# Efficient Ocular Artifacts Removal over Independent Component Analysis in BCI

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***Abstract*—Ocular Artifacts (OA) frequently occur in Electroencephalogram (EEG) recording signals. These artifacts are the phenomenon caused by eye's movements and blinking, having a significant effect on EEG-based Brain-Computer Interface (BCI) systems. Thus, OA removal is one of the most vital tasks of building a well-perform BCI system. In this paper, we propose an approach to automatic removal of OA based on Independent Component Analysis (ICA) procedure. Briefly, we first deploy ICA to decompose EEG signals into independent components. After that, for each component, we calculate the ratio of the magnitude of noise spectra to that of β and then compare the ratio to a pre-defined threshold. If the ratio is larger than the threshold, we remove the corresponding component; otherwise, we keep the component for reconstructing the signal. In order to evaluate the performance of our proposed method, we carry out an experiment to acquire the real EEG signals, run several simulations, and compare to a traditional ICA method based on peak detection algorithm. The results show that our proposed method can remove OA effectively with a slight influence in the underlying EEG signal. Besides, the proposed method outperforms the traditional one in eliminating OA from the EEG signal.**

***Index Terms*—Brain-Computer Interface (BCI), Electroencephalogram (EEG) signal, Ocular Artifacts (OA), Independent Component Analysis (ICA).**

## I. Introduction

Brain-Computer Interface (BCI) is known as an alternative communication system that can be able to translate mental activities of the brain into control commands for activating electronic devices [1]. Many BCI systems have been developed to support not only medication but also for entertainment purposes [2]. For example, authors in [3] implemented a BCI system that controls a mobile robot using imagery motor Electroencephalogram (EEG) signal; in [4], authors built a BCI system to support a 3D racing game control on Android phone based on mental states including attention and meditation; to name but a few.

Basically, BCI can be categorized into 2 types: invasive and non-invasive. The latter is more common than the former one because it does not require a surgery which is risky for users [5]. Instead, non-invasive BCI systems obtain EEG devices to measure the brain activities from the scalp. Nowadays, several companies have begun to commercialize inexpensive EEG devices to support a wide range of applications, motivating the development of non-invasive BCI systems. However, the major drawback of non-invasive BCI system is that the brain signal measured from the scalp are attenuated when it passes through the skull, leading the system to deal with EEG signals contaminated by artifacts, especially Ocular Artifacts (OA) which often occur in EEG recording. These artifacts cause difficulties in EEG analysis and can even be misread as the physiological phenomena of interest [6]. Consequently, it is necessary to remove artifacts from EEG signals.

There are existing methods that try to remove entirely or reduce the effect of OAs in literature. Based on the observation that the intensity of OAs is often maximal at 4Hz, the authors in [3] deployed a high-pass Butterworth filter with 4Hz cut-off frequency to attenuate OAs. However, OAs cannot be removed entirely because an abundant amount of OAs still exists in the range from 4Hz to 16Hz. Moreover, using the high-pass filter for artifact removal can cause losses of brain activity information because the removed spectral range contains not only the artifacts but also the desired brain signals. In [8], authors proposed another method called Adaptive Filter (AF). This method enables the ability to remove OAs with less effect on the desired EEG signals than the high-pass Butterworth filter. However, OAs have to be measured during filtering to serve as filter's referencing source. It may not be convenient for users to use the BCI system.

Recent research has shown that Independent Component Analysis (ICA) is very effective in eliminating different types of artifacts from EEG recordings with better results than those obtained other approaches [9]. However, the standalone ICA requires human intervention to identify the artifactual components to remove, posing challenges to implementing ICA based automatic removal of artifacts. To cope with that problem, authors in [10] suggested adding the collection of Electrooculogram (EOG) channels to acquire the OA sources and study the relationship between them and ICs, through that, the ICA can identify and remove the artifact components automatically. However, this approach has the same drawback

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as [8]. Authors in [11] combined ICA with a peak detection algorithm (PDAIC) to automatically identify and eliminate the artifactual sources without requiring additional EOG channels. The peak detection performance depends heavily on comparing the distance between (1) the extreme point and (2) its nearest zero point with pre-defined thresholds. However, the EEG signal is non-stationary [1] which means that this distance changes unpredictably. Whereas, the thresholds constantly remain throughout the operation, leading to the poor performance of the algorithm. On the other hand, this algorithm requires tuning parameters before applying to the BCI system. A failure in tuning one parameter will lead to the poor performance as well.

