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Reduction of Metallic Interference in MEG Signals Using AMUSE*

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Abstract— **Magnetoencephalography is a technique that can noninvasively measure the brain signal. There are many advantages of using this technique rather than similar procedures such as the EEG for the evaluation of medical diseases. However, one of its main problems is its high sensitivity to sources causing metallic distortion of the signal, and the removal of this type of artifacts remains unsolved. In this study a technique for reducing metallic interference was presented. This algorithm was based on AMUSE, a second order blind source separation method, and a procedure for choosing the artifactual independent components was also presented. The results showed that the elimination of these artifacts would be possible by means of the application of this AMUSE-based interference reduction procedure.**

Keywords— **Metallic Artifacts, BSS, ICA, MEG, AMUSE**

I. Introduction

Magnetoencefalography (MEG) is a technique that can non-invasively measure the electromagnetic brain potentials and can be used in a clinical environment to assess the brain activity of adults and children [1]. MEG can add valuable information which is not visible using other techniques such as electroencephalography (EEG) [2]. One of its strengths consists in independence of head geometry compared to EEG [3]. Prior to obtaining this information it is necessary to remove different kinds of artifacts to which the signal is sensitive. These artifacts come from several sources such as ocular, cardiac or muscular [4] and their removal can be achieved using independent component analysis, a technique that has been successfully evaluated in several studies [5-7]. AMUSE [8] is a second order BSS method which has been used successfully for EEG filtering [9-10]. A principal drawback of MEG lies on its increased sensitivity to interferences caused by metallic artifacts that may come from external or internal sources to the patient such as implants, pacemakers or vagal stimulators [11]. The current procedure used in the clinical environment when these artifacts appear is to remove the most affected channels and to apply band-pass filtering. This step results in a loss of information that could be useful for further analysis especially if the artifact masks a region that matches the possible cerebral area of interest.

Literature reports few studies evaluating the existence of this type of artifacts. For sources outside the head, Temporary Signal Space Separation (t-SSS) technique seems to be successful [12], but for sources located inside the head, such as dental implants, this problem is still open and rather unsolved.

The main aim of this paper was to assess the suitability of AMUSE-based filtering procedure to achieve the separation and extraction of the information related to metallic distortion, so that its undesirable effects can be reduced on MEG signals.

This preliminary study evaluates the effectiveness of the AMUSE algorithm for the removal of components associated with metallic artifacts from real MEG signals of subjects with dental implants. Furthermore, one of the main challenges in independent component separation is to decide which components should be removed. In this study a preliminary procedure for their selection was provided.

II. Methods

A. MEG Signals

MEG signals were recorded using a whole-head 148-channel magnetometer system (4D-Neuroimaging/BTi) and sampled at 678.19Hz (Bandwidth DC to 250Hz). Signals were acquired during ten minutes from 4 subjects with temporal lobe epilepsy and with dental ferromagnetic implants. The subjects were aged 34, 31, 19 and 13 years old.

Visual inspection revealed that the metallic artifacts distorted most channels but there were several channels whose amplitude was fairly higher than the rest although brain activity was assumed to stay masked behind them. These areas, where the artifact distorted with much more intensity, were called "artifactual foci". In this work, channels whose energy exceeded the one percent of the whole energy of all signals were marked as artifactual foci.

B. Signal pre-processing

Outer sensors (130-148) were removed from the analysis due to the low signal to noise ratio. After this, an adaptive filter [13] was performed to remove the 50 Hz interference. Signals were separated into ten 60-seconds segments in order

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to fulfill the recommendation suggested in [14] that states that the segment to be decomposed should have a number of samples equal to several times the square of the number of channels.

C. Independent Component Analysis (ICA)

ICA is a statistical signal processing technique whose goal is to express a set of random variables as linear combinations of statistically independent component variables [15]. The algorithm used in this study is named AMUSE. The model of the identification process is then expressed by:

$$x(t)=As(t) \qquad (1)$$

where $x(t)$ is the observation vector process, $s(t)$ is the vector of the unknown source signals and A is the mixing matrix representing the weights of the projection of the respective source signals at different channels.

AMUSE is a simple and very fast algorithm that exploits the second-order statistics of the independent components. In its first step, an orthogonalization transformation is constructed to estimate the number of significant values. This transformation reduces the complexity of the blind identification problem by limiting the number of components extracted. This step is called pre-whitening and is calculated by performing a Principal Component Analysis (PCA). In this work, the number of components was fixed to explain the 99 percent of the variance of the signal. After PCA, the transformation matrix was obtained from the eigen-decomposition of a modified version of the lagged covariance matrix [16].

$$\bar{C}_\tau^y = \frac{1}{2}[C_\tau + C_\tau^T] \quad \text{Where} \quad C_\tau = E\{y(t)y(t-1)\} \qquad (2)$$

In order to obtain the independent sources, separation matrix W estimation was evaluated by this transformation matrix. Independent components (IC) were obtained as the product of the separation matrix and the input signals.

