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A Least Across-segment Variance (LASV) Method for the Correction of EEG-fMRI Desynchronization

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Abstract— **Simultaneous collection of electroencephalogram (EEG) and functional magnetic resonance imaging (fMRI) is a promising neuroimaging technique, which can provide high resolution in both spatial and temporal domain. Because EEG recorded in MRI scanners is heavily contaminated with gradient artefact (GA), removal of GA from EEG is a crucial step in EEG-fMRI data analysis. To date, the most efficient methods to remove GA are the average artefact subtraction (AAS) method and its extensions. However, these methods assume perfect synchronization between EEG and fMRI recording, which could be violated in practice. In this paper, a least across-segment variance (LASV) method is proposed for correcting EEG-fMRI desynchronization. Simulation and real data tests were conducted to check the performance of LASV method. The results suggested that the LASV method is able to efficiently correct EEG-fMRI desynchronization in both synthetic and real data, providing a powerful tool for improving the performance of GA removal for desynchronized EEG-fMRI data.**

I. Introduction

Simultaneous collection of electroencephalogram (EEG) and functional magnetic resonance imaging (fMRI) (EEG-fMRI) is a promising neuroimaging technique, because it is able to provide enhanced spatial and temporal resolution in human brain activities owing to the complementary nature of EEG and fMRI [1]. However, the simultaneously collected EEG signal is severely contaminated by the electromagnetic interference from fMRI, so EEG denoising is crucial for EEG-fMRI data analysis.

Gradient artefact (GA), which is the EEG artefact caused by rapid-changing magnetic field of MRI scanning sequence [2], is the strongest artefact among various MRI-induced EEG artefacts. To date, the removal of GA is most typically achieved by applying average artefact subtraction (AAS) method [3] or its extensions [2, 4-6]. Despite the differences in technical details of these methods, all these methods assume perfect synchronization between EEG and fMRI recording, i.e., the period of GA is exactly an integer multiple of EEG sampling interval.

However, EEG-fMRI synchronization could be violated in practice for various reasons. For example, it is known that the repetition time of an fMRI sequence (which determines the period of GA) could be slightly deviated from its prescribed value due to the underlying rounding strategy of the MRI scanner [7]. Given the extremely large energy of GA, even a small violation in the synchronization could substantially reduce the effectiveness of GA removal of the AAS method or its extensions. Although EEG-fMRI recording systems with hardware-level synchronization technique are increasingly available [7, 8], many systems in use still run with independent EEG/fMRI clocks. Therefore, sophisticated signal processing methods are required for the correction of EEG-fMRI desynchronization.

In the current study, a novel signal processing method named least across-segment variance (LASV) will be proposed for correcting EEG-fMRI desynchronization. The proposed method corrects desynchronization by resampling EEG signal with an appropriate sampling rate, such that the across-segment variance of the resampled EEG signal is minimized. The effectiveness of LASV method was validated using both a simulated dataset and a real EEG dataset collected simultaneously with fMRI recording. The results demonstrated that LASV method is able to correct EEG-fMRI desynchronization efficiently.

II. Methods

The proposed least across-segment variance (LASV) method corrects EEG-fMRI desynchronization by resampling EEG signal to a new sampling rate, such that the resampled EEG signal is synchronized with fMRI sequence. It mainly consists of two steps: (1) estimate an EEG sampling rate that is synchronized with fMRI sequence; (2) resample EEG with the estimated sampling rate.

A. EEG Sampling Rate Estimation

Let $x(t)$ denote the EEG signal in a particular channel (which is zero-mean centered), where t is the time index (in seconds). The EEG signal $x(t)$ recorded simultaneously with fMRI recording could be decomposed as:

$$x(t) = g(t) + e(t), \tag{1}$$

where $g(t)$ is a periodic signal denoting the GA with a period of T (i.e., the prescribed repetition time of fMRI sequence), and $e(t)$ is the residual EEG signal containing ballistocardiogram artefacts and other EEG signals. Such additivity assumption has been commonly accepted in previous literatures given the generative process of GA [2]

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(though possible psycho-physiological coupling between EEG signal and GA could not be completely ruled out). Let $x[n]$ denote the sampled version of $x(t)$ under sampling rate f_s, that is, $x[n] = x(n / f_s)$, where n is the index of EEG samples. And similarly, let $g[n]$ and $e[n]$ denote sampled versions of $g(t)$ and $e(t)$ respectively. Further, assume that there exists an integer number m such that $T = m / f_s$ holds (i.e., perfect synchronization). In this case, $g[n]$ is a periodic signal with a period of m, so the AAS method is able to extract GA template accurately.

