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Ocular Artifact Removal Method Based on the Wavelet and ICA Transform

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ABSTRACT The electroencephalogram is a promising tool used to unravel the mysteries of the brain. However, such signals are often disturbed by ocular artifacts caused by eye movements. In this study, Independent Component Analysis and Wavelet Transform based ocular artifact removal method, which does not need reference signals, is proposed to obtain signals free from ocular artifacts. With our proposed method, firstly, the ocular artifact regions in the time domain of the signal are detected. Then the signal is decomposed into its components by independent component analysis and independent components containing artifacts are detected. Wavelet transform is only applied to these components with artifact. Zeroing is applied to the parts of the wavelet coefficients obtained as a result of the wavelet transform corresponding to the ocular artifact regions in the time domain. Finally, the clean signal is obtained by inverse Wavelet transform and inverse Independent Component Analysis methods, respectively. The proposed algorithm is tested on a real data set. The results are given in comparison with the method in which the zeroing is applied to the classical independent components. According to the results, it is seen that most of the signal is not affected by the zeroing and the neural part of the EEG signals is successfully preserved.

KEYWORDS
Electroencephalography
Electrooculogram
Independent Component analysis
Brain computer interface
Wavelet transform

INTRODUCTION

The investigation of psychophysiological signals has become an important research area by the desire for the human brain to be discovered. Researchers have been trying to understand psychophysiological signals and develop Brain Computer Interfaces (BCI) that can work in harmony with these signals in this area. Electroencephalography (EEG) the result of firing many neurons in the brain is the commonly used signal type in BCI studies (Wolpaw *et al.* 2006). The various types of artifacts could interfere) with EEG signals such as ocular artifacts (OAs), cardiac artifacts and muscle artifacts. The OAs are the important sources of noise which make access to neural information difficult in EEG. The high amplitude of OAs are distorted the neural part of EEG signals (Yang *et al.* 2015).

The electrooculogram (EOG), which leads to OAs is the result of eye blinks and movements. These artifacts affect analysis of EEG signals negatively. Therefore, EEG signals need to artefact removal process. In the literature, artifact removal methods have been proposed such as signal epoch rejection (Kirkove *et al.* 2014), regression (Krishnaswamy *et al.* 2016) and Blind Source Separation (BSS) methods(James and Hesse 2004; Vigario and Oja 2008). The Independent Component Analysis (ICA) which is a complex mathematical technique has been most commonly used to separate artifacts from EEG signals in many of these proposed methods (Bell and Sejnowski 1995; Jung *et al.* 2000; Hyvärinen and Oja 2000). Various studies have used visual inspection and manual artifact removal based methods (Akhtar *et al.* 2012; Mammone *et al.* 2011). Beside these methods, several studies that use ICA on the automatic artifacts removal method have been proposed (Sameni and Gouy-Pailler 2014; Judith *et al.* 2022). For example, it was reported an automatic method for ocular removal from simulated EEG signals based on ICA in a study (Romero *et al.* 2008, 2009). Sameni et al. used the ICA based automatic moethod to remove ocular artifacts from EEG signals (Sameni and Gouy-Pailler 2014). Çinar et al. presented OD-ICA method for determination of the OAs (Çınar and Acır 2017).

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In the processes of artifact removal, it is important to recognize the properties which are decisive of the artifact such as amplitude and frequency. In order to determine these properties, different mathematical methods can be used in signal processing. Wavelet Transform (WT) is a very useful mathematical technique that allows to analyze signals, in the scale-time domain. The WT and ICA based OA removal methods are introduced in the literature. Nguyen et al. developed a real time neural network algorithm based on Wavelet for EEG artifact (Nguyen *et al.* 2012). Kelly et al. proposed a new method for use in high dimensional neural data based on Wavelet thresholding and ICA to localize artifacts (Kelly *et al.* 2010). Similarly, Ghandeharion et al. presented a new automatic artefact detection method which based on a combination of ICA and WT (Ghandeharion and Erfanian 2010). In the previous studies, ICA used for EEG decomposition. The artifactual Independent components (AICs) are rejected and the other ICs are used in reconstruction of artefact free EEG. The WT is also used for the focus of the signal to the frequency components containing artifacts by dividing the EEG signal into frequency components.

