Integration of Amplitude and Phase Statistics for Complete Artifact Removal in Independent Components of Neuromagnetic Recordings

Jürgen Dammers*, Michael Schiek, Frank Boers, Carmen Silex, Mikhail Zvyagintsev, Uwe Pietrzyk, Member, IEEE, and Klaus Mathiak

Abstract—In magnetoencephalography (MEG) and electroencephalography (EEG), independent component analysis is widely applied to separate brain signals from artifact components. A number of different methods have been proposed for the automatic or semiautomatic identification of artifact components. Most of the proposed methods are based on amplitude statistics of the decomposed MEG/EEG signal. We present a fully automated approach based on amplitude and phase statistics of decomposed MEG signals for the isolation of biological artifacts such as ocular, muscle, and cardiac artifacts (CAs). The performance of different artifact identification measures was investigated. In particular, we show that phase statistics is a robust and highly sensitive measure to identify strong and weak components that can be attributed to cardiac activity, whereas a combination of different measures is needed for the identification of artifacts caused by ocular and muscle activity. With the introduction of a rejection performance parameter, we are able to quantify the rejection quality for eye blinks and CAs. We demonstrate in a set of MEG data the good performance of the fully automated procedure for the removal of cardiac, ocular, and muscle artifacts. The new approach allows routine application to clinical measurements with small effect on the brain signal.

Index Terms—Artifact reduction, blind source separation (BSS), independent component analysis (ICA), magnetoencephalography (MEG).

I. INTRODUCTION

FUNCTIONAL brain imaging data represent a mixture of physiological brain activity and signals originating from different noise and artifact sources. In magnetoencephalography (MEG) and electroencephalography (EEG), the most prominent biological artifacts originate from eye blinks/movements [ocular artifacts (OAs)], heart beats [cardiac artifacts (CAs)], and muscle activity (MA). The signal strength of such biological artifacts may be several orders of magnitude higher than the signal of interest. Therefore, the analysis of MEG/EEG signals requires the identification and elimination of the artificial signals prior to analysis.

Rejection of corrupted epochs or trials by visual inspection is still widely applied. A major disadvantage of this method is that it results in loss of data, and therefore, it may not be applicable if the number of trials is low. Moreover, visual inspection cannot be objective and is very time consuming.

A variety of different methods have been proposed over the last ten years to overcome this problem. Croft and colleagues, for example, investigated different regression techniques [1], [2], with the major drawback that the proposed method can be applied for OA removal only. Other approaches utilizing adaptive filter techniques [3], [4] including Kalman-filter-based methods [5], [6] that all are designed for specific types of artifacts only.

In MEG measurements, strong cardiac signals are superimposed onto brain responses; hence, compensation has to be applied. Contrary to ocular and muscle artifacts, the cardiac signal is more frequent and cannot be avoided or prevented. Standard averaging does not suppress the artificial signals sufficiently and may completely fail if the stimulus frequency is close to the range of the frequency (or any harmonics) of the subject’s heartbeat or eye blinks. Signal space projection (SSP) [7], [8] has been suggested to reduce the noise level in MEG caused by CA [9]–[11]. This approach relies on a priori spatial separation of brain and noise signal and only works well if the topographies of both signals are well defined.

Independent component analysis (ICA) [12], [13] is widely used to separate brain signals [14]–[19] from artifact components [20]–[23]. Semiautomatic ICA-based artifact removal [21], [24], [25] as well as automated procedures [26]–[31] were successfully applied to separate artifacts from brain signals. In recent publications, ocular and muscle artifacts were successfully identified by investigating scalp topographies [26] or second [30] and higher order statistics [24], [32], [33]. Effective removal of CAs using ICA was reported in MEG [20], [31], [34], [35] and magnetoencephalography (MNG) studies [36]. The ICA decomposition of the recorded signal often shows
multiple independent components (ICs), which can be attributed to CA by visual inspection [35], [36]. Since the amplitude of the ICs showing the CA can vary quite substantially, it is difficult for any automatic procedure that exclusively rely on amplitude information to identify CA-related ICs with a small signal strength.

