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A New Perspective of Noise Removal from EEG

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***Abstract*— Denoising, noise or interferences are removed from recorded signal to enhance the signal-to-noise ratio (SNR), is a crucial and ubiquitous step in the procedure of signal processing, especially for neurophysiological signal. This step facilitates following processing, such as feature extraction, classification, and data analyses. Conventional methods are based on the principle of separating noise components from the recorded signal and removing them, but these methods do not remove noise completely. In particular, conventional methods seems powerless to eliminate irregular and occasional noise bursts, which are caused by transient electrode contacting problem, head movements, or unpredictable factors. In this paper, we tackled the problem of noise removal from a new perspective, which is opposite to the conventional methods. Data portions that are contaminated by noise are entirely removed and then restored according to their relationships with the remaining signal. The rationale of this procedure is to purify the signal through addition rather than deduction that is normally executed in conventional methods. The results of both synthetic data and real EEG demonstrated that our idea is feasible and provides a new promising manner for noise removal.**

I. INTRODUCTION

Electroencephalographic (EEG) measure is widely utilized in clinical monitoring, healthcare application, and laboratory researches such as cognitive investigation and brain computer interface. It has advantages of high temporal resolution and low cost compared to magnetic field based measures (e.g., fMRI) [1]. However, diverse noise or artifacts contaminate the signal obtained from the scalp during EEG recording. In general, the main kinds of artifacts are eletrooculogram (EOG), electromyogram (EMG), electrocardiogram (ECG), and power line noise. Relatively, power line noise can be easily eliminated by a notch filter [2]. ECG and EOG can be mitigated through regression methods [3]. EMG artifact removal is more difficult because it is caused by different muscles and a variety of combinations of muscular contractions. In this case, regression and filtering methods usually do not work because a location of reference channel for EMG measurements cannot be determined and the EMG spectrum usually overlaps with the EEG spectrum.

Blind source separation (BSS) offers a promising solution to the above problem. For instance, principal component analysis (PCA) is one of BSS methods, which has been used for artifact removal [4]. Raw recorded signal is decomposed into orthogonal components, and then these components are identified to be two groups: one is relevant to neural activity and the other one is associated with artifacts. Subsequently, clean EEG is reconstructed through the back-projection of the neural activity related components. However, the assumption of orthogonality in PCA is not always met in real recorded signal. Therefore, performance is dramatically reduced when this assumption is violated. Another BBS method, namely independent component analysis (ICA), is proposed to remove artifacts, which is based on the assumption of statistical independence between components [5], [6]. This assumption seems more reasonable due to the independence nature between neural signal and artifacts.

It seems that the current artifact removal technique is matured according to the aforementioned brief review. Nonetheless, a few problems still exist which hamper subsequent data analysis due to the drawbacks of artifact removal technique. For example, trial rejection is usually performed before implementing ICA. This process removes extremely artifact-contaminated data portions and facilitates the ICA decomposition that follows. Yet, data removal could be severe disaster in the case of small-size samples. This can also hinder a continuous analysis, in which data loss is unacceptable. Moreover, random noise at individual time point is unpredictable and cannot be well eliminated by the existing methods. In order to deal with these problems, we proposed a new idea that data portions with artifacts are first deleted and then completed based on relationship information of remaining data. Our method can be seen as 'addition', which is opposite to the existing methods as 'subtraction' (see a recent review [7]).

II. MATERIALS AND METHODS

A. Materials

Both synthetic data and real EEG data were used to evaluate feasibility of the proposed idea. Synthetic data consist of 14 channels, each of which was generated by mixing a main 16 Hz sinusoidal signal with peak amplitude of 100 and zero initial phase and five subordinate sinusoidal signals. Their frequencies were randomly obtained according to a uniform distribution on the interval $[1\ 120]$ and their peak amplitudes were randomly determined using integers within the range

