A Constrained ICA Approach for Real-Time Cardiac Artifact Rejection in Magnetoencephalography

Lukas Breuer*, Jürgen Dammers, Timothy P.L. Roberts, N. Jon Shah

Abstract—Recently, magnetoencephalography (MEG) based real-time brain computing interfaces (BCI) have been developed to enable novel and promising methods of neuroscience research and therapy. Artifact rejection prior to source localization largely enhances the localization accuracy. However, many BCI approaches neglect real-time artifact removal due to its time consuming processing. With CARTA (cardiac artifact rejection for real-time analysis) we introduce a novel algorithm capable of real-time cardiac artifact (CA) rejection. The method is based on constrained independent component analysis (cICA), where a priori information of the underlying source signal is used to optimize and accelerate signal decomposition. In CARTA this is performed by estimating the subject’s individual density distribution of the cardiac activity, which leads to a subject-specific signal decomposition algorithm. We show that the new method is capable of effectively reducing CAs within one iteration and a time delay of 1 ms. In contrast, Infomax and Extended Infomax ICA converged not until seven iterations, while FastICA needs at least ten iterations. CARTA was tested and applied to data from three different but most common MEG systems (4D-Neuroimaging, VSM MedTech Inc. and Elektro Neuronag). Therefore the new method contribute to reliable signal analysis using BCI approaches.

Index Terms—Cardiac Artifact Rejection for Real-Time Analysis (CARTA), Real-Time Artifact Reduction, Independent Component Analysis (ICA), Constrained ICA (cICA), Magnetoencephalography (MEG), Cross Trial Phase Statistics (CTPS).

I. INTRODUCTION

REAL-TIME analysis of magnetoencephalographic (MEG) data offers a great potential in providing new insights into ongoing electrophysiological brain processes during the execution of the MEG measurements. However, many BCI approaches neglect the artifact rejection step, because of its time consuming operation. Usually MEG recordings consist of a mixture of brain activity and field components originating from eye blinks/movements (ocular artifacts), heartbeats (cardiac artifacts, CA), muscle activity and environmental noise. Biological artifacts have a signal strength that may be several orders of magnitude larger than the signal of interest [1]. Hence, the identification and elimination of such artifact signals prior to analysis of the MEG signals is essential.

In the MEG community a variety of artifact removal methods have been proposed [2]-[9]. In particular, two different methods are widely used to remove field contributions from cardiac activity: i) for CA removal template matching methods [10], [11] are in general fast and simple to implement. The cardiac activity is rejected by subtracting a reference signal which is usually estimated by calculating the average activity around the R-peak at each heartbeat cycle. A common problem in using such a method is that MEG signals of brain responses which occur at the same time are most likely being distorted by this subtraction. ii) Independent component analysis (ICA) is also widely used for the separation of mixed data into its underlying individual components [12], [13]. ICA-based CA rejection is performed by removing the corresponding cardiac components from the set of decomposed signals. It has been shown that artifact rejection utilizing ICA does not harm the signal of interest (i.e., brain responses) if the decomposition and the selection of the artifact components is properly applied [3]. The major challenge for all kinds of online artifact removal methods will be to cope with unaveraged, short data segments during acquisition.

In literature, most publications dealing with real-time MEG data processing are related to brain computing interfaces (BCI) [14]-[17]. In general, a BCI system translates brain activity into commands to be run on a computer [18]. The two monitoring systems best suited for BCI approaches are MEG and electroencephalography (EEG). Both modalities record brain activity non-invasively. In comparison to EEG, MEG is not a portable device, and therefore, the method is restricted to some elementary research utilizing BCI. However, it has been
shown that MEG based BCI approaches provide more specific information and thus may help to further improve EEG based BCI [18]. In the studies [14]-[17] BCI is applied with short system delays of about 44±17 ms between MEG data acquisition [17] and receiving a feedback of ongoing brain activity in sensor-space. However, the applied real-time methods did not include any kind of artifact rejection.

