Constrained ICA Based Ballistocardiogram and Electro-oculogram Artifacts Removal from Visual Evoked Potential EEG Signals Measured inside MRI

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Abstract. In the simultaneous acquisition of EEG and fMRI, analysis of EEG signals is a difficult task due to ballistocardiogram (BCG) and electro-oculogram (EOG) artifacts. It gets worse if evoked potentials are measured inside MRI for their minute responses in comparison to the spontaneous brain responses. In this paper, we propose a new method for removing both artifacts simultaneously from the evoked EEG signals acquired inside MRI using constrained Independent component analysis (cICA). With properly designed reference functions for the BCG and EOG artifacts as constraints, cICA identifies the independent components (ICs) corresponding to the artifacts. Then artifact-removed EEG signals are reconstructed after removing the identified ICs to obtain evoked potentials. To evaluate our proposed technique, we have removed the artifacts with cICA and the standard template subtraction technique and generated visual evoked potentials (VEPs) respectively which are compared to the VEPs obtained from EEG signals measured outside MRI. Our results indicate that our cICA technique performs better than the standard BCG artifact removal methods with some efficient features.

1 Introduction

Simultaneous EEG and fMRI acquisitions and analysis hold promises toward imaging spatiotemporal activities of the brain in the superior resolution of space and time, since EEG provide msec temporal resolution and fMRI mm spatial. However, EEG signals acquired inside a MRI scanner get corrupted by significant artifacts: most prominent of which are Ballistocardiogram (BCG) and Electro-oculogram (EOG) artifacts. It is known that BCG artifacts are generated by movement of EEG electrodes inside the magnetic field due to pulsatile changes in blood flow tied to the cardiac cycle and EOG artifacts by the movement of the eyes of the subject.

There have been a few previous attempts to remove these artifacts from continuous EEG signals to recover spontaneous responses of the brain. The very first technique was proposed by Allen et al. [1] where an artifact template for each channel was obtained by averaging the artifact per each heart beat and was subtracted from EEG

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signals. Although it was a straight-forward approach, it is associated with less representative templates and required the simultaneous acquisition of ECG. In 2002, Bonmassar et al. [2] used motion sensors to measure the head movements and utilized the adaptive Kalman filters to remove the artifacts. Subsequently, in 2004, Kim et al. [3] proposed an improved BCG artifacts removal technique using an efficient heart beat detector. These two techniques used an adaptive filtering scheme for the artifact removal and utilized the ECG measurements. Lately, Srivastava et al. [4] and James and Gibson [5] used conventional Independent Component Analysis (ICA) and temporally constrained ICA to remove the BCG artifacts from EEG and MEG respectively. However the former technique involved manual selection of ICs and the later dealt with MEG signals which do not contain MR-induced effects. It should be noted that the BCG artifact affects each electrode differently (i.e. non-stationary effects are present in case of EEG). Therefore the BCG artifact in EEG recordings inside MRI is more difficult to remove. Recently, we came up with an approach to remove the BCG and EOG artifacts from spontaneous EEG signals using the constrained ICA method with properly derived constrains for the artifacts [6] [Tahir et al., ISMRM 2006].

In this work, we have extended our approach to extract evoked potentials of EEG signals measured inside MRI. This task puts our artifact-removal technique on a much harder test since evoked responses measured in EEG is a few magnitude smaller than the spontaneous responses in the continuous EEG and there have been only few recent attempts to recover visual evoked responses (VEPs) recorded during fMRI with the Allen’s technique [7] [8] [Becker et al., 2005; Comi et al., 2005].

In this work, we introduce an improved artifact removal scheme utilizing constrained ICA (cICA) to recover the VEPs from EEG signals measured inside MRI. We evaluate our technique by comparing the recovered VEPs to those obtained from the outside EEG signals and the Allen’s method. Our preliminary results clearly demonstrate that our proposed approach is more effective and convenient, and outperforms the conventional techniques.