In this paper, we propose an artifactual automatic removal method for ICA based on the relationship between the magnitude of noise and that of β rhythm in the EEG signals. Firstly, ICA separates EEG signal acquires from electrodes into ICs. To compute the magnitude of each IC, we make a copy of each IC and transform the copies into the frequency domain using Fast Fourier Transform (FFT). We then compute the ratio of the magnitude of noise spectra to that of β for each IC and compare the ratio to a pre-defined threshold. If the ratio is larger than the threshold, we remove the corresponding component; otherwise, we keep that component. After eliminating the artifactual components, the rest of ICs are used to recreate the EEG signals.

Our contribution can be listed as below.

- We design an algorithm that automatically remove artifact components for ICA.
- We then implement the experiment for testing our proposed scheme.
- We also make the comparison between our scheme and a traditional one (which combines ICA and peak detection algorithm for automatic removal).

In the following, we first overview the characteristics of the EEG signal and the fundamental of ICA method in Section II. In Section III we show a detail description of our proposed method called Signal magnitude Ratio based ICA. We then demonstrate the performance evaluation of the proposed method and the comparison with the traditional ICA in Section IV. Finally, we summarize our work, discuss some disadvantages of our method and future work.

## II. PRELIMINARY

### A. Electroencephalogram (EEG) Signal

EEG signal is the electrical activity of brain measured from electrodes placed on the scalp surface. The EEG signals are often categorized into six major types according to their different frequency ranges, as shown in Table 1 [12]. Different BCI systems apply different types of EEG signals. For example, motor imagery based BCI systems which classify the imaginary movements of users typically utilize α/μ and β signal while Steady State Visual Evoked Potential (SSVEP) based BCI systems often deploy signals that lie within the range of α.

Typically, the brain signals have amplitudes of 0.5 - 1.5mV and might up to several millivolts for spikes. However, on the scalp, the amplitudes commonly lie within the range of 10 to 100μV [12]. Moreover, the brain activities measured from the scalp surface has a low Signal to Noise Ratio (SNR) due to the influence of artifacts, especially OAs which are caused by the rotation of the eyeball or eye blinking. One of the recognizable features of the OAs is that they often have a large amplitude and low frequency (i.e., from 0 to 16Hz) [7]. On this basis, we implement our method of automated artifacts removal.

TABLE I
TYPES OF EEG SIGNALS

| Rhythm | Bandwidth (Hz) |
|---|---|
| Delta (δ) | 0.4 – 4 |
| Theta (θ) | 4 – 7.5 |
| Mu (μ) | 8 – 12 |
| Alpha (α) | 8 – 13 |
| Beta (β) | 14 – 30 |
| Gamma (γ) | 30 and over |

### B. Independent Component Analysis (ICA)

ICA is a statistical and computational method used for separating a mixing signal into ICs. The method assumes that brainwaves are a linear mixture of statistically independent sources including brain activities and artifact activities [1].

Typically, ICA contains three main steps:

- First, EEG data $x = (x_1, x_2, \dots, x_n)^T$ is decomposed into independent sources $s = (s_1, s_2, \dots, s_m)^T$ by

$$s = \boldsymbol{A}x \tag{1}$$

where $n \in N^*$ is the number of sources (i.e., electrodes), $m \in N^*$ is the number of ICs ($m \leq n$), and $\boldsymbol{A} \in R^{m\times n}$ is un-mixing matrix.
- Second, components identified as artifacts are eliminated automatically using automatic removal algorithms or manually.
- Third, the rest ICs are remixed to recreate the EEG signal with less or without OA.