To our knowledge, Rongen and colleagues were the first who demonstrated real-time MEG source analysis including online CA rejection [19]. In this study, data acquisition was performed using the MAGNES 2500 WH MEG system from 4D-Neuroimaging, which is equipped with 148 magnetometer channels. Prior to source analysis Rongen and colleagues applied ICA-based, real-time cardiac artifact rejection by using a pre-calculated fixed rejection matrix for signal decomposition throughout the experiment [19].

In this paper, we present a novel and fast ICA-based method optimized for real-time CA rejection. The new algorithm is constructed for application in modern MEG systems and can therefore cope with a few hundred MEG channels. Real-time CA rejection was performed utilizing the concept of constrained ICA (cICA). In cICA prior knowledge of an underlying expected signal (e.g., the cardiac activity) is used to optimize the internal cost-function of ICA [20], [21] resulting in an acceleration of the ICA decomposition towards real-time applicable analysis.

To demonstrate general real-time applicability the new algorithm (referred to as cardiac artifact rejection for real-time analysis, CARTA) was tested using real MEG data recorded with three different, but commonly used, MEG systems (4D-Neuroimaging, VSM MedTech Inc. and Eleka Neuromag). Since we had not the opportunity to access the MEG data from Neuroimaging, VSM MedTech Inc with three different, but commonly used, MEG systems (4D-Neuroimaging, which is equipped with 148 magnetometer channels, CTF MEG with 248 channels (MAGNES-3600WH MEG), 2) a VSM MedTech Inc. whole-head axial gradiometer system with 275 channels (CTF MEG™) and 3) an Eleka Neuromag whole-head system with 306 channels, consisting of 102 magnetometers and 204 planar gradiometers (Eleka Neuromag® TRIUX™). While recordings with the 4D-Neuroimaging system were performed at the Institute of Neuroscience and Medicine (INM-4), Forschungszentrum Jülich, Germany, the recordings with the two other systems were performed at the Lurie Family Foundations’ MEG Imaging Center of the Department of Radiology, Philadelphia, USA.

MEG signals from 18 different subjects (age between 8 and 49 years) were recorded using the three different MEG systems (six subjects per MEG system). During measurements neuromagnetic field changes in response to binaural stimulation (single clicks) were recorded. For stimulation, sinusoidal tones of different frequencies where presented, where presentation times, frequencies and the experimental design slightly vary between the three MEG systems. A summary of the most important details is listed in Table 1.

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>RECORDING SETUP</th>
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<tr>
<td>4D-Neuroimaging</td>
<td>VSM MedTech Inc.</td>
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<tr>
<td>bandwidth after filtering</td>
<td>(Hz)</td>
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<tr>
<td>number of channels</td>
<td>(channel types)</td>
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<tr>
<td>number of presented stimuli (per frequency)</td>
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<tr>
<td>stimulus frequency</td>
<td>(Hz)</td>
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<tr>
<td>stimulus duration</td>
<td>(ms)</td>
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<tr>
<td>inter stimulus interval (ISI)</td>
<td>(s)</td>
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<tr>
<td>number of data samples (mean)</td>
<td></td>
</tr>
<tr>
<td>experiment duration (mean)</td>
<td></td>
</tr>
</tbody>
</table>

Recording sampling rates and bandwidth with the different MEG systems, as well as the experimental setup to record responses to auditory binaural stimulation. Different stimuli frequencies were presented in random order. For each frequency the same number of stimuli was used.

Participation in the MEG experiments was in accordance with the local Institutional Committee of Human Research. All participants gave their informed consent after explanation of the procedure and the purpose of the experiment.

All data were continuously recorded in order to allow for simulation of the real-time acquisition process. Since the sampling rate used during recordings varied between the three different MEG systems (cf. Table 1) all data were bandpass filtered to the same frequency band using a phase neutral 6th-order Butterworth filter (Table 1). The frequency range was chosen from 1-45 Hz, excluding the power line frequencies at 50 Hz and 60 Hz for data recorded in Germany and the USA, respectively. Note that filtering in real-time was not part of this study as it has already shown by Rongen and colleagues [19].

The real-time processing of CA removal was simulated by storing the filtered MEG data into memory, from which segments of data were read-out whenever CARTA was ready to start with the rejection procedure. In the following, these steps are explained in more detail.