2 Experimental Methods

Visual evoked potentials upon checker-board reversals (1 or 2Hz) were recorded from four healthy volunteers inside and outside the 3.0T whole body MRI scanner (Magnum 3.0, Medinus, Korea). The volunteers (four men, mean age of 26.6) with no previous history of neurological and psychiatric disturbance were recruited from an academic environment. We used a MRI-compatible 32-channel EEG recording system (BrainAmp MR, Brain Products GmbH, Germany) for EEG data acquisition. The EEG signals were amplified and then transformed into optical signals in the EEG amplifier to be transmitted to the EEG data acquisition system placed outside the MRI shield room. We used the sampling rate of 1 KHz and the bandwidth of 1-60Hz for band-pass filtering. All the EEG recordings were performed with the standard 10-20 uni-polar system referenced to Cz. Electrode skin impedance was kept below 1KΩ. To minimize motion artifact in EEG on the scalp electrode of the subject, we tightly fixed the EEG cap on the scalp using adhesive tapes. Furthermore, to minimize the motion artifacts of the EEG lead wires between the EEG cap and the EEG amplifier, we fixed the lead wires to a supportive structure using plastic ties. The study was approved by the institutional ethics review committee of Kyung Hee University, Korea, and written informed consent was obtained from each subject.

3 Constrained Independent Component Analysis with References

ICA performs blind source separation (BSS), assuming linear mixing of the sources. Several different implementations of ICA can be found in the literature [9]-[11]. We will not discuss those implementations in this paper and restrict ourselves to cICA with references.

Let us denote the time varying observed signal by $x(t) = (x_1(t),..., x_n(t))^T$ and the source signal consisting of independent components by $s(t) = (s_1(t),..., s_m(t))^T$. The linear ICA assumes that the signal $x(t)$ is a linear mixture of ICs:

$$x(t) = As(t) \tag{1}$$

where $x(t)$ is the observed signal. The matrix A of size nxm represents linear memory-less mixing channels.

The algorithm must find a separating or de-mixing matrix such that

$$s(t) = Wx(t) \tag{2}$$

The problem of this conventional ICA approach is that ICA yields the ICs whose number matches the given number of channels. Then users must manually identify which ICs represent what sources. This is because 1) neither energies nor signs of the ICs can be calculated and 2) there is no ordering between the ICs. In addition, it is possible that a source of interest can be represented with multiple ICs, making the selection task difficult.

In many blind signal separation problems, one may only want to reliably obtain a particular desired component or a set of desired sources, and automatically discard the uninteresting signals or noises. Constrained ICA is the best candidate for these types of applications if the constraints for cICA carry some information of the desired sources. Therefore, if we have some a *priori* information about the desired sources, we can incorporate this information into cCIA. The cICA algorithm described by J.C. Rajapakse and Wei Lu [12] uses a *priori* information about the desired IC as reference signal $r(t)$ to obtain an output which is statistically independent from other sources. The reference signal must carry some information about the desired IC. It does not need to be a prefect match, but it should be close enough to point the algorithm in the direction of a particular IC. The closeness constraint can be written as

$$g(w) = \varepsilon(y,r) - \xi \le 0 \tag{3}$$

where ε is some closeness measure and ξ some closeness threshold parameter. The measure of closeness can take any form, such as mean squared-error (MSE), correlation, or any other suitable closeness or similarity measures. In our implementation of the algorithm, we use MSE as a measure of closeness.

As in our study we need to reject multiple artifacts at a time so cICA with multi-reference is used. With the constraints in place, the cICA problem with multi-reference is modeled as follows:

$$\text{maximize:} \quad \sum_{i=1}^{l} J(y_i) \tag{4}$$

$$\text{subject to:} \quad g(W) \le 0, \quad h(W) = 0$$

where

$$J(y) \approx \rho[E\{G(y)\} - E\{G(v)\}]^2 \tag{5}$$

denotes the one-unit ICA contrast function introduced by Hyvärinen [11] [13], W is the weight vectors to be learned, $g(W)$ is the closeness constraint and $h(W)$ constrains the output to have unit variance. Equation (4) is a constrained optimization problem which can be solved through the use of an augmented Lagrangian function. Learning of the weights is achieved through a Newton-like learning process and Lagrange parameters through gradient-ascent method.

4 Artifacts Removal using cICA with Reference

In the previous attempts of BCG and EOG artifacts removal [1]-[5] [7] [8], some traces of the artifacts have been utilized. For instance, to remove eye blink- or eye movement-related artifacts, relative timing information is extracted or measured. However, the BCG artifacts are known to be non-stationary and vary channel-to-channel in its timing and waveforms, making difficult to generate a single reference template. Therefore in the Allen's technique, a standard technique in most commercial software, a template has been generated for each channel.

