Published in final edited form as:

Brain Topogr. 2016 November ; 29(6): 783–790. doi:10.1007/s10548-016-0513-3.

Removing Cardiac Artefacts in Magnetoencephalography with Resampled Moving Average Subtraction

Limin Sun^{1,2}, Seppo P. Ahlfors¹, and Hermann Hinrichs^{3,4,5,6}

Limin Sun: liminsun@nmr.mgh.harvard.edu

¹Department of Radiology, Athinoula A. Martinos Center for Biomedical Imaging, Massachusetts General Hospital, Harvard Medical School, Charlestown, MA 02129, USA

²Division of Newborn Medicine, Department of Medicine, Boston Children's Hospital, Harvard Medical School, Boston, MA, USA

³Department of Neurology, Otto-von-Guericke University, Leipziger Straße 44, 39120 Magdeburg, Germany

⁴Department of Behavioural Neurology, Leibniz Institute of Neurobiology (LIN), Magdeburg, Germany

⁵Deutsches Zentrum für Neurodegenerative Erkrankungen (DZNE), Magdeburg, Germany

⁶Forschungscampus STIMULATE, Magdeburg, Germany

Abstract

Magnetoencephalography (MEG) signals are commonly contaminated by cardiac artefacts (CAs). Principle component analysis and independent component analysis have been widely used for removing CAs, but they typically require a complex procedure for the identification of CA-related components. We propose a simple and efficient method, resampled moving average subtraction (RMAS), to remove CAs from MEG data. Based on an electrocardiogram (ECG) channel, a template for each cardiac cycle was estimated by a weighted average of epochs of MEG data over consecutive cardiac cycles, combined with a resampling technique for accurate alignment of the time waveforms. The template was subtracted from the corresponding epoch of the MEG data. The resampling reduced distortions due to asynchrony between the cardiac cycle and the MEG sampling times. The RMAS method successfully suppressed CAs while preserving both event-related responses and high-frequency (>45 Hz) components in the MEG data.

Keywords

Cardiac artefact; Moving average subtraction; Resampling; MEG

Introduction

In magnetoencephalography (MEG) electrical brain activity is studied non-invasively by recording the magnetic field outside the head. Because the neuromagnetic fields are small,

noise from various sources can severely distort the MEG data (Escudero et al. 2011; Hämäläinen et al. 1993). Environmental background noise can be greatly reduced with magnetically shielded rooms (Cohen 1972). However, biological noise from the subject, e.g., due to eye blinks, eye movements, heart beats, respiration, and muscular tension, need to be suppressed with other approaches (Hari 2005). Cardiac artefacts (CA) due to the magnetic field generated by the electrical activity of the heart are among the most prominent biological artefacts in MEG data (Jousmäki and Hari 1996), commonly more than an order of magnitude larger than the brain signals of interest. CAs can be particularly large in children due to the short distance between the heart and the MEG sensors. Signal averaging can mitigate CA effects in MEG data, but it is of limited use for studies of spontaneous or single-trial event-related brain activity.

Most methods to remove CAs in MEG data are based either on spatial patterns in multichannel data (topographies) or on time-domain templates for individual channels. Approaches based on the spatial patterns include principle component analysis (PCA) and independent component analysis (ICA) (Breuer et al. 2014a, b; Dammers et al. 2008; Escudero et al. 2007, 2011; Mantini et al. 2008; Sander et al. 2002; Shao et al. 2009), signal space projection (Uusitalo and Ilmoniemi 1997), signal space separation (Taulu et al. 2004) and spectral signal space projection (Ramirez et al. 2011). All these methods effectively suppress artefacts when the noise patterns are stationary; however, their performance deteriorates if the CAs vary over the duration of the recording. An additional challenge with the PCA and ICA methods is that an automatic and accurate identification of the artefact-related components is usually difficult.

Template subtraction methods are typically relatively simple to implement and can be made automatic in a straightforward way. Variations of the average subtraction method have been applied to remove spike artefacts in deep brain stimulation (Hashimoto et al. 2002) and magnetic resonance imaging (MRI) related artefacts in EEG data recorded in an MRI scanner such as gradient artefacts (Allen et al. 2000; Becker et al. 2005; de Munck et al. 2013; Garreffa et al. 2004; Sun and Hinrichs 2009) and ballistocardiogram artefacts (Allen et al. 1998; Ellingson et al. 2004; Goldman et al. 2000; LeVan et al. 2013; Shams et al. 2015). Generally, template subtraction techniques are efficient for spikes, nonstationary quasi-periodic noise, and baseline drift (Feuerstein et al., 2009).

