Removal of eye-blinking artifacts by ICA in cross-modal long-term EEG recording

Gan Huang, *Member, IEEE,* Zhenxing Hu, Li Zhang, Linling Li, Zhen Liang, Zhiguo Zhang

***Abstract*— Independent Component Analysis (ICA) has became the most popular method to remove eye-blinking artifacts from electroencephalogram (EEG) recording. For long term EEG recording, ICA was commonly considered to costing a lot of computation time. Furthermore, with no ground truth, the discussion about the quality of ICA decomposition in a nonstationary environment was specious. In this study, we investigated the "signal" (P300 waveform) and the "noise" (averaged eye-blinking artifacts) on a cross-modal long-term EEG recording to evaluate the efficiency and effectiveness of different methods on ICA eye-blinking artifacts removal. As a result, it was found that, firstly, down sampling is an effective way to reduce the computation time in ICA. Appropriate down sampling ratio could speed up ICA computation 200 times and keep the decomposition performance stable, in which the computation time of ICA decomposition on a 2800 s EEG recording was less than 5 s. Secondly, dimension reduction by PCA was also a way to improve the efficiency and effectiveness of ICA. Finally, the comparison by cropping the dataset indicated that performing ICA on each run of the experiment separately would achieve a better result for eye-blinking artifacts removal than using all the EEG data input for ICA.**

I. Introduction

Eye-movement related artifacts are undesired signals that may introduce changes in the measurements and affect the signal of interest in recordings of EEG. Among them, Eye-blink caused the largest distortions, mainly because of the movement of the eyelids across the surface of the eyes [1]. In recent decades, ICA has replaced other methods as the most popular method for eye-blinking artifacts removal [2]. Furthermore, the ICA based automatic artifact removal methods and standardized preprocessing toolbox [3, 4]. Onton *et al*. [5] applied ICA for brain source separated. However, because there is no ground truth about the "noise" and "signal" in EEG recording [6], the discussion about the effect of ICA artifact removal was specious. Whether a more conservative or aggressive strategy should be adopted for ICA artifact removal is still under debate among different research groups. In addition, eye-blinking artifacts are probably the easiest artifacts to identify, because of its large amplitude and belonging to spatially stereotyped artifact with the fixed topographic pattern [7]. While, non-stereotyped artifact would probably largely increase the number of "temporally independent" source in ICA, which leads separating into a finite number of component activities in an uncontrollable way [7].

Considering that the same brain neural mechanism will behave similarly in different EEG experiments, cross-modal experiments design can lead to more essential explorations of the brain neural mechanism [8-10]. While, ICA was usually applied for artifact removal in some relatively simple experiment design. The performance of ICA in a cross-modal long-term EEG recording has not been well studied. Firstly, the cross-modal experiment normally will lead to a long-term EEG recording. ICA is considered to costing a lot of computation time. This problem would be more prominent with the increasing time points. The methods of speeding up ICA computation is desired. Secondly and more importantly, the cross-modal long-term EEG recording leads the ICA decomposition into a nonstationary situation [11, 12]. The stationary assumption of the brain state, which would be kept in a relatively simple short-term experimental design, would be violated in cross-modal long-term EEG recording. On the one side, whether the eye-blinking "noise" kept in the same pattern is still unknown. On the other side, the different modal in experiment design will definitely lead to the change of "signal" in EEG recording. Furthermore, fatigue and the change of attention can cause the non-stationarity of the brain state.