In our preliminary work [6], for the artifacts removal from the continuous EEG signals to recover spontaneous responses, we proposed several approaches of generating proper references or constraints for the BCG and EOG. In this work, we have utilized the PCA-reference technique where two principle components are extracted from all EEG signals and used as reference constraints for cICA. Advantages of this approach are that 1) there is no need to record ECG, 2) it is a relatively simple procedure in comparison to other adaptive methods, and 3) all steps can be automated.

The reference signal generation depends on the application area and the type of the signal one wants to extract. The general observation about the artifacts is that they have high amplitude compared to the EEG spontaneous rhythms or evoked potentials, so if we take the PCA of the EEG data then the first one or two components, that correspond to the highest Eigen values, will represent the general features of the BCG and EOG artifacts. Other non-artifactual waveforms of interest in the recorded EEG or MEG can also be extracted given an appropriate temporal reference. Then Equation (3) in our scheme becomes,

$$
\begin{aligned}
&g_1(w) = E\{(w^T x - PC_1)^2\} - \xi \le 0 \\
&g_2(w) = E\{(w^T x - PC_2)^2\} - \xi \le 0 \\
&g(W) = (g_1(w), g_2(w))^T \le 0
\end{aligned}
\tag{6}
$$

where PC_1 is the first Principal Component, PC_2 is the second Principal Component and ξ is a threshold parameter. One should note that ECG signals cannot be used as a reference due to its non-stationary nature. We also confirmed the timing of heart activity does not quite match the occurrence of BCG.

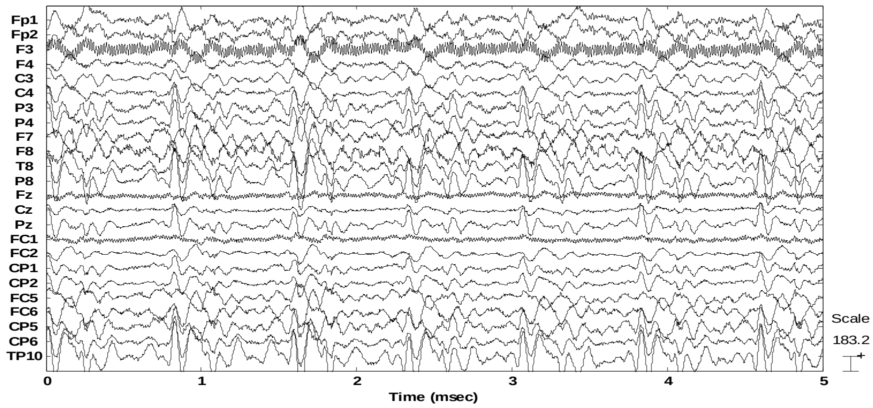
We applied the above technique to evoked EEG signals measured inside MRI and removed the artifacts. From the artifact-removed EEG signals, we applied the band-pass filter and then averaged the epochs to obtain VEPs.

5 Results

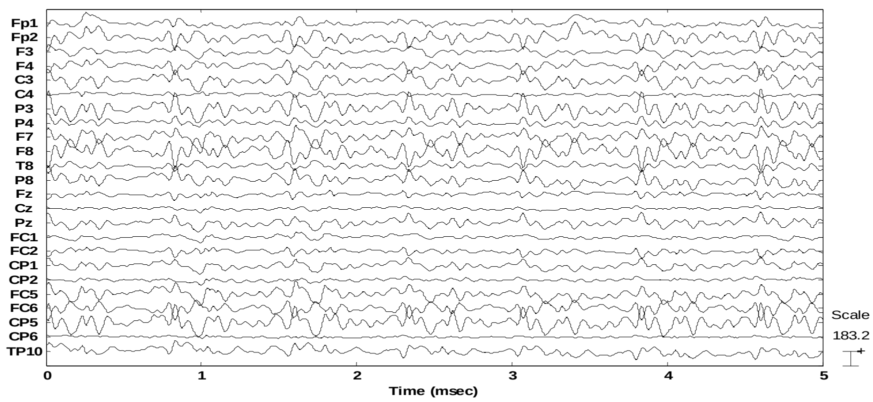
The checker-board reversal visual evoked potentials were collected with the 10-20 standard EEG setup with the sampling frequency of 1KHz. One extra channel was used for EOG and two extra channels for ECG, although ECG was not used in the artifact removal process.