One way to take into account variability in the artefacts is to estimate multiple templates using a clustering technique (de Munck et al. 2013). Tal and Abeles (Tal and Abeles 2013) proposed an average template subtraction method for MEG data in which five CA templates, based on the QRS wave amplitude, were constructed instead of a single global average. Another way to address the problem of non-stationarity of the CAs is to use a moving average subtraction method (Allen et al. 1998; Becker et al. 2005; Sun and Hinrichs 2009). This approach assumes that the artefacts vary slowly enough over time to be captured by the weighted average over subsequent occurrences of the artefact. In the present study we used a weighted moving average subtraction method in which a template for the CA was constructed for each individual cardiac cycle.

Because the averaged template subtraction methods are based on time course data, precise alignment of the CAs from different cardiac cycles is important. Although the CAs could be detected in the MEG data itself, the high signal-to-noise ratio of a simultaneously recorded electrocardiogram (ECG) helps to better align the subsequent cardiac cycles. In addition, we used a resampling technique to compensate for the asynchrony between the cardiac cycle and the MEG sampling times. Previously, a similar resampling approach has been used to enhance the removal of gradient artefacts in EEG data recorded during MRI scanning (Sun and Hinrichs 2009). Here, we tested this combined approach for removing CAs in MEG data, called Resampled Moving Average Subtraction (RMAS).

Materials and Methods

Experimental Data

Six subjects (mean age 24, range 19–30 years; two females) with no neurological disorders were recruited from the local community. Written informed consent was submitted from each participant. The study was approved by the local ethics committee of the Goethe University (Frankfurt, Germany).

MEG data were recorded using a 275-channel whole-head system (Omega 2005, VSM MedTech Ltd., BC, Canada) in a synthetic third order axial gradiometer configuration (Data Acquisition Software Version 5.4.0, VSM MedTech Ltd., BC, Canada). The data were filtered using fourth order Butterworth filters with 0.5 Hz high-pass and 150 Hz low-pass, and sampled at 600 Hz. MEG data were recorded for 8 min while the subject was resting with eyes open. A pair of ECG electrodes was placed at the subjects back close to the superior and inferior ends of the heart; this placement was chosen to minimize movement related artefacts. Electrode impedances were $<5 \text{ k}\Omega$.

In addition, we applied the proposed method to data from one subject from our previously published visual perception experiment (Sun et al. 2012), in which a random sequence of upright and inverted-scrambled Mooney face visual stimuli were presented.

Identification of Cardiac Artefacts

For CA removal, the MEG time series data were divided into epochs corresponding to cardiac cycles. CAs vary substantially across MEG channels depending on the relative distance and orientation between the sensors and the CA sources, and often it may be difficult to find the CAs in some MEG channels. Therefore, to reliably identify the cardiac cycles we used the ECG channel, in which the QRS waves were prominent and the influence of background noise or other effects (e.g., body movements, ocular artefacts) was minimal. The ECG signal was high-pass filtered using a third order Butterworth filter with a cut-off at 5 Hz. A threshold value was determined as one-third of the peak-to-peak value within a selected 6-second segment. All peaks beyond the threshold in the ECG channel were identified as R positions of the QRS wave. The epochs were aligned by maximizing the correlation coefficient between a reference QRS (usually the first one) and each individual QRS. The length of the template window was chosen to be the mean of all RR intervals plus 300 ms, and the onset time for each template was defined as the half of the window length

prior to the R position. The additional 300 ms (150 ms at each end) was included to ensure that a full cardiac cycle was always covered.

The QRS detection can be affected by other high amplitude artefacts such as those caused by sudden movements. To identify erroneous (false positive) and missed (false negative) CA detections we evaluated the distance between successive R peaks. If this distance exceeded 2 s we marked the midpoint of this interval to indicate a missed CA. If the interval was shorter than 0.3 s, we removed the subsequent CA. The final alignment of the position of each CA in the ECG channel was optimized to produce a maximum cross correlation with a standard CA averaged over all CAs.