In this study, an eye artefact removal algorithm has been proposed. The eye artefact removal algorithm, unlike the studies in the literature, applies the zeroing operation only to the artifact-containing time segment of the relevant frequency component of the artifact. The proposed eye artefact removal algorithm apply a series of ICA decompositions to the EEG signal. The algorithm detects and extracts artifactual ICs (AICs) by selecting the best estimation with high correlation for automatic artifact detection. Thus, the proposed method, achieved much improvement in terms of removing OAs and preserving the neural part of EEG signals.

MATERIALS AND METHODS

EEG Acquisition

The data acquisition experiments is performed by 8 adult subjects. During the experiments, the subjects are imagined that they write Turkish syllables which are 'mer', 'ha', 'ba' and 'ar', 'ka', 'daş' on the screen. These syllables are the pieces of sound used to vocalize the 'hello' and 'friend' words in Turkish. The brain signals are recorded during the experiments by using 8 EEG gold-plated electrodes placed on scalp. Sampling rate is selected as 500 Hz. Electrodes placement is shown in Figure 1. The experimental procedure is also given in Figure 2. Before the recording, the subjects performed the experiment in a short training session. Each trial is recorded for 4 seconds duration which has rest period for one second. The EEG signals are obtained by use a Bioradio device which has been developed by Great Lakes NeuroTechnologies. The dataset is also published on Kaggle under the name "EEG Dataset with Ocular Artifact".

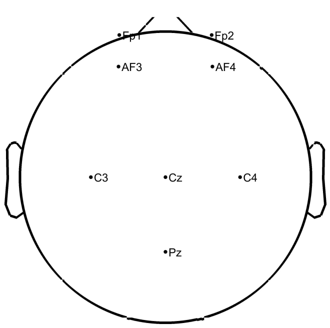

Figure 1 Electrodes placement.

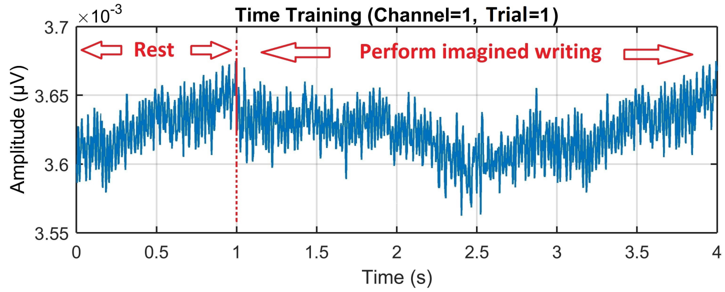

Figure 2 The experimental procedure.

Independent Component Analysis (ICA)

For BCI systems, it is essential to remove artifacts from the acquired signals as a result of eye movements, heartbeats, muscle activities and similar noises (Sahonero-Alvarez and Calderon 2017; McMenamin *et al.* 2011). The ICA method is used to convert a linearly mixed set of signals into another set that is independent of each other (Hyvärinen and Oja 2000; Stone 2002). The base of ICA relies on statistical independence. The general ICA approach is given by Equation 1. $x(t)$, A and $s(t)$ represent the signal vector received from the electrodes, the mixing matrix and the original source vector, respectively.

$$x(t) = \gamma s(t) \tag{1}$$

ICA method tries to determine unmixing matrix U that an approximately inverse of γ and given in Equation 2.

$$Ux(t) = O(t) \tag{2}$$

O(t) is approximate original signal which separated from sources. The FastICA algorithm is preferred for the parallel implementation convenience in this paper (Behera 2009). The FastICA algorithm uses kurtosis for the independent components estimation (Langlois *et al.* 2010).

FastICA performs by the following procedure;

1. Initialize U_i (randomly)
2. $U_i^+ = E(\phi'(U_i^T X))U_i - E(x\phi(U_i^T))$
3. $U_i = \frac{U_i^+}{||U_i^+||}$
4. if i = 1, go to step 7. otherwise continue with step 5.
5. $U_i^+ = U_i - \sum_{j=1}^{j-1} U_i^T U_j U_j$
6. $U_i = \frac{U_i^+}{||U_i^+||}$
7. If converged go back to step 1 with $i = i + 1$ until all components are extracted else go back to step 2.