Here, we present a novel fully automated artifact-rejection method for MEG and EEG data analysis utilizing ICA. For the identification of the strong and weak cardiac components, we analyze the cross trial phase statistics (CTPS) of the trials being defined by the R-peaks of the electrocardiography (ECG) signal. For the rejection of the OA and MA, the statistical properties (second and higher order moments and entropy) of the ICs are investigated. In contrast to CTPS, statistical analysis of ICs usually relies on amplitude information only. The procedure is performed in three steps: 1) ICA decomposition is applied to the raw signal using the Infomax algorithm [13]; 2) a combination of different algorithms investigating the statistical properties of the ICs is applied for the automated rejection of the biological artifacts; and 3) a quantitative measure provides a control of the performance of the artifact rejection, before the ICs are back transformed into the signal space for further analysis.

II. METHODS AND SIGNALS

A. Real MEG Data Set Examples

To test the automatic artifact rejection, we used MEG signals of ten experiments recorded in six different subjects. All subjects had either normal or corrected-to-normal visual acuity. Participation in this MEG experiment was in accordance with the Institutional Committee on Human Research. All volunteers gave their informed consent after explanation of the procedure and the purpose of the experiment. We recorded auditory (single clicks) and visual (black and white checkerboard) neuromagnetic field responses (for details, see [37]) using the 4D-Neuroimaging Magnes 2500 system, a whole-head magnetometer with 148 channels. In both auditory and visual experiments, each measurement lasted about 8–10 min. The neuromagnetic activity was continuously recorded with a sampling rate of 1017.25 Hz and a bandwidth from 0.1–400 Hz. In all experiments, separate auxiliary ECG and electrooculography (EOG) channels were continuously recorded in synchrony with the MEG channels. Eye blinks as well as eye movements were recorded using bilateral monocular vertical EOG (VEOG) and binocular horizontal EOG (HEOG), respectively. After acquisition, all data were bandpass filtered from 1–200 Hz, including notch filters at the power line frequency (50 Hz and the harmonics).

B. Independent Component Analysis

ICA was developed for solving the blind source separation (BSS) problem with the basic assumption that the recorded data in a sensor array are linear sums of temporally independent components originating from spatially fixed sources [12], [38]. The challenge here is to recover $N$ independent source signals $s(t) = [s_1(t), s_2(t), \ldots, s_N(t)]^T$ from $N$ linearly mixed observed signals $x(t) = [x_1(t), x_2(t), \ldots, x_N(t)]^T$ recorded by $N$ detectors.

$$x = As$$

with $A$ being the unknown mixing matrix. The key problem in ICA is to find an unmixing matrix $W$ (similar to a pseudoinverse $A^{-1}$) while imposing that the sources $s$ are statistically independent.

$$y = Wx.$$  

In simpler words, ICA transforms an $N$-sensor data array into an $N$-dimensional component space, where the time courses of the basis vectors $y$ are (maximally) independent as determined by specific algorithms over the time series. Thereby, for solving (2), the method makes no assumption about the mixing process except that it is linear. The estimated full rank square matrix $W$ in (2) can be treated as a spatial filter matrix that linearly inverts the mixing process. Note that independence is not equivalent to uncorrelatedness, as it would be for Gaussian distributions. In fact, estimating independent components is based on maximization of the non-Gaussianity of $Wx$ [39].

Different ICA algorithms have been used to separate brain signals from those induced by artificial sources. Recently, Delorme et al. [32] tested three different ICA approaches—Infomax ICA [13], SOBI [40], and FastICA [41]—for artifact detection in EEG signals. In general, the three algorithms have the same overall goal [19], [32], [42], but the detection performance was best using the Infomax ICA [32].

Although generalizations of the ICA method exist for handling nonlinear mixing processes (e.g., [43]), we use a linear approach since we focus on the detection of artifacts originating from external (i.e., nonbrain) magnetic fields, and thus, superimpose linearly the brain signals.

In our analysis, we use the Infomax ICA [13] instead of its extended version [42] to perform a faster computation since our data did not show any sub-Gaussian components (kurtosis < 0). For the application of ICA, the continuous MEG data from all experiments were chopped into segments of 60 000 time points, with duration of 59 s, leading to more than 14 000 independent components.