D. Artifactual IC selection and filtering

After extracting the ICs of the signal it was necessary to choose which of them were associated with metallic artifacts and therefore had to be removed. Each channel was projected on an IC so that each IC had a corresponding weight vector that quantified these projections. Intuitively, it was expected that the components related to metallic sources had a higher projection on the MEG channels marked as artifactual foci.

A sum of weights (SW) was calculated for each IC (SW_{ICi}) by the percentage of the sum of wheights associated with the channels included in the artifactual foci with respect to the total weights. ICs that fulfilled the following criterion were selected as sources of the artifacts:

$$SW_{ICi} > 3 * median(SW_{ICi}) \quad \text{for i=1..N} \qquad (3)$$

were N is the total number of ICs after pre-whitening.

Then, the selected ICs were removed, and MEG signals were reconstructed as the product of the mixing matrix with the remaining components.

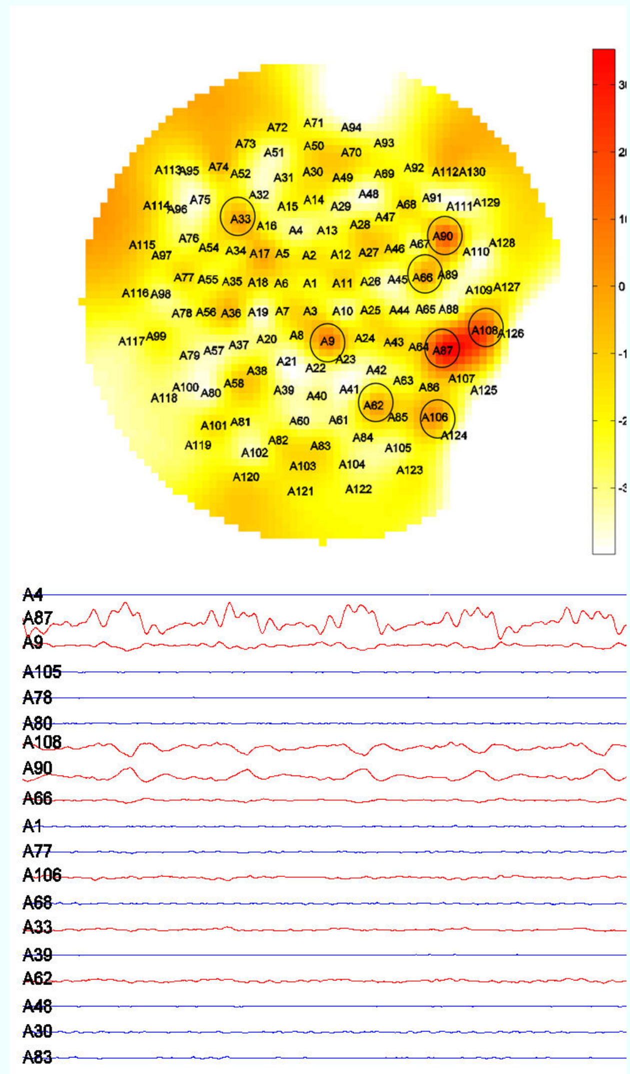

Figure 1. Subject 1. A) Topographic distribution of energy in dBs for the 130 channels. Rounded channels were selected as artifact foci (energy higher than 1% of the whole signal). B) Five seconds corresponding to MEG signals. Eight artifactual channels (red) and eleven artifact-free channels (blue) are plotted. Note that scale is the same in all channels.

III. Results

A. Selection of Artifactual Foci.

Fig. 1A shows as an example the topographic plot of energies for subject 1. The number of channels selected as artifactual foci for the four subjects was 13.25±4.57 (mean±SD). This high variability was due to the localization of the energy of the artifacts. In cases where the energy was focused mainly on one or two channels, the number of channels selected as artifactual foci was lower than when energy appeared more spread. Clearly, this suggested that the effect of the metallic contamination depended on its dispersion over the scalp and it could be different in each subject.

MEG signals are shown in Fig. 1B. Channels with more energy displayed a very different pattern from the brain activity. In the four cases under study the metallic interference produced such a slow artifact. It is noticeable that low amplitude signals had also some slow activity in the same frequency range than high amplitude signals so the artifact reduction is not possible with a simple high pass filtering.