In this study, the EEG data was recorded from 23 subjects with rich types of experimental paradigms, including resting state with eye open and closed, transition and steady state visual, auditory and vibrotactile stimulation, and Brain Computer Interface (BCI) related P300, Steady State Visual Evoked Potential (SSVEP) and Sensory Motor Rhythm (SMR) experiment. Several methods were proposed for speeding up ICA computation. 1) Down sampling is the simplest way to reduce the time point of the data input for ICA acceleration. Empirically, it is recommended to have at least $25 \times (\text{number of channel})^2$ time points for a reliable ICA decomposition [13], which obviously would be not hold since the sampling rate is not considered. Therefore, how much down sampling ratio can speed up ICA and keep the performance not degraded needs to be investigated. 2) Dimension reduction with PCA is another method for ICA acceleration. Artoni *et al.* [14] claimed that applying PCA prior to ICA can adversely affect both the dipolarity and stability of independent component extracted from high-

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Gan Huang, Zhenxing Hu, Li Zhang, Linling Li, Zhen Liang, and Zhiguo Zhang are with the at the School of Biomedical Engineering, Health Science Center, Shenzhen University, Shenzhen, 518060, China (email to huanggan1982@gmail.com; zgzhang@szu.edu.cn)

density EEG data, but there are no direct evidence shew influence of dimension reduction by PCA before ICA to the eye-blinking noise removal and EEG signal preservation. 3) Cropping the dataset is another method to reduce the time points input for ICA acceleration [15] In the nonstationary environment with cross-modal long-term EEG recording, it is still unknown the performance of ICA with all cross-modal EEG data input is better, or the result from single run of experiment is better. In the following the proposed three methods (down sampling, PCA and cropping) were investigated for ICA eye-blinking artifacts removal. The efficiency of these methods for ICA acceleration was evaluated by comparing the computation time for ICA decomposition with different parameters. And the effectiveness of these methods in the nonstationary environment is evaluated with investigation of the "signal" (P300 waveform) and the "noise" (averaged eye-blinking artifacts) [16].

II. METHODS

A. Experiment design

In this study, a cross-modal long-term EEG recording dataset with 23 healthy participants were analyzed. EEG signal were collected via 64 electrodes based on international 10-20 system and the EEG amplifier (BrainAmp, Brain Products GmbH, Germany) with the sampling rate of 1000 Hz. Channel FCz was set to be reference. The experiment includes several types of EEG paradigm arranged in 15 runs, which includes 1) resting state with eyes closed in run01 and run14, eyes open in run02 and run 15; 2) visual, auditory and somatosensory evoked potential with transient state in run04 and run11, and steady state in run05, run 09 and run12; 3) Brain Computer Interface related paradigm P300 in run07, SSVEP in run08, and SMR in run03, run 06, run 10 and run13. The whole experiment would take around 2 hours with almost 50 minutes of EEG recording.

For simplicity, ICA was applied on all runs, but the results were compared on run02, run07, run15. For resting state with eye open in run02 and run15, the participant was asked to open their eyes for 1 minute and keep their eyes gazing at the front and try to blink as less as they can. For P300 paradigm in run07, visual oddball experiment with the red square as the target stimuli and white square as the nontarget stimuli was displayed on the screen. Each square lasts 80ms with the ISI 200ms. 600 trials of the stimuli in all was arranged in a 2 minutes EEG recording. Target stimuli came with the possibility of 5%. The participant was asked to count the number of red square and report in the end of the run to make he/her keep attention on the screen. For data preprocessing of the P300 Signal, the EEG signal was firstly re-referenced to TP9 and TP10, and then band-pass filtered with 0.1-30Hz, finally segmented from -500ms to 1000ms with the target stimulus.

B. Procedures for eye-blinking artifacts removal

An overview of the ICA procedures for eye-blinking artifacts removal used in the current study is shown in Fig. 1. For each subject, the ICA procedure was performed in the following steps. Firstly, the raw EEG signal were filtered with 0.01-200 Hz band-pass filter. And then, the proposed down sampling, PCA and cropping methods were applied before the computing the ICA weights and sphere matrix. After the ICA

