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Ballistocardiogram Artifact Removal with a Reference Layer and Standard EEG Cap

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Abstract

Background—In simultaneous EEG-fMRI, the EEG recordings are severely contaminated by ballistocardiogram (BCG) artifacts, which are caused by cardiac pulsations. To reconstruct and remove the BCG artifacts, one promising method is to measure the artifacts in the absence of EEG signal by placing a group of electrodes (BCG electrodes) on a conductive layer (reference layer) insulated from the scalp. However, current BCG reference layer (BRL) methods either use a customized EEG cap composed of electrode pairs, or need to construct the custom reference layer through additional model-building experiments for each EEG-fMRI experiment. These requirements have limited the versatility and efficiency of BRL. The aim of this study is to propose a more practical and efficient BRL method and compare its performance with the most popular BCG removal method, the optimal basis sets (OBS) algorithm.

New Method—By designing the reference layer as a permanent and reusable cap, the new BRL method is able to be used with a standard EEG cap, and no extra experiments and preparations are needed to use the BRL in an EEG-fMRI experiment.

Results—The BRL method effectively removed the BCG artifacts from both oscillatory and evoked potential scalp recordings and recovered the EEG signal.

Comparison with Existing Method—Compared to the OBS, this new BRL method improved the contrast-to-noise ratios of the alpha-wave, visual, and auditory evoked potential signals by 101%, 76%, and 75% respectively, employing 160 BCG electrodes. Using only 20 BCG electrodes, the BRL improved the EEG signal by 74%/26%/41% respectively.

Conclusion—The proposed method can substantially improve the EEG signal quality compared with traditional methods.

Keywords

EEG-fMRI; ballistocardiogram; BCG artifact; removal; reference layer; OBS

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1. Introduction

With the high temporal resolution of EEG and high spatial resolution of fMRI, simultaneous EEG and fMRI acquisition (Huang-Hellinger et al., 1995; Bonmassar et al., 1999; Lemieux et al., 2001; Goldman et al., 2002; Benar et al., 2002; Laufs et al., 2003) should provide more accurate information about cognitive processes in the cerebrum. Today, EEG-fMRI has become an important noninvasive neuroimaging tool for clinical diagnosis and cognitive neuroscience research (Laufs, 2012). Nevertheless, technical challenges still exist in EEG-fMRI, and one of them is the ballistocardiogram (BCG) artifact (Ives et al., 1993; Allen et al., 1998; Bonmassar et al., 2002), i.e., the artifacts caused by cardiac pulsation. The BCG artifacts result from three physical processes driven by the cardiac cycle (Yan et al., 2010): the gross translations and rotations of the head induced by the momentum changes of blood (Ives et al., 1993), the local scalp movements due to the expansion and contraction of scalp arteries (Allen et al., 1998), and the Hall effect produced by the blood flow (Muri et al., 1997). In the magnetic field of MRI, the head/scalp motions will induce movements of the EEG electrodes and leads, which in turn generate voltages in the EEG channels due to the electromagnetic induction effect (Faraday's Law). In a 3 T MRI system, the amplitude of the BCG artifacts can exceed 200 μV (Debener et al., 2007), so the BCG amplitude can be tens of times larger than the EEG signal induced by spontaneous and evoked neural activities. While gradient artifacts can be much larger, they are precisely repeatable and readily removed by template subtraction methods (Allen et al., 2000; Niazy et al., 2005) unless there is substantial head motion. BCG artifacts, by contrast, vary from heart beat to beat, so a unique template that describes all cardiac events can not be derived. Hence, BCG noise often requires more attention than the gradient artifact (Laufs et al., 2008) and is the main obstacle for detecting neural events in the EEG signal concurrently acquired with fMRI (Huang-Hellinger et al., 1995; Krakow et al., 1999; Bonmassar et al., 2002).

To assure the EEG signal quality in EEG-fMRI, various methods have been used to remove the BCG artifact (Laufs et al., 2008). In general, all the methods are composed of two processing steps: first, detecting the artifact and creating a template and, second, utilizing the template to reconstruct and subtract the BCG artifacts in the contaminated EEG data. BCG removal methods can be divided into two categories according to the source of the signal used for obtaining the templates: self-extraction and external-referenced methods. The self-extraction methods directly extract the artifact templates from the contaminated EEG data. The methods in this category include the averaged artifact subtraction (AAS) (Allen et al., 1998; Goldman et al., 2000; Ellingson et al., 2004; de Munck et al., 2013) and the algorithms based on principal component analysis (PCA) (Niazy et al., 2005), independent component analysis (ICA) (Srivastava et al., 2005; Briselli et al., 2006; Nakamura et al., 2006; Mantini et al., 2007), non-Kirchhoffian overcomplete representation (Dyrholm et al., 2009), maximum noise fraction transformation (Sun et al., 2009), cyclostationary source extraction (Ghaderi et al., 2010), and joint short and long-term prediction (Ferdowsi et al., 2013). Among the self-extraction methods, the PCA-based optimal basis sets (OBS) algorithm (Niazy et al., 2005) is most widely used in EEG-fMRI studies, and it shows a better performance than the AAS (Niazy et al., 2005) and is more robust and easier to use than the ICA-based methods (Vanderperren et al., 2010). In OBS, the continuous data in

each channel is segmented into epochs time-locked to the cardiac pulsations. A PCA is applied to the epoch data channel by channel. Since BCG artifacts are usually much larger than the desired EEG signal, the first several (3 or 4) principal components (PCs) are assumed to contain pure BCG noise and thus are used as the artifact templates in the corresponding channel. However, due to the large variability of BCG effects in the time domain, the artifact may also extend to the PCs with lower ranks. In addition, in some cases high amplitude EEG signals can be present in the first several PCs, resulting in their partial suppression along with the BCG artifacts. Thus, the first three or four PCs are unable to fully capture the temporal characteristics of BCG artifacts and may contain valid EEG signals. Furthermore, this problem cannot be ultimately solved by using more PCs as the artifact templates, because the lower-rank PCs may include both artifacts and neural activity. This will not only limit the robustness of BCG noise removal but may also suppress the EEG signal. Hence, the presence of EEG signal limits the accuracy of artifact template extraction and the performance of the OBS method.

Another category of BCG removal methods (Bonmassar et al., 2002; Masterton et al., 2007; LeVan et al., 2013) creates BCG artifact templates from external (non-EEG) reference signals. These signals are usually the time courses of head movement detected by external devices such as piezoelectric sensors (Bonmassar et al., 2002), wire loops (Masterton et al., 2007), or optical motion-tracking systems (LeVan et al., 2013). By assuming a linear relationship with head motions, the BCG artifact templates can be obtained from these reference signals. Since these motion detectors operate in ways uncoupled from neural activity, the creation of the artifact template is not confounded by the EEG signal. Thus, using such external-referenced methods should in principle improve the accuracy of BCG artifact reconstruction by minimizing the possibility of removing EEG signals. Nonetheless, while motion detection devices can provide information about global head movement, they assume the head is rigid and are therefore insensitive to local scalp movements and the Hall effect. Thus, the externally-referenced methods lack the ability to remove those artifact components induced by the local expansion of scalp arteries and the Hall effect.

