Complete artifact removal for EEG recorded during continuous fMRI using independent component analysis

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The simultaneous recording of EEG and fMRI is a promising method for combining the electrophysiological and hemodynamic information on cerebral dynamics. However, EEG recordings performed in the MRI scanner are contaminated by imaging, ballistocardiographic (BCG) and ocular artifacts. A number of processing techniques for the cancellation of fMRI environment disturbances exist: the most popular is averaged artifact subtraction (AAS), which performs well for the imaging artifact, but has some limitations in removing the BCG artifact, due to the variability in cardiac wave duration and shape; furthermore, no processing method to attenuate ocular artifact is currently used in EEG/fMRI, and contaminated epochs are simply rejected before signal analysis. In this work, we present a comprehensive method based on independent component analysis (ICA) for simultaneously removing BCG and ocular artifacts from the EEG recordings, as well as residual MRI contamination left by AAS. The ICA method has been tested on event-related potentials (ERPs) obtained from a visual oddball paradigm: it is very effective in attenuating artifacts in order to reconstruct clear brain signals from EEG acquired in the MRI scanner. It performs significantly better than the AAS method in removing the BCG artifact. Furthermore, since ocular artifacts can be completely suppressed, a larger number of trials is available for analysis. A comparison of ERPs inside the magnetic environment with those obtained out of the MRI scanner confirms that no systematic bias in the ERP waveform is produced by the ICA method.

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Introduction

The integration of simultaneous electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) is an emerging method in human brain mapping. The first modality provides signals associated to the electrophysiological cerebral activity with high temporal resolution, whereas the second one provides signals related to the hemodynamic response with high spatial resolution; consequently, it has been possible to make use of the strengths of these two techniques, combining their complementary information (Bonmassar et al., 2001; Krakow et al., 2000; Lemieux et al., 2001a; Salek-Haddadi et al., 2002).

Simultaneous recording of EEG and fMRI proved to be effective in studying epileptic activities (Bénar et al., 2003; Krakow et al., 2001; Lemieux et al., 2001b), the alpha rhythm (Goldman et al., 2002; Laufs et al., 2003), event-related brain responses (Bonmassar et al., 1999; Comi et al., 2005; Kruggel et al., 2000) and cerebral activation during different sleep stages (Czisch et al., 2002; Liebenthal et al., 2003).

However, in EEG/fMRI studies, some technical difficulties are induced by the combined use of the two modalities; in particular, EEG data acquired in the MRI scanner are contaminated by artifacts of biological and non-biological origin that may prevent the correct determination of the characteristics of the brain signals.

In general, there are three main kinds of disturbances that could contaminate the EEG signal changes associated to cerebral activity and that should be removed from the recordings before further analysis: imaging, BCG and ocular artifacts. Among them, imaging and BCG artifacts are produced by the MRI environment, whereas ocular artifacts can also be found if the acquisition is performed out of the MRI scanner.

The imaging artifact is induced by the switching of gradient magnetic fields used for spatial encoding in MRI, with intensity being 10 to 100 times larger than that of the EEG signal (Allen et al., 2000; Felblingen et al., 1999). Although the artifact shape and amplitude are fairly regular for each EEG channel, it can change from one channel to another depending on the location of the electrodes and the wire connections.
The BCG artifact arises from slight electrode movements in the high static magnetic field, due to the subject's pulsatile scalp and blood movement. It is associated to the cardiac cycle and may be enhanced by whole-body movements, especially when the subject lies in the supine position. The amplitude of the BCG artifact can be comparable to or higher than that of EEG (Allen et al., 1998; Bonmassar et al., 2002). The basic waveform of the BCG artifact in any single EEG channel is similar from one occurrence to the subsequent, but the artifact shape, amplitude and scale over time present significant variations related to changes in heart rate and cardiac wave duration.

The ocular artifact is a biological, non-neural disturbance generated by subject eye blinks and eye movements. This signal is irregular, mainly distributed in EEG over the frontal region, with large differences across subjects; it can be much larger in amplitude than EEG signals, hence posing a serious problem for further analysis, especially in the case of ERP studies, because they might be time-locked to experimental events (Jung et al., 2000).