Suppose that the actual GA period $\tilde{T}$ deviates slightly from its prescribed value T. In this case, $g[n]$ is no longer a periodic signal with period m, so the AAS method fails to extract GA template accurately. To correct this problem, LASV method estimates a new EEG sampling rate such that the resampled GA is a periodic signal with period m.

Further, suppose that the corrected EEG sampling rate is $\tilde{f}_s$. The corrected EEG sampling rate could be regarded as a scaling transformation of f_s as $\tilde{f}_s = f_s / h$, where h is a frequency scaling factor. Based on this representation, f_s is denoted as a function of h in the following (i.e., $\tilde{f}_s(h)$). The goal of the current step is reformulated as finding an appropriate scaling factor h, such that:

$$\tilde{T} = m / \tilde{f}_s(h). \tag{2}$$

To solve the above equation, suppose that h_0 is a solution, and consider the characteristic of EEG signal resampled with $\tilde{f}_s(h_0)$. Let $\tilde{x}_h[n]$ denote the sampled version of $x(t)$ under the corrected sampling rate $\tilde{f}_s(h)$, that is, $\tilde{x}_h[n] = x(n / \tilde{f}_s)$. Similarly, let $\tilde{g}_h[n]$ and $\tilde{e}_h[n]$ denote sampled versions of $g(t)$ and $e(t)$ with the corrected sampling rate respectively. Furthermore, suppose that $\tilde{x}_h[n]$ is divided into segments (length = m) as $\tilde{x}_{h,k}[q] = \tilde{x}_h[q + km]$, where $\tilde{x}_{h,k}[q]$ denotes the k-th segment ($k = \{1, 2, \ldots, K\}$), and $q \in \{0, 1, \ldots, m-1\}$ denotes the index of samples in each segment. The sample variance of $\tilde{x}_k[q]$ across segments could be expanded as:

$$\begin{aligned} \mathrm{var}_k(\tilde{x}_{h,k}[q]) &= \mathrm{var}_k(\tilde{g}_h[q+km]) + \mathrm{var}_k(\tilde{e}_h[q+km]) \\ &\quad + 2\,\mathrm{cov}_k(\tilde{g}_h[q+km], \tilde{e}_h[q+km]). \end{aligned} \tag{3}$$

In above equation, $\mathrm{var}_k(f)$ denotes the sample variance of function f across dependent variable k, and $\mathrm{cov}_k(f_1, f_2)$ denotes the sample covariance between functions f_1 and f_2.

The convergence of each additive component in (3) (when $K \to \infty$) is analyzed as follows. It is easy to verify that:

$$\lim_{K \to \infty} \mathrm{var}_k(\tilde{g}_h[q+km]) = \begin{cases} 0, & \text{if } h = h_0, \\ C_{q,h}, & \text{if } h \neq h_0, \end{cases} \tag{4}$$

where $C_{q,h}$ is a non-negative value. And it is reasonable to assume that:

$$\lim_{K \to \infty} \mathrm{var}_k(\tilde{e}_h[q+km]) = C, \quad \forall h > 0, \tag{5}$$

where C is a positive constant. In addition, since GA $g(t)$ and residual EEG signal $e(t)$ are generated from very different processes, it is reasonable to assume that $g(t)$ and $e(t)$ are uncorrelated, which means that their sampled covariance converges to zero:

$$\lim_{K \to \infty} \mathrm{cov}_k(\tilde{g}_h[q+km], \tilde{e}_h[q+km]) = 0. \tag{6}$$

According to (4), (5) and (6), the convergence of (3) is determined as:

$$\lim_{K \to \infty} \mathrm{var}_k(\tilde{x}_{h,k}[q]) = \begin{cases} C, & \text{if } h = h_0, \\ C + C_{q,h}, & \text{if } h \neq h_0. \end{cases} \tag{7}$$

That means, h_0 is a global minimum of $\mathrm{var}_k(\tilde{x}_{h,k}[q])$ as K approaches infinity. The local smoothness of $\mathrm{var}_k(\tilde{x}_{h,k}[q])$ around $h = h_0$ is also easy to verify. Therefore, it is possible to approximate h_0 by minimizing across-segment variance $\mathrm{var}_k(\tilde{x}_{h,k}[q])$ around $h = 1$. To increase statistical stability of the estimation, LASV method defines an objective function $J(h)$ as the average of $\mathrm{var}_k(\tilde{x}_{h,k}[q])$ across q:

$$J(h) = \frac{1}{m} \sum_{q=0}^{m-1} \mathrm{var}_k(\tilde{x}_{h,k}[q]). \tag{8}$$

And h_0 is approximated by minimizing the above objective function. Batch gradient descent method [9], which is a popular numerical method for the optimization of smooth functions, is applied to solve the above optimization problem. During each iteration of gradient descent, the values of $x(t)$ at the timings that are not sampled by $x[n]$ should be assessed, which are approximated by linear interpolation of $x[n]$.