Most recently, two groups (Chowdhury et al., 2013; Xia et al., 2013) have proposed BCG artifact removal methods based on a BCG reference layer (BRL). In BRL, one group of electrodes (scalp electrodes) directly contact the scalp to perform the normal EEG recording, while others (BCG electrodes) are exclusively used for detecting the reference signals of BCG effects. The BCG electrodes are placed on a thin conductive layer (reference layer) that is mechanically attached to but electrically insulated from the scalp. It is assumed the BCG artifacts on the reference layer resemble those on the scalp, so that the reference signals directly reflect the BCG effects produced by both the gross head motions and local scalp movements, but are free of neurally-generated EEG signals. Although the BRL is also insensitive to the Hall effect, the contribution of Hall effect to the BCG artifact is much smaller than the head movements and local expansions of scalp arteries (Mullinger et al., 2013). Therefore, the BRL methods are able to remove the predominant BCG noise components without suppressing the EEG signal. The previous studies (Chowdhury et al., 2013; Xia et al., 2013) have demonstrated that BRL can more effectively remove the BCG artifact than the AAS and OBS algorithms.

The two different BRL methods (Chowdhury et al., 2013; Xia et al., 2013) have their own advantages and disadvantages. In Chowdhury's work (2013), the BRL method was implemented on a customized EEG cap composed of electrode pairs. In each electrode pair, one electrode is overlapped above the other to respectively serve as the BCG and scalp electrodes. A PVC insulating layer is inserted between the scalp and BCG electrodes, and a hemispherical reference layer made of agar covers the top of the electrode pairs. Since this electrode pair-based BRL method adopts a fixed design on the EEG cap and reference layer, the cap can be reused and easily set up in an EEG-fMRI experiment after a one-time production. Nonetheless, to use this method on conventional EEG systems, it is necessary to perform hardware modifications to convert the standard EEG caps into the form of the electrode pairs. Moreover, it may be difficult to realize this method on some types of EEG systems. For example, the electrode used in one vendor's EEG system is secured in a cylindrical chamber with a height of ~1 cm. The design of electrode pairs for this system would mean that the reference layer would extend about 2 cm away from the scalp. Such a large radial distance would not only deviate from the basic design rule of BRL (i.e., reference layer closely and mechanically attached to the scalp to accurately reflect scalp movements), but would also substantially increase the volume occupied by the subject's head and EEG cap, which may exceed the limit of the head coil in the MRI scanner.

In Xia and colleagues' method (2013), a standard EEG cap is used, and a sheet of plastic film (insulation layer) and damp thin paper (reference layer) are overlapped together and placed between the standard EEG cap and the scalp. Prior to the real EEG-fMRI data acquisition, a model-building experiment is performed first to select a subset of the electrodes (BCG electrodes) that can optimally estimate the BCG artifacts in all the others (scalp electrodes) on the EEG cap, and then openings are cut on the film and paper at the positions corresponding to the scalp electrodes to make them contact the scalp. By using this reference layer design, the standard EEG cap can be directly used in the BRL method, so its application will not be limited by the type of EEG system. However, in each EEG-fMRI experiment, the custom insulation and reference layers need to be newly constructed according to the results from the model-building experiment. In principle, the experiment-dependent reference layer design can optimize the selection of BCG electrodes and the performance of BRL, but on the other hand, the procedures of the model-building and the production of the custom reference layer will increase the time and complexity of performing the experiment. For example it may require the subject to return for the actual experiment after constructing the reference layer based on the calibration experiment. More importantly, the long experimental time may induce the natural fatigue of subjects and degrade their performance, especially in experiments on patients. In addition, the extended experimental duration can have negative impacts on other experimental conditions, e.g., the stability of the contact between the BCG/scalp electrodes and the reference layer/scalp. All these factors could reduce the reliability and practicability of experimental results. Hence, this custom reference layer based method (Xia et al., 2013) is impractical for many EEG-fMRI studies due to its low efficiency and added cost for scanner time.

As described above, some limitations still exist in the current BRL methods. Without hardware modifications, the electrode pair based BRL (Chowdhury et al., 2013) cannot be directly used on standard EEG caps and the EEG systems that use thick electrodes. These

restrictions were removed in the standard EEG cap based BRL method (Xia et al., 2013), but the additional model-building and reference layer production procedures reduce the efficiency of EEG-fMRI experiments.

In order for the BRL to be more widely applied in EEG-fMRI, a more practical and efficient BRL method based on a standard EEG cap is proposed in the present study. In this work, the reference layer is designed as an added cap (BCG cap) to facilitate the standardized placement and measurement of BCG and scalp electrodes. With the BCG cap, a standard EEG cap is used without modification for measuring both the EEG and the BCG reference signals. Furthermore, according to the electrode layout of the standard EEG cap, the spatial distribution of BCG and scalp electrodes are preset and fixed on the BCG cap. After a one-time production of the BCG cap, no model-building experiment and reference layer production will need to be performed in an EEG-fMRI experiment. Since the BCG cap is a passive, permanent and reusable design, little additional preparation and setup work is needed to use this BRL method on conventional EEG systems. Therefore, these technical improvements should be able to completely overcome the limitations in the previous BRL methods (Chowdhury et al., 2013; Xia et al., 2013).

In this manuscript, alpha band EEG signals modulated by eyes open/closed as well as visual and auditory stimulations are recorded on human subjects with the EEG and BCG caps. The BCG artifacts in the acquired EEG data are removed with the BRL and OBS methods, respectively. Finally, the performance of BRL is compared to that of OBS by evaluating the signal quality of the alpha wave and visual and auditory evoked potentials (VEPs and AEPs) before and after the BCG artifact removal. The acronyms and abbreviations used in this manuscript are listed in Table 1.

2. Material and methods

2.1. Experimental setup

A 256-channel MR-compatible EEG system (Net Amps 300/HCGSN v.1.0; Electrical Geodesic, Inc., Eugene, OR) was used to record the EEG data at 250 Hz inside a 3.0 T GE MRI scanner (Discovery MR750; GE Healthcare Systems, Milwaukee, WI). During the EEG recording, a BCG cap was worn by the subject together with the EEG cap in order to use the BRL method for removing the BCG artifact. The BCG cap was located between the EEG cap and scalp. Figure 1 shows the design of BCG cap and its setup on the subject. The BCG cap was produced by embedding a vinyl shower cap into a satin slumber cap that serve as the insulating and reference layers, respectively. Rubber grommets were inserted at the standard 10–20 montage locations for the EEG electrodes to pass through. The standard electrolyte saline solution (KCl with concentration of 11g/L) was applied to the satin layer to make its conductance similar to the scalp. It was found that the satin layer can effectively preserve the conductivity afforded by the saline solution. No significant dry out was observed within 1.5 hrs, and the saline was applied once in the entire experiment. In the BCG cap, the built-in grommets provide a pathway for the electrodes on the EEG cap to penetrate the BCG cap and directly contact the scalp without electrical connection to the reference layer. In this way, the electrodes in the grommets served as the scalp electrodes and all others were BCG electrodes. The BCG cap is thus passive, serving only to provide a

scalp-like conductive connection between BCG electrodes while insulating them from the scalp and the scalp electrodes. In this study, we employed a total of 32 grommets (scalp electrodes) on the BCG cap, but more could easily be added. The BCG electrodes had resistances similar to those of the scalp electrodes, approximately 20 K Ω .