A variety of procedures for specifically attenuating the effects of a single class of artifacts have been reported in the literature, whereas, to our knowledge, no method able to simultaneously remove different kinds of disturbances has been proposed for processing EEG data acquired during continuous fMRI.

A common strategy to avoid interference from ocular artifacts in EEG/fMRI studies is to reject all EEG epochs containing artifacts larger than some arbitrarily selected EEG voltage value. However, when limited data are available, or when blinks and eye movements occur too frequently, the amount of data lost to artifact rejection might be unacceptable.

The most popular processing technique for the attenuation of imaging artifact is averaged artifact subtraction (AAS) (Allen et al., 1998; Allen et al., 2000). AAS takes advantage of the repetitive pattern of the artifact to generate an average artifact template and then subtract it from the EEG data. The effectiveness of this method has been demonstrated for the imaging artifact; however, it requires a high sampling frequency and some residual contamination may remain in some channels (Allen et al., 2000; Bénar et al., 2003; Niazy et al., 2005).

A similar approach is typically used for attenuating the BCG (Allen et al., 1998); unfortunately, simply subtracting the average heartbeat waveform within a predetermined interval can introduce errors into the processed EEG because of the changes in cardiac wave duration and morphology. An interesting alternative technique for the elimination of BCG artifacts is the independent component analysis (ICA), which has proved to perform better than AAS, because it makes no assumptions about the shape of the source signals and does not require the use of a reference signal (Srivastava et al., 2005).

ICA is a signal processing technique that can be used to recover independent sources (or components) from a set of simultaneously recorded signals that result from a linear mixing of the source signals (Comon, 1994; Hyvärinen et al., 2001; James and Hesse, 2005; Lee, 1998). In the last years, several studies have been performed in neurobiological data analysis, and ICA has become increasingly popular for characterization of brain activations (Delorme and Makeig, 2004; Debener et al., 2005; Jung et al., 2001; Makeig et al., 2002); it has also been successfully used for removal of eye blinks, eye movements and electrocardiogram (Flexer et al., 2005; Friarte et al., 2003; James and Gibson, 2003; Jung et al., 1998, 2000). Up to now, the main limitation of ICA for EEG data acquired in the MRI scanner is its intrinsic difficulty in processing recordings containing high-power disturbances (Niazy et al., 2005). This has allowed its use only for EEG data that are not simultaneous to MRI scanning, collected from interleaved EEG/fMRI acquisitions (Srivastava et al., 2005). In our work, we developed a stable processing method for EEG data obtained from simultaneous fMRI acquisitions. We successfully used ICA after subtracting imaging artifact by means of AAS. We were able to concurrently remove BCG and ocular artifacts from EEG acquired in the fMRI scanner, as well as residual MRI contamination. This allowed us to reconstruct dependable and noise-free brain signals that could be possibly used in clinical studies based on EEG/fMRI integration.

Material and methods

**EEG/fMRI acquisition**

Functional images were acquired with a Siemens Magnetom Vision scanner at 1.5 T by means of T2*-weighted echo planar imaging (EPI) free induction decay (FID) sequences with the following parameters: TE 60 ms, matrix size 64×64, FOV 256 mm, in-plane voxel size 4 mm×4 mm, slice thickness 7 mm and no gap. Functional volumes consisted of 16 bicommissural slices, acquired with a volume TR of 2500 ms and a scan time of 1620 ms.

For EEG data collection, a 32-channel MR-compatible BrainAmp system (Brain Products GmbH, Germany) was utilized, along with a specially designed electrode cap (BrainCap). All the electrodes, which were placed on the scalp according to the international 10–20 system, were ring-type sintered nonmagnetic Ag/AgCl electrodes. An additional channel, dedicated to the electrocardiogram (ECG), was placed over the subject chest (fifth intercostal space, left midclavicular line); furthermore, two channels (EOG1, EOG2) were positioned over the subject's earlobes, and their average was used as reference. The impedance of each electrode was maintained lower than 5 kΩ using an electrode paste. The resolution and dynamic range of the EEG acquisition system were 100 nV and ±3.2 mV, respectively. Data were collected with a sampling rate of 5 kHz; band-pass filtering from 0.016 to 250 Hz was applied, along with 50 Hz notch filtering.

