of the power of 12-13 Hz during the eye blink and its recovery to previous level after it (denoted by circles), although considered in both studys blinks are different. Those changes are preserved after the filtering, fig. 2b, because they are as a result of the subject's mental activity and appear locally in P3.

Duration of polluted interval is user-dependent. For subject 1 it varies from approximately 0.8-0.2 s before and 1.9-1.5 s after the time of blink's max amplitude. For subject 2 values are respectively 1.1-0.2 s before and 1.9-1.5 s after.

Beta rhythm was not a subject to this study but we will only mention that during the eye blink changes are seen in D3 too.

Following conclusions could be made: Together with EMG part, eye blinks artefacts contain issued by the brain EEG part, which is difficult to filter. This way only rejecting contaminated by eye blinks segments could really clean the EEG. A possibility exists to foresee time segments for blinks during EEG recording and rely that in other parts of the EEG eye blinks, if exist, are an exception.

The results will be used to extract and process clean EEG samples from the existing database with EEG records and later, during the BCI's work.

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