During the EEG recordings, cardiac pulsations were monitored to provide heart beat timing information for the OBS algorithm. Usually the cardiac events are detected from ECG signals concurrently recorded with the EEG data using chest or back electrodes. However, the ECG setup usually takes a relatively long time and also is inconvenient on female subjects. In addition, the amplitude of ECG contamination from dB/dt induced by the switching imaging gradients is very high at a distance from the head near the heart, which sometimes makes reliable ECG recording difficult in MRI. To avoid these problems, photoplethysmography (PPG) signals were used instead of ECG to track the cardiac cycles in this study. The standard PPG device built into the MRI scanner was worn on the left thumb of the subject to measure the cardiac pulsations. The PPG signal was processed online with in-house software to detect the peak times of heart beats. At each peak time, a TTL trigger pulse was output to the EEG system and was synchronously recorded with the EEG data. To demonstrate the reliability of using the PPG signal, EEG data were acquired with PPG and ECG signals on a subject in the MRI scanner (without scanning). Due to the hardware limitation, the PPG and ECG signals could not be simultaneously input to the EEG amplifier, so the EEG data were recorded in two separate runs, one with the PPG and the other with the ECG signals. The processing result of OBS when using the PPG signal was compared to that using the ECG signal on a subject. As shown in supplementary information Fig. S1A, the BCG noise was substantially reduced after applying the OBS with the PPG triggers to the EEG data. Furthermore, it was found that the noise level (i.e. temporal standard deviation of signal) in each channel is similar to the case using the ECG triggers (Fig. S1B), and the noise level averaged over all the channels when using the PPG is slightly (~ 12%) lower than the ECG signal. This small difference may be due to the difference of BCG artifact and EEG signal in the two different runs. From these experimental results, it can be concluded that the performance of OBS with PPG is comparable to that using ECG.

2.2. Stimulation tasks

Three stimulation tasks were used to respectively elicit spontaneous (alpha-wave), visual, and auditory evoked activities in the brain. Each task was implemented in a separate paradigm using E-Prime (v.1.2; Psychology Software Tools, Inc., Sharpsburg, PA). To generate the alpha-wave activity, the subject was instructed by recorded voice to open/close eyes for 15/15 s and repeat 15 times. The visual and auditory paradigms were block-designed and composed of 10 blocks. Each block included a resting and a task epoch with the duration of 15 s, and one extra resting epoch was added to the end of paradigm. No stimulus was present during the resting epochs. During the task epochs, the visual or auditory stimuli were delivered to the subject with an inter-stimulus interval of 1 s. The visual stimulus was a full field checkerboard pattern with the duration of 100 ms, and a random-pitch tone of 250 ms was used as the auditory stimulus.

2.3. Data acquisition

EEG data were acquired on five healthy volunteers (two female and three male, aged 23–71) inside the MRI scanner. Informed consent was obtained from each subject prior to the experiments in accordance with a Stanford IRB protocol. Two runs of EEG recording were performed with each stimulation paradigm. One run was acquired without MRI scanning and aimed to evaluate the performance of BRL on the BCG removal without the impact from the artifacts related to MRI scan, e.g., the gradient artifact (Allen et al., 2000). In another run, EEG and fMRI data were simultaneously recorded to simulate the realistic conditions in EEG-fMRI experiments. The fMRI data were acquired using a gradient echo spiral in/out pulse sequence (Glover and Law, 2001) with the following imaging parameters: TR/TE = 2040/30 ms, flip angle = 80°, matrix size = 64 × 64, FOV = 22 cm, and thirty contiguous axial slices covering the whole brain. In addition, 150 s of EEG data was recorded with eyes open outside the MRI room immediately after the data acquisition in the MRI scanner. Since the outside data was free of BCG artifacts, it was used as the gold standard to evaluate the level of residual BCG noise after the OBS and BRL processing of data recorded in the scanner.

2.4. Data preprocessing

All the data preprocessing and analyses were performed in MATLAB (v.7.14; The Mathworks, Inc., Natick, MA) and EEGLAB version 12.0 (Delorme and Makeig, 2004). Firstly, the gradient artifact in the EEG data with MRI scan was removed using the FMRIB plug-in in EEGLAB, and then all the EEG data (with and without scan) were band-pass filtered at 0.5–50 Hz. The EEG data in the BCG and scalp electrodes were re-referenced to their corresponding average.

2.5. BCG artifact removal with OBS

The OBS algorithm in the FMRIB plug-in (Niazy et al., 2005) of EEGLAB was applied to remove the BCG artifacts. When processing the eyes open/closed datasets with the OBS, since the optimal number of principal components (N_{PC}) value has not been investigated on spontaneous activity, the artifact removal was performed on the EEG data separately using all the integers between 1 and 20 as the N_{PC} value. The value of N_{PC} was set to the default value of 3 when removing the BCG artifacts in the visual and auditory evoked potential data. The previous study (Vanderperren et al., 2010) has shown that $N_{PC} = 3$ is the optimal value used in experiments of sensory evoked activities.

2.6. BCG artifact removal with BRL

The BRL-based method was also used to suppress the BCG noise in the EEG data. As in the previous study (Xia et al., 2013), it is also assumed in this study that the BCG artifact in a scalp electrode can be estimated by a linear combination of the signals in the BCG electrodes, so the signal in an EEG channel (V) can be expressed as

$$V = S + B + \varepsilon = S + \sum_{k=1}^{N_B} \beta_k R_k + \varepsilon \quad (1)$$

where S is the EEG signal induced by the neural activity, B is the BCG noise in the EEG channel, and ε is the noise from other sources. N_B is the number of BCG electrodes used for reconstructing the artifact in the EEG channel, R_k is the signal in the k th electrode on the reference layer, i.e., BCG electrode, and β_k is the corresponding fitting coefficient. From Eq. (1), the β and B values were estimated by a linear fitting between V and R , which was calculated in Matlab ($\beta=R \backslash V$). Finally, the EEG signal (S) was retrieved by subtracting the estimated BCG artifact (B) from the contaminated EEG signal (V).

