2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Removing EOG Artifacts from the EEG signal of Methamphetamine Addicts

Zuoting Song[1], Tao Fang[1], Shuang Li[2], Lan Niu[2], Yuan Zhang[1], Song Le[1], Gege Zhan[1], Xueze Zhang[1], Hui Li[3], Min Zhao[4,5], Haifeng Jiang[4,5], Lihua Zhang[1, 2], and Xiaoyang Kang[1, 2, 6]

***Abstract*— EEG can be used to characterize the electrical activity of the cerebral cortex, but it is also susceptible to interference. Compared with the other artifacts, Electrooculogram (EOG) artifacts have a greater impact on EEG processing and are more difficult to remove. Here, we mainly compared the regression and ICA algorithms both based on the EOG channels for the effect of removing EOG artifacts in the Stroop experiment of methamphetamine addicts. From the perspective of time domain and power spectral density, the ICA algorithm based on the EOG channels is more effective. However, the regression algorithm based on the EOG channels is less complex, more time-saving, and more suitable for real-time tasks.**

***Clinical Relevance*— For clinical purposes, this research has a certain reference value for selecting appropriate methods of removing EOG artifacts when processing the EEG of methamphetamine addicts.**

I. Introduction

EEG can be used to record the electrical activity of the cerebral cortex, which is of great significance to the study of people's cognitive processes. However, both the amplitude and signal-to-noise ratio of the EEG are low, and EEG is susceptible to interferences[1]. Electrooculogram (EOG) artifacts are the most influential and difficult to remove among various artifacts. Brain activity can be severely affected by eye movement and blinking[2]. The easiest way to solve EOG artifacts is to let the subjects close their eyes to measure, but this may change the dynamics of the collected EEG signals[3].

In recent years, there have been many researches on the removal of EOG artifacts, but there is no uniform method. Among them, the independent component analysis (ICA) algorithm and regression algorithm are the most used methods[4]. ICA is a blind source separation algorithm that can isolate components without assuming a model[5]. ICA can be used not only for dimensionality reduction[6], but also for the classification of EEG data[7]. Besides, the ICA algorithm is mainly used to remove artifacts caused by eye movement and blinking[8]. Fast ICA is one of the common ICA algorithms[9]. Although the ICA algorithm can separate components better, the ICA algorithm also needs to manually select the corresponding artifact components. The manual selection can cause some errors and it is difficult for beginners. Besides, the manual selection will waste more time. On the other side, the removing artifacts methods based on the regression algorithm are mainly used to remove the EOG artifacts in the recorded evoked potential[10, 11]. However, if the coefficients in the regression algorithm are the same, the result of removing artifacts is not accurate enough. Therefore, the coefficients in the regression algorithm need to be selected appropriately. In this paper, we mainly compare the difference between the ICA algorithm and regression algorithm based on the EOG channels.

II. Methods

A. Recordings

The dataset including EEG signals of 6 methamphetamine addicts was collected from Shanghai Mental Health Center. The scalp EEG recordings were collected using Brain Products 64-channel EEG equipment at a sampling rate of 1000 Hz. It contained two EOG channels: the IOLeft channel and the IORight channel. The scalp electrodes were placed according to the position of the extended international 10-20 system. The participants involved in the experiment signed informed consent for the protocol approved by the Institutional Review Board (IRB) of Shanghai Mental Health Center, Shanghai Jiao Tong University School of Medicine (IRB#: 2015KY-21).

The task in the experiment is the Methamphetamine Addiction Stroop Task which is mainly used to evaluate the attention bias of methamphetamine addicts to words related to methamphetamine. The words used here included two words related to methamphetamine and two neutral words. Each of the words was presented on the screen in four different colors, and each appeared eight times, displayed for 3000 ms. Each

*Research supported by the National Natural Science Foundation of China grant no. 61904038 and no. U1913216; Shanghai Sailing Program No. 19YF1403600; Shanghai Municipal Science and Technology Commission grant no. 19441907600, no19441908200, and no. 19511132000; Fudan University-CIOMP Joint Fund FC2019-002; Opening Project of Shanghai Robot Industry R&D and Transformation Functional Platform; Opening Project of Zhejiang Lab grant no. 2021MC0AB01; Ji Hua Laboratory grant no. X190021TB190; Shanghai Municipal Science and Technology Major Project 2021SHZDZX0103; National Key R&D Program of China no. 2017YFC1310400 and no. 2021YFC0122702.

