Applying Independent Component Analysis to the Artifact Detection Problem in Magnetoencephalogram Background Recordings

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INTRODUCTION

The analysis of the electromagnetic brain activity can provide important information to help in the diagnosis of several mental diseases. Both electroencephalogram (EEG) and magnetoencephalogram (MEG) record the neural activity with high temporal resolution (Hämäläinen, Hari, Ilmoniemi, Knuutila, & Lounasmaa, 1993). Nevertheless, MEG offers some advantages over EEG. For example, in contrast to EEG, MEG does not depend on any reference point. Moreover, the magnetic fields are less distorted than the electric ones by the skull and the scalp (Hämäläinen et al., 1993). Despite these advantages, the use of MEG data involves some problems. One of the most important difficulties is that MEG recordings may be severely contaminated by additive external noise due to the intrinsic weakness of the brain magnetic fields. Hence, MEG must be recorded in magnetically shielded rooms with low-noise SQUID (Superconducting QUantum Interference Devices) gradiometers (Hämäläinen et al., 1993).

Unfortunately, the external noise is not the only undesired signal in MEG data. In these recordings, noncerebral sources (i.e., artifacts) appear mixed with the useful brain signals. The artifacts could bias the brain activity analyses, since both kinds of signals may have similar power and share the same frequency band. In MEG data, the main artifact is the cardiac one, whose amplitude is usually high enough to be visible in raw recordings (Jousmäki & Hari, 1996). Similarly, the ocular artifacts can be evident in MEG data (Antervo, Hari, Katila, Ryhänen, & Seppänen, 1985), and they can disguise the actual brain activity in long recordings. Finally, power line noise may also be present in MEG signals (Hämäläinen et al., 1993).

Diverse approaches have been used to detect and reject artifacts from EEG and MEG data, such as epoch rejection, regression methods (Croft & Barry, 2000), or principal component analysis (PCA) (Sadasivan & Dutt, 1996). In the early 1990s, a new method to obtain a blind source separation (BSS) became available: the independent component analysis (ICA) (Comon, 1994; Jutten & Herault, 1991). Since then, ICA has been increasingly used in the artifact rejection problem (Delorme, Makeig, & Sejnowski, 2001; Escudero, Hornero, Abásolo, Poza, Fernández, & López, 2006; James & Hesse, 2005; Jung, Makeig, Humphries, Lee, McKeown, Iragui, & Sejnowski, 2000; Sander, Wübbeler, Lueschow, Curio, & Trahms, 2002; Vigário, 1997; Vigário, Jousmäki, Hämäläinen, Hari, & Oja, 1998). One of the main advantages of ICA over other approaches is that artifacts must not be orthogonal to brain signals, and reference channels are not needed, although they can help to detect the artifacts (Barbati, Porcaro, Zappasodi, Rossini, & Tecchio, 2004; Flexer, Bauer, Pripfl, & Dorffner, 2005; Joyce, Gorodnitsky, & Kutas, 2004).

BACKGROUND

The use of ICA in the artifact rejection problem can be summarized as follows. Firstly, ICA finds a separating matrix, which decomposes the multidimensional input data (the EEG or MEG channels) into several independent components (ICs). Next, the ICs which account for artifacts are marked by visual inspection (Vigário, 1997; Vigário et al., 1998) or automatic methods (Barbati et al., 2004; Escudero et al., 2006; Flexer et al., 2005; Joyce et al., 2004; Li, Ma, Lu, & Li, 2006; Ting, Fung, Chang, & Chan, 2006), and they are removed. Finally, the pseudo-inverse of the separating matrix is used to build the output data (i.e., the signals without artifacts) from the retained ICs.

In this process, the main open issue is the artifact recognition. Several automatic criteria have been proposed. For instance, Delorme et al. (2001) used kurtosis and entropy to identify artifacts in EEG data. Adding a correlation criterion to these parameters, Barbati et al. (2004) proposed a semiautomatic approach to detect various artifacts in MEG signals. Similarly, Joyce et al. (2004) used a correlation metric, together with other simple procedures to remove ocular artifacts from EEG data. Recently, three criteria based on amplitude thresholds, power in frequency bands, and scalp distributions of the ICs were used by Ting et al. (2006) to deal with muscular and ocular artifacts in EEG. Moreover, Escudero et al. (2006) showed that a criterion based on the skewness of the IC amplitude distributions could detect the cardiac-related ICs better than kurtosis in MEG data.

In addition, it is important to select the number of ICs correctly. Whereas some papers set a power threshold (Ting et al., 2006), other studies set this parameter to the number of available channels (Flexer et al., 2005; Joyce et al., 2004; Jung et al., 2000; Li et al., 2006; Sander et al., 2002). Nevertheless, few statistical criteria have been used (Cao, Murata, Amari, Cichocki, & Takeda, 2003; Escudero et al., 2006; Ikeda & Toyama, 2000).

As it can be noted, very different approaches have been proposed to remove artifacts from EEG and MEG data with ICA. However, none has been generally adopted. This could be due to the intrinsic complexity of the MEG signals and the ICA algorithms. Because of this reason, straightforward artifact detection criteria might be preferred to complex ones, in order to keep the whole artifact rejection process at a suitable level of complexity. Therefore, in this study, we evaluated the usefulness of three criteria based on higher order statistics and spectral properties to detect the cardiac, ocular, and the power line artifacts in MEG data.

MAGNETOENCEPHALOGRAM RECORDING

Seven elderly subjects without past or present neurological disorders—age = 65.6 ± 7.9 years; mean ± standard deviation (SD)—participated in this study. They were asked to stay awake with closed eyes, and to reduce eye and head movements while they were lying on a patient bed to record the MEG signals. These conditions are similar to the recording protocol used in diagnostic studies. All subjects gave their informed consent for the participation in this study, which was approved by the local ethics committee.

For each subject, five minutes of MEG data were acquired at a sampling frequency of 678.17 Hz with a 148-channel whole-head magnetometer (MAGNES 2500 WH, 4D Neuroimaging) in a magnetically shielded room. The recordings were downsampled to 169.549 Hz. Fourteen epochs of 50 s (8,477 samples) with artifacts were selected for off-line analysis. All of them had cardiac artifacts, and some also presented ocular and/or power line ones. The epochs were digitally filtered using a band-pass filter with cut-off frequencies at 0.5 Hz and 60 Hz.

ARTIFACT REJECTION METHOD

Independent Component Analysis

The ICA model assumes that the n MEG channels, $\mathbf{x}(t) = [x_1(t), \ldots, x_n(t)]^T$, are a linear mixture of m ICs, $\mathbf{s}(t) = [s_1(t), \ldots, s_m(t)]^T$, with $m \leq n$ (James & Hesse, 2005). In order to represent the external additive noise, an n-dimensional vector of spatially uncorrelated Gaussian noise, $\mathbf{v}(t)$, can also be included in the model (Barbati et al., 2004; Cao et al., 2003; Ikeda & Toyama, 2000; Ting et al., 2006):