Resampling Procedure

Because of the sharp peaks in the QRS wave, even a small misalignment across epochs due to the finite sampling rate may distort the template and, thereby, result in suboptimal removal of the artefact. To address this issue, a resampling technique was applied, in which data sample values were calculated at a predefined shifted grid of virtual sampling times using a cubic spline interpolation scheme. The resampling algorithm derived an individual temporal adjustment of the signal sampling while keeping the original sampling frequency. This algorithm was previously used by Sun and Hinrichs (2009) to correct for asynchrony between EEG sampling and the timing of MRI gradient switching to remove artefacts in EEG data recorded in an MRI scanner. In principle the procedure of resampling is comparable to upsampling, aligning the current artefact to a reference artefact, and subsequently downsampling, while avoiding the large increase in data volume and computational load required by oversampling approaches.

RMA Method

Moving Average Subtraction (MAS) (Allen et al. 2000; Becker et al. 2005) is a template subtraction method in which a separate template is constructed for each occurrence of an artefact, in our case for each cardiac cycle. Here, the template $T_i(n, t)$ for the i^{th} epoch was obtained as a weighted average:

$$T_i(n, t) = \sum_{k=-N+1}^{N-1} w_k X_{i+k}(n, t), \quad (1)$$

where $X_{i+k}(n, t)$ is the MEG signal for the $(i + k)^{\text{th}}$ epoch at channel n , and t is the time index within each epoch relative to the R peak. The weighting coefficients w_k were

normalized such that $\sum_{k=-N+1}^{N-1} w_k = 1$. The template was filtered by a third order Butterworth band pass filter with cutoff frequencies of 0.1 and 100 Hz before the subtraction in order to remove the DC level and high frequency noise.

We refer to the MAS approach combined with the resampling technique for epoch alignment as the RMA method. The corrected signal was obtained by subtraction:

$$X_i^{\text{RMAS}}(n, t) = X_i(n, t) - T_i(n, t). \quad (2)$$

To prevent signal fragments from being integrated into the artefact corrected signals, we increased the length of each epoch with 150 ms at each side. In this way, one can concatenate the artefact-corrected signals seamlessly by cutting off the overlap between the previous epoch and the current epoch.

We used a linear weighting function defined as

$$w_k = (1 - |k|/N)/N, \quad -N < k < N. \quad (3)$$

Increasing the number of epochs to be included in the weighted average is expected to improve the quality of the template by reducing the contributions from affect the quality of the template. A larger N also means higher computational loads signals not related to the CA. However, variation in the CA patterns for epochs separated over long time periods may adversely. We chose the total number of epochs included in the moving average to be $2N-1 = 49$. This is a trade-off for being large enough such that noise unrelated to CA is substantially reduced by the averaging, yet small enough (corresponding to less than one minute of recording) that non-stationarity of the CA is expected to have only a minor effect on the quality of the template.

Performance Evaluation

The degree of distortion between two signals, $S1$ and $S2$, for frequencies $< F$ was quantified by the Relative Spectral Difference (RSD):

$$\text{RSD} = \sum_{f=1}^F \left| P_f^{S1} - P_f^{S2} \right| / \sum_{f=1}^F P_f^{S1}, \quad (4)$$

where P_f^{S1} and P_f^{S2} are power spectral densities at frequency f . The power spectral densities were calculated by using the Matlab Welch method (Welch 1967) for 10-s data segments with 0.29 Hz frequency resolution (2048 points FFT for 600 Hz sampling rates). Attenuation of artefacts was also quantified using the root-mean-squared error and the correlation coefficient between the artefact-removed signal and the artefact-free signal.

CA reductions were assessed in different scalp regions (groups of MEG sensors) by RSD for frequencies less than 45 Hz. RSD values for signals before ($S1$) to after ($S2$) CA removal were calculated over the 8-min recorded data per subject per channel. RSD values were averaged over the channels in each region for each subject, and the mean and the standard deviation of the RSD across subjects were calculated for each region.