[1]Zuoting Song, Tao Fang, Yuan Zhang, Song Le, Gege Zhan, Xueze Zhang, Lihua Zhang and Xiaoyang Kang are with the Engineering Research Center of AI & Robotics, Ministry of Education, Shanghai Engineering Research Center of AI & Robotics, MOE Frontiers Center for Brain Science, Institute of AI and Robotics, Academy for Engineering & Technology, Fudan University, Shanghai, China. (corresponding author is Xiaoyang Kang; e-mail: xiaoyang_kang@fudan.edu.cn; Zuoting Song: 19210860038@fudan.edu.cn; Tao Fang: 19210860039@fudan.edu.cn; Yuan Zhang: 19210860061@fudan.edu.cn; Song Le: 19210860075@fudan.edu.cn; Gege Zhan: 20210860027@fudan.edu.cn; Xueze Zhang: 19110860014@fudan.edu.cn; Lihua Zhang: lihuazhang@fudan.edu.cn)

[2]Shuang Li, Lan Niu, Lihua Zhang and Xiaoyang Kang are also with the Ji Hua Laboratory, Foshan, Guangdong Province, China. (Shuang Li: lishuang@jihualab.com; Lan Niu: niulan@jihualab.com)

[3]Hui Li is with the Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen, China. (hui.li1@siat.ac.cn)

[4] Min Zhao and Haifeng Jiang are with Shanghai Mental Center, Shanghai Jiao Tong University School of Medicine, Shanghai, China. (Min Zhao: drminzhao@smhc.com.cn; Haifeng Jiang: dragonjhf@hotmail.com)

[5] Min Zhao and Haifeng Jiang are also with CAS Center for Excellence in Brain Science and Intelligence Technology (CEBSIT), Chinese Academy of Sciences, Shanghai, China.

[6]Xiaoyang Kang is also with the Research Center for Intelligent Sensing, Zhejiang Lab, Hangzhou 311100, China.

word appeared randomly, but the word of each type of word meaning did not appear more than three consecutive times, and the possibility of the words of the two types of word meanings alternately appeared to a certain extent.

Before the start of the experiment, the participants sat in a dark and quiet room with a display screen placed in front of them. When a word appeared on the screen, participants need to ignore the specific meaning of the word and press the button corresponding to the color of the word at this time. The markers in the EEG signals recorded in this experiment are mainly divided into two types. The first is to mark the meaning of words in the picture: it is divided into methamphetamine-related and neutral. The second is to mark whether the right button is pressed.

B. *Preprocessing*

Before all the operations, we first identified the EOG channels. The other preprocessing steps were performed before removing eye movement and blinking artifacts from the collected EEG signals. A bandpass filter of 0.5-60 Hz was used to filter the EEG signals. At the same time, a 50Hz notch filter is used to filter out power frequency interference. Relevant information about the events was read from the comments. Because we want to compare the two methods of removing eye movement and blinking artifacts on the dataset, we first divided the epochs according to the event labels. According to the divided epochs, the baseline correction of epochs is performed to reduce the impact of data drift.

C. *Removing eye movement and blinking artifacts*

The main purpose of this experiment is to compare the removing EOG artifacts effects of the regression method based on the EOG channels and the ICA method based on the EOG channels. The ICA algorithm that we chose in the experiment was the fast ICA method. Both methods are implemented by the MNE library of Python 3.7. It is well known that the influence of the EOG signal on the EEG signal collected by electrodes at different positions on the scalp is different. Therefore, it is unreasonable to subtract the same EOG signal at different electrodes. A more appropriate approach is to estimate the propagation coefficients of electrodes at different positions, and subtract the EOG signals scaled according to the corresponding coefficients from the EEG signals collected at different electrode positions. The regression algorithm is based on this principle to correct the EEG signals.

The fast ICA algorithm based on the EOG channels used in this experiment is mainly to evaluate the correlation between the EEG signals collected at different electrode positions and the signals collected by the EOG channels. It is common to use ICA to decompose EEG signals and observe and determine which are artifact components. But when there are many independent components, manually judging the artifact components is more time-consuming and less accurate. In this experiment, we used the fast ICA algorithm to decompose the EEG into a certain number of independent components and use the find bad EOG function to automatically find the independent component that is closest to the EOG signals, and the degree of match between each component and the EOG signals is measured by the calculated correlation score. When the score obtained exceeds a certain threshold, it will be judged as a component related to EOG artifacts. Finally, all the related EOG artifacts determined were removed.

In order to compare the two methods for removing EOG artifacts, we mainly compared the time-domain signal, power spectral density, and corresponding topographical map distribution of the processed EEG signals.

III. Results

In this experiment, we mainly compared two methods based on the EOG channels for removing EOG artifacts from the EEG signals collected by the Stroop experiment of the methamphetamine addicts.