Wavelet Transformation (WT)

Wavelet transform is a very useful mathematical technique that allows to analyze EEG signals, in the scale-time domain. The WT is used to analyze in more detail the AICs. WT expresses the signal at different scales and time relative to the main wavelet. WC and ψ show Wavelet Coefficients and the mother wavelet respectively. The WCs are calculated in Equation 3 (Liu *et al.* 2023).

$$WC(Sca, Pos) = \int_{-\infty}^{+\infty} x(t)\psi(Sca, Pos, t)dt \tag{3}$$

Much more efficient WT, Discrete Wavelet Transform (DWT) which scaled and shifted by powers of two. The DWT calculation is given in Equation 4.

$$DWT(i, m) = \sum_{i}\sum_{m} x(m)2^{-i/2}\psi(2^{-i}n - m) \tag{4}$$

The Daubechies mother wavelet which is the fundamental function to analyze the analog signals is used in DWT (He *et al.* 2007). 3 Level DWT decomposition is applied to the ICs by using Daubechies mother Wavelet. DWT levels of the ICs are given in Figure 3. The zeroing process is applied to only 3th level of the approximate DWT coefficients.

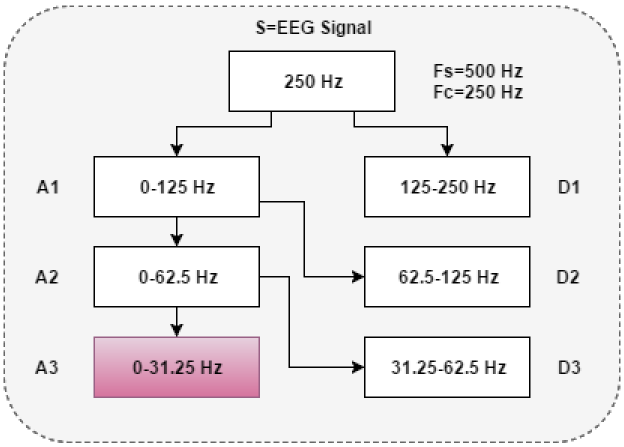

Figure 3 DWT levels of the ICs.

Eye Artefact Remover

In this section, the OA removal approach is given detailed.

Threshold Determination Determination of the threshold value is also important process in removal methods. The threshold value is determined according to each EEG signal by the proposed algorithm, although the value is usually fixed in existing studies (Kelly *et al.* 2010; Çınar and Acır 2017). Previous studies have found that blinking occurs in the 0.5 to 3.5 Hz frequency range. We used approximately this frequency range in our study (Nguyen *et al.* 2013). The threshold determination process is given in Figure 4.

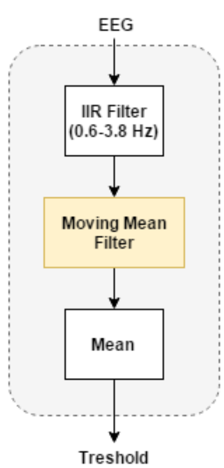

Figure 4 The threshold determination process.

The threshold value is obtained by the IIR and moving mean filtering. The frequency range is chosen as 0.6-3.8 Hz.

Artifact Detection OAs are components of lower frequency and higher amplitude than the neural part of the signal. The OAs are detected by using peak properties such as PPV and PVD which represent peak prominence value and peak distance value. The PPV that the minimum vertical distance that the signal must descend on either side of the peak before either climbing back to a level higher than the peak and the PDV that the distance between the two peaks are given in Figure 5. OAs create peaks in a certain band range in EEG signals. Determining the threshold value in this band range directly affects the OA detection success of the system. The minimum PPV and the minimum PDV are chosen as 0.3 s and $1.3e-04\ \mu V$ respectively. After determining the peak of the artifact by threshold, the bottoms of the artifact are determined by descending from both points of the artifact peak.