From Eq. (1), it can be seen that the result of BRL may depend on the number of BCG electrodes used in the artifact reconstruction (N_B). To investigate the relationship between the performance of BRL and N_B , the EEG data were processed with six different N_B values: 5, 10, 20, 40, 80, and 160. After discarding the EEG electrodes located outside the BCG cap's BRL, the total number of BCG electrodes on each subject was in the range of 165–172, from which 160 electrodes were selected and used in the case of $N_B = 160$. The BCG electrodes for $N_B = 5$ –80 were selected using the following two methods: (i) *Uniform selection*: the electrodes used in the case of $N_B = 80$ were manually and uniformly picked from that of $N_B = 160$. Similarly, the electrodes of $N_B = 40$ were taken from $N_B = 80$, and the cases of the other N_B values were created in the same manner. In this way, the BCG electrodes used at a smaller N_B value were always a subset of those at larger N_B values. (ii) *Random selection*: Due to the variation of head shape and the limited number of electrodes, the distribution of BCG electrodes cannot be perfectly uniform in practice and the distribution patterns can vary on different subjects, especially at N_B values smaller than 40. To evaluate the impact of this variation on the performance of BRL, the BCG electrodes for the cases of $N_B = 5$ –80 were randomly selected from those of $N_B = 160$. The random selection was completed by using Matlab's random integer generator (function "randi"), and 50 random selections were generated for each N_B value.

To validate the assumption about the linear combination in Eq. (1), the BRL method was also applied to the data from the BCG electrodes. Since there was no EEG signal in the reference layer, Eq. (1) can be simplified for the signal in a BCG channel as

$$R_i = B_i + \varepsilon_i = \sum_{k=1, k \neq i}^{N_B-1} \beta_k R_k + \varepsilon \quad (2)$$

where the subscript i represents the i th BCG electrode. With Eq. (2), the BCG artifacts in each BCG electrode of interest (EOI) were estimated with the signals from the $N_B - 1$ other BCG electrodes (fitting electrodes), and then the estimated artifacts were subtracted from the data. Supplementary information Fig. S2 shows the analysis results when $N_B = 160$. The data were taken from the eyes open/closed experiments without MRI scanning. Figs. S2A illustrates the topomaps of correlation coefficients between the signals in one EOI and the other 159 fitting electrodes. It can be seen that the spatial distribution patterns of correlation coefficients varied with the positions of the electrode of interest and also with different subjects. However, the variation of the correlation coefficients with electrode position was smooth, and highly correlated electrodes were always found near the EOI. In addition, some distant electrodes can also show a large correlation with the EOI. This implies that common

artifact components exist between the EOI and both the neighbor and remote areas. As shown in the corresponding topomaps of fitting coefficients (Fig. S2B), although the largest β values are located at the neighbor fitting electrodes, the remote areas also contributed to the fitting result. In the Figs. S2A and S2B, it is found that some fitting electrodes have large correlation but β values close to zero. Note that the β values represent the degree of correlation between the signal of EOI and the independent signal components rather than the original signals in the fitting electrodes. Since the signals in the adjacent channels are highly correlated (see Fig. S2A), the number of independent signals provided by the fitting electrodes are less than the number of the fitting electrodes. Thus, a fitting electrode with a high correlation but zero fitting coefficient value means that this electrode includes the signal components correlated with the EOI but these components are not independent, i.e., they can be represented by a linear combination of the signals in the other fitting electrodes. Fig. S2C shows the temporal standard deviations (S.D.) of the BCG electrode signals before and after the artifact removal. In the raw data, it can be seen that the signal amplitudes vary with the BCG electrode positions. This suggests that the strength of the BCG effect depends on the spatial locations. Also, it was noticed that there were larger spatial gradients across the signals near the temporal areas. This phenomenon is likely caused by the loose mechanical contact between the BCG electrodes and reference layer in the temporal areas, where the fit to different head shapes is often poor in some subjects. Compared to the raw data, the noise level (i.e., the S.D. values) in the BCG channels after the BCG removal was dramatically reduced. After averaging over all the BCG channels and subjects, the S.D. value after the BCG removal is about 6% of that in the raw data. This suggests that the BCG noise in one BCG electrode can be well predicted by the linear combination of the BCG channels. In other words, Eqs. (1) and (2) are valid.

2.7. Performance comparison of BRL and OBS

The efficacy of BRL for suppressing BCG artifacts was compared to that of OBS by assessing the qualities of their corresponding EEG signals. To evaluate the signal quality of the spontaneous EEG recording, the data epochs during eyes open and closed were extracted from the EEG data after the BCG artifact removal. 15 epochs of eyes open and closed were obtained from each EEG data set, and each epoch lasted 15 s. The average power spectra of the eyes open and closed epochs were calculated with EEGLAB, which uses Welch's method (function 'pwelch' in Matlab) to estimate the power spectra with the following parameters: Hamming window length = 512, window overlap = 0, length of FFT = 1024, and sampling frequency = 250 Hz. The peak frequency at the alpha band (8–12 Hz) was identified from the power spectrum during eyes closed. The alpha peak power was calculated by integrating the spectral power within the range of the peak frequency ± 1 Hz. Finally, the alpha peak power ratio (pPR) of eyes closed to eyes open was calculated to represent the quality of the spontaneous EEG signal. If eyes open is considered as the baseline state, then the pPR would be equivalent to the contrast-to-noise ratio (CNR) of the alpha-wave signal. To examine the level of residual BCG artifacts, the alpha-band power spectra of the data after the OBS and BRL at eyes-open were visually compared with the data acquired outside the MRI room.

In order to determine the optimal choice of N_{PC} in the OBS, the pPR values at the different N_{PC} settings ($N_{PC} = 1-20$) were calculated in the data without MRI scan and then normalized to their maximum value. The normalized pPR values were averaged over the subjects to obtain the pPR vs. N_{PC} curve. The optimal N_{PC} value was determined through the following two steps: first, all the data points exceeding 95% of the maximum pPR value were identified from the pPR vs. N_{PC} curve, and then the N_{PC} providing the smallest standard deviation was considered to be the optimal N_{PC} setting. In this way, the optimal N_{PC} value ensures that the OBS has maximally robust performance across the different subjects.

To compare the performance between BRL and OBS, the increase of pPR when using the BRL relative to the OBS with the optimal N_{PC} was calculated from the spontaneous EEG data without and with MRI scanning on each subject. At each N_B value, a one-sample t-test was performed on the value of pPR increase averaged over the subjects to determine if it is significantly larger than zero. If the pPR increase value exceeded the significance level ($p < 0.05$), it would mean that the performance of the BRL is better than that of the OBS, otherwise they are equivalent. In addition, the averaged pPR increases at different N_B values were plotted to examine the performance dependence of BRL on the number of BCG electrodes.