B. Independent Component Analysis

Since CARTA is based on independent component analysis (ICA), we will briefly review the basic concept of ICA. If \( X = (X_1, X_2, ..., X_n)^T \) are the \( n \)-dimensional observed signal mixtures, and \( S = (S_1, S_2, ..., S_n)^T \) the \( n \)-dimensional true source signals, then the classical ICA model can be expressed as the following linear relationship:

\[ X = AS \]
with \( A \) being the unknown mixing matrix of dimension \( n \times n \).
The difficulty in solving Eq. (1) is that neither the mixing matrix \( A \), nor the source signals \( S \) are known. The challenge therefore is to find an unmixing matrix \( W \), such that:

\[
C = W \cdot X.
\]

In this way ICA transforms an \( n \)-sensor data array into an \( n \)-dimensional component space, where each of the time varying components in \( C \) carries a minimum amount of mutual information and thus is maximally independent \([22]\).

Signal rejection, i.e. the cleaning process, is performed by zeroing columns in \( W^{-1} \) which reflect signal contributions from unwanted (e.g. artifact) sources, resulting in a new mixing matrix \( \tilde{W}^{-1} \). Artifact removal or the cleaning of measured signal is performed by back transformation of \( C \), which results in a new set of MEG data \( X' \):

\[
X' = \tilde{W}^{-1} \cdot C.
\]

Multiple realizations of ICA co-exist and are widely used in the MEG community for different applications \([23]-[25]\). Here, we use the constrained ICA concept of Barriga and colleagues \([20]\) which is based on Infomax ICA \([26]\).

Since all MEG systems we used for testing our approach are equipped with a few hundred MEG channels this leads to an over-determined mathematical problem if we assume a few cardiac sources only. Therefore, we applied principal component analysis (PCA) \([27]\) to reduce the number of MEG channels prior to ICA. Dimension reduction is achieved by using \( k \) principle components corresponding to the first \( k \) eigenvalues which explain \( V\% \) of the data variance. We use 95\% of explained variance here for subsequent signal decomposition by ICA.

With respect to real-time application it is necessary to find a trade-off between the length of input data and signal separation quality. Therefore, in the next section handling of the input data length is explained in more detail.

C. Stationarity Test

Often ICA-based signal decomposition is performed on the whole data set at once. In our experiments this would translate to 168333, 830400 and 345167 time samples on average for 4D-Neuroimaging, VSM MedTech Inc. and Elekta Neuromag, respectively (Table 1). In case of real-time MEG data analysis of much smaller data segments are required. When performing ICA some requirements and limitations have to be considered. A basic requirement for data to be decomposed using ICA is stationarity \([23],[26],[28]\). Stationarity is often interpreted in the sense that too long data epochs may result in non-stationary signals due to slight movements of the sources (i.e., the subject’s head moved). Another possibility is that the brain may change the strategy to process different tasks during the measurement. In such cases, the mixing process becomes non-stationary. On the other hand, there is a minimum amount of data to be used when extracting the underlying sources. With regard to short-time data segments the requirement of stationarity refers to the existence of a representative

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![Fig. 1. Schematic illustration of the CARTA data processing structure.](image-url)
distribution of the underlying true source [22]. In other words, to perform reliable signal separation on short data segments the amount of data must be long enough to reflect the temporal time course of the underlying source by means of its probability density distribution. The question to be addressed for real-time applications is: “how small can these samples be at the same time fulfilling the stationarity requirement?”

As a rule of thumb it has been reported that the number of data samples should be at least a few times the square of the number of ICs to be estimated [29]. However, for real-time applications we used of a much stricter criterion to estimate the optimal sample length. The well-known Augmented Dickey-Fuller (ADF) test [30] was used to test for stationarity in the MEG data before real-time cardiac artifact reduction was applied.