C. Automatic Extraction of Artificial Components

The aim of the ICA-based automatic procedure for artifact rejection is to find all components in the set of $y$ in (2) that can be attributed to magnetic fields generated outside the brain (i.e., artificial source signals) using predefined measures. By zeroing the identified components, we get a new set of independent components $y'$ that can be accounted for activations from distinct brain areas. The clearing of the measured data is then performed by back transformation of $y'$

$$x' = W^{-1}y'.$$  

For artifact rejection, we considered eight measures $(q_1, \ldots, q_8)$. The first six parameters $(q_1, \ldots, q_6)$ purely depend on the amplitude distributions of the ICs, by means of
analyzing second and higher order statistics or entropy. The other two parameters \((q_1\) and \(q_2\)) rely on additional information provided by the auxiliary channels EOG and ECG analyzing the linear cross correlation between the ICs and these auxiliary channels \((q_1)\) or the CTPS of the ICs \((q_2)\), where the trials are defined by the R-peaks of the ECG.

**D. Artifact Detection Measures**

The observed time series \(\mathbf{X}\) and the source signals \(\mathbf{S}\) are interpreted as stochastic processes. If we assume that the processes are stationary in the strict sense (with ergodicity of the derived measures), we can consider the stochastic process as realizations of a random variable \([44]\).

The \(n\)th order central moment of all activity values is defined as \(m_n = E[(x - m_1)^n]\) with \(E\) being the expectation function. The mean and the variance of all data values are expressed as \(m_1 = E(x)\) and \(m_2 = E[(x - m_1)^2]\), respectively.

**Measure 1:** In order to identify unusual large data values (outliers) in the set of \(y\), we calculated the variance in each of the ICs

\[
\text{variance: } i_{q_1} = \frac{y_i m_2}{m_2} \quad (4)
\]

where \(y_i\) denotes the \(i\)th IC with \(i = 1, \ldots, N\). This quantity typically shows large values in cases of muscle artifacts, eye blinks, or when large transient noise signals are present.

**Measure 2:** The third order central moment, known as the skewness, is a measure of the degree of asymmetry of a distribution. A negative or positive skewness shows an elongated tail at the left or right side of the distribution, respectively. A large absolute skewness value, for example, is present in ICs contaminated with eye blinks, but also indicates other types of artifacts (e.g., MA). The skewness is expressed as

\[
\text{skewness: } i_{q_2} = \frac{y_i m_3}{(y_i m_2)^{3/2}}. \quad (5)
\]

**Measure 3:** The distribution of peaked activity is characterized by a large kurtosis value (kurtosis \(> 0\)). This is, for example, evident in strong transient muscle or cardiac activity, which typically have super-Gaussian distributions. The Kurtosis has the following expression:

\[
\text{kurtosis: } i_{q_3} = \frac{y_i m_4}{(y_i m_2)^2} - 3. \quad (6)
\]

Components with a high positive kurtosis values indicate peaked activity, which is likely to be an artifact.

The source code of the analysis software was written using IDL version 6.4 [45], and we applied IDL’s built-in functions for the calculation of the measures 1–3.

**Measure 4:** Artifact rejection using Shannon’s entropy was successfully applied in [24], [26], [31], and [33]. Here, we use the same approximation to estimate the Shannon’s entropy of the \(i\)th component

\[
\text{entropy: } i_{q_4} = H(i) = -\sum_y p_i(y) \log(p_i(y)) \quad (7)
\]

with \(p_i(y)\) being the probability of observing the amplitude values \(y\) in the distribution of the amplitude from the \(i\)th IC. The entropy can be construed as a measure of disorder, where higher entropy values correspond to more disorder, i.e., the probability density tends to a uniform distribution. On the other hand, small entropy values correspond to signals showing a nonuniform probability density, often caused by outliers. Signals with such a characteristic probability density are likely to correspond to an artifact.

For the calculation of the entropy estimation, we used the definition of the MATLAB (http://www.mathworks.com/) built-in function entropy.m, whereas the number of bins was estimated as reported in [46].

