The algorithm of automatic localization of EOG artifacts in a multichannel EEG signal

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Abstract. The problem discussed in the paper is automatic localization of abnormal areas (artifacts) of the electroencephalogram (EEG), which are recorded at the moments of time when physiological disturbances caused by eye movement and blinking occur (electrooculogram, EOG). The authors propose a new algorithm for automatic search and removal of electrooculogram artifacts. The base of the algorithm is the relationship between the standard deviations of the electroencephalogram eye lead amplitudes (Fp1-A1 and Fp2-A2). The standard deviations of every epoch in eye lead are compared with the mean standard deviation over this lead. The epochs with localized EOG artifacts are removed in all EEG leads. The algorithm is implemented in MATLAB. The program allows obtaining data on the artifacts detected in an EEG recording: number, localization by epochs, a reconstructed purified electroencephalogram and remote areas. The algorithm was tested on 600 EEG samples collected during experiments in the Tver State Technical University. The participants in the experiments were 20 people. In the received EEG records the experts identified areas containing electrooculogram artifacts of different activity. The results of the research on the algorithm operation using the examples of electroencephalogram recordings have shown its practical effectiveness.

Keywords: electroencephalogram, electrooculogram, lead, epoch, artifact, localization, algorithm.

1 Introduction

When recording an electroencephalogram (EEG), artifacts of a various nature arise. These are records of extraneous processes that are not direct evidence of the brain electrical activity [1]. In this regard, EEG signals demand preliminary processing.

We divide artifacts into two groups by origin [1- 2], which are physical (hardware) and biological (physiological). Physical artifacts appear due to violating the equipment technical regulations and EEG recording rules, as well as due to the equipment imperfection. The cause of appearing physiological artifacts is additional recording of

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the functional activity of organs and systems of the body in addition to the brain. The reasons might be the evoked potentials of blinking and eye movement (electrooculogram, EOG), muscle contractions (electromyogram), muscles and the conducting system of the heart (electrocardiogram), galvanic skin reflexes, swallowing movements.

There is an intensive development [1-2] in the field of solving problems related to localization of different types of artifacts in EEG signals. In particular, various mathematical methods of analysis are used to efficiently localize and remove artifact EOG patterns. There are various approaches based on frequency filtering [3-4], a regression analysis [3; 14], a wavelet analysis [4; 11-13], a principal component analysis (PCA) [5], an independent component analysis (ICA) [6-8], artifact subspace reconstruction (ASR) [7], a correlation analysis [7; 15], a neural network approach [9; 10], a variational mode decomposition [16], sparsity-based techniques [17], etc. All these approaches have their own advantages and disadvantages, thus the problem of localization of EOG artifacts has yet to been solved.

The paper proposes a new algorithm that allows automatic localization of EOG electrooculogram artifacts in a multichannel EEG signal.

2 Materials and Methods

The algorithm is based on the correlation of the standard deviations of the amplitudes for each EEG eye lead (Figure 1). For each eye lead (time series (TS)), using the calculation window d with the length equal to one epoch (d = 250 readings, 1 sec), the TS amplitude standard deviation (SD) is calculated:

$$SD(j) = \sqrt{N^{-1} \cdot \sum_{i=1}^{N} (x_l - \bar{x})^2} \qquad (1)$$

Where SD(j) is SD for the j-th epoch; x_l is the l-th element of the j-th epoch; $l = \overline{1, N}$; N is the total number of elements in the j-th epoch; $\bar{x}$ is the arithmetical mean of the j-th epoch.

Then the calculation window moves to the right by its own length and the feature calculation is repeated. The SD(j) feature estimates are compared with the estimate of the mean SD over the entire lead (SD(s)):

$$SD_i(s) = M^{-1} \cdot \sum_{k=1}^{M} SD(k) \qquad (2)$$

Where k is the number of the epoch in the i-th lead; $k = \overline{1, M}$; M is the total number of epochs in the i-th lead; $i = \overline{1, P}$; P is the total number of EEG leads.