$$\tilde{x} = \boldsymbol{A}^{-1}s \tag{2}$$

## III. PROPOSED SCHEME

As we mentioned in section II, the OAs often occur at a lower frequency, and its amplitudes are substantially higher than the underlying EEG signals. From the experiment with components containing artifacts after applying ICA, we observe that results from the division of the magnitude of the noise spectra and that of the β are usually similar with a small deviation. Based on that, the fundamental of our method is to compute the ratio of the magnitude of the noise spectra to that of the β (as Eq. (3)). After that, we set a threshold and then compare the ratio to that threshold to consider whether removing the component or not.

$$\mu_i = \frac{\sum_{j=0}^{L_{16}} |s_i[j]|}{\sum_{j=L_{16}}^{L_{30}} |s_i[j]|} \tag{3}$$

where $s_i$ is an array that stores the $i^{th}$ IC in the frequency domain, $L_{16}$ and $L_{30}$ is the index of 16Hz and 30Hz,

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respectively.

Fig. 1 illustrates an example of the ratio computation. In which, the ratio μ is calculated by dividing the area of the orange domain (i.e., the total magnitude of the noise spectra) by that of the green domain (i.e., the total magnitude of the approximate β rhythm).

The process of identifying and eliminating the OAs can be summarized as follows:

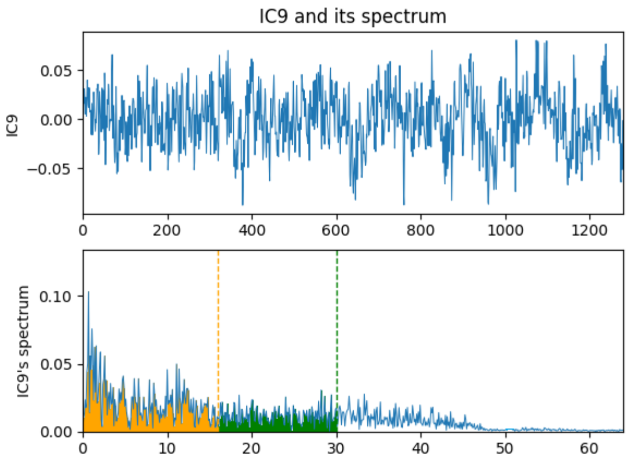


Fig. 1. The ninth IC and its spectrum.

- **Step 1**: The EEG signals are decomposed by fast ICA to obtain the un-mixing matrix ***A*** and ICs *s* as Eq. (1).
- **Step 2**: Each IC in the previous step then is copied, and the copies are transformed to the frequency domain using FFT.
- **Step 3**: For each of the copy of IC, the ratio $\mu$ is calculated as Eq. (3) and compared to a pre-defined threshold. If the ratio is larger than the threshold, the corresponding IC is removed. Otherwise, the IC is kept to recreate the EEG signal.
- **Step 4**: Inverse ICA is performed as Eq. (3) to remix the EEG signals from the rest ICs.

## IV. Performance Evaluation

### A. Experiment Setup

The EPOC headset [14] is used to collect the EEG signals. This device contains 14 measuring electrodes and two reference electrodes. All these electrodes are arranged according to the standard EEG system (as shown in Fig. 2). The device operates at the sampling rate at 128Hz, with 14-bit resolution. These specifications are sufficient for our experiments.

To collect the data, we conducted experiments on a 22-years old healthy man. The participant was required to record 20 trials to collect 20 datasets using the software TestBench provided by Emotiv company. The duration of each dataset is from 30 to 40 seconds. Before the data acquisition process, the participant removed stuff like the smartphone, watch so that he can focus on tasks of the experiment. During the process, the participant was requested to do some tasks such as blinking eyes, rolling eyes and winking eye.

After being recorded, the data from the EPOC device has a large DC offset because they are transmitted as an unsigned integer. Additionally, noises from the electrical grid (i.e., noises that range from 50 to 51Hz) can easily affect the EEG signals via the computer we used to acquire the signal. Consequently, we first apply a high-pass filter with the cut-off frequency of 0.16Hz [15] to remove the offset and then apply a band-stop filter with the cut-off frequency from 50 to 51Hz to remove the effect of the electrical sources.