B. Independent Component Selection

For the four subjects, ICA was performed with previous PCA. The number of components extracted from this preliminary step was 38.35±8.07 (mean±SD). Afterwards, the sum of the percentage of the weights of the artifactual foci was calculated for each IC (SWICi) and those whose value fulfilled Eq. 3 were selected for further removing. Fig. 2 shows the results for the four subjects.

Knowing that AMUSE algorithm orders components by variance, in all cases the components selected were the ones with higher variance and also matched the low frequency components associated mainly to the metallic artifacts.

C. Filtering

Signals were filtered by removing the selected ICs before the reconstruction of the MEG signals. Fig. 3 shows several MEG channels from subject 1 after applying the AMUSE-based metallic interference reduction. The shown channels correspond to the same ones depicted in Fig 1B before filtering. After filtering, channels identified as artifactual foci displayed comparable levels of amplitude and energy to the rest of the channels.

Brain activity was observed in all channels, even in those where their high energy was caused by artifacts. These results were similar on the other 3 subjects.

In order to evaluate the effect of the metallic interference filtering, the correlation coefficient of each channel before and after filtering was calculated. Fig. 4 shows a topographic map for the four cases studied. On one hand, in those channels belonging to the artifactual foci, the correlation was close to zero. On the other hand, it was assumed that there was no interference from metallic sources in those channels whose coefficient was close to one and the filtering preserved their brain activity. Although in all subjects there was a region or a few channels with very high levels of interference, it is important to note that other areas were also cleaned after the metallic interference reduction procedure.

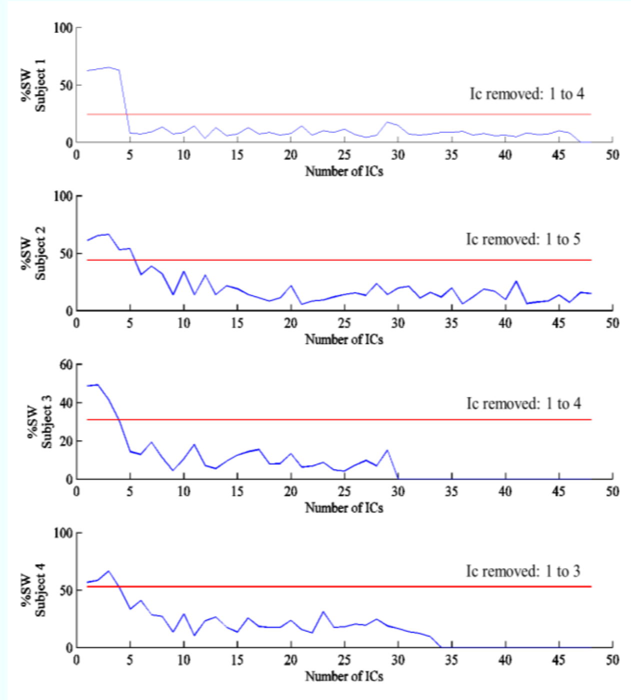

Figure 2. Sum of the weights for each IC (SW_{ICi}) for the four subjects. The red line corresponds to the result of Eq. 3. For each IC associated with artifacts were selected when SW_{ICi} was higher.

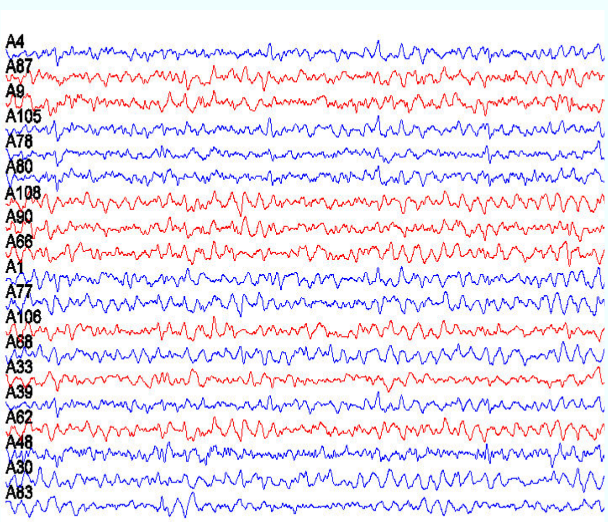

Figure 3. Five seconds corresponding to post filtered signals from subject 1. Eight artifactual channels(red) and eleven artifact-free channels (blue) are plotted.

IV. Conclusion and Discussion

MEG signals are particularly sensitive to artifacts of metallic nature. Blind Source Separation techniques, and particularly AMUSE, have shown their effectiveness to remove artifacts from other nature in MEG signals.