The epochs (EOG artifacts) for which SD(j)>SD(s) (1, 2) in at least one of the eye leads are removed in all EEG leads.

The algorithm is implemented in the MATLAB that enables obtaining the following information about the localized EOG artifacts from a multichannel signal of EEG: the number of artifacts, a graphical representation of the localized artifacts and the reconstructed purified EEG.

The proposed algorithm was tested on EEG records collected at the Tver State Technical University. The test EEG records were obtained from the experiments that took place during the study on human cognitive activity. The testees were 20 people between the age of 18 to 27 years old. The obtained database of samples included 600 EEG records of 10 seconds each.

The research instrumentation is a hardware and software tool that includes several personal computers with suitable software and a computer encephalograph "Encephalan-131-03" connected to them (Medicom MTD Ltd, Taganrog, Russia).

EEG signals were recorded according to the international 10–20 system; the recording was made by 19 leads: O2-A2, O1-A1, P4-A2, P3-A1, C4-A2, C3-A1, F4-A2, F3-A1, Fp2-A2, Fp1-A1, T6-A2, T5-A1, T4-A2, T3-A1, F8-A2, F7-A1, Pz-A1, Cz-A2, Fz-A1. EEG records were saved in .EEG and .ASCII formats with sampling frequency 250 Hz and lasting 5 minutes.

The obtained EEG samples were analyzed by three neurophysiologists. The experts identified EOG artifacts (blinking and eye movement) of different activity in each EEG. According to the analysis results, each EEG sample contained from 1 to 6 EOG artifacts.

3 Results and Discussion

Figure 2 shows an example of an initial EEG lasting 2500 readings (10 seconds). The sample contains EOG artifacts in eye leads (Fp1-A1 (left) and Fp2-A2 (right)), detected by an expert. Epochs 2, 5, and 9 are noted by experts as containing ocular artifacts.