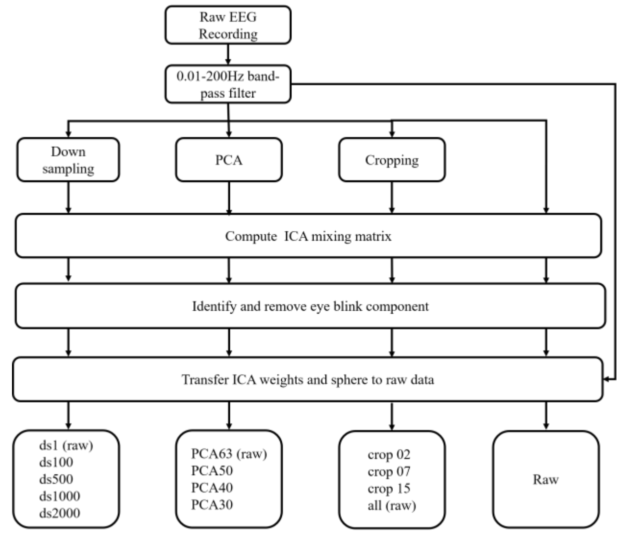

Fig.1 Diagram of the procedures applied for eye-blinking artifacts removal in this study.

matrix were calculated with the logistic infomax ICA algorithm [17]. The eye-blinking components were identified manually with a conservative strategy, in which the components would be removed with clear artifact and no or very little signal. Then the ICA weights and sphere matrix were transferred to the raw EEG signal and the identified components were removed by subtracting the projection of the artifactual components from the original data of the subject. Here, the following three methods for ICA acceleration were applied before the computation of ICA, which are down sampling, PCA and cropping.

- *Down sampling* the dataset to accelerate the ICA matrix calculation, in which we applied the different ratio of down sampling with 100, 500, 1000 and 2000 as compared with the result of no down sampling.
- *PCA* to reduce the dimension of the ICA input to decrease the computation load, in which we applied the different dimension for PCA with 50, 40 and 30 as compared with the result of no dimension reduction.
- *Cropping* the dataset to one run to the ICA matrix calculation. In this study, run02, run07 and run15 were used separately to calculate the ICA matrix, as compared with the ICA result from the whole dataset (marked as "all").

C. Evaluation procedures

To compared the efficiency and effectiveness of the three different methods in ICA-based eye-blinking artifacts removal, we mainly investigated the computation time of ICA and the change of "noise" and "signal" after ICA artifact removal.

Firstly, the computation time of calculating ICA weights and sphere matrix was compared with different parameters setting in the three proposed methods. All the results were obtained in the environment of Matlab 2018b, Windows 10 with an 8-core 3.60Hz Intel Core i9-9900KF CPU and 64 GB RAM. Secondly, averaged waveform of the time-locked blink activities were treated as the "noise" to evaluate the effect of eye-blinking artifacts removal, in which the peak of eye-blinking signal were marked as the zeros point, with the preprocessing of 0.1 - 10Hz bandpass filter, and segmentation from -1 s to 1 s and averaging. Thirdly, P300 results from the main channel Pz and the frontal channel Fp1 were used for observing the "signal" distortion in the three proposed methods with different parameters.

III. RESULTS

A. Computation time for ICA calculation

Table 1. The computation time of calculating the ICA weights and sphere matrix with different parameters in the three methods.

down sampling					
ds ratio	1	100	500	1000	2000
Time (s)	802.4 ± 76.0	40.4±14.3	10.0±1.8	4.3±1.4	3.9±0.9

PCA				
dim	63	50	40	30
Time (s)	802.4 ± 76.0	710.1±84.1	635.4±84.1	585.3±84.1

Cropping				
run	all	02	07	15
Time (s)	802.4 ± 76.0	77.8±12.4	146.4±33.3	82.3±10.3

Table I illustrated the computation time in the calculation of ICA weights and sphere matrix with different parameters in the three proposed methods.