In order to test for the minimal size of MEG data segments prior to ICA decomposition the ADF test was applied multiple time across different data segments by means of a Jackknife test [31]. The Jackknife test was used to estimate the bias of the applied ADF test. For this, the recorded data (i.e., the whole MEG measurement) were segmented into small data segments with 50% overlap. On each segment the ADF test was applied separately, which resulted in significance values \( p_i, i = 1, \ldots, m \). Bias is then given by

\[
\text{bias} = (m - 1) \cdot (\bar{p} - \tilde{p}) ,
\]

where \( \bar{p} \) is the significance value of the ADF test performed on the full MEG data set and \( \tilde{p} \) being the mean over the \( m \) estimated significance values \( p_i, i = 1, \ldots, m \). If the bias is close to zero and the maximal \( p_i \) is lower than the significance level of 1%, stationarity of the tested MEG signals is assumed.

D. Workflow of Data Cleaning in Real-Time

As mentioned above performing ICA is computationally demanding. Thus with respect to real-time application, here we use an algorithm performing two tasks in parallel. One task is to perform the cleaning process, while the other task is to estimate a new demixing matrix including the identification of CAs (Fig. 1). This means that the computationally demanding parts of the algorithm are all performed in the second task (right side Fig. 1). The cleaning process (left side Fig. 1) consists of only transforming MEG signals in ICA-space (cf. Eq. 2), remove CAs and back-transform the signal to MEG-space (cf. Eq. 3). Mathematically, these are two matrix-matrix multiplications, or rather two matrix-vector multiplications since these multiplications can be applied separately on the data recovered at each point in time.

To perform CA removal on the actual data segment, \( t \), using an optimal unmixing matrix, \( W_t \), it is important to estimate \( W_t \) as quickly as possible. Thus, decomposition is performed using the minimum amount of data required by using a sliding window of \( L \) seconds.

While calculating the actual unmixing matrix \( W_t \) the previous unmixing matrix \( W_{(t-1)} \) is used for data decomposition. After \( W_t \) is estimated, it is necessary to identify ICs that refer to the CAs. This is carried out by cross trial phase statistics (CTPS)[3]. In the cleaning process (left side Fig. 1) identification of ICs that refer to the CAs does not have to be repeated since using \( W_t \) for data decomposition the

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**Fig. 2.** Schematic illustration of the real-time simulated CARTA cleaning process.
indices of the ICs referring to CAs does not change.

In the next two sections calculation of \( \mathbf{W}_i \) including source identification is elucidated in more detail.

E. Constrained ICA for Cardiac Artifacts

With respect to real-time analysis, the goal is to optimize ICA for speed without loss of the signal separation accuracy. We thus use a constrained ICA (cICA) approach [20], [21], [32] and incorporate prior knowledge of the underlying expected signal in the internal cost function to perform optimal signal decomposition. Prior knowledge can be incorporated in one of three ways: i) in the initial unmixing matrix, ii) a source specific cost-function and iii) by measuring the similarity between a reference signal and the extracted sources. We here use the first two methods.

ICA is applied successively on several different data segments. The cardiac activity of these segments must, to some degree, be the same since the segments overlap. Therefore, the latest unmixing matrix \( \mathbf{W}_{i-1} \) from the previous ICA calculation at segment \( (i-1) \) serves as an optimal initial matrix for the signal decomposition at the \( i \)-th segment (cf. Fig. 1).

The cost-function is optimized in line with the approach of Barriga [20], CARTA is based on a modified version of the Infomax principle [26] with the important difference that we introduce a cost-function for optimized signal separation for CA rejection. Starting from Eq. (2), we use the natural-gradient version of Infomax [28], [33]:

\[
\Delta \mathbf{W} = \epsilon (\mathbf{I} + (1 - 2\epsilon) \mathbf{C}^T) \mathbf{W},
\]

with \( \epsilon = \frac{1}{1 + e^{-\eta t}} \).