The principal components of the 29 channels were calculated and two PCs that correspond to the highest Eigen values were used as references to the cICA algorithm. We consider that the first and second PCs contain enough information to represent the BCG and EOG artifacts. The EEG signals were centered, whitened and then fed into the cICA algorithm along with the two reference signals. The reference signals were also centered and whitened. The two independent components extracted by cICA that correspond to the BCG and EOG artifact are then projected back into the measurement space and then subtracted form the EEG signals to get the artifact free EEG signals. Fig. 1 (a) and (b) show the EEG signals before and after the artifact removal. Most channels show that our method is effective, removing the BCG and EOG artifacts, except few channels affected by improper electrode contacts. Fig. 2 shows one representative channel (P4) showing one original EEG (blue) and its artifacts-removed signal (red). The dashed vertical bars indicate the BCG artifacts. There is a significant reduction of the artifacts in the signal.

The VEPs were obtained from the artifacts-removed EEG signals which were bandpass filtered (0.1-30Hz) and averaged according the event timings. To validate the VEPs obtained inside MRI, we have computed the VEPs from the EEG signals acquired outside MRI with the identical experimental settings and used them as the gold-standard. Linear correlation coefficients (cc) were used to measure the similarity of the VEPs after correcting a few msec time delay of the VEPs inside MRI which has been observed by other groups as well [7] [8]. The cc values are in the range of 0.6 to 0.9. Fig. 3 shows a typical result where the recovered VEP is shown against the outside VEP and the VEP obtained from the artifact-present EEG. It is clear that the recovered VEP is very much similar (cc=0.84) to the outside VEP. The occipital P1 and N1 peaks can be identified at similar latencies in both recording conditions. The P1-N1 complex was detected in all the case. The cc values of a few other channels are also given in Table 1, showing high correlations to the standard.



(a)



(b)

Fig.1. Continuous EEG signals. (a) 24 channels before artifact removal and (b) after artifact removal, new patterns are now visible.

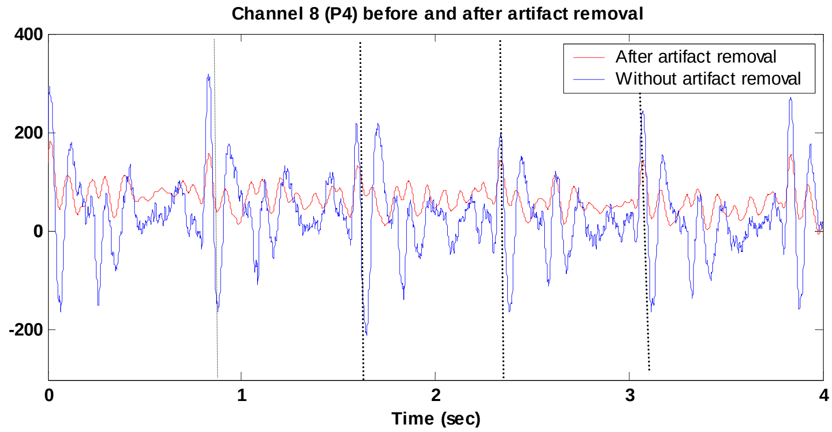


Fig. 2. EEG signal at Channel P4 before removal (blue) and after (red).

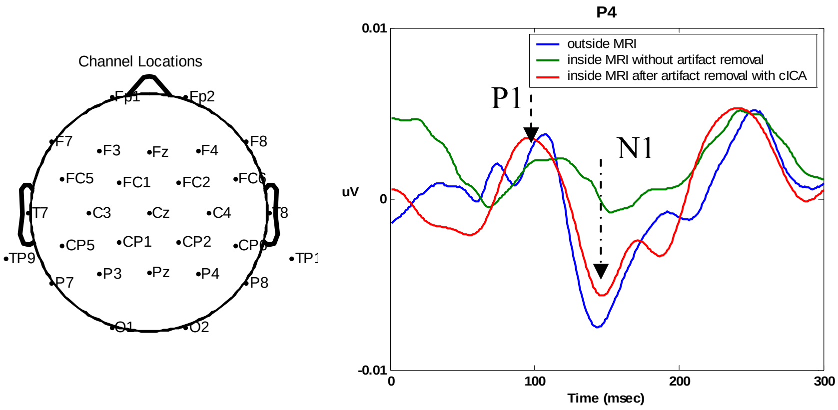


Fig. 3. Electrode locations and visual evoked potentials at P4 showing the response outside MRI (blue), inside MRI after removal (red), and with out removal (green).