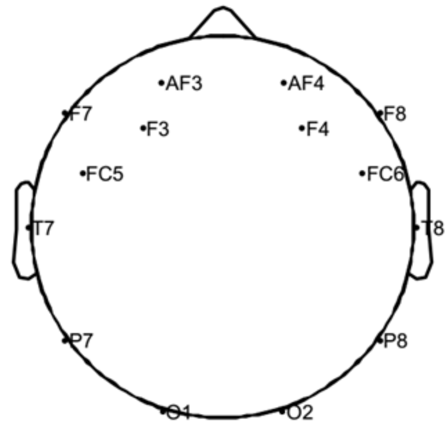


Fig. 2. Position of measuring electrodes of the EPOC device.

### B. Performance

Fig. 3 shows the discrepancy between the signal before and after being processed by our proposed method. In the upper figure, we test our proposed method with a signal contaminated by OA. Whereas in the lower figure, the proposed method is applied to a signal without OA. The results demonstrate that our method successfully removes OA from the signal with OA (the upper figure on Fig. 3) while it almost reserves the information of the signal without OA (the lower figure on Fig. 3).

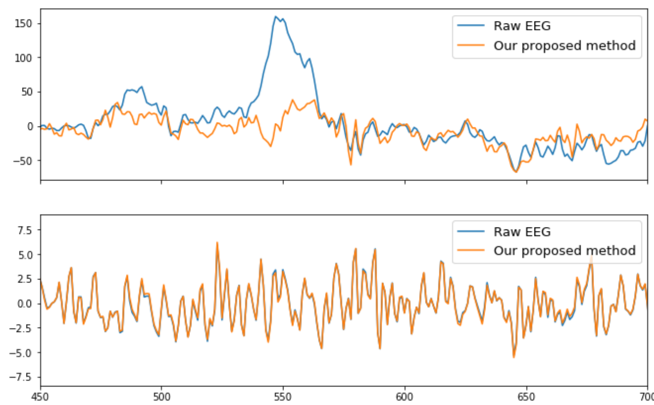


Fig. 3. EEG signal before and being applied our proposed method.

We also illustrate ten examples of typical waveforms of artifacts which can be successfully detected and eliminated using the proposed method in Fig. 4.

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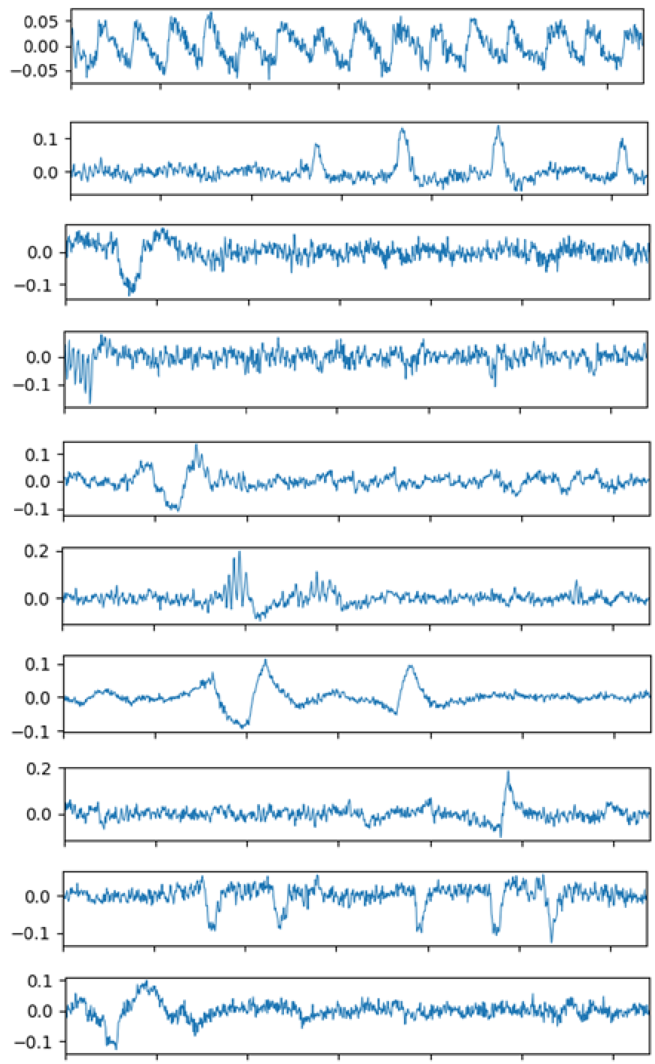

Fig. 4. Ten examples of typical waveforms of OA successfully detected by our proposed method.