**EEG data processing**

**Preprocessing**

The imaging artifact was attenuated using the AAS method (Allen et al., 2000) implemented in the Vision Analyzer software (Brain Products). Subsequently, data were downsampled to 1 kHz and digital filtered between 0.5 and 40 Hz by means of a Chebyshev II-type filter with 40 dB attenuation and zero-phase distortion.

**Independent component analysis**

Independent component analysis (ICA) was used for the processing of the filtered EEG recordings. ICA is a signal processing technique that models a set of input data in terms of statistically independent variables: it is able to separate independent components produced by distinct sources from linearly mixed signals (Comon, 1994; Hyvärinen et al., 2001; Lee, 1998). The ICA model is described as:

\[ x(t) = A s(t) \]
where \( \mathbf{x}(t) = [x_1(t), \ldots, x_m(t)]^T \) is the vector of source signals, \( \mathbf{x}(t) = [x_1(t), \ldots, x_m(t)]^T \) stands for the vector of mixtures, and \( A \) denotes the \([n \times m]\) mixing matrix (Comon, 1994). The minimal required a-priori information is the independence of the source signals and the fact that at most one of the signals can have Gaussian distribution. The mutual independence of the sources is defined as:

\[
f(s_1, s_2, \cdots, s_m) = \prod_{i=1}^{m} f_i(s_i)
\]

where \( s_1, s_2, \ldots, s_m \) are the source signals, \( f_i \) is the probability density function (pdf) of \( s_i \), and \( f \) is the joint probability density function of \( s_1, s_2, \ldots, s_m \).

A solution for the ICA problem is possible if two additional conditions are met: the mixing matrix is full column rank and the number of recordings is at least equal to the number of source signals (Comon, 1994; Hyvärinen et al., 2001). In this case, the independent components (ICs) can be retrieved by determining a \([m \times n]\) matrix \( W \), named unmixing matrix. Then, the \( m \)-dimensional vector

\[
y(t) = W x(t)
\]

is the best estimate of the source vector \( x(t) \). According to the ICA theory, \( y(t) \) can be found by minimizing the average mutual information (AMI)

\[
AMI = \int f(y) \log \frac{f(y)}{\prod_{i=1}^{m} f_i(y_i)} \, dy
\]

The ICA decomposition of the 30 EEG recordings into 30 source signals was performed by means of the FastICA algorithm (Hyvärinen, 1999). FastICA, in order to solve the ICA problem, preprocesses the data with centering and whitening (Hyvärinen and Oja, 1997). Centering is the subtraction, for each recording, of the average value; whitening is a linear transformation that decorrelates the signals and normalizes them to unitary variance. After the preprocessing phase, the minimization of the AMI among ICs is achieved by maximizing the non-Gaussianity of the estimated source signals. The non-Gaussianity is expressed in terms of the differential entropy \( J \), called negentropy (Comon, 1994), that is the difference between the entropy \( H \) of a Gaussian random variable \( y_{\text{gauss}} \) (having the same mean and variance of the observed random variable \( y \)) and the entropy of \( y \):

\[
J(y) = H(y_{\text{gauss}}) - H(y)
\]

FastICA uses simple estimates of negentropy based on the maximum entropy principle (Hyvärinen, 1998), which requires the use of an appropriate non-linear function \( G \) for the learning rule of the optimization algorithm. The function \( G(u) = \exp(u^2/2) \) was used for EEG data (Hyvärinen, 1999), ensuring robustness and fast convergence. According to the ICA theory, the ICs were retrieved by FastICA in random order (Comon, 1994); they could be optionally sorted after the separation, for example, with respect to their relative power in the EEG recordings (James and Hesse, 2005).

### Artifact removal

The source signals \( y_i(t) \) separated by FastICA were categorized into two signal categories: brain signals and artifacts. This classification was performed either with a manual or with an automated approach. In the first case, the categorization was carried out by visual inspection of the time course of each signal, along with the corresponding scalp map and power spectrum. The second approach was based on the use of reference signals, such as the ECG and EOG recordings (whenever available), and the estimate of the imaging artifact: the occurrence of a large correlation value between the single IC and one of these reference signals indicated that the source signal had to be considered as an artifact.