The method of removing EOG artifacts based on the ICA algorithm mainly compares the matching degree of each component with the EOG channels, and their matching degree is mainly displayed by the score. Fig.1a and Fig.1b respectively indicate the matching degree of each component with the two EOG channels, and the components whose scores exceed the set threshold are shown in red. It can be seen that the scores of the first component and the second component

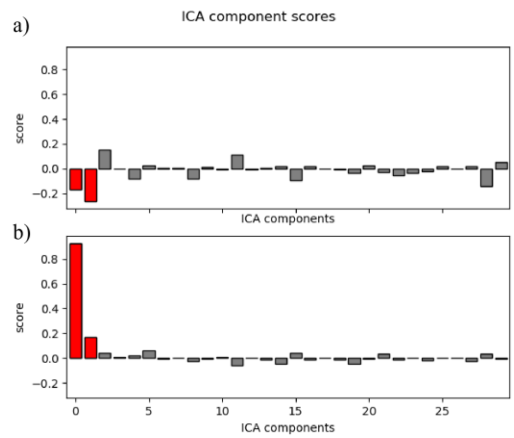

Figure 1. ICA component scores. a) the ICA component scores related to IOLeft channel; b) the ICA component scores related to IORight channel. The red part shows that the score exceeds the threshold.

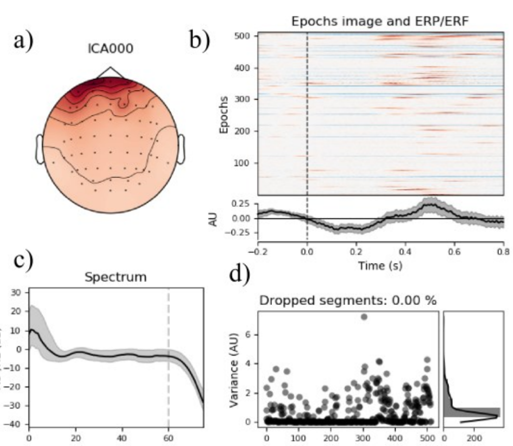

Figure 2. The removed ICA component properties. a) the topography of the removed ICA component; b) epochs image and ERP/ERF of the removed ICA component; c) power spectrum of the removed ICA component; d) epoch variance of the removed ICA component.

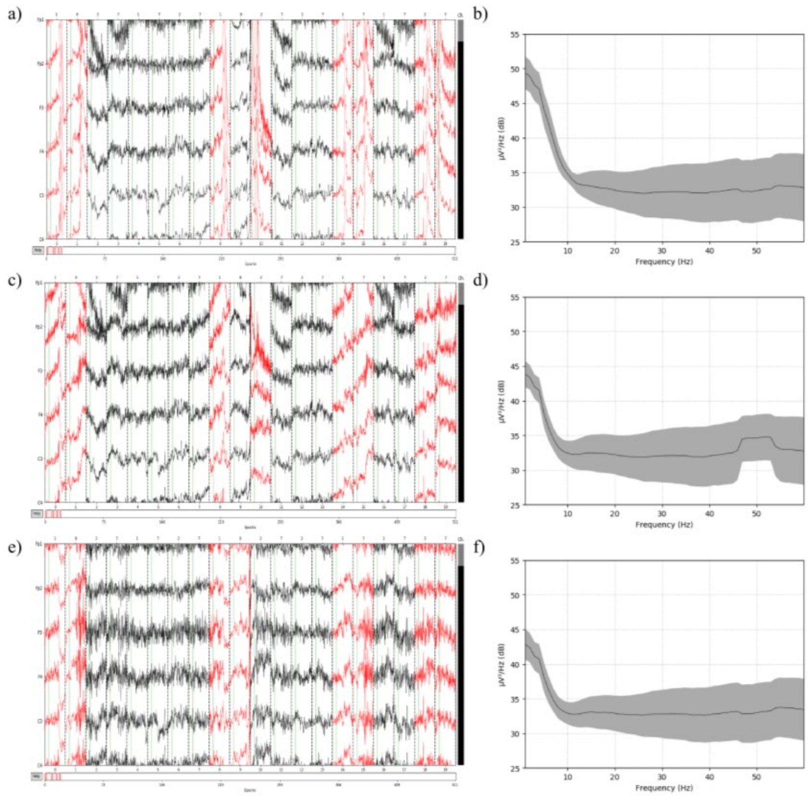

Figure 3. The comparison between the original EEG signals and the EEG signals after using the two removing EOG artifacts algorithms. a) and b): the time domain and power spectral density of original EEG signals; c) and d): the time domain and power spectral density of EEG signals after removing EOG artifacts by regression algorithm; e) and f): the time domain and power spectral density of EEG signals after removing EOG artifacts by fast ICA algorithm.