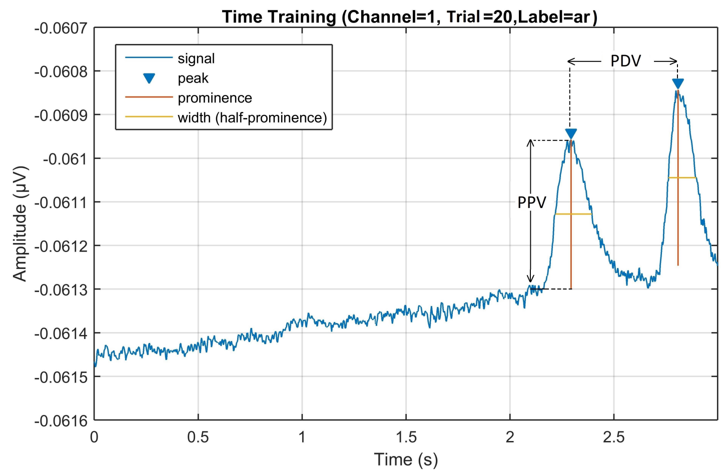

Figure 5 The sample EEG trial with OAs.

The height of descending point are determine the downward trend of the point. The bottom points of the artifact are reached, when the downward trend finish. The bottom points of the artifact determines the OA region which is on the wavelet coefficients of the AICs to use in the zeroing. However, Savitzky Golay filter was preferred for signal smoothing. The threshold value, smoothed signal, the OA region and peak bottoms are shown in Figure 6.

The artifact detection process is also applied to the ICs which obtained by ICA decomposition. Thus, AICs which are related with OAs are obtained. The result of a sample ICA decomposition is given in Figure 7. The OA regions, which given in Figure 6 and Figure 7 are suppressed by the zeroing process. The estimated AICs by the eye artefact removal algorithm are shown by yellow triangle marker in Figure 7.

Artifact Removal Process The block diagram of eye artefact removal is given in Figure 8. In Figure 8, first, It is applied ICA decomposition to the trials OA-containing by the eye artefact removal. After performing the ICA decomposition, the AICs are automatically identified by eye artefact removal and WT is applied to the AICs. The zeroing is applied only to the OA regions of AICs' third level approximate wavelet coefficients. Thus, the neural part of EEG signals is more successfully protected. Finally, the OAs free EEG signal is obtained by the inverse WT and ICA composition. The original EEG signal, training of the OA extraction process and

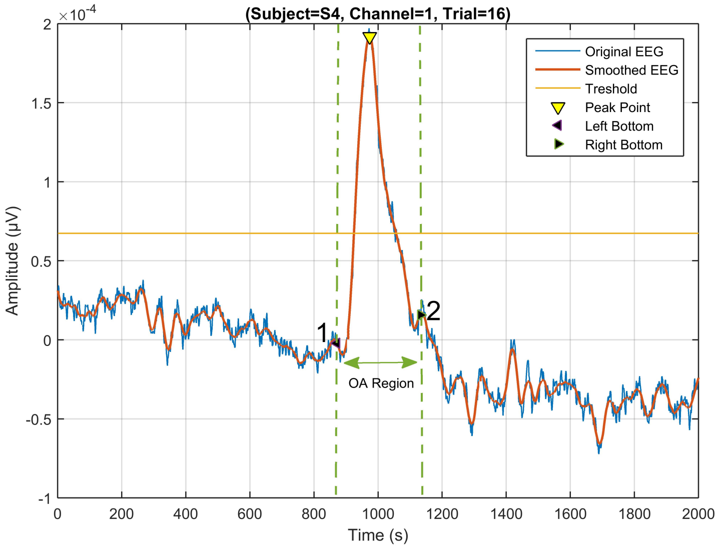

Figure 6 Sample EEG signal.