The above contents described the method of sampling rate estimation for a single EEG channel. For multi-channel EEG signal, sampling rate estimation is performed on a representative EEG channel. The EEG channel is selected automatically by finding the channel with the lowest signal-to-noise ratio (SNR) (i.e., the channel with the strongest GA), which is estimated by calculating the variance ratio of residual EEG signal (signal) and GA (noise) isolated by the AAS method.

B. Resampling EEG Signal

After the new EEG sampling rate is estimated, the next step is to resample the original EEG signal with the new sampling rate. That is, given the observations at $x(n / f_s)$ (i.e., $x[n]$), interpolate at $x(n\hat{h} / f_s)$. In the current implementation, cubic spline interpolation was applied for this purpose, since it could achieve this goal with sufficient accuracy and computational efficiency. After resampling, GA removal methods (e.g., the AAS method) could be applied to the resampled EEG signal.

Restoring original EEG sampling rate after GA removal is not recommended to avoid possible signal degradation. But in the current paper, this step was still applied because we need to compare the residual signal after GA removal with the ground truth in the performance test (Section III).

III. Performance Test

A. Simulation Test

Synthetic single-channel EEG data were constructed as the linear superposition of simulated GA and residual EEG signal, which were generated respectively as follows.

On one hand, simulated GA was generated by sampling (sampling rate = 5000 Hz, which equals to the EEG sampling rate) the following sine wave signal:

$$s(t) = A\sin(2\pi \cdot 15.5 \cdot t / h_0), \tag{9}$$

where A is a parameter modulating the strength of $s(t)$ (and hence the SNR of synthetic signal), and h_0 is a frequency scaling factor (taken as the ground truth) modulating the deviation of the actual frequency of $s(t)$ from its base frequency 15.5 Hz. Apparently, when $h_0 = 1$, the simulated GA is perfectly synchronized with the EEG sampling rate. $s(t)$ was generated with different combinations of the parameter values listed in TABLE I.

TABLE I. Parameter Values for Generating $s(t)$

Parameters	Values
h_0	$(1 - 10^{-5}) - (1 + 10^{-5})$ in steps of 10^{-7}
SNR (modulated by A)	–30dB, –20dB, –10dB, 0dB

On the other hand, the residual EEG signal was generated by directly using the real EEG signal recorded from a healthy subject with a 32-channel MR-compatible EEG cap (Brain Products GmbH, Munich, Germany; sampling rate: 5000 Hz; reference: FCz; duration: 5 mins) in an MRI recording environment without starting the MRI sequence. EEG signals in all EEG channels were band-pass filtered (pass-band: 1 – 100 Hz), and normalized to have zero mean and unit variance. The signal from each EEG channel was added with the above simulated GA, yielding multiple synthetic EEG data for each possible combination of the parameter values.

To assess the performance of the LASV method, the following tests were conducted (based on synthetic EEG signal divided into 150 segments). First, the accuracy of the estimated frequency scaling factors $\hat{h}$ under varying SNR was assessed. More specifically, the estimated scaling factors $\hat{h}$ was compared with the ground truth h_0 by calculating their mean squared error (MSE) under varying degree of desynchronization (controlled by h_0) and SNR for each channel, and then the MSE values were averaged across channels. Second, the influence of the LASV method on the performance of the AAS method was assessed under a reasonable SNR in real data (SNR = –20 dB). In the current test, the AAS method was applied to remove the simulated GA from the synthetic dataset before and after LASV correction. The MSE between the residual synthetic signal after GA removal and the ground truth was calculated and averaged across all channels to measure the performance GA removal in both simulation conditions.

B. Real Data Test

A real EEG dataset collected simultaneously with fMRI was applied in the current test (based on EEG signal divided into 450 segments). The dataset was collected from 21 healthy subjects (11 males and 10 females) aged 22.8 ± 3.7 years (mean ± SD; range = 20 - 33 years). All volunteers signed their informed consent before the experiment, and the experimental procedure was approved by a local research ethics committee. The subjects were instructed to be engaged in an eyes-closed resting condition, during which EEG-fMRI data were recorded. EEG data were recorded using a 65-channel MR-compatible cap (Neuroscan; sampling rate: 5000 Hz). Functional MRI data were recorded using a Philips Achieva 3T scanner with EPI sequence (repetition time = 2 s). The EEG signals were band-pass filtered (pass-band: 1 – 100 Hz) to remove artefacts that are not in the frequency range of EEG.