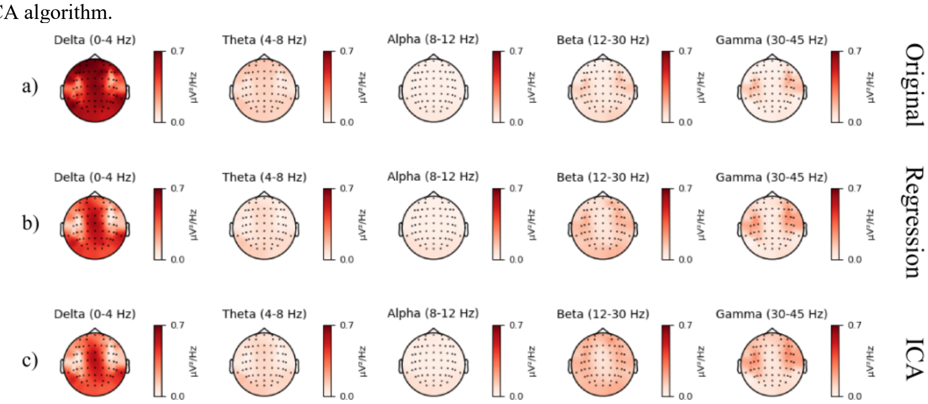

Figure 4. The comparison of the topographic maps of the power spectral density. a) the topographic map of the power spectral density of original EEG signals; b) the topographic map of the power spectral density of EEG signals after removing EOG artifacts by regression algorithm; c) the topographic map of the power spectral density of EEG signals after removing EOG artifacts by fast ICA algorithm.

both exceed the threshold and they are identified as EOG components, which are removed in the subsequent processing. This is consistent with the cognition that the EOG components are generally important principal components, mainly because the EEG signal itself is relatively weak, and the EOG components will have a great impact. The properties of one of the removed ICA components are illustrated in Fig.2. The properties include the topography, epochs image, ERP/ERF, power spectrum, and epoch variance.

Fig.3 shows the comparison between the original EEG signals and the EEG signals after using the two removing EOG artifacts algorithms. The left half shows the comparison in the time domain, and the right half shows the comparison of the power spectral density. Fig.3a shows the time-domain diagram of the EEG signals after other preprocessing steps except for the removal of EOG artifacts. The red parts show the obvious artifacts in the observed original EEG signals. Fig.3c and Fig.3e show the EEG signals after removing the EOG artifacts using the regression algorithm and the fast ICA algorithm respectively. The red parts correspond to the parts with obvious artifacts in Fig.3a.

From the left half of Fig.3, it is not difficult to find that the two algorithms for removing EOG artifacts have achieved good results, and the obvious artifacts have been removed. Besides, we can find that the ICA algorithm based on the EOG channels has a better effect in removing EOG artifacts, and the EEG signals processed by the ICA algorithm are smoother.

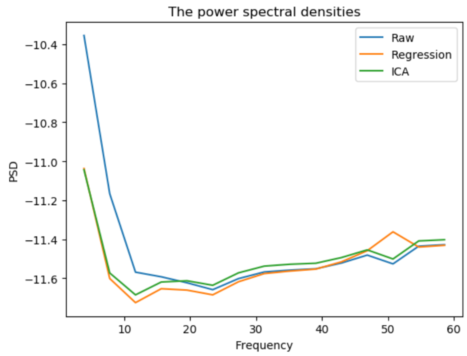

Figure 5. The comparison of the logarithmic mean value of the power spectral density

The right half of Fig.3 mainly shows the comparison of power spectral density. The shaded parts in each figure represent the power spectral density values of the EEG signals of different channels, forming a range, and the black solid lines part in the middle represent their average value. Regardless of the EEG signals processed by the regression algorithm or the EEG signals processed by the ICA algorithm, their power spectral density is significantly reduced in the low-frequency part, but the difference in the high-frequency part is not very significant. Whether it is the original signal or the EEG signal processed by the two algorithms, the power spectral density of their high-frequency part is lower than that of the low-frequency part. Comparing the two algorithms, compared with the regression algorithm, the changing trend of the power spectral density of the EEG signal processed by the ICA algorithm is more stable. Also, the power spectral density of the EEG signal processed by the regression algorithm fluctuates significantly around 50 Hz, which does not match the trend of the original data.

