Co-recording of EEG and fMRI data: EEG artifact removal

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Abstract—The electroencephalogram (EEG) is a standard technique to record and study the brain activity with a high temporal resolution (ms). BOLD fMRI (Blood Oxygenation Level Dependent functional Magnetic Resonance Imaging) is a non-invasive imaging method that allows the localization of activated brain regions with a high spatial resolution (mm).

The co-recording of these two complementary modalities can give new insights into how the brain functions. However, the interaction between the strong electromagnetic field (3T) of the MR scanner and the currents recorded by the electrodes placed on the scalp generates artifacts that obscure the EEG and diminish its readability.

With this work we aim at comparing two techniques, namely the Optimal Basis Set (OBS), based on Principal Component Analysis, and the Average Artifact Subtraction (AAS), both of them relying on the accurate detection of the pulse artifact. We will investigate the effect of a random time delay on this detection using simulated and real data.

Keywords-EEG, fMRI, PCA

I. INTRODUCTION

THE co-registration of EEG and fMRI has become a valur able tool for the understanding of brain functioning during cognitive and behavioral studies. The good temporal resolution of the EEG and the high spatial resolution of the fMRI offers an insight in the brain dynamics not achievable with any other technique. However, the presence of the strong magnetic field of the MR scanner generates artifacts on the EEG, such as the pulse artifact (PA), which obscure the EEG. Different methods have been suggested in literature in order to remove this artifact, all of them based either on Blind Source Separation or averaging techniques. With this work we aim at comparing two techniques, namely the Optimal Basis Set (OBS) [1], based on Principal Component Analysis, and the Average Artifact Subtraction (AAS) [2].We will investigate the effect of a random time delay on the detection of the artifact using simulated and real data.

II. MATERIALS AND METHODS

A. Dataset

SIMULATED DATA: as described in [2], we assume an additive model for the pulse artifact. In order to simulate one channel of an EEG recording inside the scanner, we add to background EEG some α -activity and a simulated ECG, scaled by an appropriate factor. The background EEG consists of white noise filtered between 0.5Hz and 100Hz and multiplied in the frequency domain by g(f) = 1/f to obtain a 1/f spectrum. The α -activity is modeled as sum of sinusoids with frequencies normally distributed according to N(10.2,0.9). The ECG is simulated as described in [3]. REAL DATA: the real data consists of one channel of a multichannel EEG recorded from an epileptic patient inside the scanner during MR image acquisition. An additional ECG channel is also recorded. The sampling rate is 4096Hz and the signal is then subsampled to 256Hz and filtered with a band pass filter (0.5Hz-40Hz); no epileptic activity is identified in the recording.

B. Methods

It has been shown [2] that the PA occurs 0.21s after the QRS complex on the ECG. Therefore, the PA occurrences are obtained by shifting the detections of the QRS complex, identified using [1], by an amount of 0.21s. In both datasets a random delay, uniformly distributed according to U(0.3,0.6), is added to the PA occurrences, in order to simulate inaccuracy of the detection of the PA artifact.

AVERAGE ARTIFACT SUBTRACTION (AAS) [2]: this method assumes that the shape of the PA is constant over time. The EEG is windowed around each PA occurrence with a symmetric window of length equal to the distance between two consecutive QRS complexes. The EEG segments are then averaged: the random background EEG is thus averaged out and only the deterministic activity is highlighted. The template is then subtracted from the original EEG after synchronization with the pulse artifact.

OPTIMAL BASIS SET (OBS) [1]: this method allows the PA to change over time and the current shape is defined as a linear combination of a subset of possibly weighted shapes. The EEG is windowed around each PA occurrence with a symmetric window of length equal to the distance between two consecutive QRS complexes and the EEG segments are arranged in a matrix. Principal Component Analysis is applied to that matrix. The signal is reconstructed leaving out the components that, after visual inspection, are recognized to be responsible for the artifact. In the following we use OBS(nth) to indicate that the first nth components have been removed.