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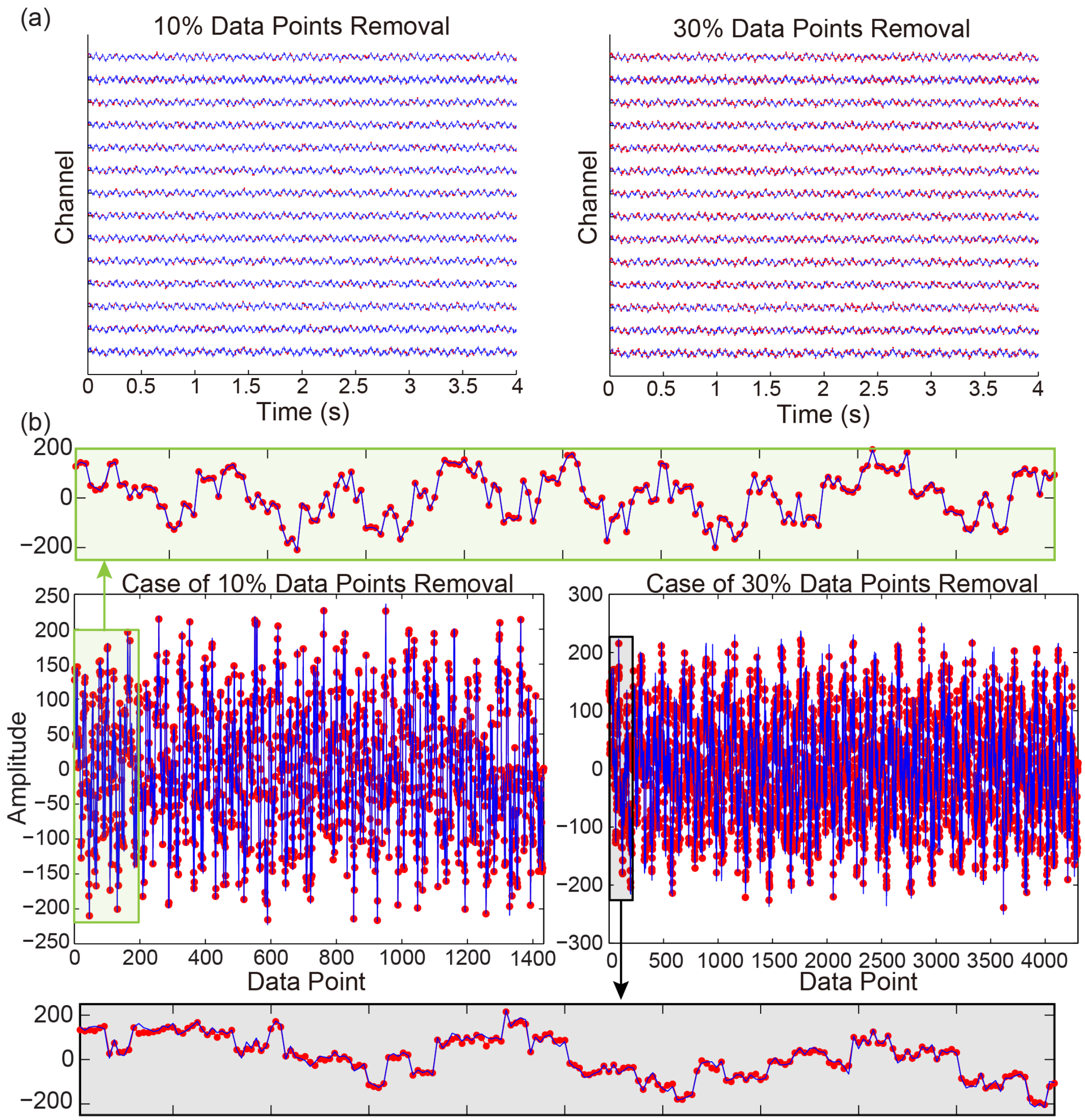

Fig. 1. Examples of data removal and data recovery in the case of data point removal for the synthetic data

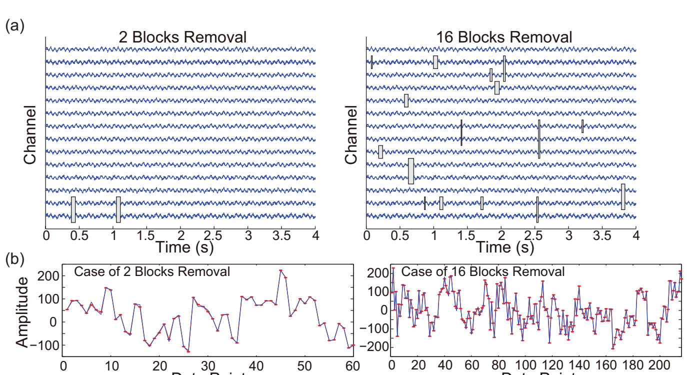

Fig. 2. Synthetic data removal and data recovery for the case of block removal

of [1 80]. All initial phases were set as zeros. Real EEG data were obtained from our previous experiment [8]. A total of 14 channels over sensorimotor area were used to record EEG at a sampling rate of 256 Hz and all channels were grounded at the anterior frontal midline and referenced at the linked earlobes. A four-second EEG segment (considered as artifact-free data) was selected from a male participant while he was motionlessly sitting in a wheelchair before starting the task. We simulated two situations (data point removal and block removal) with different percentages of removed data points (from 10% to 50% with incremental step of 10%) or different numbers of removed blocks (from 2^1 to 2^4 with exponentially incremental step of 1). Locations of removed data and the size of blocks were randomized.