The performances of BRL and OBS were also compared using EEG signals evoked by the visual and auditory stimulations. In each dataset, the continuous signals in the scalp electrodes were segmented into epochs of 1 s length by applying a time window of 200 ms before to 800 ms after stimulus onset. The period of 200 ms pre-stimulus was used as the baseline. The epoch data were baseline corrected and re-referenced to the average of the scalp electrodes. The epoch data were averaged to obtain the corresponding visual or auditory evoked potential (VEP or AEP) signal, and the CNR curve of VEP/AEP was calculated by dividing the original VEP/AEP signal by the pooled standard deviation (σ_p) at each time point. The σ_p at the i th time point $\sigma_{p,i}$ was calculated with the formula:

$\sigma_{p,i} = \sqrt{(\sigma_{s,i}^2 + \sigma_b^2)/2}$, where $\sigma_{s,i}$ is the standard deviation of VEP or AEP signal across epochs at the i th time point, and σ_b is the standard deviation of all the baseline data points in all the epochs. The calculation of CNR is essentially equivalent to a group t-test between the signal at a time point and the baseline, and the CNR is proportional to the t-value. The response peaks were identified from the CNR curves. To ensure the reliability of the comparison results, the response peaks were selected for further analyses only if they were present in the EEG signals of all the subjects. The response peaks were separated into two categories: primary and secondary responses. The peaks within 0 to 200 ms after stimulus onset were considered as the primary responses and the peaks after 200 ms were the secondary responses. The peak CNR (pCNR) was obtained by averaging CNR values over the full-width-at-half-maximum (FWHM) window of the corresponding response peak. Finally, the averaged pCNRs of VEP and AEP over the subjects was used as the criterion to compare the performances of BRL and OBS. The pCNR increases of BRL relative to OBS were calculated at the different N_B values to investigate the relationship between them. The statistical significance of these pCNR increase values were also evaluated using the one-sample t-test.

Finally, the variations of pPR and pCNR when using the randomly selected BCG electrodes were calculated to investigate the performance dependence of BRL on the spatial distribution of BCG electrodes. At each N_B value, the alpha pPRs and pCNRs of VEP and AEP were separately calculated with the 50 random BCG distribution patterns. The variations of performance were evaluated by using the percent ratios of the standard deviations of the pPRs and pCNRs to their corresponding average values (i.e., relative errors). The variations of performance were averaged over the subjects to obtain the dependence of performance on BCG electrode positions at the group level. In addition, a statistical analysis was performed to compare the difference of performance between the uniform and random BCG electrode selection methods. On each subject, the percent difference of pPR/pCNR values between the uniform and random selections were calculated at each N_B value. The one-sample t-test was applied to the percent difference values across the subjects to examine if the difference is statistically significant at $p < 0.05$.

3. Results

Figure 2 shows the dependence of alpha pPR values on the N_{PC} setting in the OBS. It can be seen that the pPR value initially increases with N_{PC} and reaches its maximum at $N_{PC} = 4$, and then further increase in N_{PC} results in the reduction of pPR. This phenomenon suggests that when $N_{PC} < 4$, the OBS algorithm can remove more BCG noise by using a larger N_{PC} value. Furthermore, when $N_{PC} > 4$, using a larger N_{PC} may suppress more EEG signal components and degrade the signal quality. In addition, it was found that the pPR values at $N_{PC} = 2-5$ all exceeded 95% of the maximum, and among these N_{PC} values, the variation of pPR across different subjects at $N_{PC} = 3$ was substantially (> 4 times) smaller than the others. Therefore, $N_{PC} = 3$ is the optimal setting of N_{PC} when using the OBS algorithm to remove the BCG artifacts in our spontaneous EEG data, which agrees with the findings of (Vanderperren et al., 2010).

Figure 3 illustrates a segment of raw data measured by the BCG (Fig. 3A) and scalp (Fig. 3B) electrodes, and also the corresponding scalp EEG traces after the BCG artifact removal with the OBS ($N_{PC} = 3$) and BRL ($N_B = 160$). The data is taken from the EEG recordings during the eyes open/closed task and without MRI scan. In the raw data of both BCG and scalp electrodes, the signal peaks induced by the BCG effects are strong and can be clearly observed in all the channels, though the amplitude and polarity of the BCG artifact vary in different channels. Also, the adjacent BCG and scalp electrodes (e.g., BCG electrode 7 and scalp electrode 2) showed similar signal time courses at eyes open. However, at the eyes-closed state, the alpha-wave signal (contaminated by the artifact) is presented in the scalp electrodes but not in the BCG electrodes. This suggests that the reference layer can capture the BCG artifact and insulate the neural signal as well. After processing with the BRL, the BCG artifacts were substantially suppressed and the alpha-wave signals were well retrieved. Compared to the BRL, the data after the artifact removal with the OBS still had relatively large residual BCG artifacts, and their amplitudes can reach tens of μV in some channels. Some residual artifacts occurred during the bursts of alpha oscillations and they altered the EEG signal of alpha wave to some degree. In addition, it is found that the performance of BRL decreases when reducing N_B . As shown in supplementary information Fig. S3, the residual artifact in the BRL data increases with the decrease of N_B . However, the

effectiveness of BCG artifact removal of the BRL is still visually better than the OBS when reducing N_B to 20.

Figures 4A and C present the power spectra of the EEG signals generated by the eyes open/closed task for a typical subject (Subject 2). The data shown in Fig. 4A were acquired in the magnet but without MRI scanning, while Fig. 4C shows the data with concurrent fMRI scan. The power spectra obtained by using the OBS with $N_{PC} = 3$ and the BRL with $N_B = 80$ (BRL-80) and 160 (BRL-160) are displayed in the figure, respectively. From the power spectra of both OBS and BRL, a response peak at 10.4 Hz was observed during eyes closed. This suggests that alpha oscillations elicited during eyes closed can be detected in the data after the BCG artifact removal. However, it is noticed that the alpha-band power of OBS during eyes open is substantially higher than that of BRL-80 and BRL-160. Since alpha oscillation is largely suppressed by the eyes open task, the power difference between the OBS and BRL is predominantly caused by the BCG artifact instead of neural activity. In other words, the residual artifacts in the EEG data after applying the OBS were larger than the BRL. This conclusion was further demonstrated by comparing the power spectra of OBS and BRL with that of the outside recording. From the power spectra at the alpha band during eyes-open (see supplementary information Fig. S4), it was observed that the average spectral power of the OBS data without/with scan were 2.0/2.8 times larger than that of outside data. In contrast, there is only a slight difference (7.4%/16.9% for the data without/with scan) between the BRL and outside data. This suggests that the BRL more effectively removed the BCG artifact than the OBS algorithm. Due to the lower residual BCG noise level in the BRL data, the power ratios of eyes closed to open when using the BRL were substantially higher than with the OBS at the alpha-band, both in the case without (Fig. 4B) or with (Fig. 4D) scan. In addition, there is only a slight difference in the power spectrum and power ratio curve between BRL-80 and BRL-160, so the performance of BRL using 80 BCG electrodes is comparable to that using 160 BCG electrodes. When using a N_B value smaller than 80, the power ratios at the alpha band decreased with the decrease of N_B (shown in supplementary information Fig. S5), but they are still larger than that of the OBS in all the subjects when $N_B \geq 20$.