F. Automatic Identification of Components Related to Cardiac Activity

Recently, cross trial phase statistics (CTPS) have been shown to reliably identify components related to strong and weak cardiac activity in a fully automated fashion [3], [34]. The method is based on statistically testing phase-locked activity with reference to a given event (e.g., the R-peak from the QRS complex) in phase space across multiple trials. In brief, phase values of the independent components are estimated using the well-known Hilbert transform [35]. For this the data are band limited to the frequency range from 10-20 Hz covering the strongest energy from the QRS complex [3]. After filtering, the resulting phases are normalized and split into time windows (trials) of 1 s around the R-peak of the ECG signal. Kuiper’s test [36] is used to estimate the significance of phase-locked activity at each time point separately, but across trials. In CTPS we use a normalized version of the Kuiper’s statistic, where the significance value \( p_K \) ranges between [0,1]. In case of uncorrelated activity \( p_K \) will be close to 0, while for perfectly synchronized activity the significance value will be 1.

G. Quality Measures for Cardiac Artifact Removal

In order to evaluate the cardiac artifact rejection results obtained by CARTA across different subjects and MEG systems we use the rejection performance measure as introduced in [3]. The rejection performance value \( R_p \) is given by:

\[
R_p = \frac{r(s-s')}{r(s)} \quad \text{with} \quad r = \frac{1}{N} \sum_{t=1}^{N} \frac{1}{\sqrt{\sum_{t=1}^{N} (s'_t - s_t)^2}}.
\]

where \( r \) expresses the average root mean square (rms) value across the \( N \) channels of the MEG recordings. The signal \( s' \) here is the cross trial averaged signal of the \( i \)-th sensor. Thus, \( r(s) \) expresses the mean rms value before the artifact rejection and \( r(s - s') \) represents the mean rms value of the difference signal between the signal before \( (s) \) and after \( (s') \) the ICA rejection, respectively. With respect to cardiac artifact rejection, \( R_p \rightarrow 0 \) can be interpreted as a complete failure of the rejection process. For \( R_p \) being close to 1, artifact rejection is maximal. If the method is applied to stimulus onset averages, we expect \( R_p \) values close to 0 indicating the signal of interest stays unaffected.

Since the rejection performance value \( R_p \) as introduced by Dammers and colleagues [3] is sensitive to changes in signal amplitude only, we additionally used a second metric that is sensitive to changes in the frequency domain. This metric was introduced by [6] and measures correlation in the frequency domain:

\[
f_c = 0.5 \cdot \frac{\sum_{n=1}^{w1} (\bar{s}_c \bar{s}_c' + \bar{s}_c \bar{s}_c') / \sqrt{\sum_{n=1}^{w2} \bar{s}_c \bar{s}_c' \cdot \sum_{n=1}^{w2} \bar{s}_c \bar{s}_c'}}{w1 + w2},
\]

where \( w1 \) and \( w2 \) are the bounds of the frequency window (in our case 1 and 45 Hz), \( \bar{s} \) and \( \bar{s}' \) are the Fourier coefficients of \( s \) and \( s' \), and \( \bar{s}^* \) and \( \bar{s}'^* \) are the complex conjugations of \( \bar{s} \) and \( \bar{s}' \). \( f_c \) equals 1 if the frequency content of the signal after
CARTA application is unaffected, while \( f_c \to 0 \) tends to a complete loss of the frequency content.

### III. RESULTS

We tested the CARTA algorithm on data recorded with three different MEG systems. To achieve optimal signal decomposition for CA removal CARTA requires a minimum amount of data. For this, an ADF Jackknife test was performed using a sliding window with a window width ranging from 9 to 13 s and 50% overlap (Table 2). Our results indicate that the minimal segment size must be 12 s or more in order to fulfill the stationarity request. Based on this result a minimum of 12 s of recordings of e.g., resting state activity is necessary before the actual experiment can start. Since the data accumulate during recordings there will be only a short delay at the very beginning of the experiment (cf. Fig. 1).

The optimal cost-function for CARTA is estimated by fitting the cdf of the individual ECG signal according to Eq. (7). This leads to 95% confidence intervals for \( a_0 \) of [0.5, 1.3], [0.7, 4.7] and [0.4, 3.5] for 4D-Neuroimaging, VSM MedTech Inc. and Elekta Neuromag, respectively. Analogous the 95% confidence intervals for \( a_1 \) are [10.5, 28.0], [10.3, 23.4] and [10.1, 21.2].