Additionally, we adopted the correlation analysis in time domain in [11] to show the averaged effect of OAs on the EEG signals. The correlation coefficient (CC) are calculated by Eq. (4).

$$\rho(x, \tilde{x}) = \frac{E[x\tilde{x}]}{\sqrt{E[x^2]E[\tilde{x}^2]}} \quad (4)$$

where $E[.]$ is the expectation, $x$ and $\tilde{x}$ are the measured EEG (i.e., the signal before being applied our proposed method) and estimated EEG (i.e., the signal after being applied our proposed method), respectively.

Fig. 5 illustrates the results of the correlation analysis over 14 measuring electrodes of the device. We obtain a low CC value between the measured EEG and the estimated EEG at electrodes located near the frontal lobe (i.e., the electrodes AF3, F7, F8, and AF4 corresponding to the indices 1, 2, 13, and 14 in Fig. 5). By contrast, the CC value at electrodes located near the parietal and occipital lobe reach high values (e.g., CC value at T8 corresponding to the index 9 in Fig. 5 reaches 0.98). The reason is that the OAs mostly influence at electrodes near the eyes and its amplitudes over the scalp is attenuated nearly with the square of the distance from the eyes [13]. It demonstrates that our proposed method slightly affect the underlying signals when eliminating the artifacts and this observation meets the criterion in [7]. However, the standard deviation of the CC values over the electrodes are still significant because of the quality of the EPOC device and the emergence of some unexpected factors when recording the EEG datasets.

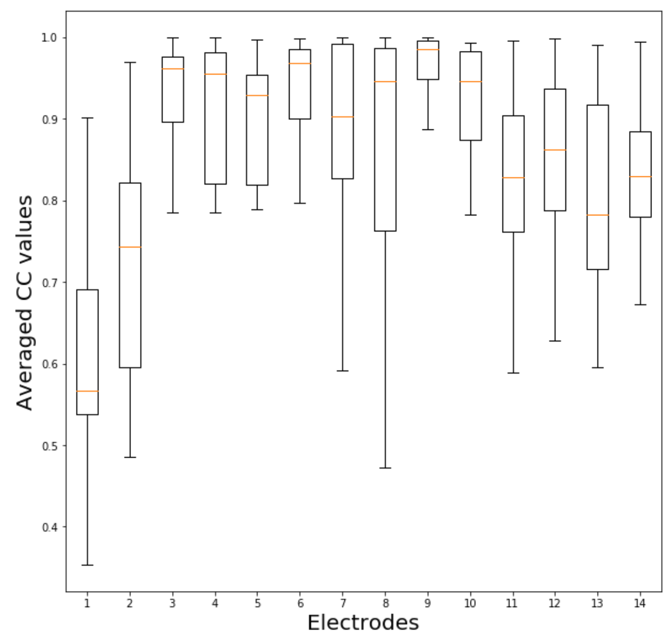


Fig. 5. The averaged CC values and their standard deviations on different electrodes between the measured and estimated EEG signals.

### C. Comparison to PDIAC

To further illustrate the performance evaluation of our proposed method, we rebuilt the PDIAC from the description in [11] and then conducted a comparison between the method and PDIAC.

As mentioned in Section I, the PDAIC method deploys a peak detection algorithm to identify and remove artifacts in the time domain of an IC. However, several disadvantages of this method are already discussed in Section 1. As mentioned in Section I, the PDAIC method deploys a peak detection algorithm to identify and remove artifacts in the time domain of an IC. However, several disadvantages of this method are already discussed in Section 1. In this section, we illustrate an example of the difficulty in tuning the parameter distance threshold which represents the threshold of the distance between the extreme point and its nearest zero point. That is, if we set this parameter too small, the algorithm will not be able to detect most artifacts. By contrast, if we set this parameter too large, the algorithm will remove most of the underlying EEG information.