**Measure 5–6:** The kurtosis \(_{\text{trial}}\) \((q_5)\) and the entropy \(_{\text{trial}}\) \((q_6)\) have the following form:

\[
\text{kurtosis}_{\text{trial}}: \quad i_{q_5} = \frac{i m_4 - 3 i m_2^2}{m_2} \quad (8)
\]

\[
\text{entropy}_{\text{trial}}: \quad i_{q_6} = \frac{i q_4(j)}{\sqrt{2} m_2} \quad (9)
\]

with \(j\) being the \(j\)th trial within the data segment of the \(i\)th component.

For the definition of the previous two measures, we divide each data segment of 60 000 samples (59 s) into subsegments (trials) of 1000 sample points (~1 s) and calculate \(q_5\) (kurtosis) and \(q_4\) (entropy) for each trial separately, as suggested by [26] and [33]. If a certain percentage of the trials exceeds a predefined threshold (see threshold settings and data normalization later), the corresponding IC is marked for rejection.

**Measure 7:** To identify ocular and cardiac activity in the sets of ICs, a correlation analysis was performed by calculating the Pearson’s linear correlation coefficients between each IC and the ECG and EOG channels (HEOG and VEOG). Due to the acquisition of the ECG and EOG (we used Synamps from Compumedics Neuroscan, Germany), these leads may be contaminated with some drifts, whereas the decomposed MEG signals usually have larger power in the frequency range above 20 Hz as compared to ECG or EOG signal. Therefore, for correlation analysis, all data were bandpass filtered to the range of 1–20 Hz. To avoid a polarity mismatch between the signals from the electrical leads and the ICs, the absolute value of the Pearson’s linear correlation coefficient \(q_7\) is used.

\[
I_{q_7} = \frac{E[(x - \bar{x} m_1)(y_i - \bar{y} m_1)]}{(\sqrt{2} m_2 - \sqrt{2} m_1)} \quad (10)
\]

with \(x\) being the signal from ECG, VEOG, or HEOG for \(q_{TECG}, q_{TEOG}, \) and \(q_{THEOG}\), respectively.

**Threshold settings and data normalization:** All distributions derived from \(q_1, \ldots, q_6\) were normalized to zero-mean and a standard deviation (SD) of 1 with respect to all ICs. For the measures \(q_1, \ldots, q_4\) (statistic of the full data segment), the threshold of was set to \(\pm 3.5\). For both \(q_5\) and \(q_6\), a component was marked for rejection if 30% or more of all trials exceeded the threshold of \(\pm 2\). For the correlation analysis \((q_7)\), we used an absolute threshold of \(\geq 0.5\).

The assumption here is that most of the ICs refer to brain sources with similar measure values (e.g., similar kurtosis values), while only a few artifact components have values far away from the mean.
from the mean measure value [24], [26], [33]. With such threshold settings, we have tried to minimize false positive artifact detection. These settings were validated by source localization of the a priori marked ICs (cf. Fig. 1). Depending on the localization results, we have increased our threshold if one of the artifact components was localized within the brain.

As an alternative method, receiver operating characteristic analysis (ROC) was recently applied in [47] to define an optimal set of thresholds.

Measure 8: CA detection using CTPS: Recently, we showed that artifact rejection based on the statistical properties of the ICs reliably identifies strong decomposed artificial signals [48]. However, all amplitude-based methods are limited and less sensitive in cases where the strength of the IC is weak, thus, exhibiting a low signal to noise ratio [49]. For example, the decomposition of signals containing CAs often shows multiple ICs [35], [50]. The second and third cardiac components usually have weak peak amplitudes that may be identified by visual inspection, but hardly by its statistical properties in the amplitude domain. We, therefore, established a method based on the analysis of CTPS for the identification of CAs (for a similar approach in the context of synchronization analysis, see [51]). Cross trial distributions are time-dependent histograms (in our case, phase histograms) that are calculated across trials (data segments) for each time point relative to the onset of an event (e.g., the R-peak). Each trial is defined by a 1-s time window of the ICs with the center defined by the R-peak of the ECG signal. Since the cardiac magnetic fields are synchronous with the ECG, they will disclose themselves by a nonuniform cross-trial phase distribution.