Figure 5 illustrates the relative performance of BRL to the OBS method for the alpha-wave signal at different N_B values. Each data point represents the result averaged over the five subjects. The BCG electrodes at each N_B setting were approximately uniformly distributed on the reference layer. It was found that the alpha pPR of the BRL is significantly ($p < 0.05$) higher than that of OBS when N_B is larger than 20/10 in the data with/without MRI scan. In addition, the pPR is higher at larger N_B . In the simultaneous EEG-fMRI experiments, the pPR of the BRL method using 20–160 BCG electrodes was 1.74–2.01 times of that of the OBS. In addition, it was also observed that the pPR increase of BRL relative to the OBS in the data with scan was larger than that without scan, and the difference between them varied in the range of 11% to 33%, depending on the value of N_B .

Figure 6 shows the VEP and AEP signals after the BCG artifact removal with OBS ($N_{PC} = 3$) and BRL ($N_B = 80$ & 160) for a representative subject (Subject 2). In the average VEP signals without (Fig. 6A) and with (Fig. 6B) MRI scan, two visual response peaks (P1 and N1) appeared at approximately 110 ms and 170 ms after the stimulus onset, respectively. In

addition, there was also a late and relatively long response peak (P2) at about 300 ms. Two positive and one negative response peaks were observed in the AEP signals (Figs. 6C and 6D). However, only the negative (N1) peak was present in the signals from all the subjects, and the positive peaks were too weak to be detected on some subjects. Thus, the positive peaks were ignored to ensure the reliability of the analysis results. From Figs. 6A–D, it can be seen that the standard errors of the VEP and AEP signals in the OBS data are larger than those in the BRL data. This means that there is more trial-by-trial variation in the OBS data. The signal qualities of VEP and AEP were quantitatively described by their corresponding CNR curves (Figs. 6E–H). It was found that the BRL has higher CNR than the OBS on both the primary (P1 and N1) and secondary (P2) response peaks. Especially, the P2 peaks had high CNRs when using the BRL, but were quite weak in the data processed with OBS. Similar to the results of VEP, the CNR of the N1 peak when using the BRL was larger than the OBS. The average and CNR curves of VEP and AEP signals when using the smaller N_B values were shown in supplementary information Fig. S6. Similar to the eyes open/closed experiments, it was observed that the peak CNRs of VEP and AEP were generally lower at smaller N_B values, but larger than those in the OBS data when $N_B \geq 20$.

Figure 7 shows the comparison results between BRL and OBS on the pCNR of VEP and AEP when using different N_B settings. The data in the figure represent the averaged results of all the subjects. Similar to the results from eyes open/closed data, the performance of BRL was found to be increased with increasing N_B in both the VEP and AEP data. In the data without scan, the pCNRs were significantly ($p < 0.05$) increased by the BRL relative to the OBS when using more than 10 (VEP)/80 (AEP) BCG electrodes. In the EEG data concurrently acquired with fMRI, the pCNRs of primary VEP and AEP responses showed a significant improvement at $N_B = 10$, and $N_B = 20$ for the secondary VEP response. With the increase of N_B from 20 to 160, the pCNR ratio of BRL relative to the OBS was elevated from 1.26/1.41 to 1.76/1.75 on the primary VEP/AEP response, and from 1.68 to 1.39 on the secondary VEP response. In addition, it was also found that the values of pCNR increase in the primary VEP and AEP responses with scan were larger than that without scan when $N_B \geq 40$, while the opposite phenomenon was observed in the secondary VEP response.

The performance dependence of BRL on the spatial distribution of BCG electrodes is shown in Fig. 8. From the data using the random BCG electrode selections, it was found that the pPR of alpha wave, and the pCNR of VEP and AEP changed with the distribution of BCG electrodes at a given N_B . Also, the variations of these parameter values were smaller at larger N_B values. When N_B increased from 5 to 80, the variation of pPR relative to its average value decreased from 26% to 6% in the simultaneous EEG-MRI experiments, and the pCNR variations of the primary visual/auditory responses was reduced from 19%/19% to 7%/6%. Similar results were also found in the EEG data acquired without MRI scanning. In addition, no statistically significant difference was found in the pPR and pCNR values between the uniform and random selections at all N_B values.

4. Discussion

In this work, we propose to remove the BCG artifact in EEG-fMRI experiments by introducing a practical and efficient BRL method. Our experimental results on human

subjects demonstrate that this new method is able to effectively suppress the BCG noise and retrieve the EEG signals elicited by both spontaneous and evoked sensory neural activities. Furthermore, the comparison results show that in the simultaneous EEG-fMRI experiments, the BRL method can improve the EEG signal quality of the alpha-wave, VEP and AEP to an extent greater than the OBS algorithm by up to 101%, 76%, and 75%, respectively. This suggests that the BRL has a better performance than the traditional method in the BCG artifact removal.

Unlike the BRL method based on the EEG/BCG electrode pairs [Chowdhury et al., 2013], the number of scalp (N_S) and BCG (N_B) electrodes in the present method are not necessarily equal and can be arbitrarily assigned when the BCG cap is produced. In this study, a large N_B value (=160) was set in order to cover the maximum achievable range of N_B values when investigating the performance dependence of BRL on N_B . In practice, the N_S and N_B should be chosen according to the specific demands of the EEG-fMRI study. From Figs. 5 and 7, it can be seen that after the BCG artifact removal, the signal quality of individual EEG traces increases with the increase of N_B , although there are decreasing advantages at higher values. On the other hand, since the sum of N_S and N_B can not exceed the total number of electrodes on the EEG cap, setting a larger N_B will reduce the number of channels that can be used for the scalp recording, resulting in the degradation of spatial resolution of EEG signal. Thus, the choice of N_S/N_B is a compromise between the SNR (in temporal domain) and spatial resolution of EEG signal. In an EEG-fMRI study, one way to optimize the setting of N_S/N_B could be firstly choosing the minimum N_S value that satisfies the requirement of spatial resolution, and then using all the rest channels as the BCG electrodes to obtain the best signal quality.