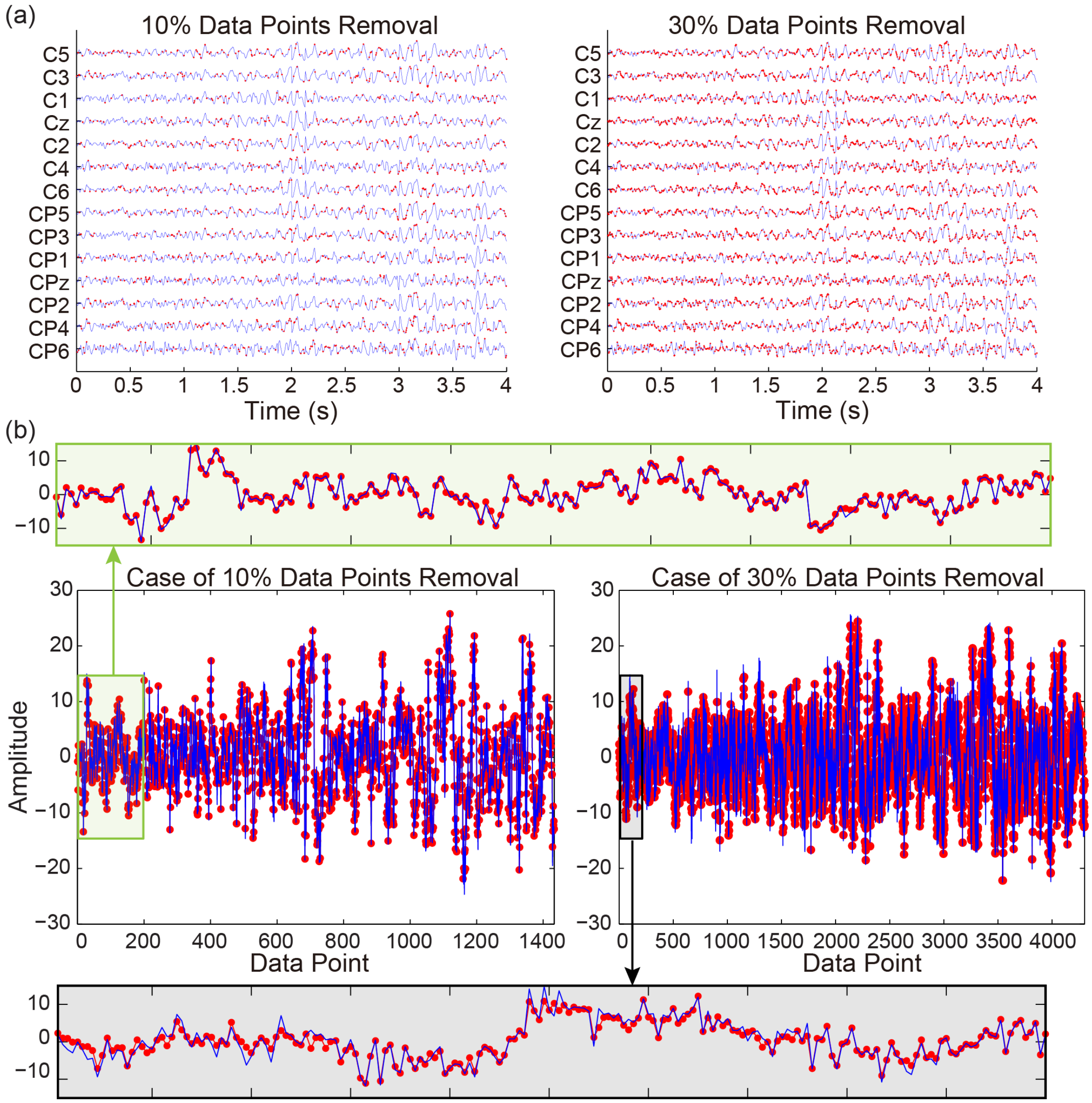

Fig. 3. Real EEG data removal and data recovery for the case of data point removal