For down sampling, with no down sampling (marked as "ds1"), segmentation in preprocessing would reduce the dataset with $2.82 \pm 0.12 \times 10^6$ points (equal to 47 ± 2 minutes) for the raw EEG recording into $9.38 \pm 0.12 \times 10^5$ points. It took more than 800 seconds to obtain the ICA matrix for the raw data. Down sampling could greatly reduce the time for the ICA matrix computation, but the computation time does not proportional with the down sampling ratio. With down sampling ratio 1000, it took 4.3 ± 1.4 seconds in average to finish the ICA computation, which is almost 200 times faster than the computation time in the case of no down sampling. But further acceleration effect was limited with down sampling ratio 2000.

For PCA dimension reduction, the size of entries was $63 \times 63 = 3936$ for each time point with 63 components, which would be decreased with the number of components in PCA at the rate of square. But the computation time did not decrease proportional with the number of entries. It even decreased slower than the decreasing of components in PCA.

For cropping, the time points of the dataset were fixed, which were 60000 in run02 and run15, and 120000 in run07 for all subjects. In results, the computation time is 77.8 ± 12.4 seconds for run02, 82.32 ± 10.25 seconds for run15, and 146.4 ± 33.4 seconds for run07.

B. Waveforms of eye blinking artifacts

The waveforms of eye-blinking artifacts after ICA with different parameters in the proposed methods was shown in Fig. 2. It was shown that, no method could remove the eye-blinking artifacts completely. For the grand averaged eye-blinking signal, the residual peak still could be observed from Fig. 2(a) to Fig. 2(i).

For down sampling, the result in Fig. 2(a-c) showed that ICA worked well even in the quite some aggressive down sampling ratio, like 1000, in which the number of data time points is even much less than the number of elements in weight

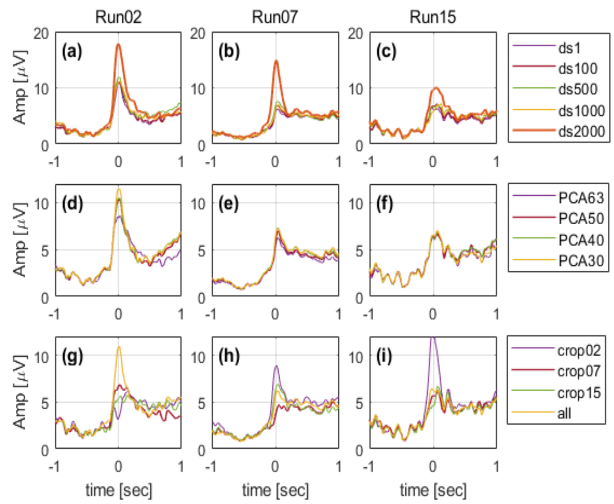

Fig. 2 Grand-average waveform of the time-locked averaged eye blink artifacts at electrode Fp1 after artifact removal of ICA with down sampling (a-c), PCA (d-f) and cropping (g-h) in run02 (resting state with eye open), run07 (P300) and run15 (resting state with eye open).

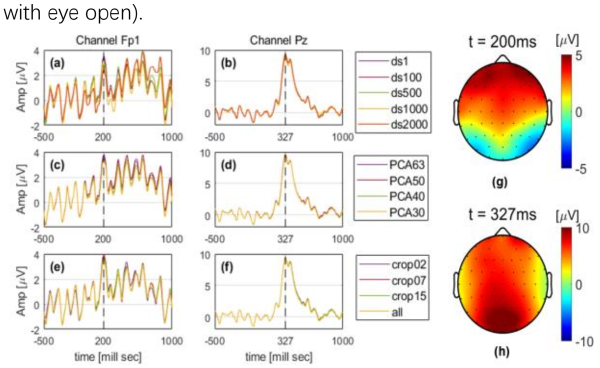

Fig.3 Grand-average ERP waveform at electrode Fp1 (a, c and e) and Pz (b, d and f) in run07 (P300) with the corresponding topographies at 200 ms (g) and 327 ms (h).