The IC detection was used to create a \([30 \times 30]\) diagonal matrix \( Z \); each element \( z_{ij} \) was set equal to 1 if the \( i \)-th component was an artifact, while it was set equal to 0 otherwise. The vector of artifact-free EEG recordings \( x_i(t) \) could be then obtained by

\[
x_i(t) = x(t) - A Z y(t)
\]

In this way, the artifacts were subtracted from the EEG recordings with appropriate weights for each channel, and the direct reconstruction of artifact-free EEG signals was accomplished, maintaining their correct spatial distribution.

### Validation

We used seven EEG datasets acquired during fMRI scanning (right-handed healthy subjects, age 19–24 years) for the validation of the proposed method. The protocol was approved by the local Ethics Committee, and all subjects signed a written informed consent prior to participation in the study.

Data were obtained from an ERP visual oddball study. The visual images were prepared using the MATLAB software, specifically the Cogent 2000 toolbox. The stimuli consisted of yellow (80%) and blue (20%) disks, appearing on a black background, and were presented in random sequence every 2.5 s with 200 ms duration. Images were delivered via a NEC LCD projector working at 60 Hz refreshment rate onto a screen placed behind the subject head projection. The time instants of the stimulus presentation were delayed with respect to the triggers and were recorded by means of a photoelectric cell placed on the screen. The data recording lasted about 8 min, with a total number of 38 rare and 152 frequent stimuli.

For all subjects, a second acquisition session was performed, according to the same paradigm, out of the MRI environment.

The performances of the ICA method were tested in terms of:

1. BCG artifact attenuation;
2. ocular artifact removal;
3. overall noise reduction in ERP;
4. ERP scalp map reconstruction. Its outcomes were compared with those of a standard processing method, consisting of band-pass filtering between 0.5 and 40 Hz, cancellation of imaging and BCG artifacts by means of AAS (Allen et al., 1998, 2000), and rejection of epochs containing ocular artifacts.

The efficacy in the removal of the BCG artifact was evaluated analyzing the EEG data, before and after the artifact removal, respectively. The QRS complexes of ECG channel were used as trigger points in order to calculate average signals from the EEG recordings. The average peak-to-peak artifact amplitude before and after artefact rejection with ICA was calculated. The same parameter was also calculated for the standard artefact rejection method. The comparison of the above parameters assessed the efficacy of the BCG artifact attenuation.

Given the characteristics of eye movements, which are fast and occur randomly, the ability of ICA to remove ocular artifacts was
Fig. 1. Illustrative example of 10 s of raw EEG data collected during simultaneous EEG/fMRI (a), and of the same traces after band-pass filtering and imaging artifact attenuation using AAS (b). The acquired ECG signal is also shown (c).
tested by setting an amplitude threshold to the EEG recordings: all epochs with amplitude larger than 80 μV were assumed to contain this kind of artifacts and were considered not to be useful for further analysis. Consequently, for each dataset acquired in the MRI environment, the total number of acquired ERP epochs was compared with the number of epochs available for analysis before and after ICA processing respectively.

As regards the overall noise reduction, after application of both artifact rejection procedures to each dataset, epochs of 600 ms starting 100 ms before each visual stimulus were obtained (baseline correction from 100 ms to 5 ms prestimulus). The segments with amplitude larger than 80 μV were rejected. The noise amplitude in ERPs was calculated as the average root mean square (RMS) of the signal corresponding to the prestimulus interval.

The same averaging procedure was used to obtain ERPs from recordings performed outside the MRI scanner. The averaged signals from acquisitions inside and outside the scanner were compared qualitatively and quantitatively. For each available dataset, the average signals obtained from EEG data outside the scanner were used as a reference. The difference between the latter signals and the average signals acquired inside the MRI scanner, and processed both with AAS and with ICA, was quantified by means of the parameter $d$, hereafter called difference, defined as follows

$$
d = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (s_1(i) - s_2(i))^2}\tag{7}
$$

where $s_1$ and $s_2$ are two signal waveforms of length $N$. Smaller values of $d$ indicate a closer correspondence of waveforms. A similar approach was used to quantify the similarity of scalp maps at a given latency and therefore to assess the quality of the reconstructed scalp maps.