To compare CARTA with PCA [27], Infomax [26], Extended Infomax [23] and FastICA (using \( \tanh \) as contrast function) [24], we performed real-time cleaning on a MEG data set as explained (cf. Fig. 1), but with using PCA, Infomax, Extended Infomax, FastICA and CARTA to estimate the unmixing matrices \( W_i, i = 0, ..., n \) (cf. right side Fig. 1). Fig. 3 illustrates MEG signals of one data segment (12 s) averaged with respect to the R-peak of ECG before (red) and after (black) the PCA, Infomax, Extended Infomax, FastICA and CARTA cleaning process, respectively. In case when PCA was used, the CAs were not sufficiently suppressed (\( R_p = 46\% \)), while when using CARTA with only one iteration in the cICA part all CAs were sufficiently removed (\( R_p = 92\% \)). Infomax ICA performing only one iteration (as in CARTA) yields to a \( R_p \) value of 72%. To achieve \( R_p \) value results in the range of CARTA seven iterations are necessary. Using Extended Infomax we achieved results comparable to Infomax with \( R_p \) values of 71% and 87% for one and seven iterations, respectively. For FastICA, \( R_p \) values of 34% and 87% are obtained for one and ten iterations, respectively.

Within CARTA, the dimension of the input data is reduced to the number of components explaining 95% of data variance.

#### TABLE II

<table>
<thead>
<tr>
<th>Time</th>
<th>4D-Neuroimaging</th>
<th>VSM MedTech Inc.</th>
<th>Elekta Neuromag</th>
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</thead>
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<td>0.009/0.00</td>
<td>0.009/0.00</td>
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<tr>
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<td>0.009/0.00</td>
<td>0.990/0.37</td>
</tr>
<tr>
<td>10 s</td>
<td>0.009/0.00</td>
<td>0.990/0.99</td>
<td>0.990/6.990</td>
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<tr>
<td>9 s</td>
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<td>0.990/1.72</td>
<td>0.990/5.69</td>
</tr>
</tbody>
</table>

Values are given as \( \text{max} / \text{median} / \text{bias} \)

Stationarity test in MEG signals of two different recordings using three different MEG systems. Small \( p_l \) and small bias values indicate stationarity in the given data segment. At a data length of 12 s the \( p_l \) and bias value are sufficiently small.

This on average yields 25, 24 and 54 components for 4D-Neuroimaging, VSM MedTech Inc. and Elekta Neuromag, respectively. Computation times for estimating the unmixing matrices and identify the ICs related to CAs (cf. right side Fig. 1) using 12 s of data were found to be 2.2, 2.4 and 2.9 s on average (on an Intel Core i5-2410M, 2.3 GHz, 6 GB RAM) for the 4D-Neuroimaging, VSM MedTech Inc. and Elekta Neuromag system (Table 3).

CFTS-based source identification revealed 1-3 components that can be attributed to cardiac activity in all measurements. The average number of ICs related to CA were found to be 2.3, 2.3 and 2.1 for the 4D-Neuroimaging, VSM MedTech Inc. and Elekta Neuromag system, respectively. The cleaning process (cf. left side Fig. 1) was measured online for each data segment and lasts 1 ms for all three systems.

To detect changes in the time and frequency domain, the rejection performance \( R_p \) and frequency correlation \( f_c \) were calculated on all data segments before and after the cleaning procedure (Table 3). In averages the mean \( R_p \) values with onset of the R-peak were found to be 94, 92 and 92% for 4D-
The subject's mean around R-peak onset (%). This indicates that the amplitude of cardiac artifacts is sufficiently suppressed in all subjects and different MEG systems after CARTA was applied. For stimulus onset averages, the mean $R_p$ values were found to be 24, 19 and 26% with respect to the three different MEG systems (cf. Table 3). In the frequency domain we found mean $f_c$ values across measurements of the three MEG systems to be 58, 63 and 66% for R-peak onset based averages. More importantly, for the stimulus onset based averages the mean $f_c$ values were found to be 97, 98 and 96%. This indicates that the frequency content of the signal of interest is preserved.