B. Methods

After removing artifact portions, we folded two-dimensional EEG data into a third-order tensor, denoting by $\underline{\mathbf{X}} \in \mathbb{R}^{14\times 64\times 16}$. The removed data points were marked in an index tensor $\underline{\mathbf{W}} \in \mathbb{R}^{14\times 64\times 16}$, in which entries with 0 indicate positions of removed data. A convex tensor decomposition was utilized to restore the removed data according to their relationship with the remaining data. The removed data points can be reconstructed by solving the following optimization problem

$$\begin{aligned} &\min f(\underline{\mathbf{Y}}, \mathbf{Z}_1, \mathbf{Z}_2, \mathbf{Z}_3) \\ &= \sum_{i=1}^{3} \|\mathbf{Y}_{(i)} - \mathbf{Z}_i\|_{\mathcal{F}}^2 + \lambda \sum_{i=1}^{3} \|\mathbf{Z}_i\|_* \\ &s.t. \quad P_{\underline{\mathbf{W}}}(\underline{\mathbf{Y}}) = P_{\underline{\mathbf{W}}}(\underline{\mathbf{X}}) \end{aligned} \tag{1}$$

where $\underline{\mathbf{Y}}$ denotes the reconstruction of $\underline{\mathbf{X}}$, and $\mathbf{Y}_{(i)}, i \in \{1, 2, 3\}$, represents its unfolding matrix along the ith mode. $\mathbf{Z}_i, i \in \{1, 2, 3\}$, is an auxiliary matrix, which is used to simplify the iteration algorithm. The operator $P_{\underline{\mathbf{W}}}(\underline{\mathbf{X}})$ is to take entries of the tensor $\underline{\mathbf{X}}$ according to index tensor $\underline{\mathbf{W}}$. λ is a tuning parameter, and $\|\mathbf{Z}_i\|_*$ denotes the nuclear norm of $\mathbf{Z}_i$, which is defined as a sum of singular values of $\mathbf{Z}_i$. In order to efficiently solve the optimization problem (1), we implemented the algorithm shown in **Algorithm 1**, where the tuning parameter was set as $\lambda = 0.01$ and the stopping criterion is that the normalized error change between two successive iterations is less than 10^{-5} or the number of iterations reaches to the maximum of 50000.

In **Algorithm 1**, the operator $ten(\cdot)$ reshapes a matrix into a tensor, which is opposite to the unfolding operation. The operator $D(\cdot|\cdot)_+$ denotes soft-thresholding of singular values of a matrix using a certain scalar (i.e., λ) to obtain a low rank

Algorithm 1 Convex Tensor Decomposition

Input: The incomplete EEG $\underline{\mathbf{X}}$, the index tensor $\underline{\mathbf{W}}$, and the tuning parameter λ

Output: the reconstructed tensor $\underline{\mathbf{Y}}$

Initialize $\underline{\mathbf{Y}}^0$ = using $\underline{\mathbf{X}}$, filling removed entries by zeros. $k = 0$

repeat

$k = k + 1$

for $i = 1, 2, 3$ *% Update Z*

$\mathbf{Z}_i^k = \mathbf{Y}_{(i)}^{k-1}$

$\mathbf{Z}_i^k = D\left(\mathbf{Z}_i^k | \lambda\right)_+$

end for

% Update $\underline{Y}$

$\underline{\mathbf{Y}}^k = \sum_{i=1}^{3} ten(\mathbf{Z}_i^k)/3$

$P_{\underline{\mathbf{W}}}(\underline{\mathbf{Y}}^k) = P_{\underline{\mathbf{W}}}(\underline{\mathbf{X}})$

until the stopping criterion is met

approximation. That is, let $\mathbf{E} = \mathbf{U\Sigma V}^{\mathrm{T}}$ is the Singular Value Decomposition (SVD) of $\mathbf{E}$, then $D(\mathbf{E}|\lambda)_+ = \mathbf{U}\bar{\mathbf{\Sigma}}\mathbf{V}^{\mathrm{T}}$, where any entry $\bar{\mathbf{\Sigma}}_{ij}$ satisfies

$$\bar{\mathbf{\Sigma}}_{ij} = \begin{cases} \mathbf{\Sigma}_{ij} - \lambda, & \mathbf{\Sigma}_{ij} > \lambda \\ 0, & otherwise \end{cases}. \tag{2}$$

We used three quantitative measures to evaluate the performance of data recovery. Root square error on removed data points (RSEr) is defined as the normalized Frobenius norm of the difference between recovered data and ground truth data relevant to the Frobenius norm of the ground truth data. Moreover, root square error was also evaluated on the entire data (RSEa). The third measure is the correlation (Corr) between recovered data and the ground truth data.