**Results**

An example of raw EEG recordings acquired within the magnetic environment is shown in Fig. 1, as well as the same traces after filtering and imaging interference attenuation with AAS; a residual MRI artifact contamination still remains within these signals, although it is not easily detectable because other disturbances with larger amplitude are superimposed. Three to six BCG components can be expected after ICA processing, whereas one or two ICs related to both ocular and imaging artifacts are generally separated. Among the 30 ICs retrieved from the same dataset of Fig. 1, four corresponding to BCG artifact, one to ocular artifact and two to imaging artifact were detected (Fig. 2). The signals in time and frequency domain and the scalp maps were used for manual classification of the brain signals and the disturbances; an illustration of the corresponding plots used for the categorization is shown in Fig. 3.

For the BCG artifact components, the correlation values with the ECG signal ranged between 0.25 and 0.47 ($p<0.001$); conversely, the remaining ICs showed correlations lower than 0.07 ($p<0.001$). The frequency distributions of the correlations values for the two groups are illustrated in Fig. 4. The

![Fig. 2. Sample segments of the 30 ICs separated with FastICA using the traces presented in Fig. 1b. The ICs 1, 2, 3 and 4 are BCG artifact components; the IC 5 is an ocular artifact component; the ICs 6 and 7 are components that can be ascribed to the imaging artifact residual. The amplitudes are arbitrary because the components are normalized.](image-url)
automatic identification of the BCG components could be correctly performed for all the analyzed datasets, selecting for example those with a correlation value larger than 0.20.

The disturbances were subtracted from the preprocessed recordings with appropriate weights for each channel; the result of the artifact removal is shown in Fig. 5. The quantitative analysis for the BCG artifact rejection is summarized in Table 1; for five out of seven datasets, the ICA method resulted in better artifact rejection than the AAS method. The removal of ocular artifacts was tested on a total of 1330 acquired ERP epochs: an increase from 84% to 100% of epochs available for analysis was obtained with the ICA method.

An example of ERPs obtained from recordings outside the MRI scanner, and inside the MRI scanner using AAS and ICA processing respectively, is shown in Fig. 6. The ICA method shows a higher signal quality due to a more effective artifact removal. This outcome is consistent with the results of the comparison regarding the difference between signal waveforms inside and outside the scanner: ICA performed better for all the seven datasets (Table 2). The results of the artifact rejection presented in Table 3 can further confirm that the quality of signals obtained with ICA was always superior to those of the standard processing method. In addition, the ICA method seems to provide a more reliable reconstruction of the field distribution: the difference between scalp maps at P300 latency for data acquired inside and outside the MRI scanner was always lower for ICA. This can also be qualitatively appreciated from the scalp maps shown in Fig. 7, which refers to the same subject of Fig. 6.

**Discussion**

**Separation of source signals**

ICA have been successfully used for signal extraction in the field of biomedical signal processing. It has proved to be effective in neuroimaging research for the extraction of underlying sources, as well as for the cancellation of interference, from multi-channel electromagnetic brain signals (James and Hesse, 2005). The main advantage of ICA for the attenuation of biological and non-biological artifacts is mainly in its ability to recover the independent activity originating from distinct sources, without relying on a-priori information about their dynamics and/or their spatial structure. Conversely, ICA has also some inherent limitations (Hyvärinen et al., 2001; Lee, 1998). The first one is the loss of information about the amplitude and polarity of ICs, which are normalized to unit variance. Furthermore, the optimal number of temporally independent signals mixed in the EEG recordings is unknown. Unless a dimension reduction procedure is previously performed, the typical ICA model assumes that the number of underlying sources is the same as the number of recording channels: in this case, the ICA decomposition could generally produce a residual number of non-relevant ICs, depending on the correct number of active sources. As a consequence of the problems described above, it is worth noting that the identification of the ICs of interest, which can be carried out in either manual or automatic manner, is unquestionably a non-trivial task (Iriarte et al., 2003; James and Gibson, 2003).