In this study, AMUSE was applied to four subjects with metallic dental implants in order to evaluate the effectiveness of the algorithm in real signals. Results shown in Fig. 3 and Fig. 4 confirmed that metallic artifacts can be removed from MEG signals effectively.

The artifacts presented high energy channels selected as artifactual foci, but that does not mean that the rest of the channels were artifact-free. In fact, it was observed that the metallic interference was reflected in other channels scattered across the head but with less amplitude. In order to confirm this assumption and to justify the application of the separation into independent components to all available MEG channels (not only from artifactual foci), the normalized correlation between the channel with highest energy and the rest of them was performed (Fig. 5).

Comparing this map with Fig. 4 (Subject 1) it can be inferred that some areas where the correlation with the channel determined as the main artifactual focus was high,

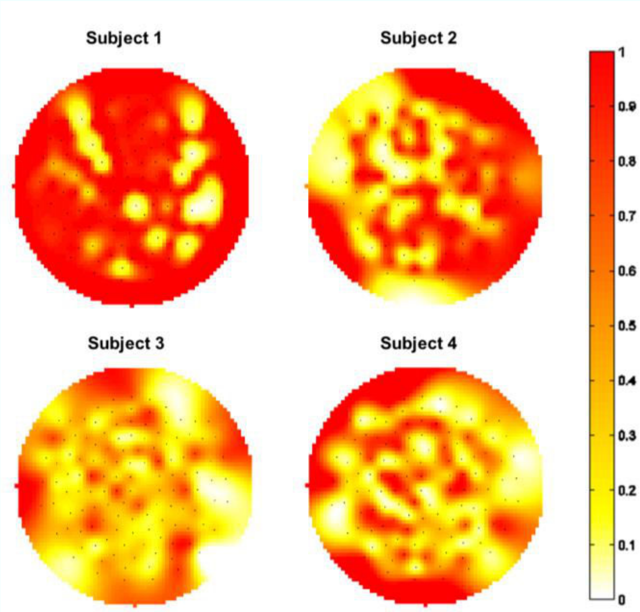

Figure 4. Topographic maps of correlations of each channel before and after filtering. White areas with low correlation show lot of change due to filtering, red areas come from channels practically unaffected by filtering.

showed low correlation values before and after filtering than the others regions, respectively. As shown in Fig. 5 these areas did not necessarily coincide with channels with highest energies and belonging to artifactual foci but they did with zones with low correlation before reducing the effect of metallic interference (Fig. 4). In this way, it was verified that many low-amplitude channels were also contaminated and that ICA filtering could effectively restore them.

Further work is needed to validate the approach presented in this work. On one hand, the use of the described procedures in more subjects will help to understand the nature of this kind of artifacts and their successful removal. On the other hand, analysis with simulated signals is needed to evaluate quantitatively the algorithm methodology.

Analysis with other high order ICA methods would also be useful to compare algorithms and to elucidate which of them works better not only for reduction of metallic artifacts but also for other artifacts of different sources. All these steps should lead to the development of an automatic filtering tool capable of removing artifacts of diverse nature including the metallic ones for MEG signals.

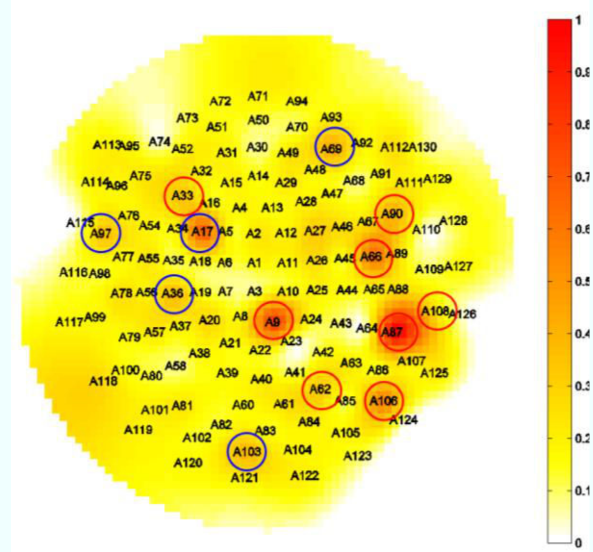

Figure 5. Subject 1. Correlation between each channel and A87, which had the highest energy and thus was mainly associated with metallic artifacts. Red-circled channels correspond to those detected as artifactual foci. Blue-circled channels correspond to other channels whose correlation is high with respect to the most of channels that do not contain the artifact presented in channel A87 in spite of these red-circled channels do not belong to the artifactual foci.

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