Fig. 4 shows both signal averages with onset to R-peak before and after CARTA application; this is also reflected by the performance measures, with $R_p = 20\%$ and $f_c = 98\%$. Fig. 4c illustrates that most of the signal of interest is retained by showing the signal before (red) and after (black) CARTA application; this is also reflected by the performance measures, with $R_p = 20\%$ and $f_c = 98\%$. Fig. 4d illustrates the difference between the signal of interest before and after CARTA application.

To evaluate the effect of the CARTA cleaning process with respect to source localization, we applied magnetic field tomography (MFT) [37] to six trials from a single subject who showed strong CAs during auditory stimulation (data were recorded with the 4D-Neuroimaging system). The trials were selected by visual inspection and showed strong cardiac activity within the time range of the evoked auditory response (N100m). After averaging of the selected trials, source localization was applied at peak latency (N100m, 100 ms after stimulus onset) before and after artifact rejection. Fig. 5 shows the averaged MEG signals, a corresponding time-frequency plot using Stockwell transformation [38] and the source localization before (Fig. 5a) and after (Fig. 5b) the application of CARTA. For comparison, results obtained by template matching [10] are shown in Fig. 5c. Source localization is shown at the maximum activity of the N100m after artifact rejection: $x = -7$, $y = -66$, $z = 33$ mm (individual subject space). Before artifact rejection the maximum activity was found at: $x = 18$, $y = -25$, $z = -7$ mm.

### IV. Discussion

We have introduced a novel approach optimal for cardiac artifact (CA) reduction for real-time MEG data analysis. The method, called CARTA, is based on a constrained ICA approach [21], where a priori information of the underlying source signal is used. In CARTA this is performed by estimating the individual subject's density distribution of the cardiac activity. With this a subject specific signal decomposition was achieved by incorporating prior knowledge about the underlying sources leading to a constrained ICA approach [15], [20], [21]. The subject's individual cumulative density function of the cardiac activity served as the internal cost-function within CARTA. As a result, we perform individual and therefore optimal signal

**TABLE III**

<table>
<thead>
<tr>
<th>Table Title</th>
<th>4D-Neuroimaging</th>
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<th>Elekta Neuromag</th>
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<td>2.1 ± 0.19</td>
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<td>92.1 ± 5.00</td>
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<td>98.2 ± 1.68</td>
<td>96.4 ± 1.76</td>
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Performance values of CARTA applied to three different MEG systems. All measures were performed on an Intel Core i5-2410M, 2.3 GHz, 6 GB RAM. The number of iterations is given for estimating the unmixing matrices $W_i$ (where no special initial matrix exist) / $W_i, i = 2, ..., n$, with $n$ being the number of different segments, where the previous unmixing matrix can be used as initial matrix.
We tested the new algorithm in 18 subjects utilizing three different, but common, MEG systems (4D-Neuroimaging, VSM MedTech Inc. and Elekta Neuromag). In all measurements we demonstrate that the new method is capable of effectively reducing CAs when applied to the three different MEG systems. CARTA sufficiently removed cardiac activity within 1 iteration (3 iterations only for estimating the first unmixing matrix). In addition, for real-time application cross trial phase statistics (CTPS) is implemented in CARTA for the automatic identification of cardiac activity [3].

It has been demonstrated in various publications that other ICA approaches also effectively separate artifacts from the signal of interest [3], [38]-[40]. However, there are two major problems when applying “standard ICA” approaches: i) the applied ICA method must be selected carefully in particular with respect to the separation strategy, i.e. the internal cost-function. In general the internal cost-function in ICA algorithms is not optimized to extract a specific source, rather than multiple types of non-Gaussian sources. ii) Assuming the mixed signals are adequately separated into its underlying source signals (i.e., signal of interest and non-interest), identification of the signal of interest must be performed quickly and user independently for real-time analysis.