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**Fig. 3.** Example of the information used for the ICs classification: signals in time domain, spectra and scalp maps. The IC 1, 5 and 6, which are respectively BCG ocular and imaging artifacts, can be recognized without difficulty. The IC 14 is a brain signal characterized by alpha rhythm variations: the scalp map shows a dipolar distribution that is associated to an electrophysiological activation in the occipital region.
Artifact removal

The separation of source signal performed by ICA provides a tool for processing EEG recordings, where the signals of interest are generally mixed with other background activity and electrode noise and are contaminated by artifacts of both physiological and environmental origin: ICA has proved to be able to recover the desired signals even when the SNR of the acquired data was quite poor.

In this work, we have presented the results obtained from EEG data recorded during fMRI scanning, demonstrating that the ICA method could also be successful for simultaneously removing BCG and ocular artifacts, as well as residual MRI contamination left after AAS. A remarkable result is that the ICA method performs better than the AAS method for the cancellation of the BCG artifact: AAS relies on averaged artifact subtraction and is affected by the variability in BCG artifact morphology and duration; conversely, ICA is able to isolate the BCG artifact components simply on the basis of their statistical independence from those produced by other neural signal generators and other artifact sources. In case of manual classification of ICs, it can be used without the availability of a...
reference ECG channel (Srivastava et al., 2005). This is an important difference with respect to other processing techniques (Allen et al., 1998; Bonmassar et al., 2002).

As regards the ocular artifacts, the ICA method allowed to preserve all the recorded trials in all the processed datasets. This is a particularly important advantage, especially when limited data are available, or when blinks occur too frequently. As a consequence of the increase in the number of available trials, the SNR improves in the averaged ERP, if compared to rejection-based methods. Moreover, it should be emphasized that ICA, unlike other methods for ocular artifact cancellation (Verleger et al., 1982; Woestenburg et al., 1983), is able to recover useful EEG data at all scalp channels, including frontal and periocular sites, which are mainly affected by signals produced by eye movements.

<table>
<thead>
<tr>
<th>Subject no.</th>
<th>Difference of signal waveforms</th>
<th>Difference of scalp maps</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Standard processing</td>
<td>ICA processing</td>
</tr>
<tr>
<td>Subject no. 1</td>
<td>2.20</td>
<td>2.08</td>
</tr>
<tr>
<td>Subject no. 2</td>
<td>1.87</td>
<td>1.78</td>
</tr>
<tr>
<td>Subject no. 3</td>
<td>3.29</td>
<td>3.06</td>
</tr>
<tr>
<td>Subject no. 4</td>
<td>2.77</td>
<td>2.47</td>
</tr>
<tr>
<td>Subject no. 5</td>
<td>2.35</td>
<td>1.98</td>
</tr>
<tr>
<td>Subject no. 6</td>
<td>3.01</td>
<td>1.66</td>
</tr>
<tr>
<td>Subject no. 7</td>
<td>2.92</td>
<td>2.68</td>
</tr>
</tbody>
</table>

Differences of ERPs acquired inside the MRI scanner, and processed with ICA and AAS respectively, were calculated with respect to ERPs acquired from the same subjects outside the MRI scanner. The differences, which are expressed in microvolt, refer to the average signals calculated for rare events. The comparison of waveforms is performed using the signals from electrode Cz, whereas the comparison of scalp maps is performed using the time instants corresponding to maximum signal amplitude.