III. Results

Fig. 1 illustrates examples of data removal and data recovery in the case of data point removal for the synthetic data. Red dots in Fig. 1(a) highlight the removed data points. The middle row of Fig. 1(b) shows recovered data (in red) and ground truth data (in blue) together. Note that the horizontal axis only represents number count and does not mean continuity of these data points. The upper and bottom panels in Fig. 1(b) show the enlargements of the regions enclosed by rectangles for the clarity purpose. The deleted data points can be precisely recovered for the case of 10% of data points removal, and can be well recovered for the case of 30%. Similar results were also observed in the case of block removal (see Fig. 2). Rectangles filled with gray color in Fig. 2 mark the deleted data. Fig. 2(b) shows recovered data and ground truth data together. Good recovery performance was replicated for real EEG data (see Fig. 3 and Fig. 4). The performance was relatively worse for the case of block removal. All results of quantitative evaluations were listed in Table I.

IV. Conclusion

We proposed a new idea for artifact removal, whose principle is opposite to that taken by existing methods. Artifact-contaminated data were completely deleted and then recovered based on the relationship of remaining data. This very preliminary work paves a new way for the research of artifact removal towards a new direction.

TABLE I
QUANTITATIVE EVALUATIONS

	Synthetic Data			Real EEG		
			Data Point Removal			
Percentage	RSEr	RSEa	Corr	RSEr	RSEa	Corr
10	0.0454	0.0142	0.9991	0.0907	0.0295	0.9965
20	0.0989	0.0437	0.9956	0.1598	0.0720	0.9888
30	0.1362	0.0747	0.9917	0.2008	0.1096	0.9822
40	0.1717	0.1080	0.9866	0.2800	0.1767	0.9648
50	0.2011	0.1436	0.9820	0.3663	0.2592	0.9381
			Block Removal			
Block No.	RSEr	RSEa	Corr	RSEr	RSEa	Corr
2	0.0424	0.0025	0.9990	0.4799	0.0255	0.9406
4	0.0277	0.0026	0.9996	0.6017	0.0458	0.8322
8	0.0332	0.0041	0.9994	0.4763	0.0723	0.8912
16	0.0464	0.0055	0.9989	0.4926	0.0820	0.8897

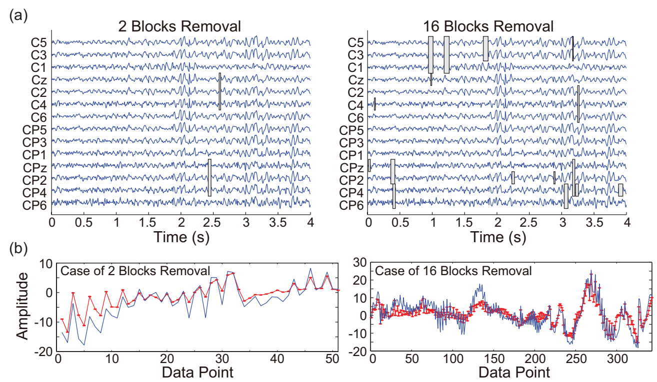

Fig. 4. Real EEG data removal and data recovery for the case of block removal

References

[1] R. Cooper, J. W. Osselton, and J. C. Shaw. EEG technology, Butterworth-Heinemann, 2014 Jun 28.

[2] K. T. Sweeney, T. E. Ward, and S. F. McLoone, Artifact removal in physiological signals-practices and possibilities, IEEE Trans. Inf. Technol. Biomed., vol. 16, no. 3, pp. 488-500, 2012.

[3] T. T. Pham, R. J. Croft, P. J. Cadusch, and R. J. Barry, A test of four EOG correction methods using an improved validation technique, Int. J. Psychophysiol., vol. 79, no. 2, pp.203-210, 2011.

[4] N. Ille, P. Berg, and M. Scherg, Artifact correction of the ongoing EEG using spatial filters based on artifact and brain signal topographies, J. Clin. Neurophysiol., vol. 19, no. 2, pp. 113-124, 2002.

[5] T. P. Jung, S. Makeig, C. Humphries, T. W. Lee, M. J. Mckeown, V. Iragui, and T. J. Sejnowski, Removing electroencephalographic artifacts by blind source separation, Psychophysiology, vol. 37, no. 2, pp. 163-178, 2000.

[6] A. Delorme, T. Sejnowski, and S. Makeig, Enhanced detection of artifacts in EEG data using higher-order statistics and independent component analysis, Neuroimage, vol. 34, no. 4, pp.1443-1449, 2007.

[7] J. A. Urigen, and B. Garcia-Zapirain, EEG artifact removal: State-of-the-art and guidelines, J. Neural Eng., vol. 12, no. 3, pp. 031001, 2015.

[8] J. Li, J. Liang, Q. Zhao, J. Li, K. Hong, and L. Zhang, Design of assistive wheelchair system directly steered by human thoughts, Int. J. Neural Syst., vol. 23, no. 3, pp. 1350013, 2013.