The RMAS was compared with an implementation of the fastICA method (Hyvärinen 1999; Hyvärinen 1997). We divided the whole brain area into three groups depending on the distribution of CAs from Fig. 1: Group 1 includes MLT, MRT, MLO, and MRO; Group 2 includes MLF, MRF, MLC, MRC, MZF, and MZC; and Group 3 includes MLP, MRP, and MZO. The fastICA method was applied to each group independently. The CA-components were simply identified by a fixed threshold on the correlation between the ECG channel and each independent component. Any IC with larger correlation coefficient (>0.1) was marked as CA-contaminated independent component. For Group 1, 105 MEG channels were selected from temporal and occipital lobes where CAs can be discerned clearly. The corrected data were obtained by removing 15 CA-contaminated independent components from the total of 105 independent components for subject S. For the same subject S, 118 MEG channels were in Group 2 and 18 CA-contaminated independent components were identified. 47 MEG channels were in Group 3, and 6 CA-contaminated independent components were identified. The number of CA-contaminated independent components varied from 14 to 21 for Group 1, from 7 to 20 for Group 2, and from 5 to 12 for Group 3 for all six subjects. During the comparison of ICA and RMAS, we also manually checked and Oja if all CAs were detected and removed correctly for both methods to guarantee we did not induce extra noise.

Results

A four-second segment of MEG data with prominent CAs that were notably reduced by the application of RMAS is illustrated in Fig. 1a. The topographic maps of the data (Fig. 1b) indicated largest CAs in the right temporal lobe sensors during the R and T wave periods. During the S wave period, strong CAs were seen over both temporal lobes, but with opposite polarities. In these data, CAs corresponding to the Q wave were not visible. This kind of spatial and temporal variability greatly increases the complexity of identifying CA components with blind source separation methods. Spectral analysis demonstrated that the frequency content of the CA components removed by RMAS or MAS was mostly below 45 Hz (Fig. 1c). The RSD (<45 Hz) for different groups of MEG channels indicated that the largest effects of the CA suppression after the application of RMAS, MAS, or fastICA occurred in the temporal and occipital channels (Fig. 2).

A reduction in residual artefacts achieved by the resampling algorithm is illustrated in Fig. 3. The resampling resulted in moderate improvement in the quality of CA removal within the time interval in which the change in the CA was largest.

The effect of CA removal with RMAS and fastICA, respectively, for a 10-s MEG segment is shown in Fig. 4a. Both RMAS and fastICA removed CAs successfully, and the residual cardiac artefacts were barely observable in the time domain. In the spectral domain, differences were visible over a wide range of frequencies (Fig. 4b). Above 45 Hz, the spectrum after RMAS was almost identical to the original spectrum, whereas after fastICA the spectrum showed increased high-frequency content (see the details at 90–110 Hz in Fig. 4b). Note, however, that the fluctuations in the spectrum could be suppressed if more complex procedures were used to identify the relevant independent components.

An example of MEG recording of spontaneous activity before and after the application of RMAS is shown in Fig. 5a, demonstrating prominent suppression of CAs. Topographies of the averaged visual evoked responses suggested that characteristic brain activation related patterns were preserved after the application of the RMAS method (Fig. 5b).

Discussion

The RMAS method is an automated time-varying template subtraction technique for removing CAs in MEG data that combines moving average template subtraction with alignment by resampling. RMAS was found to efficiently suppress CAs in MEG data. Template subtraction methods, which operate in the time domain and on channel-by-channel basis, provide an effective alternative to methods like signal space projection, PCA, and ICA, which remove spatial patterns from multisensory array data.

Non-stationarity of the CAs can adversely affect the performance of the artefact removal methods. Several potential factors can cause variability in CAs over time, including physiological fluctuations in cardiac function, or subtle body motion such that the position of the heart changes with respect to the MEG sensor array. For template subtraction approaches, incorporating a weighted moving average over several cardiac cycles allows the template to adapt to changes in the CAs. An optimal choice of the parameters for the moving average weighting function is a trade-off between including only a small number of cardiac cycles, such that each template is only minimally affected by variation in the CAs (and the computational demands is low), and including many cycles to reduce the contributions from non-cardiac signals (such as brain activity and other types of noise) in the template. For the present data the linear weighting function covering about 49 cycles provided good results in CA suppression. The moving average approach assumes that the CAs vary only slowly over time. In the case of high variability in the CAs among subsequent cardiac cycles, a more effective approach may be to cluster the CAs from the whole recording session into groups based on mutual similarity and calculate the template for each group separately (Tal and Abeles 2013).

Associated with the CA, there may also be additional small contributions from brain activity related to the cardiac cycle. Therefore, a more complex interaction of cardiac-related effects may co-exist with event-related brain responses (Rodin et al. 2005). However, the RMAS method, to the extent that this brain activity is time locked with the ECG, is expected to suppress those as well.