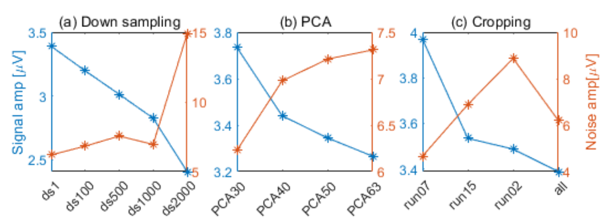

Fig.4 Peak amplitude of grand-average eye-blinking artifacts (orange line) at electrode Fp1 during the interval of -50ms to 50ms and grand-average ERP waveform (blue line) at electrode Fp1 during the interval of 180ms to 220ms for (a) down sampling, (b) PCA and (c) cropping.

matrix. The performance of ICA began to degrade with the extreme down sampling ratio 2000.

For PCA dimension reduction in Fig. 2(d-f), lower dimension components in PCA led to a better artifacts control for the eye blinking artifacts, which could be observed clearly in run02 (Fig. 2(d)).

For cropping, the results in Fig. 2(g-i) showed the performance of ICA on run02, run 07 and run 15 with different input data for ICA decomposition. The best results on each run were always achieved with the input of themselves. It is out of our expectation that no cropping method did not necessarily lead to the best results. Quite the opposite, its results would be the worst in some case, as is shown in Fig. 2(g) on run02. Waveforms of P300.

C. Waveform of P300

The grand-average waveforms of P300 (run07) were illustrated in Fig. 3(a, c and e) for channel Fp1 and Fig. 3(b, d and f) for channel Pz, with the corresponding topographies at 200ms and 375ms were shown in Fig. 3(g-h). The typical P300 waveform could be observed at channel Pz, which was less sensitive to the eye-blinking artifacts. Hence all methods with different parameters produced similar results on channel Pz. The frontal channels Fp1 was influenced by ICA greatly. The signal distortion could be observed around 600-800ms, since the subjects would habitually blink in this time interval after the target stimuli. In addition to this, a strong rhythm activity with 5Hz and its harmonic frequencies could be observed in FP1, which is caused by the fixed stimuli with 200ms ISI. The peak appears at around 200ms with its topography in Fig.3(g).

For further comparison, the peak amplitude of the “signal” (the peak amplitude in Fig. 2(b) from -50 ms to 50 ms) and “noise” (Fig. 3 (a) from 180 ms to 200 ms) on channel Fp1 were shown in Fig. 4. All the results indicated that the better methods for eye blinking “noise” removal would also preserve the EEG “signal” to a greater degree.

IV. CONCLUSION

In this study, we evaluated the efficiency and effectiveness of three methods in ICA with cross-model long-term EEG recording. Because of no ground truth for the “signal” and “noise” in EEG signal, the discussion about the quality of ICA decomposition for eye-blinking artifacts removal in a nonstationary environment becomes specious. In this work, the P300 signal and the averaged eye-blinking signal were treated as “signal” and “noise” correspondingly for the investigation. The main focus was on the ICA acceleration and the performance in the non-stationary environment. In result, all the proposed three methods could speed up the computation of ICA.

For down sampling, a close to 200 times speed up was achieved with the down sampling ratio 1000, in which the time for ICA decomposition on a 2800 s EEG recording was less than 5 s with the performance not degraded. With the down sampling ratio 1000, the sampling rate is reduced to 1 Hz, which is lower than the typical frequency range of eye-blinking artifacts (1 - 4Hz). The number of time points is much lower than the lower limit given by the empirical formula (at least $25 \times (\text{number of channel})^2$ time points in Ref. [13]). It should be noted that here the performance of ICA was evaluated on eye-blinking artifacts removal.

For PCA, the acceleration effect is not as significant as down sampling. But out of our expectation, the performance of ICA decomposition would be better with less principle components for ICA input. With the same length of time points, lower number of principle components may give a better decomposition for less parameter estimation. It should be noted that with the same ICA weight matrix the results were inconsistent across different experiment runs (Fig. 2(d-f)), which indicates the non-stationarity of the eye-blinking artifact.