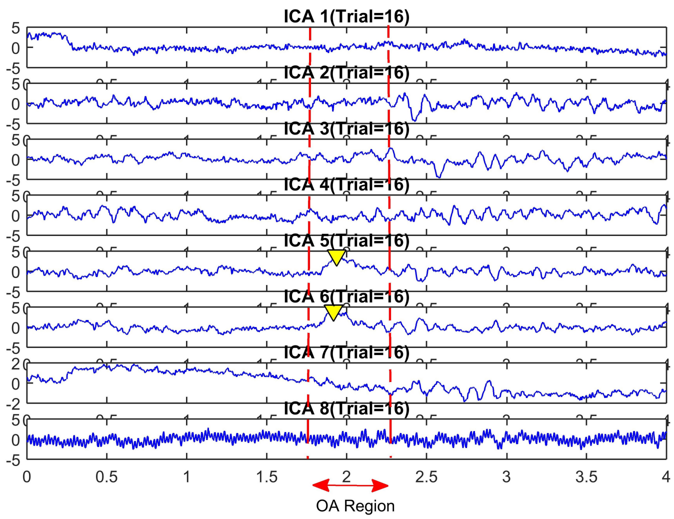

Figure 7 The result of a sample ICA decomposition.

clean EEG signal are given in a, b, c of Figure 9 which is the eye artefact removal application screenshot respectively.

The FastICA method is used for signal separation. The eye artefact removal obtains the best possible separation result by six iterations for one EEG trial.

Performance Evaluation

There is no general performance evaluation for artifact removal methods. As is known, EEG includes OA from a separate source such as eye muscles. These signals are highly inconsistent due to volumetric differences in their source. Therefore, after applying a perfect OA removal algorithm, the originally artifact-free portions of the signal should remain the same after EOG removal. This situation can best be expressed with the CC and STD parametrics (Kelly *et al.* 2010). For artifact removal evaluation has been used EEG experts or synthetic EEG data in the literature (Islam *et al.* 2016). Beside the non objective methods, Correlation Coefficient (CC), standard deviation difference (STD D.) and exterior standard

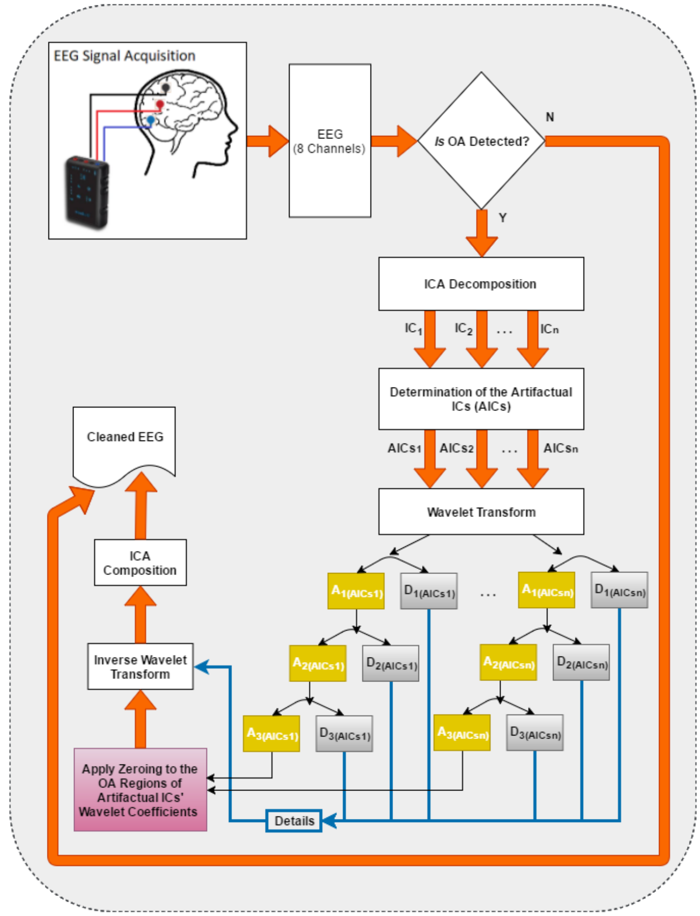

Figure 8 The general block diagram of the eye artefact removal algorithm.