Methods in which spatial patterns are removed from multichannel data have been widely applied for CA removal. For example, the ICA-based cardiac artefact rejection for real-time analysis method effectively reducing CAs by calculating cross trial phase statistics (Breuer et al. 2014a). Good results have also been achieved with various other ICA methods (Dammers et al. 2008; Escudero et al. 2011; Mantini et al. 2008). However, a concern with methods that remove spatial components is that the brain signals and the artefacts are not necessarily orthogonal, thereby potentially leading to partial suppression of the brain signal of interest. The single channel based time-domain template subtraction methods largely avoid this problem. In addition, with blind source separation methods like the ICA, a

complex component-identification procedure is needed to implement a good separation strategy, whereas template subtraction methods like RMAS do not involve a complex processing strategy and can be automated in a straightforward way.

Because the template subtraction methods operate on the signal time courses, accurate alignment of the waveform for different cardiac cycles is critical for these methods. Due to the steep slopes in the QRS waveform, even small variability in the relative timing of the QRS and the MEG sampling time points may cause distortions in the template. The proposed resampling method, previously applied to EEG-fMRI data, is a computationally efficient way to address this issue (Sun and Hinrichs 2009). With resampling precise results are achieved with faster computation and without the large increase in the amount of data, compared with the use of higher data sampling rates. Although the improvements achieved by the resampling in the present study were relatively modest (cf. Fig. 3), it helped to further enhance the reduction of cardiac artefacts in MEG data. The resampling method is expected to be most beneficial when low sampling rates are used for the MEG data acquisition; this could be the case, e.g., in sleep studies with long-duration recordings.

The resampling procedure is the most time consuming part of the RMAS; in our sample data, omitting the resampling reduced the computation time from 3.45 to 0.005 s. Naturally, in real-time analysis, only data from the past cardiac cycles can be used. The choice of a rectangular function, $w_k = 1/N$, for $-N < k \leq 0$, and $w_k = 0$, for $0 < k < N$, for the moving average weights in Eq. (1) would allow a simple adaptive updating of the template in real time applications. Real-time artefact suppression is expected to be of importance, e.g., in applications related to brain-computer interface (Mellinger et al. 2007), neurofeedback (Florin et al., 2013), and dynamic connectivity network analyses (Fonteneau et al. 2015).

Conclusion

We evaluated the RMAS method, which combines moving average subtraction and alignment by resampling, to accurately extract an individual template for each CA. RMAS is an efficient approach for the removal of CAs. The method can be applied with minimal user interaction, and is also suitable for real time applications.

Acknowledgments

Experimental data were collected while Dr. -Ing. Sun worked in Max Planck Institute for brain research, Frankfurt am Main, Germany. This work was supported in part by the National Institutes of Health Grant NS037462 and by The National Center for Research Resources (P41RR14075).

References

- Allen PJ, Polizzi G, Krakow K, Fish DR, Lemieux L. Identification of EEG events in the MR scanner: the problem of pulse artifact and a method for its subtraction. *Neuroimage*. 1998; 8:229–239. [PubMed: 9758737]
- Allen PJ, Josephs O, Turner R. A method for removing imaging artifact from continuous EEG recorded during functional MRI. *Neuroimage*. 2000; 12:230–239. [PubMed: 10913328]
- Becker R, Ritter P, Moosmann M, Villringer A. Visual evoked potentials recovered from fMRI scan periods. *Hum Brain Mapp*. 2005; 26:221–230. [PubMed: 15954138]