Cropping is another efficient way for ICA acceleration. The computation time of ICA with 1 minute’s data input would achieve 10 times speed up of ICA decomposition. No cropping with the whole dataset as the ICA input may not achieve a better performance for eye-blinking artifacts removal. The run-specific ICA is recommended for only one experiment paradigm is investigated but need to be further validated. For cross-modal study, no cropping is still suggested for a unified signal preprocessing.

REFERENCES

[1] M. Iwasaki *et al.*, "Effects of eyelid closure, blinks, and eye movements on the electroencephalogram," *Clinical Neurophysiology,* vol. 116, no. 4, pp. 878-885, 2005.

[2] J. A. Urigüen and B. Garcia-Zapirain, "EEG artifact removal—state-of-the-art and guidelines," *Journal of neural engineering,* vol. 12, no. 3, p. 031001, 2015.

[3] A. Pedroni, A. Bahreini, and N. Langer, "Automagic: Standardized preprocessing of big EEG data," *NeuroImage,* 2019.

[4] M. T. Akhtar, W. Mitsuhashi, and C. J. James, "Employing spatially constrained ICA and wavelet denoising, for automatic removal of artifacts from multichannel EEG data," *Signal processing,* vol. 92, no. 2, pp. 401-416, 2012.

[5] J. Onton and S. Makeig, "Independent component analysis (ICA) source locations vary according to task demands," *Organization for Human Brain Mapping Abstracts,* 2005.

[6] L. Frølich and I. Dowding, "Removal of muscular artifacts in EEG signals: a comparison of linear decomposition methods," *Brain informatics,* vol. 5, no. 1, pp. 13-22, 2018.

[7] S. Makeig and J. Onton, "ERP features and EEG dynamics: an ICA perspective," *Oxford handbook of event-related potential components,* pp. 51-87, 2011.

[8] E. C. Hames *et al.*, "Visual, auditory, and cross modal sensory processing in adults with autism: An EEG power and BOLD fMRI investigation," *Frontiers in human neuroscience,* vol. 10, p. 167, 2016.

[9] G. Sanchez, J. N. Frey, M. Fuscà, and N. Weisz, "Decoding across sensory modalities reveals common supramodal signatures of conscious perception," *bioRxiv,* p. 115535, 2017.

[10] J. R. Wessel and D. E. Huber, "Frontal cortex tracks surprise separately for different sensory modalities but engages a common inhibitory control mechanism," *BioRxiv,* p. 572081, 2019.

[11] F. Artoni, D. Menicucci, A. Delorme, S. Makeig, and S. Micera, "RELICA: a method for estimating the reliability of independent components," *NeuroImage,* vol. 103, pp. 391-400, 2014.

[12] R. Grandchamp, C. Braboszcz, S. Makeig, and A. Delorme, "Stability of ICA decomposition across within-subject EEG datasets," in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2012: IEEE, pp. 6735-6739.

[13] J. Onton and S. Makeig, "Information-based modeling of event-related brain dynamics," *Progress in brain research,* vol. 159, pp. 99-120, 2006.

[14] F. Artoni, A. Delorme, and S. Makeig, "Applying dimension reduction to EEG data by Principal Component Analysis reduces the quality of its subsequent Independent Component decomposition," *NeuroImage,* vol. 175, pp. 176-187, 2018.

[15] M. Mennes, H. Wouters, B. Vanrumste, L. Lagae, and P. Stiers, "Validation of ICA as a tool to remove eye movement artifacts from EEG/ERP," *Psychophysiology,* vol. 47, no. 6, pp. 1142-1150, 2010.

[16] P. Berg and M. B. Davies, "Eyeblink-related potentials," *Electroencephalography and clinical neurophysiology,* vol. 69, no. 1, pp. 1-5, 1988.

[17] A. J. Bell and T. J. Sejnowski, "An information-maximization approach to blind separation and blind deconvolution," *Neural computation,* vol. 7, no. 6, pp. 1129-1159, 1995.