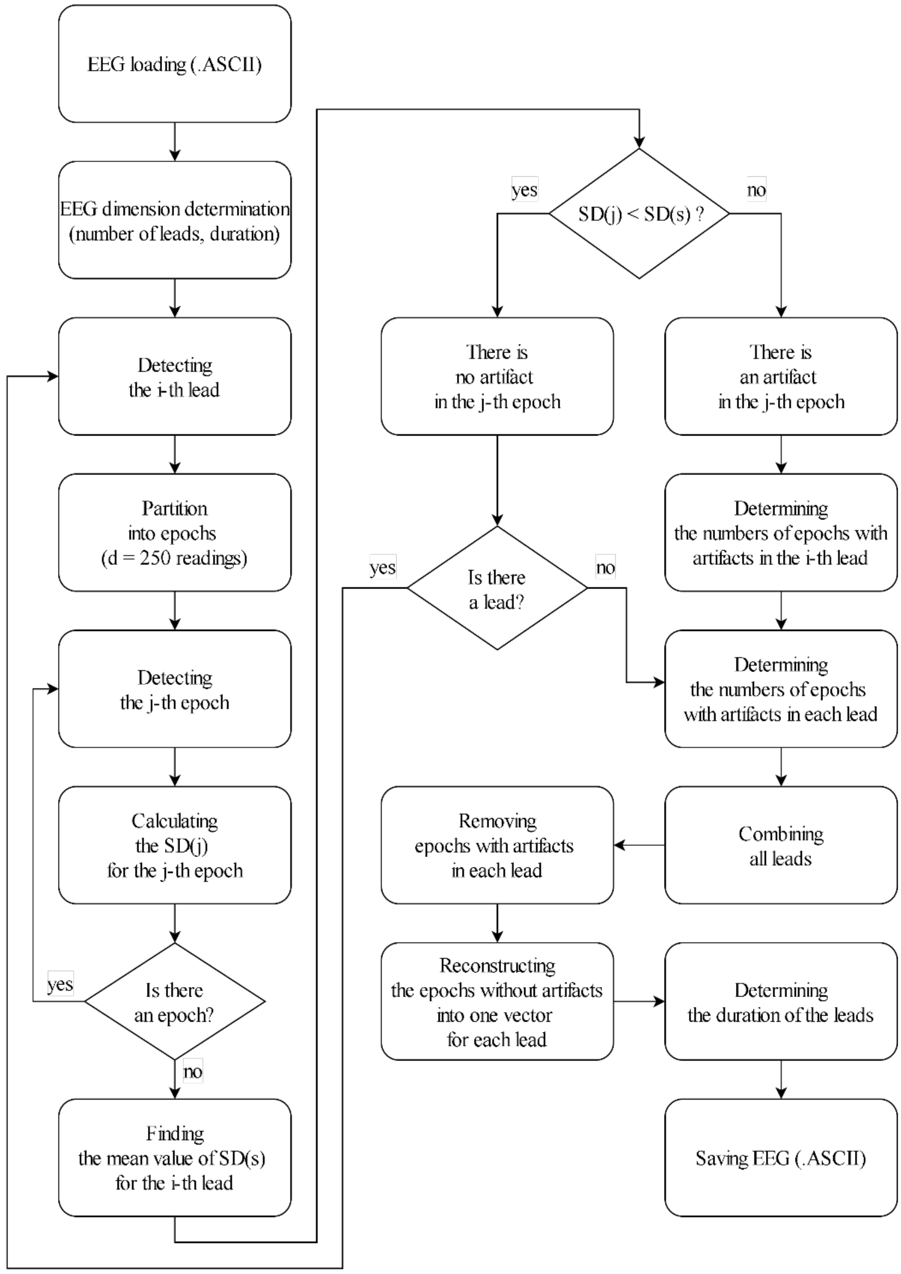


Fig. 1. The algorithm for automatic localization of EOG artifacts.