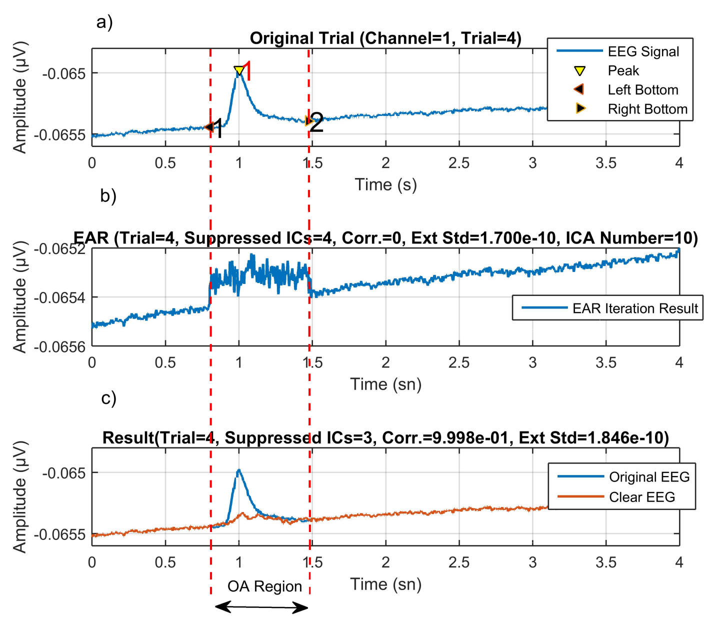

Figure 9 The eye artefact removal application screenshot.

deviation difference (E. STD) can be used to conduct a comparison. The CC and E. STD are given in Equations 5 and 6 respectively:

$$CC(x,y) = \frac{\sum(S_o - \bar{S_o})(S_c - \bar{S_c})}{\sqrt{\sum(S_o - \bar{S_o})^2(S_c - \bar{S_c})^2}} \tag{5}$$

$$E.STD(x,y) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(S_o - S_c)^2} \tag{6}$$

where $\bar{S_o}$ and $\bar{S_c}$ represents mean of the original $EEGS_o$ and clean EEG S_c. The N represents length of the selected window in Equation 4. The CC and STD respectively, show how well the shape of the result signal is preserved and how much the signal power is affected. The high CC represents minimum changing between original and result EEG signal. Another evaluation criteria is the mean squared error between the STD of the original and result EEG signal. This is called as exterior STD (E. STD). (Kelly *et al.* 2010; Jafarifarmand *et al.* 2017). The CC, STD D. and E. STD are calculated for both original and result EEG signals.

RESULTS

Data were obtained from 8 healthy subjects. The number of trials, the number of trials containing OA, the mean number of AICs and the OA detection success are given in Table 1. The OA detection success is also confirmed by the expert.

Table 1 The results of the experiments

Subject	Number of trials	Number of trials with OA	Mean number of AICs	OA detection success %
S_1	227	108	3.07	96.30
S_2	233	122	3.07	98.36
S_3	230	125	3.24	95.20
S_4	231	147	3.15	95.92
S_5	231	158	3.01	98.73
S_6	230	183	3.06	98.91
S_7	118	28	3.26	96.43
S_8	116	30	2.62	100

The mean number of AICs is observed about 3 in Table 1. It means that the zeroing process affects about 3 ICs for each EEG signal. The comparison of eye artefact removal and classical zeroing method results is given in Table 3.

Table 2 OA removal by eye artefact removal-ICs zeroing

Subject	CC ($x10^{-2}$)	STD ($x10^{-6}$)	E. STD ($x10^{-9}$)
S_1	64.24±19.97	87.75±86.32	3.33±4.55
S_2	57.43±19.71	75.67±90.07	3.99±6.78
S_3	53.57±19.04	78.38±62.08	3.78±4.24
S_4	55.75±19.20	67.52±56.17	2.13±2.34
S_5	48.43±16.03	85.68±57.54	1.28±1.38
S_6	55.18±16.76	66.78±48.86	0.93±0.84
S_7	61.40±18.92	72.97±49.09	1.34±1.66
S_8	79.87±19.73	53.04±66.23	0.86±2.30