For a reasonable definition of the instantaneous phases, we tested five different frequency bands (2–4, 4–8, 8–16, 10–20, and 20–32 Hz), thus covering the main energy of the power spectrum of the ECG. After bandpass filtering, normalized phases were calculated as

$$\Phi_i = \frac{\psi_i(t)}{2\pi \mod 1}$$  \hspace{1cm} (11)

with $\psi_i(t)$ being the instantaneous phases from the $i$th IC estimated using the well-known Hilbert transform [52].

All instantaneous phases were calculated for the full length of each data segment (60 s) and then split into time windows (trials) of 1 s around the R-peak of the ECG signal. The deviation of the cross trial distribution of the normalized phases $g(\Phi)$ from a uniform distribution $k(\Phi)$ indicates a CA. The Kuiper index $V$ [53] was used to quantify these deviations

$$V = \max_{0 \leq \Phi \leq 1} [G(\Phi) - K(\Phi)] + \max_{0 \leq \Phi \leq 1} [K(\Phi) - G(\Phi)]$$  \hspace{1cm} (12)

with $G(\Phi)$ and $K(\Phi)$ are the cumulative probability density functions of $g$ and $k$. The index $V$ describes the maximum distance of $G(\Phi)$ above and below $K(\Phi)$. The significance level $P_K$ can be approximated by

$$P_K(\lambda) = 2 \sum_{k=1}^\infty \left[ (4k^2\lambda^2 - 1)e^{-2k^2\lambda^2} \right]$$  \hspace{1cm} (13)

with $\lambda = V(\sqrt{N} + 0.155 + 0.24/\sqrt{N})$ and $N$ being the number of data points.

The null hypothesis here is the assumption that the two functions $G(\Phi)$ and $K(\Phi)$ have the same distributions. In the case of a disproof of the null hypothesis (i.e., $g(\Phi)$ has a nonuniform distribution), $P_K$ becomes 0 in the limit of $V \to 1$. Since $P_K$ becomes very small for $V \to 1$, we introduced the negative logarithmic value $p_K = -\log_{10}(P_K)$. For CA detection, a threshold of $p_K \geq 20$ was applied. ICs with a CTPS just above this threshold may be barely detectable by visual inspection (see later).

E. Rejection Performance

To estimate the performance of the cardiac and OA rejection, we introduce the rejection performance quantity $R_p$ with

$$R_p = \frac{r(s_{\text{diff}})}{r(s)} \quad \text{with} \quad r = \frac{1}{N} \sum_{i=1}^N \sqrt{\frac{1}{T} \sum_t (s_i(t))^2}.$$  \hspace{1cm} (14)

In (14), $r$ expresses the average rms value across $N$ channels of the MEG recordings. The signal $s'$ here is the cross trial averaged signal of the $i$th sensor aligned to the onset of the R-peak or the peak latency of the eye blink, respectively. From the ECG- and EOG-peak-based averages, the rms calculation was performed for each channel using a time window of $\Delta t = 500$ ms and $\Delta t = 1000$ ms, respectively. The mean rms value before artifact rejection is expressed by $r(s)$; $r(s_{\text{diff}})$ represents the mean rms value based on the difference signal $s_{\text{diff}} = s - s'$, with $s$ and $s'$ denoting the averaged artifact signal before and after the ICA cleaning procedure, respectively. The limit $R_p = 0$ indicates that the automatic artifact rejection failed completely, since $s_{\text{diff}}$ will be zero due to $s' = s$. If the artifact rejection was maximal, $s'$ becomes very small (depending on the residual noise signal) resulting in an $R_p$ value close to 1. Thus, the relative rms value $R_p$ can be interpreted as an estimate of how much of the artifact signal was rejected.