Fig.4 mainly shows the brain topographic maps of the normalization of the power spectral density of the five frequency bands: delta (0-4Hz), theta (4-8Hz), alpha (8-12Hz), beta (12-30Hz), and gamma (30-45Hz). It is not difficult to find from the figure that regardless of the frequency band, the distribution of the brain topographic map of the power spectrum density of EEG after artifacts removing is roughly the same as the distribution of the original EEG. The brain topographic map of the processed data is significantly weakened in the delta frequency band, but significantly enhanced in the beta and gamma frequency bands. Among them, the EEG signals after processing by the ICA algorithm have more significant changes in the beta band.

Although the right half of Fig.3 has compared the power spectral density of the original data and the data processed by the two algorithms, the comparison may not be obvious because they are displayed separately. The comparison of the logarithmic mean value of the power spectral density is demonstrated in Fig.5. The changing trend shown in Fig.5 is consistent with it shown in the right half of Fig.3.

IV. Discussion and Conclusion

Through the comparison of the time domain and power spectral density of the original EEG signal and the EEG signal after removing EOG artifacts, it can be found that the fast ICA method and the regression method both have removed the artifacts, and obtained higher quality EEG. Judging from the brain topographic maps of the power spectrum density, the EEG data processed by the fast ICA algorithm based on EOG channels showed significant enhancement in both the beta band and the gamma band. When the methamphetamine addicts are completing the task, they are visually stimulated and their attention is highly concentrated at this time, so the beta and gamma signals are in the main position at this time. In this regard, the effect of using the fast ICA algorithm to remove artifacts is better than that of the regression algorithm. At the same time, the power spectral density of the EEG data processed by the regression algorithm fluctuates significantly around 50 Hz. In terms of the degree of conformity with the original data, the effect of the ICA algorithm is even better.

From the effect of the time-domain diagram, EEG processed by the ICA algorithm based on EOG channels is smoother. Besides, the power spectral density of EEG processed by the fast ICA algorithm is obviously enhanced in the high-frequency band. From the two aspects, the ICA algorithm has the better effect. However, in terms of algorithm complexity and computing time, the regression algorithm is better. The difference in the effects of the two algorithms is not particularly large. When real-time tasks are required, it is better to choose the regression algorithm. These two algorithms realize automatic artifact removal without the manual screening of EOG artifacts, which are promising to reduce the workload and error rate in clinic. At the same time, although the two algorithms have achieved good results on this dataset, it does not mean that these two algorithms can be commonly used on other datasets. The versatility of these two algorithms needs further exploration.

References

[1] M. Teplan, "Fundamentals of EEG measurement," Measurement science review, vol. 2, no. 2, pp. 1-11, 2002.

[2] R. J. Croft, and R. J. Barry, "Removal of ocular artifact from the EEG: a review," Neurophysiologie Clinique/clinical Neurophysiology, vol. 30, no. 1, pp. 5-19, 2000.

[3] Robert, J., Barry, and, Adam, R., Clarke, and, Stuart, and J., "EEG differences between eyes-closed and eyes-open resting conditions," Clin. Neurophysiol., 2007.

[4] J. Urigüen, and B. Garcia-Zapirain, "EEG artifact removal—state-of-the-art and guidelines," Journal of Neural Engineering, vol. 12, no. 3, pp. 031001, 2015.

[5] A. C. Tang, B. Pearlmutter, M. Zibulevsky, and S. A. Carter, "Blind source separation of multichannel neuromagnetic responses," Neurocomputing, vol. 32-33, pp. 1115-1120, 2000.

[6] A. Subasi, and M. I. Gursoy, "EEG signal classification using PCA, ICA, LDA and support vector machines," Expert Systems with Applications, vol. 37, no. 12, pp. 8659-8666, 2010.

[7] S. N. Yu, and K. T. Chou, "Selection of significant independent components for ECG beat classification," Expert Systems with Applications, vol. 36, no. 2p1, pp. 2088-2096, 2009.

[8] A. Delorme, and S. Makeig, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis," J. Neurosci. Methods, vol. 134, no. 1, pp. 9-21, 2004.

[9] C. Bielza, and P. Larrañaga, "Independent Component Analysis (ICA)," Dictionary of Bioinformatics and Computational Biology, 2004.

[10] R. Verleger, T. Gasser, and J. Mcks, "Correction of EOG artifacts in event-related potentials of the EEG: aspects of reliability and validity," Psychophysiology, vol. 19, no. 4, pp. 472-480, 2010.

[11] J. C. Woestenburg, M. N. Verbaten, and J. L. Slangen, "The removal of the eye-movement artifact from the EEG by regression analysis in the frequency domain," Biol. Psychol., vol. 16, no. 1-2, pp. 127-147, 1983.