As regards the ocular artifacts, the ICA method allowed to preserve all the recorded trials in all the processed datasets. This is a particularly important advantage, especially when limited data are available, or when blinks occur too frequently. As a consequence of the increase in the number of available trials, the SNR improves in the averaged ERP, if compared to rejection-based methods. Moreover, it should be emphasized that ICA, unlike other methods for ocular artifact cancellation (Verleger et al., 1982; Woestenburg et al., 1983), is able to recover useful EEG data at all scalp channels, including frontal and periocular sites, which are mainly affected by signals produced by eye movements.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Noise level of ERP after preprocessing</th>
<th>Noise level of ERP after standard processing</th>
<th>Noise level of ERP after ICA processing</th>
</tr>
</thead>
<tbody>
<tr>
<td>no. 1</td>
<td>Rare events               0.93±0.48          0.81±0.34            0.38±0.15</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Frequent events           0.44±0.26          0.37±0.14            0.20±0.10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>no. 2</td>
<td>Rare events               1.37±0.73          0.89±0.35            0.64±0.34</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Frequent events           0.58±0.31          0.50±0.14            0.30±0.11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>no. 3</td>
<td>Rare events               1.98±0.87          0.62±0.43            0.36±0.16</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Frequent events           0.52±0.19          0.34±0.24            0.19±0.10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>no. 4</td>
<td>Rare events               1.71±0.51          0.97±0.13            0.72±0.12</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Frequent events           0.87±0.27          0.43±0.07            0.40±0.08</td>
<td></td>
<td></td>
</tr>
<tr>
<td>no. 5</td>
<td>Rare events               1.93±0.66          1.07±0.35            0.62±0.28</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Frequent events           0.66±0.26          0.57±0.26            0.26±0.09</td>
<td></td>
<td></td>
</tr>
<tr>
<td>no. 6</td>
<td>Rare events               1.94±0.48          1.41±0.37            0.72±0.18</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Frequent events           0.73±0.19          0.60±0.22            0.26±0.07</td>
<td></td>
<td></td>
</tr>
<tr>
<td>no. 7</td>
<td>Rare events               1.39±0.51          0.85±0.26            0.66±0.22</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Frequent events           0.46±0.15          0.47±0.25            0.21±0.07</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group</td>
<td>Rare events               1.61±0.70          0.94±0.44            0.58±0.28</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Frequent events           0.61±0.28          0.47±0.25            0.26±0.11</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

For each subject, noise amplitude in the 100 ms prestimulus baseline after preprocessing, as well after ICA-based artifact removal and standard artifact removal, is shown for rare and frequent events respectively. The same parameters are also provided for the group of 7 subjects. Amplitudes, which are expressed in microvolt, correspond to the mean value and the standard deviation calculated from all the recording channels.
The imaging artifact, too large to be directly separated by ICA, was attenuated in the preprocessing phase. Nevertheless, the proposed method succeeded in detecting and subtracting the residual imaging artifact left in the recordings.

Reliability of ERPs

The comparative analysis of noise level in ERP between AAS and ICA demonstrates that the latter method, being superior in the elimination of artifacts, is consequently able to provide more dependable signals. This is an important requirement, in particular for ERP studies that necessitate the identification of the correct timing of particularly weak waves. The comparison of ERP scalp maps corresponding to the two recording environments (inside and outside the MRI scanner) suggests that no systematic bias is induced by the ICA-based artifact removing procedure.

Conclusion

The integration of EEG and fMRI is becoming increasingly important for neuroimaging research. However, simultaneous recording of EEG and fMRI leads to some problems related to the quality of both signals. The image quality of fMRI data is affected by the change of susceptibility produced by EEG electrodes; however, this kind of disturbance can be easily minimized with the use of MR-compatible EEG systems (Bonmassar et al., 2001; Krakow et al., 2000). In contrast, the EEG recordings are affected by strong fMRI environment artifacts, which should be removed for the correct determination of brain signals (Allen et al., 2000; Bonmassar et al., 2002; Niazy et al., 2005). Many efforts are at present being made to develop effective digital signal processing techniques for the cancellation of these disturbances: high-field MRI scanners are becoming increasingly popular, so that the problem of disturbances in EEG data acquired in the MRI environment will become even more severe in the next future.

In order to contribute to the solution of this problem, we have presented a new artifact removal method based on ICA. We have tested its efficacy on recordings of ERPs within the magnetic environment, obtaining a good correspondence with data acquired outside the MRI scanner. Although our findings need further verification on larger populations and other study protocols, it is our opinion that the proposed method is more effective and reliable than the currently used methods based only on the adaptive artifact subtraction.

In conclusion, the ICA method for EEG artifact removal demonstrated to be able to provide reliable EEG time series; hence it might be an important tool for human brain mapping studies based on EEG/fMRI integration.

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