III. RESULTS

The general concept was to remove all components that were classified as artifactual due to at least one of the measures $q_1, \ldots, q_s$. This approach reliably detects a variety of different
artifact components that can be attributed to muscle, ocular, or cardiac activity (see Fig. 1). The measures $q_1, \ldots, q_7$ were sensitive to a wide range of different artifacts. Measure $q_8$ (CTPS), by its construction, was extremely sensitive to extract strong and weak CA components. The CTPS method was tested for different frequency bands (2–4, 4–8, 8–16, 10–20, and 20–32 Hz). The results of the different bands resembled each other, but the most consistent extraction of components containing CAs in the frequency range of the QRS-complex were obtained for the band ranging from 10 to 20 Hz. In the following, we present results from this frequency band only.

On average, 6.5 (±1.5 SD) out of 148 ICs containing artifacts were automatically identified for rejection in each of the 97 data segments. First, the identified artifact (and the remaining) components were validated by visual inspection. Additionally, we extracted a few tens of identified artifact components based on their strength or those being identified just above the parameter threshold, and reconstructed the corresponding MEG field distribution. The source of activity was then localized using magnetic field tomography (MFT) [54], a method that has been reported to effectively reconstruct superficial and deeper sources [37, 35, 36].

In Fig. 1, a variety of different artifacts were selected from two different subjects showing multiple types of artifact ICs within one data segment, i.e., CA, OA, and MA. For ICs recognized as OA, the reconstructed source activity was localized close to the subject’s eyes. In case of CA, the reconstructed source activity was localized at the bottom of the source space (the lower part of the individual subject brain) as it is the case for distant sources below the subject’s brain1 (see Fig. 1). ICs representing MA (e.g., from the neck or due to swallowing), were localized either on the left and/or right side or in the middle of deeper brain regions (cf. Fig. 1 IC24). The reconstructed field maps of cardiac and muscle activities in Fig. 1 show that such activities originate from distant sources, and thus, corroborate the artificial nature of the detected components.

In the analysis of all ten experiments, we encountered 220 out of 622 (35%) components in total that were phase correlated with the R-peak of the ECG. This is more than one-third of all identified artifact components or 2.3 CA (±0.8 SD) components on average within each data segment.

The contribution of each of the measures ($q_1, \ldots, q_8$) to the final set of 622 identified artifact components was calculated and summarized separately for ocular and muscle (OA/MA, 402 components) and CAs (CA, 220 components) in Table I. Moreover, the relevance of each measure was estimated by computing the percentage of components that were identified by one measure only.

Table I illustrates that the highest sensitivity and relevance for the identification of CA contaminated ICs is provided by measure $q_8$, the CTPS. In contrast, the correlation analysis detects exactly one component in each data segment. However, no CA was identified by the measures $q_1, \ldots, q_7$ that has not been detected by CTPS (see Table I); hence, for the identification of CA in a set of ICs requires no other measure than CTPS. Although the parameters $q_1, \ldots, q_8$ and $q_{ECG}$ are sensitive to cardiac activity, 21% of all CA components were solely identified by CTPS ($q_8$).

In the set of OA/MA (i.e., non-CAs), the first four measures (variance, skewness, kurtosis, entropy) contribute most (36%–55%) to the list of identified OA/MA marked ICs (see Table I). To a lesser extend, but still significant, measure $q_{VEOG}$ performs with a high sensitivity in detecting OA as expressed by its contribution (21%). However, all measures perform with a low relevance value (<10%) with respect to the identification of OA/MA alone, i.e., none of the measures is specific in detecting these components. This indicates that a combination of measures is required to identify OA and MA.

Fig. 2 compares representative time courses and reconstructions of cardiac components from three different subjects (S3, S4, and S5). The first IC of subject S3 (in blue) serves as a reference for both, the amplitude of the IC and the strength of the maximum modulus of the reconstructed current density ($||J||_{max}$; Fig. 2). All other ICs in Fig. 2 were solely identified by CTPS and represent typical weak cardiac components that can sometimes hardly be identified by visual inspection (cf. S4 in Fig. 2). The validation revealed that all of the identified cardiac components were localized at the bottom of our source space with typical field maps indicating distant sources, as illustrated in Fig. 1. Moreover, the source strength (i.e., $||J||_{max}$) found for the detected CA with weak amplitudes reached 20% of the strength of the reference IC (cf. S4 in Fig. 2). This remaining source contribution could significantly influence the data analysis if not removed from the signal.