Since dense-array EEG systems have at least 128 recording channels, there is more freedom in selecting the N_S and N_B values than conventional EEG systems (64-channel or less). The results (Figs. 5 and 7) show that the BRL method will have an overall better performance than the OBS when $N_B \geq 20$. If the N_B value is set to 20, then the number of scalp electrodes (N_S) that can be used on a 128 and 256-channel EEG system would be up to 108 and 236, respectively. In other words, approximately 84%/92% of the total electrodes on the 128/256-channel system can be used for recording the scalp EEG signal. Therefore, when using the BRL method on dense-array (128 and 256-channel) systems, a superior signal quality can be obtained from single EEG channels, and at the same time, there is no significant loss in the spatial resolution of EEG signal compared to the OBS method. In addition, for a given N_S value, more channels can be used as the BCG electrodes on the dense-array than conventional systems. Thus, when using the BRL method to removal the BCG artifact, the dense-array systems can provide higher EEG signal quality than the conventional systems at the same spatial resolution. However, it should be emphasized that although the BRL method favors dense-array EEG systems, it will also be useful for conventional systems with 64 recording channels. Such systems could use the BRL with 20 BCG electrodes, which would improve the EEG signal quality of alpha-wave/VEP/AEP relative to the OBS by approximately 75%/26%/41% or greater, if fewer EEG channels were required

From the VEP data, it was found that the performance difference between the BRL and OBS on the secondary response is substantially larger than that on the primary responses. From

the CNR curves of OBS in Figs. 6A and B, it can be seen that the maximum CNR value in the FWHM window of the P2 peak is comparable to that of the P1/N1 peaks. However, the FWHM of P2 is about six times of that of the P1/N1 peaks. Since the signal energy increases with its duration, the energy of the secondary response peak will be far larger than the primary responses. The OBS is a PCA-based algorithm, and the PCs to be subtracted are ranked by their corresponding energy (variance). Thus, compared to the primary responses, the components of the secondary response will have much higher possibility to be included in the first three PCs. In other words, the secondary peak is more likely to be removed by the OBS algorithm, resulting in a lower pCNR value and larger difference from the BRL method, and then the pCNR increase of the BRL relative to OBS would be higher in the secondary response than the primary response.

It was found that the percent increase in the quality of the alpha-wave and primary VEP and AEP signals acquired with fMRI scan exceeded that without scan, while the opposite result was found in the secondary VEP response. These results suggest that the fMRI scan may have an either positive or negative impact on the relative performance of BRL to OBS, depending on the stimulation task. The fMRI scan can induce two effects related to the EEG signal. One is the artifact generated by the MRI gradients (Allen et al., 2000). Even if the gradient artifact removal was performed in the data preprocessing procedure, there may remain residual gradient artifacts in the EEG data due to head movement. Another effect produced by fMRI scan is the modulation from the background scanner noise to the brain state (Gaab et al., 2008). The previous study (Gaab et al., 2008) has demonstrated that the scanner noise can suppress the major components of the default-mode network, which is believed to be involved in the procedures of neural activation in many brain areas. Thus, the scanner noise may alter the strength of neural activities in the cortical areas activated by stimulation tasks. Due to these two effects, the SNR of the EEG signal with scan may differ from that without scan. Since the performances of BRL and OBS depend on the SNR, the variations in their relative performance may be attributed to the SNR changes induced by fMRI scan.

In the present BRL method, the reference and insulation layers are integrated into the BCG cap. Since the BCG cap uses a permanent and reusable design, the spatial distribution of scalp and BCG electrodes were preset and fixed during the production process. In this study, the calculations based on the approximately uniform BCG electrode distribution aimed to illustrate an easy and unbiased method for setting the positions of BCG electrodes. Nonetheless, an absolutely uniform distribution can not be guaranteed in practice due to the non-uniform electrode distribution on the EEG cap and the irregular head shape. Especially when $N_B = 40$, it is difficult to achieve a uniform distribution (see Fig. 5). The results when using the random distributions showed that the performance of BRL varied with the spatial distribution of BCG electrodes. Thus, the deviation from the uniform distributions may induce the variation in the performance of the BRL method. However, as shown in Fig. 8, the performance variation decreased with the increase of N_B . Depending on the stimulation tasks, the relative errors of performance were in the range of 8%–12% when $N_B = 20$ and all below 7% when N_B reached 80. Since these performance variation values are much smaller

than the improvement values of the BRL relative to the OBS, the error in the spatial distribution of BCG electrodes will not affect the conclusions drawn from the present study.

In this study, the BCG artifact at a scalp position is estimated by the linear combinations of the signals on the reference layer, which are measured by the BCG electrodes. Since the temporal and spatial characteristics of BCG effect depend on the subject's biophysical parameters (e.g., head shape and the scalp blood vessel distribution) and experimental conditions (e.g., the position and orientation of the head in B_0), the correlation relationships of the BCG artifact between one electrode and the others can vary with the electrode position, subject, and experiments (see the supplementary information Fig. S2A). Thus, one BCG electrode position can have different weights in estimating the artifacts at different scalp locations or on different subjects (see the supplementary information Fig. S2B). This phenomenon implies that the accuracy of artifact estimation depends on the spatial distribution of the BCG electrodes, and one fixed distribution pattern can not provide the highest accuracy in all experiments and subjects. To maximize the artifact removal, Xia et al. (2013) proposed to use a greedy Orthogonal Matching Pursuit (OMP) approach to optimize the distribution pattern of BCG electrodes in the BRL method. However, as described in the Introduction section, this optimization method requires a calibration experiment and the production of a custom reference layer, so it may be impractical to apply the OMP approach in conventional EEG-fMRI experiments. In this study, an unbiased and fixed BCG electrode distribution pattern (i.e., the uniform distribution) was used to sample the signals on the reference layer. Although it may be sub-optimal compared to the OMP approach, it is more practical and enables the present BRL method to perform substantially better than the OBS method, even if using as few as 20 BCG electrodes. In addition, the results (Fig. 8) show that the dependence of performance on the distribution pattern can be reduced by increasing the N_B . When sampling the reference layer with dense BCG electrodes (e.g., 80 electrodes), their distribution pattern unlikely needs to be optimized because this will not be a critical factor for the performance of BRL.

Since the design of the BCG cap in this study does not change the EEG cap, the BRL method proposed here can be easily extended to other types of EEG systems. In addition to the EGI's system used in the present work, we have also applied a similar design of reference layer on a 64-channel EEG system manufactured by Brain Products (BP) GmbH (Gilching, Germany) and performed the same experiments as in this study with the setting of 32/32 scalp/BCG electrodes. It was found that the results with the BP system agreed well with this study (data not shown). This suggests that the proposed BRL method has robust performance on EEG systems from different manufacturers having markedly different electrode designs.

In the setup of BRL, the reference electrode on the EEG cap is placed on the scalp and insulated from the BCG electrodes, so there is no closed loop between the reference and BCG electrodes. Since EEG systems use high impedance amplifiers, there is a high-impedance resistance between each EEG channel and the reference electrode, and any electric potential difference drives minimal current flow between the electrodes. Thus, the open loop between the BCG and reference electrodes will not act as an antenna and no RF dissipation will occur in the EEG channels. No safety issue was observed with either EGI or

Brain Product systems when using the BRL setup. In addition, the impedances of the BCG electrodes ($\sim 20 \text{ K}\Omega$) were comparable to those of the scalp and reference electrodes. Thus, introduction of the BRL should not significantly affect the performance of the common mode rejection (CMR) circuitry in the EEG system, which is determined by the electrode impedance and the input impedance of the amplifier (Kappenman et al., 2010). Finally, the EEG data recorded on the scalp and reference layer were separately re-referenced to their corresponding average signal. All signal components common to all the scalp or BCG electrodes are removed by the re-reference procedure. The original output signals from the scalp/BCG channels represent the potential differences between the scalp/BCG and reference electrodes. However, after the re-reference procedure, the signal in the reference electrode is removed from all the BCG electrodes, and the remaining signal should only contain BCG artifacts from the reference layer. Thus, the placement of the reference electrode on the scalp will not affect the waveforms of the signals in the BCG electrodes and their relationships with the scalp EEG signals.