EVALUATION: in order to evaluate the two techniques addressed in this paper, we use different approaches, depending on the analyzed dataset. With the simulated EEG, we compute the distance between the original background EEG and the cleaned EEG. With the real dataset, we use two measures. (1) We compute the percentage of the residual PA power: the signal, windowed around the PA occurrences, is averaged in order to remove any random activity, namely the background EEG, and to maintain only the deterministic activity, namely the PA. The power of the residual artifact (P_{res}) is then calculated as a ratio between the power after and before artifact removal. This measure assumes that the residual artifact is not random. (2) We compare the energy in the most important EEG frequency

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bands, δ (1-4 Hz), θ (4-8 Hz), α (8-13 Hz) and β (13-35 Hz), before and after artifact removal. This measure is an indication of the amount of energy removed by the technique used. The limitation is that the frequency content of the EEG and the ECG are overlapping.

III. RESULTS

Both the AAS and the OBS technique are used to removed the PA from the datasets, with and without the introduction of inaccuracy in the detection of the artifact (i.e., time delay).

SIMULATED DATA: table I shows the results obtained from the simulated dataset. The AAS outperforms the OBS. In the simulations without delay, the first principal component captures the PA (explained variance 50%), in the simulations with a delay at least the first two principal components are needed to account for the PA (explained variance 40%).

TABLE I DISTANCE BETWEEN THE BACKGROUND EEG AND THE CLEANED EEG, CALCULATED AS $d = \frac{1}{N} \sum (\|EEG_b(i) - EEG_c(i)\|).$

Method	Distance	Distance
	without delay	with delay
AAS	4,96	9,00
OBS(1)	9,43	12,36
OBS(2)	11,93	11,88
OBS(3)	13,25	13,89
OBS(4)	13,96	13,54
OBS(5)	14,55	14,73

REAL DATA: The residual energies in the EEG frequency bands are shown in fig.1 and fig.2. Without delay the performances of the AAS and OBS are comparable and the first principal component accounts for the 75% of the variance. This result is also reflected in table II, where the P_{res} is shown. The most affected frequencies are in the δ and θ range, where the harmonics of the ECG signal are most prominent.

TABLE II

 ${\cal P}_{res}$ expressed as a percentage of the original power.

Method	P_{res}	P_{res}
	without delay	with delay
AAS	1,10	34,12
OBS(1)	1,21	21,86
OBS(2)	0.98	2,11
OBS(3)	0,89	1.43

When the delay due to detection inaccuracy is introduced, the AAS is not able to capture the artifact in the template, as confirmed by P_{res} . In this case, the artifact is spread over the first two principal components (explained variance 75%). If these two components are removed, OBS outperforms AAS, as reflected in P_{res} . Again the most affected frequencies are in the δ



Fig. 1. Residual energy in the EEG frequency bands expressed as a percentage of the original energy, without delayed detections.



Fig. 2. Residual energy in the EEG frequency bands expressed as a percentage of the original energy, with delayed detections.

and θ range.

IV. CONCLUSIONS

In simulations using an additive model for the PA artifact, the AAS always outperforms the OBS. However, when dealing with real data, the performances of the two methods are comparable. Moreover, the introduction of a random delay to simulate inaccuracy in the artifact detection deteriorates the AAS results, since the artifact is not synchronized anymore but spread over more than one principal component. We can conclude that the AAS is more sensitive than the OBS to inaccuracies in the detection of the PA, which is more difficult when dealing with real noisy ECG data.

Future research will address this problem and look for a method to avoid the identification of the QRS on the ECG channel. Moreover, a criterion in OBS is needed, to define the number of principal components to be removed from the original signal.

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REFERENCES

- R.K. Niazy, C.F. Beckmann, G.D. Iannetti, J.M. Brady, and S.M. Smith, "Removal of fMRI environment artifacts from EEG data using optimal basis sets," *NeuroImage*, vol. 28, pp. 720–737, 2005.
- [2] P. J. Allen, G. Polizzi, K. Krakow, D. R. Fish, and L. Lemieux, "Identification of EEG events in the MR scanner: the problem of pulse artifact and a method for its subtraction," *Neuroimage*, vol. 8, pp. 229–239, 1998.
- [3] P. McSharry, G.D. Clifford, L. Trassenko, and L.A. Smith, "A dynamical model for generating synthetic electrocardiogram signal," *IEEE Transaction on Biomedical Engineering*, vol. 50, pp. 289–294, 2003.