- Breuer L, Dammers J, Roberts TP, Shah NJ. A constrained ICA approach for real-time cardiac artifact rejection in magnetoencephalography. *IEEE Trans Biomed Eng.* 2014a; 61:405–414. [PubMed: 24001953]
- Breuer L, Dammers J, Roberts TP, Shah NJ. Ocular and cardiac artifact rejection for real-time analysis in MEG. *J Neurosci Methods.* 2014b; 233:105–114. [PubMed: 24954539]
- Cohen D. Magnetoencephalography: detection of the brain's electrical activity with a superconducting magnetometer. *Science.* 1972; 175:664–666. [PubMed: 5009769]
- Dammers J, Schiek M, Boers F, Silex C, Zvyagintsev M, Pietrzyk U, Mathiak K. Integration of amplitude and phase statistics for complete artifact removal in independent components of neuromagnetic recordings. *IEEE Trans Biomed Eng.* 2008; 55:2353–2362. [PubMed: 18838360]
- de Munck JC, van Houdt PJ, Goncalves SI, van Wegen E, Ossenblok PP. Novel artefact removal algorithms for co-registered EEG/fMRI based on selective averaging and subtraction. *Neuroimage.* 2013; 64:407–415. [PubMed: 22995780]
- Ellingson ML, Liebenthal E, Spanaki MV, Prieto TE, Binder JR, Ropella KM. Ballistocardiogram artifact reduction in the simultaneous acquisition of auditory ERPS and fMRI. *Neuroimage.* 2004; 22:1534–1542. [PubMed: 15275910]
- Escudero J, Hornero R, Abasolo D, Fernandez A, Lopez-Coronado M. Artifact removal in magnetoencephalogram background activity with independent component analysis. *IEEE Trans Biomed Eng.* 2007; 54:1965–1973. [PubMed: 18018691]
- Escudero J, Hornero R, Abasolo D, Fernandez A. Quantitative evaluation of artifact removal in real magnetoencephalogram signals with blind source separation. *Ann Biomed Eng.* 2011; 39:2274–2286. [PubMed: 21509634]
- Feuerstein D, Parker KH, Boutelle MG. Practical methods for noise removal: applications to spikes, nonstationary quasi-periodic noise, and baseline drift. *Anal Chem.* 2009; 81:4987–4994. [PubMed: 19449858]
- Florin E, Bock E, Baillet S. Targeted reinforcement of neural oscillatory activity with real-time neuroimaging feedback. *Neuroimage.* 2013; 88C:54–60.
- Fonteneau E, Bozic M, Marslen-Wilson WD. Brain network connectivity during language comprehension: interacting linguistic and perceptual subsystems. *Cereb Cortex.* 2015; 25:3962–3976. [PubMed: 25452574]
- Garreffa G, Bianciardi M, Hagberg GE, Macaluso E, Marciani MG, Maraviglia B, Abbafati M, Carni M, Bruni I, Bianchi L. Simultaneous EEG-fMRI acquisition: how far is it from being a standardized technique? *Magn Reson Imaging.* 2004; 22:1445–1455. [PubMed: 15707794]
- Goldman RI, Stern JM, Engel J Jr, Cohen MS. Acquiring simultaneous EEG and functional MRI. *Clin Neurophysiol.* 2000; 111:1974–1980. [PubMed: 11068232]
- Hari, R. Magnetoencephalography in clinical neurophysiological assessment of human cortical functions. 5. Niedermeyer, E.; da Lopes Silva, F., editors. Lippincott Williams & Wilkins; Philadelphia: 2005. p. 1165–1197. *Electroencephalography: basic principles, clinical applications, and related fields*
- Hashimoto T, Elder CM, Vitek JL. A template subtraction method for stimulus artifact removal in high-frequency deep brain stimulation. *J Neurosci Methods.* 2002; 113:181–186. [PubMed: 11772439]
- Hyvärinen A. Fast and robust fixed-point algorithms for independent component analysis. *IEEE Trans Neural Netw.* 1999; 10:626–634. [PubMed: 18252563]
- Hyvärinen A, Oja E. A fast fixed point algorithm for independent component analysis. *Neural Comput.* 1997; 9(7):283–292.
- Hämäläinen M, Hari R, Ilmoniemi RJ, Knuutila J, Lounasmaa OV. Magnetoencephalography—theory, instrumentation, and applications to noninvasive studies of the working human brain. *Rev Mod Phys.* 1993; 65:413–497.
- Jousmäki V, Hari R. Cardiac artifacts in magnetoencephalogram. *J Clin Neurophysiol.* 1996; 13:172–176. [PubMed: 8849972]
- LeVan P, Maclaren J, Herbst M, Sostheim R, Zaitsev M, Hennig J. Ballistocardiographic artifact removal from simultaneous EEG-fMRI using an optical motion-tracking system. *Neuroimage.* 2013; 75:1–11. [PubMed: 23466939]