Since blood is a conductive fluid, the positive and negative ions in the blood flow will be separated by the static magnetic field (Hall effect), resulting in cardiac-related variations in the electric field on the scalp (Muri et al., 1997), so the Hall effect also contributes to the BCG artifact. Due to the insulation between the scalp and reference layer, the BCG electrodes are unable to detect the BCG artifact induced by the Hall effect. Thus, BRL methods can not directly remove the Hall effect artifact components. Although the artifacts produced by the Hall effect are much smaller than the effects of head movements and local blood vessel expansions, they have more pulse-to-pulse variability than the latter two effects (Mullinger et al., 2013), and the artifact variability is believed to be the main source of the residual artifacts after the BCG artifact removal procedure. However, both the previous (Chowdhury et al., 2013; Xia et al., 2013) and present studies showed that the residual BCG artifact in the BRL methods are much smaller than the traditional methods (i.e., AAS and OBS). This may imply that compared to the AAS and OBS methods, the BRL is able to more effectively suppress the artifact components induced by the head motions and blood vessel expansions. Thus, the BRL still shows better performance than the AAS and OBS, even if it can not completely remove the artifact residuals due to the Hall effect. In addition, it should be noted that although the physical mechanism of Hall effect differs from the head movement and blood vessel expansion, it does not necessarily mean that the time courses of the artifacts induced by the Hall effect are completely uncorrelated with the latter two effects. Since all these effects are driven by the same source - cardiac pulsations, they may include common temporal characteristics. In other words, the Hall effect may be partially correlated with the other two effects. For this case, the correlated components can be predicted by the linear combination of the BCG electrode signals. This means that the Hall effect can be partially removed by the present BRL method.

In summary, the present study demonstrated a practical and efficient BRL method for suppressing the BCG noise in simultaneous EEG-fMRI experiments. Compared to the traditional method (OBS), this new method shows superior performance on spontaneous and sensory evoked neural activities. By applying this BCG artifact removal strategy, concurrent EEG and fMRI signals can be better fused and may provide a more reliable and powerful spatiotemporal tool for studying brain function.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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Highlights

- A method based on BCG reference layer (BRL) are used to remove BCG artifacts
- Both reference and EEG signals are recorded with a standard EEG cap
- The BRL effectively suppresses BCG artifacts and retrieves EEG signals
- The recovery of EEG signal is higher than the traditional method by up to two-fold

Fig. 1. Design and setup of BCG cap. (A) Schematic drawing of BCG cap. (B) and (C) show the BCG cap taken from outer and inner views, respectively. (D) Setup of BCG and EEG caps on a subject's head.

Fig. 2.

Dependence of the performance of OBS on the N_{PC} used in the algorithm. The normalized alpha pPRs were calculated from the eyes open/closed data without MRI scan. The data points are expressed as the averaged value over the subjects $\pm$ standard error of mean (SEM).

Fig. 3.

A segment of EEG recordings with the eyes open/closed task. (A) Raw data measured in the BCG electrodes. (B) EEG traces from the raw data recorded in the scalp electrodes and the corresponding data after the BCG artifact removal with the OBS and BRL methods. The topomaps in (A) and (B) indicate the BCG and scalp electrode positions, respectively. The red and green arrows indicate the BCG artifact and alpha wave signal, respectively. All the data are taken from the same time window, with the task timing shown at the bottom.

Fig. 4.

Performance comparison of the OBS and BRL in the spontaneous alpha-band EEG data from a typical subject (Subject 2). (A) Power spectra of a scalp electrode during eyes open and closed in the EEG data acquired without fMRI scan. The green dot on the topomap shows the electrode position, which is the same as the electrode 6 in Fig. 3B. The figure shows the results when using the OBS with $N_{PC} = 3$ and BRL with $N_B = 80$ (BRL-80) and 160 (BRL-160) to remove the BCG artifacts. The BCG electrodes at $N_B = 80$ were selected from the case of $N_B = 160$ using the uniform selection method. (B) The ratios of the power spectra at eyes closed to those at eyes open in the OBS and BRL data without MRI scan. (C) and (D) illustrate the power spectra and the power ratio curves in the EEG data concurrently recorded with fMRI scan.

Fig. 5.

Ratios of alpha pPR of BRL to OBS when using different number of BCG electrodes. The pPR ratios are the values averaged over the five subjects and expressed as the mean $\pm$ SEM. The topomaps in the figure show the corresponding spatial distribution of the BCG electrodes, where the red dots represent the locations of BCG electrodes on the scalp.

Fig. 6.

VEP and AEP signals after the artifact removal with the OBS and BRL in a representative subject (Subject 2). (A) shows the VEP signals of a scalp electrode averaged from the 150 trials without the MRI scan, and (B) shows the case with the scan. (C) and (D) show the AEP signals without and with the scan, respectively. The shade areas indicate the standard error of mean (SEM) across the trials. (E) and (F) illustrate the CNR curves of the VEP signals without and with MRI scan, respectively. (G) and (H) present the corresponding results of AEP. The green dot on the topomap shows the electrode position.

Fig. 7.

Ratios of pCNR of BRL relative to OBS when using different number of BCG electrodes. Each data point represents the result averaged over the five subjects. (A) and (B) shows the results from the VEP and AEP data, respectively.

Fig. 8.

Variation of the performance of BRL on spatial distribution of BCG electrodes. (A) Variations of pPR during eyes open/closed. The data are expressed as mean $\pm$ SEM of the five subjects. (B) and (C) show the variations of pCNR of VEP and AEP, respectively.

Table 1

Acronyms and abbreviations

AAS	Averaged Artifact Subtraction
AEP	Auditory Evoked Potential
BCG	Ballistocardiogram
BRL	BCG Reference Layer
CNR	Contrast-to-Noise Ratio
EOI	Electrode of Interest
FWHM	Full-Width-at-Half-Maximum
ICA	Independent Component Analysis
N_B	Number of BCG Electrodes
N_{PC}	Number of Principal Components
N_S	Number of Scalp Electrodes
OBS	Optimal Basis Sets
PC	Principal Component
PCA	Principal Component Analysis
pCNR	Peak CNR
PPG	Photoplethysmography
pPR	Peak Power Ratio
SEM	Standard Error of Mean
S.D.	Standard Deviation
SNR	Signal-to-Noise Ratio
VEP	Visual Evoked Potential