6 Comparison against the Template Subtraction Method

Although there have been a few independent studies to recover spontaneous brain waves from EEG data acquired inside MRI [1]-[6], there are few studies of evoked potentials of EEG inside MRI. Two recent studies [7] [8] used the Allen's template subtraction method available from the commercial software and showed its effectiveness in recovering the VEPs.

In the Allen's method, the BCG artifact can be reduced by subtracting the BCG template, thus requiring the estimation of an artifact template. This template is estimated by averaging every channel with epochs time-locked to the complex ECG waveform and using a linear regression to eliminate slow baseline trends. The estimated template is then subtracted from an each heart-beat section of EEG.

To test our technique against the Allen’s, we have implemented the Allen’s method and obtained the VEPs. Fig. 4 shows the performance of our artifact removal against the Allen’s method. A set of eight EEG channels are shown with the VEPs from the Allen’s (black) and our cICA method (red) against the VEP from outside EEG (blue). As the correlation values indicate, in Table 1, our cICA method performs much better than the standard Allen’s method.

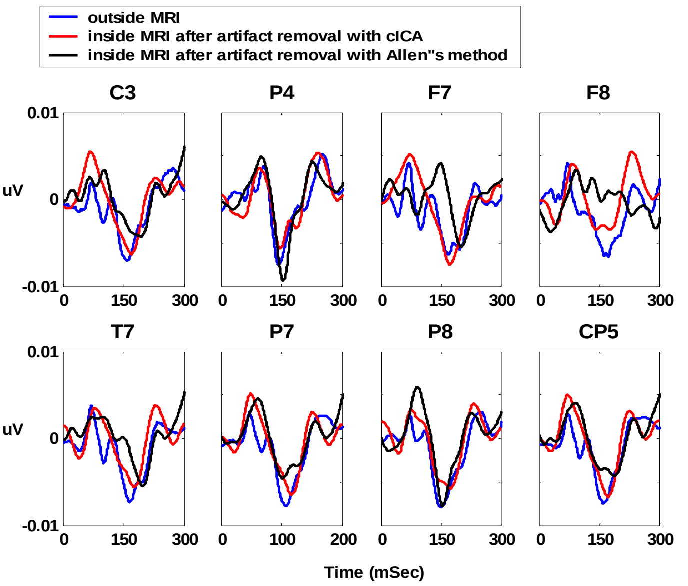


Fig.4: Comparisons between our cICA and the Allen’s Methods.

Table.1: Correlation Coefficients between the outside VEPs and the VEPs after artifact removal with the cICA and Allen’s Method respectively.

Channel Name		**C3**	**P4**	**F7**	**F8**	**T7**	**P7**	**P8**	**CP5**
Correlation	**cICA Method**	0.76	0.84	0.78	0.6	0.81	0.81	0.9	0.84
	Allen’s Method	0.7	0.84	0.35	0.4	0.64	0.78	0.8	0.77

7 Discussion and Conclusions

In this study, we have introduced a new way of removing the BCG and EOG artifacts simultaneously from EEG signals measured inside MRI. The technique uses the cICA technique utilizing a priori information of the artifacts as references or constraints in the algorithm. Previously, a motion sensor signal was utilized in an adaptive filter scheme to remove the motion-related artifacts [2] and the recent reports

[7] [8] utilized the ECG signals in the template subtraction scheme. However our technique requires no extra sensor measurements and derives artifact references from data themselves. In fact, motion and ECG signals are very much non-stationary (i.e., the effect of this artifact at different electrodes is different in time domain) and the artifact removal methods depend much on the quality of them. Other advantages of our method include that 1) multiple artifacts can be removed simultaneously, 2) artifact removal can be fully automated with our technique, 3) our technique can be generalized for any other artifacts if a *priori* information is available, and 4) other non- artifactual wave form can be extracted, giving a proper reference. Based on the results we have presented in this work, our proposed scheme seems to outperform the current standard schemes with some convenient features.

We believe that the cICA with the proposed reference function generation scheme could be an effective tool for the BCG and EOG artifact removal from EEG data measured inside MRI to extract evoked potentials. The proposed technique could facilitate the simultaneous EEG and fMRI studies involving evoked responses of the brain.

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