Fig. 6 illustrates an example, in which, we tried to set a large value of the parameters distance, leading the PDAIC removes most information of an EEG signal without artifacts while our proposed method successfully reserves the EEG information.

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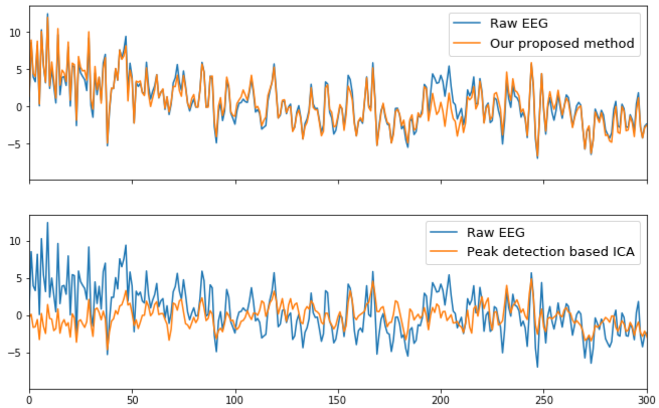

Fig. 6. A signal after being applied our proposed method compared to PDAIC.

To quantitatively compare the performance of our proposed method and PDAIC, we adopt the ratio $R^2$, or also known as Artifact to Signal Ratio (ASR) proposed in [7]. We calculate the values of $R^2$ as Eq. (5) for the electrodes AF3, F7, F8, AF4 to see how effective our automatic removal method compared to PDAIC.

$$R^2 = \frac{\sum_{i=1}^{N}\left(x^{(i)} - \tilde{x}^{(i)}\right)^2}{\sum_{i=1}^{N}\left(\tilde{x}^{(i)}\right)^2} \tag{5}$$

where N is the number of samples.

Intuitively, if an automated artifacts removal performs well, most artifacts will be removed from the signal. As a result, the difference between the measured and the estimated signal increase, leading to the increase of the numerator and so the $R^2$ value. Thus, the higher the value of $R^2$ is, the better the OA removal is.

The results in Fig. 7 demonstrate that the proposed method outperforms the PDAIC.

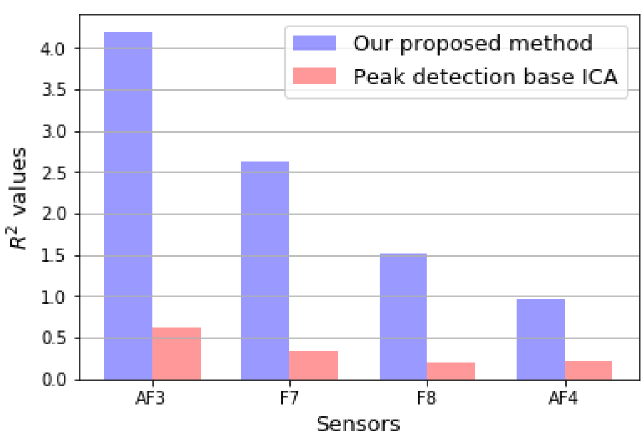

Fig. 7. $R^2$ values of our proposed method compared to that of PDAIC.

## V. CONCLUSION

In this paper, we proposed an automatic removal of OA based on the ratio of the magnitude of noise spectra to that of β. The proposed method has a better performance compared to the PDAIC. The reason is that our method is performed in the frequency domain and the parameter we use is more stable with the non-stationary signal like EEG. Moreover, the proposed method outperforms the PDAIC because the parameter of our method is less sensitive with the non-stationary of the EEG signal than that of PDAIC. Last but not least, our method requires smaller number of parameters than PDAIC.

In future research, we are going to design an adaptive threshold to improve further our method of removing OA. Besides, we will consider deploying our method to eliminate other types of artifacts like Electromyogram (EMG) and Electrocardiogram (EKG).

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