To assess the performance of the LASV method on this dataset, the AAS method was applied to remove GA before and after LASV correction. Since the ground truth is unavailable in the current test, standard deviation (SD) of residual EEG signal (instead of MSE) was used to measure the performance of GA removal. Usually, a lower residual energy (as indexed by SD here) is an indicator of a more efficient GA removal [2, 10]. To avoid circularity problem, SD was calculated within the EEG segments. The SD (averaged across all channels) between the two conditions were compared at group level using paired t-test. To provide further insight in the difference in SD in the above test, the power spectral density (PSD) of residual EEG signal was also compared between the two conditions.

IV. Results

A. Simulation Test

TABLE II shows the MSE between the estimated scaling factor and ground truth under different SNR level (averaged across channels), suggesting high estimation accuracy of LASV under realistic SNR (in our experience, the SNR of real data is typically –15 to –25 dB).

TABLE II. The MSE between the Estimated Scaling Factor and Ground Truth

SNR	0	-10	-20	-30
MSE (mean ± SD; × 10^{-12})	0.3071 ± 0.3339	0.0330 ± 0.0399	0.0037 ± 0.0043	0.0004 ± 0.0004
MSE (mean ± SD; % Scale*)	0.8774 ± 0.9541	0.0942 ± 0.1139	0.0105 ± 0.0123	0.0011 ± 0.0013

*: percentage with respective to the MSE between h_0 and 1.

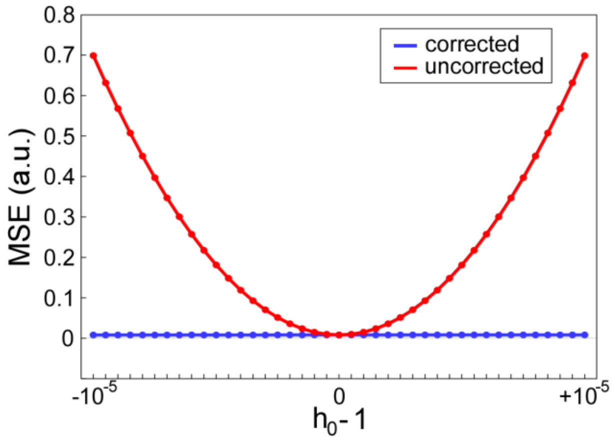

Figure 1. The MSE between the residual synthetic data after GA removal (SNR = -20 dB before GA removal) and ground truth (averaged across channels) with (blue) and without (red) LASV correction.

Fig. 1 shows the MSE between the residual synthetic data after GA removal (SNR = –20 dB before GA removal) and ground truth before and after LASV correction, which clearly illustrated that the influence of desynchronization was removed after LASV correction.

B. Real Data Test

Fig. 2(A) shows the within-segment SD of residual EEG signal before and after LASV correction, suggesting improved GA removal performance after LASV correction. Fig. 2(B) further illustrates the PSD of residual EEG signal before and after GA removal. The PSD of uncorrected signal shows a strong comb-like distribution (which should be closely related to residual GA) that are largely suppressed in the LASV-corrected signal, suggesting that the reduction in SD after LASV correction in Fig. 2(A) mainly reflects the removal of residual GA.

V. Conclusion

In the current study, a novel signal processing method called LASV for correcting EEG-fMRI desynchronization has been proposed, which achieves its goal by minimizing across-segment variance of EEG signal. Through simulation and real data tests, it has been demonstrated that the LASV method is able to efficiently remove the effect of EEG-fMRI desynchronization. This LASV method could be flexibly embedded in various popular GA removal methods (e.g., the AAS method and its extensions), holding great promise to improve their GA removal performance in desynchronized EEG-fMRI data.

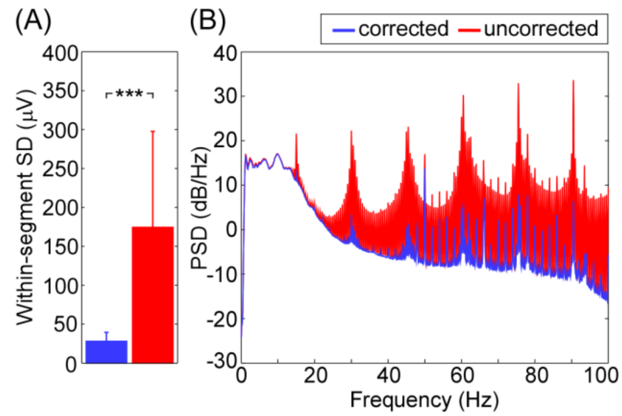

Figure 2. (A) The within-segment SD of the residual EEG signal after GA removal before and after LASV correction. (B) The PSD of residual EEG signal before and after GA removal. ***: $p < 0.001$.

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