Table 3 OA removal by eye artefact removal

Subject	CC ($x10^{-2}$)	STD ($x10^{-6}$)	E. STD ($x10^{-9}$)
S_1	98.82±0.35	3.87±4.27	1.32±1.75
S_2	98.70±0.39	5.37±6.22	1.74±1.92
S_3	98.42±0.40	4.74±4.80	2.11±1.88
S_4	98.05±0.44	4.76±6.09	1.38±1.27
S_5	98.98±0.34	3.70±4.18	0.83±0.60
S_6	99.34±0.19	2.92±3.06	0.68±0.45
S_7	97.01±0.54	5.18±5.80	1.05±1.16
S_8	98.22±0.49	5.10±5.46	0.38±0.65

The success of the eye artefact removal algorithm is shown in Table 3 and a,b of Figure 10. The comparison of three signals which original, cleared by eye artefact removal and cleared by classic ICA zeroing is also given in b of Figure 10. The values are given in Table 2 and Table 3 as mean ± standard deviation.

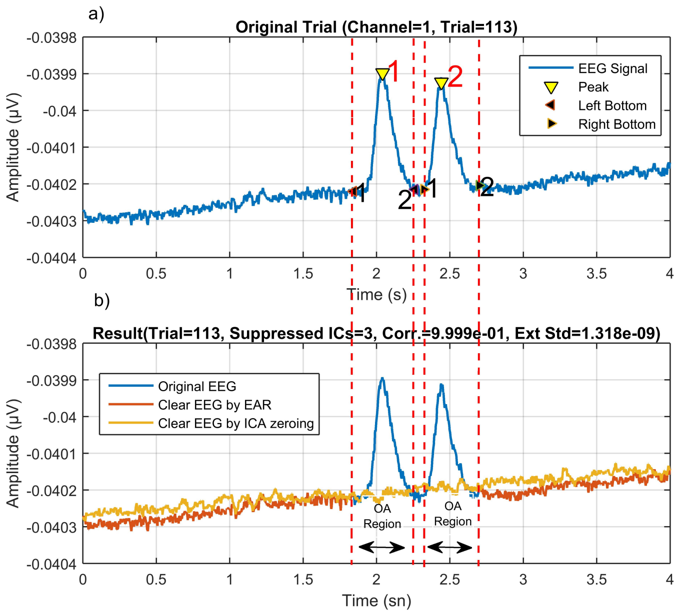

Figure 10 Visual comparison of eye artefact removal.

CONCLUSION

According to the experimental results, we have obtained that the proposed eye artefact removal algorithm shows superior performance over several commonly-used ICA based methods on OA removal. As seen from Table 2 and Table 3, the proposed method is better than classical zeroing method. As given in Table 3, 99.34±0.19 CC value is achieved with Subject 6. The eye artefact removal algorithm never disturb any part of the signal except the OA regions which are shown as sample in Figure 7.

The eye artefact removal obtains the best possible separation result by six iterations for one EEG trial. The algorithm is used the FastICA method for signal separation. The selected separation method is also suitable for parallel programming. In the future, it is intended to increase of the eye artefact removal algorithm effectiveness with the parallel program version and analyze of the results of the eye artefact removal on classification.

In this paper, the eye artefact removal algorithm is proposed to remove OAs full automatically from OA contaminated EEG signals without any reference signals and user intervention. The performance of the eye artefact removal algorithm is tested on a real EEG dataset. The results are shown that the proposed algorithm could successfully eliminate OAs from real EEG signals and protect neural information with minimum loss. And also, the proposed algorithm is superior to the classical ICs zeroing method. The WT ensured that the signal was better separated and focused on the responsible frequency domain. The proposed algorithm, similar to the studies in the literature, detects OA on the EEG signal and performs OA reset. However, unlike the studies in the literature, applies the zeroing only to the artifact-containing time segment of the relevant frequency component of the artifact. By the applying of the zeroing to the OA regions of AICs' wavelet coefficients with a novel approach, a large amount of the EEG signal is not affected by the zeroing and the neural part of EEG signals was successfully protected.

Acknowledgments

The acquisition of EEG signals is approved by the Non-Interventional Clinical Research Ethics Committee at the University of Karabuk in Turkey.

Availability of data and material

The dataset used in the study is available on Kaggle under the name "EEG Dataset with Ocular Artifact".

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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