The rejection performance measure (cf. equation (12)) for ocular and CAs was calculated for all ten MEG measurements. Fig. 3 shows averages with respect to peaks of the two most prominent biological artifacts: the cardiac activity and the fields induced by eye blinks, before and after the ICA cleaning process.

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1Source reconstruction was limited to the individual segmented brain, which served as the source space. Hence, reconstruction out of brain activity (e.g., cardiac activity) will always be mirrored into the brain space.

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### TABLE I

<table>
<thead>
<tr>
<th>MEASURE</th>
<th>CONTRIBUTION (%)</th>
<th>RELEVANCE (%)</th>
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<tbody>
<tr>
<td>CA:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$q_1$</td>
<td>78.6</td>
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</tr>
<tr>
<td>$q_7$</td>
<td>44.5</td>
<td>0.0</td>
</tr>
<tr>
<td>$q_{ECG}$</td>
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<tr>
<td>OA/MA:</td>
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<td></td>
</tr>
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<td>$q_1$</td>
<td>50.2</td>
<td>6.7</td>
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<td>$q_2$</td>
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<td>6.7</td>
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<td>$q_{VEOG}$</td>
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<td>$q_{VEOG}$</td>
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</table>

The contribution counts how many artifact components were identified by each of the measures. The relevance is the percentage of how many artifact components were found by the respective measure alone. CA and OA/MA denote cardiac and noncardiac (ocular and muscle) artifact classification, respectively.
Representative CA components from three different subjects (S3, S4, and S5). The IC shown in the first row (IC8 of subject S3 in blue) was extracted using all measures ($q_1, \ldots, q_8$) and served as a reference of the maximum strength of the reconstructed current density ($\|J\|_{\text{max}}$) after source localization. ICs shown in row 2–7 (in black) were solely detected by CTPS ($q_8$) and represent 21% of all CA components. Although the amplitudes of these ICs are small, they exhibit about one-fifth of the source strength as compared to a typical example as demonstrated in row 1.

The figure shows that most of the CA and OA were eliminated by the automatic artifact rejection cleaning. The rejection performance $R_p$, in this case, was 95% and 81% for cardiac and OA rejection, respectively. In the comparison of the rejection performance of ocular versus CAs, the higher sensitivity of the CTPS method was evident (see Table I). However, it should be noted that the rejection performance value $R_p$ also depended on the residual noise within the time window of $\Delta t$, and thus, was influenced by the number of trials used for the calculation of the average. The rate of the heart beat is typically about 1 s, whereas the frequency of eye blinks strongly varies from subject to subject and the task given, but is usually about 3–5 times smaller than the rate of the heart beat [57]. In our experiments with 8–10 min duration, we typically extracted 500–700 and 100–200 trials to construct ECG and

<table>
<thead>
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<th>EXPERIMENT</th>
<th>$R_p$ CARD (%)</th>
<th>$R_p$ Ocular (%)</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>92.2</td>
<td>83.8</td>
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<td>2</td>
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<td>82.7</td>
</tr>
</tbody>
</table>

Rejection performance values for cardiac and OA rejection.
eye-blink-based averages. Therefore, the noise content in the VEOG averages was larger, which results in a smaller performance value $R_p$ for OA rejection (see Table II).

The performance values after CA rejection using different methods for one representative subject are illustrated in Fig. 4. If only correlation analysis ($q_{TECG}$) is applied, the rejection performance in this experiment was about 62%, whereas in three of ten experiments, the $R_p$ values were even below 20%. Moreover, the CA rejection performance was improved by 3% only when measure $q_1, \ldots, q_7$ were applied [cf. Fig. 4(a)–(b)]. In contrast, the CTPS method ($q_8$) revealed a remarkably high rejection performance with $R_p = 88.6\%$.