- Mantini D, Franciotti R, Romani GL, Pizzella V. Improving MEG source localizations: an automated method for complete artifact removal based on independent component analysis. *Neuroimage*. 2008; 40:160–173. [PubMed: 18155928]
- Mellinger J, Schalk G, Braun C, Preissl H, Rosenstiel W, Birbaumer N, Kubler A. An MEG-based brain-computer interface (BCI). *Neuroimage*. 2007; 36:581–593. [PubMed: 17475511]
- Ramirez RR, Kopell BH, Butson CR, Hiner BC, Baillet S. Spectral signal space projection algorithm for frequency domain MEG and EEG denoising, whitening, and source imaging. *Neuroimage*. 2011; 56:78–92. [PubMed: 21315157]
- Rodin E, Funke M, Hauelsen J. Cardiorespiratory contributions to the magnetoencephalogram. *Brain Topogr*. 2005; 18:37–46. [PubMed: 16193265]
- Sander TH, Wubbeler G, Lueschow A, Curio G, Trahms L. Cardiac artifact subspace identification and elimination in cognitive MEG data using time-delayed decorrelation. *IEEE Trans Biomed Eng*. 2002; 49:345–354. [PubMed: 11942726]
- Shams N, Alain C, Strother S. Comparison of BCG artifact removal methods for evoked responses in simultaneous EEG-fMRI. *J Neurosci Methods*. 2015; 245:137–146. [PubMed: 25721269]
- Shao SY, Shen KQ, Ong CJ, Wilder-Smith EP, Li XP. Automatic EEG artifact removal: a weighted support vector machine approach with error correction. *IEEE Trans Biomed Eng*. 2009; 56:336–344. [PubMed: 19272915]
- Sun L, Hinrichs H. Simultaneously recorded EEG-fMRI: removal of gradient artifacts by subtraction of head movement related average artifact waveforms. *Hum Brain Mapp*. 2009; 30:3361–3377. [PubMed: 19365799]
- Sun L, Grutzner C, Bolte S, Wibral M, Tozman T, Schlitt S, Poustka F, Singer W, Freitag CM, Uhlhaas PJ. Impaired gamma-band activity during perceptual organization in adults with autism spectrum disorders: evidence for dysfunctional network activity in frontal-posterior cortices. *J Neurosci*. 2012; 32:9563–9573. [PubMed: 22787042]
- Tal I, Abeles M. Cleaning MEG artifacts using external cues. *J Neurosci Methods*. 2013; 217:31–38. [PubMed: 23583420]
- Taulu S, Kajola M, Simola J. Suppression of interference and artifacts by the signal space separation method. *Brain Topogr*. 2004; 16:269–275. [PubMed: 15379226]
- Uusitalo MA, Ilmoniemi RJ. Signal-space projection method for separating MEG or EEG into components. *Med Biol Eng Comput*. 1997; 35:135–140. [PubMed: 9136207]
- Welch PD. The use of fast Fourier transform for the estimation of power spectra: a method based on time averaging over short, modified periodograms. *IEEE Trans Audio Electroacoust*. 1967; 15(2): 17–20.

Fig. 1. Comparison of MEG signals before and after cardiac artefact (CA) removal with the RMAS, MAS, and fastICA methods. **a** One MEG channel (*bottom*) shown together with the ECG channel (*top*). **b** Spectra of the MEG signal before and after CA removal with different methods. **c** MEG signal topographies at R, S, and T peaks

Fig. 2.

Averaged relative spectral difference (RSD in sensor groups over different brain regions after CA removal with RMAS, MAS, and fastICA). The mean and standard deviation across six subjects are shown. Channel group coding: *M* magnetic sensor, *L* left, *Z* middle, *R* right; *F* frontal, *C* central, *P* parietal, *T* temporal, *O* occipital. The locations of the regions are shown in the *inset*

Fig. 3. Effect of the resampling method on the CA removal. At the bottom, the waveforms for one CA epoch after subtracting the template with (RMAS) or without (MAS) resampling are superimposed. The residual CA at the R wave period is smaller with the template obtained with resampling (*arrow*)

Fig. 4. MEG signals before and after the CA removal using RMAS and fastICA. **a** Time domain signal. **b** Power spectral density (PSD)

Fig. 5.

An example of CA removal using RMAS and fastICA for two MEG data sets. **a** Spontaneous activity in six channels over the right hemisphere. Prominent suppression of CAs is evident. **b** Visual evoked responses averaged over 50 trials before (*top*), after the application of RMAS (*middle*), and after the application of fastICA (*bottom*). The CA removal did not substantially distort the brain signals of interest