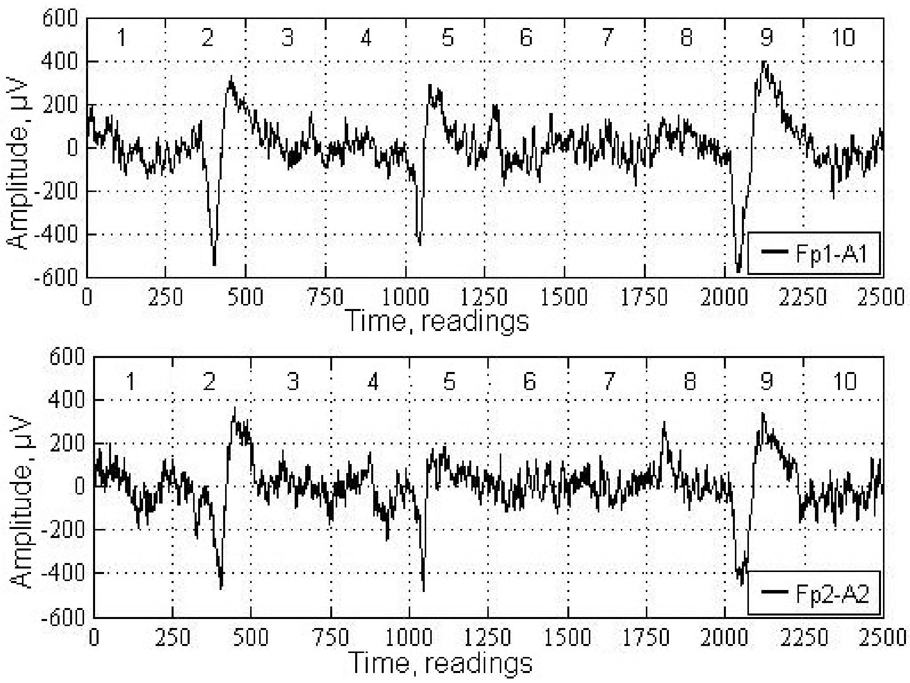


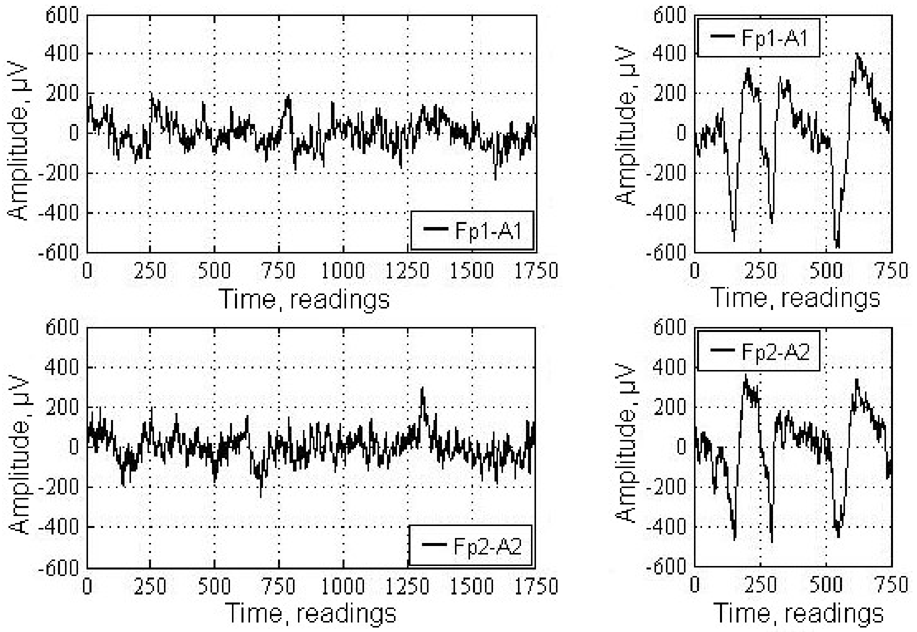
Fig. 2. The initial EEG.

Table 1 presents the algorithm output.

Table 1. The results of EOG artifacts localization in one EEG sample

Epoch	1	2	3	4	5	6	7	8	9	10
Lead	Fp1-A1									
SD (j)	78.3	199.2	71.6	47.3	164.3	82.7	60.5	54.1	264.4	58.8
SD (s)	108.1									
Lead	Fp2-A2									
SD (j)	76.7	196.0	57.2	78.6	123.9	57.5	48.4	78.1	217.0	57.6
SD (s)	99.1									
Artifact localized	no	yes	no	no	yes	no	no	no	yes	no

Figure 3 shows graphic representations of the reconstructed artifact-free EEG signal and localized EOG artifacts.



a b

Fig. 3. The reconstructed purified EEG (a) and localized EOG artifacts (b).

After processing all 600 EEG samples, the algorithm successfully localized 96% of the EOG artifacts noted by experts. Thus, 600 artifact-free EEG fragments were obtained, the minimum fragment duration was 4 seconds.

The algorithm was unable to identify 4% of the artifacts noted by experts. This happened with EEG samples, which contained the largest number of artifacts (6 of 10 epochs in the sample had artifacts). The *SD(s)* value in this case was overestimated and the algorithm considered the epochs with artifacts to be clean.

The proposed algorithm has a disadvantage as it leads losing EEG sections due to cutting out the entire section of a multichannel signal, even though EOG artifacts are mostly manifested in the Fp1-A1 and Fp2-A2 eye leads.

The further development of the algorithm is seen in the field of artifact detection by frequency features.

4 Conclusion

In this paper we consider an algorithm for automatic localizing EOG artifacts that is based on the correlation of the amplitudes SD for each eye EEG lead. The proposed algorithm allows detecting artifacts as well as restoring a purified signal with high reliability. The efficiency of the algorithm for detecting artifacts of EOG has been confirmed when applied to real EEG signals.

The proposed algorithm can be used for preliminary processing of EEG signals.

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