Finally, we investigated whether or not the localization of the signal of interest is affected by the ICA filter process. We, therefore, selected 30 trials from a single subject who showed strong ocular and CAs during auditory stimulation (single clicks). The artifact trials were selected by visual inspection and showed strong artifactual activity within the time range of the evoked auditory response (N100m). After averaging the selected trials, source localization was applied at the peak time of the N100m (98 ms after stimulus onset) before and after artifact rejection. For comparison, source reconstruction was computed on the average of 30 artifact-free trials (see Fig. 5).

As expected, for the artifact-free trials, the source of the N100m (here, the prominent left side) does not change in space and signal strength (see Fig. 5 right column) neither before and nor after the ICA process. In the case of strong ocular and CAs, the ICA process greatly removed the unwanted sources with almost no change in the strength of the auditory activity (see Fig. 5 left column). The localization of the N100m revealed maximum activity at: $x = -58$, $y = -27$, $z = 4$ [Montreal Neurological Institute (MNI) space in millimeter] before and after the ICA filtering in the artifact-free data set. Even when strong artifacts influence the signal of the N100m, the location of the auditory activity after ICA filtering is exactly the same (maximum value at: $x = -58$, $y = -27$, $z = 4$) as found in the artifact-free data (cf. Fig. 5 left column). According to the Jülich cytoarchitectonic atlas, this is close to the center of gravity (at $x = -47$, $y = -21$, $z = 7$) of the left primary auditory cortex (TE1.0).

IV. DISCUSSION

The presented method for automatic artifact rejection in MEG/EEG data combines information based on amplitude and phase statistics. We demonstrated the sensibility and reliability in ten MEG experiments recorded from six different subjects (auditory and visual stimuli) for the identification and elimination of ocular, cardiac, and muscle artifacts simultaneously (see Fig. 1). The fully automated procedure estimates the rejection performance for the two most prominent artifacts: the cardiac activity and eye blinks.

The individual performance of each of the eight measures ($q_1, \ldots, q_8$) was investigated. The first six measures ($q_1, \ldots, q_6$) are purely based on the amplitude distributions of the ICs analyzing second and higher order statistics or entropy. In contrast, measure $q_8$ (CTPS) uses CTPS of the ICs with trials being defined by the R-peak of the ECG. In all of our tests, visual inspection of the time courses, field maps, and source localization exposed the identified ICs as artifactual (see Fig. 1).

A variety of measures have been proposed in the last few years to identify artifacts automatically from decomposed signals by means of ICA [26]–[31]. Previous work implies a combination of different methods to reliably separate multiple types of artifacts from brain signals [31], [32]. Moreover, earlier studies showed that the cardiac activity is often decomposed in multiple components [35], [49], [50], where the second and following components have smaller amplitudes, and so, are difficult to extract.
Our results support previous work that a combination of second and higher order statistics is necessary to identify multiply types of artifacts (OA, CA, MA). However, for CA rejection, only the CTPS method was capable of identifying all ICs that are related to cardiac activity. In our data, this method achieved the best performance for this type of artifact (cf. Table I and Fig. 4). In contrast, the correlation analysis identified only the strongest (first) component, whereas the CTPS method extracted also the weaker (second and third) cardiac components, where all amplitude-based methods fail (see Figs. 2 and 4).

With the introduction of the rejection performance value \( R_p \), we were able to estimate the overall ICA cleaning performance for the two most prominent artifacts, the heart beat and eye blink artifact (see Fig. 3). In our automatic cleaning procedure, a warning is given when the performance is below a given threshold. The results of the rejection performance are then automatically plotted for both the full data set and for each data segment separately (cf. Fig. 3). This makes it easy to extract data segments for further visual inspection, where the artifact rejection was not optimal.

V. CONCLUSION

Our observer independent algorithm extracted the most relevant types of artifact components automatically from the ICs of the MEG data. Using a single measure, such as the CTPS, we were able to extract cardiac activity with a very high sensitivity. The detection is efficient even in cases where the amplitudes of the ICs are weak and simple visual inspection does not reveal the artifact. For the identification of ocular and muscle artifacts in a set of ICs, a combination of different measures is needed (e.g., \( q_1, \ldots, q_4 \) and \( q_{TEOG} \)).

REFERENCES


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