In the literature one can find a variety of different ICA and cICA approaches. Most of them are designed to decompose a diversity of different non-Gaussian source signals using, for example, the sigmoidal (Infomax) or the tanh function (FastICA) as the nonlinear contrast function. With regard to the quality of the signal decomposition the contrast function used in these ICA routines can only be considered as a good compromise to decompose different types of non-Gaussian source signals. Optimal signal separation is performed when the contrast function used matches best the cumulative density function (cdf) of the source to be extracted [42]. This strategy has been used and implemented in CARTA, since the algorithm is designed for CA rejection only. In CARTA the contrast function is estimated using the subject’s own cardiac signal to ensure optimal signal decomposition with respect to the cardiac activity.

Concerning computation time, previously reported ICA, cICA and other on-line ICA algorithms are not fast enough to be considered for real-time analysis. In [17], for example, the average computation time and learning steps to estimate independent components related to CAs are reported to last more than 3.3s and 274 iterations, respectively. (Note, that in [17] only four (!) sources have been used). With respect to real-time application this is quiet slow. In contrast, CARTA quickly converges with 1-3 iteration only (∆< 2.9s) (Note, with 54 sources including dimension reduction from originally 306 sources).

For evaluation of CA removal, we used two different quality measures: one sensitive for measuring changes in the signal amplitude and another one for changes in the frequency domain. As a metric for amplitude changes we used the rejection performance value $R_p$ introduced in [3]. The authors reported a mean $R_p$ value of 91% for their off-line CA rejection method, which compares very well to our results (mean $R_p$ values around R-peak: 94, 92 and 92%). Analysis in the frequency domain showed that signal around the stimulus...
onset is marginally changed through CARTA application 
(mean $f_c$ values were 97, 98 and 96%). In Fig. 3-4 we demonstrated that cardiac artifacts were sufficiently rejected, while the signal of interest remains. We also showed that with respect to the number of iterations CARTA performed 7 – 10 times faster compared to the other tested ICA algorithms. When comparing source localization before and after CARTA application, we found that the source location is strongly affected by the CA (cf. Fig. 5). Therefore, in order to archive meaningful results CA reduction is mandatory prior to source localization.

Template matching procedures are widely used for artifact removal in MEG and EEG signal processing. Fig. 5c nicely show that the template matching procedure effectively removed the cardiac signal, but at the expense of losing signal of interest. The loss of signal is also evident in the time-resolved frequency plot (cf. Fig. 5b-c).

Since the real-time capability of the algorithm is limited by the stationarity requirement of ICA, a minimum of 12 s of recordings (using for example resting state activity at the very beginning of an experiment) is required before the actual experiment starts. Thereafter, estimating a new unmixing matrix and identification of ICs belonging to CAs is performed parallel to data cleaning. Since the cleaning process based on the design chosen here consists of only two matrix-vector multiplications for each measured point in time, the cleaning procedure is performed with a time delay of 1 ms. Since Lauer and colleagues [43] reported that humans notice delays between movement intention and device’s reaction being longer than 0.2 s, we assume computation times below 0.2 s can be treated as real-time. Thus, our CARTA algorithm can be added to BCI algorithms [14]-[17] to reduce the CAs without losing real-time capability.

However, to improve the results a faster estimation of the demixing matrix (CARTA needs at least 1.8 s) is desired and maybe realized by using digital signal processors (DSP) or field programmable gate arrays (FPGA). Other on-line ICA approaches which update the demixing matrix within a few milliseconds have been reported [33], [44]. Although these approaches seem to be very promising, however, these approaches have been tested on simulated data only using a mixing scenario of only a few sources (i.e. 3-5 simulated sources) [33], [44]. In CARTA the number of components used ranged from 24 – 54, while extra time is needed to apply dimension reduction of the much larger data matrix defined by the number of MEG sensors used. Nonetheless, a combination of the above approaches may help to further develop real-time capable algorithms to reduce other sources of artifacts, in particular, eye blinks/movements or muscle activity.

V. CONCLUSION

We conclude that our new developed ICA algorithm is fast and optimized for signal decomposition with respect to cardiac artifacts. Combing this algorithm with CTPS, a fast and robust method to extract cardiac activity with a very high sensitivity, leads to an optimal cardiac artifact reduction method. In summary, we have demonstrated the real-time capability of the new algorithm referred to as cardiac artifact rejection for real-time analysis, CARTA.

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REFERENCES

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