Chapter 6

Biomedical data analysis

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6.1 Introduction

In a combination of expert efforts from the Laboratory of Computer and Information Science and the Brain Research Unit (both from the Helsinki University of Technology), we have, over the past 5 years, introduced ICA as a tool for the analysis of electroencephalographic (EEG) and magnetoencephalographic (MEG) recordings. In the early years we have shown that ICA is very suited for the identification and removal of artifacts, as well as the decomposition of several types of evoked brain responses.

In the period spanned by this report, we have started to introduce further information in the search for meaningful signal components. This has, at times, lead to relaxing, but not rejecting, the independence assumptions.

Additionally, we have started to enlarge our areas of application to biomedical image processing.

The global list of publications, at the end of this report, contains further references to this work. The ones in this chapter should give a good starting point to the understanding of the results achieved within the project.

Validation of the linear ICA model for EEG and MEG

The application of ICA to the study of EEG and MEG signals assumes that several conditions are verified: the existence of statistically independent source signals, their instantaneous linear mixing at the sensors, and the stationarity of both the source signals and the mixing process.

In [1], making use of very few and plausible assumptions, we validate the use of ICA for the analysis of EEG and MEG recordings.

References

[1] R. Vigário, J. Särelä, V. Jousmäki, M. Hämäläinen, and E. Oja. Independent component approach to the analysis of EEG and MEG recordings. IEEE Trans. Biomed. Eng., 47:589–593, 2000.

6.2 Dipole modeled ICA decomposition of evoked responses

When applied to the decomposition of evoked responses, independent component analysis is often used in a blind source separation framework, *i.e.*, the goal is to identify underlying source signals from their instantaneous linear mixtures, with no prior knowledge on the sources or the mixing process. Yet, often some modeling is explicitly or implicitly added when attempting to give a physiological plausible interpretation to the result of the decomposition.

In [1], we propose a dipole modeled ICA decomposition (see [2], for better explanation). There, we assume that all the relevant independent components can be modeled using equivalent current dipoles. The incorporation of this modeling information simplifies the search for the underlying brain activated sources, while giving better physiological grounds to ulterior interpretations of the decomposed signals.

Figure 6.1 shows the complete set of 122 averaged magnetic evoked responses to combined auditory and somatosensory stimulation. Four inserts in the figure highlight equal number of interesting signal types present in the measurements: IV corresponds to step-like signal; III, a sharp and early response, originates in the primary somatosensory cortex; II and I are broader signals, with longer latencies than the previous one, and are associated with the primary auditory responses from the right and left hemispheres.

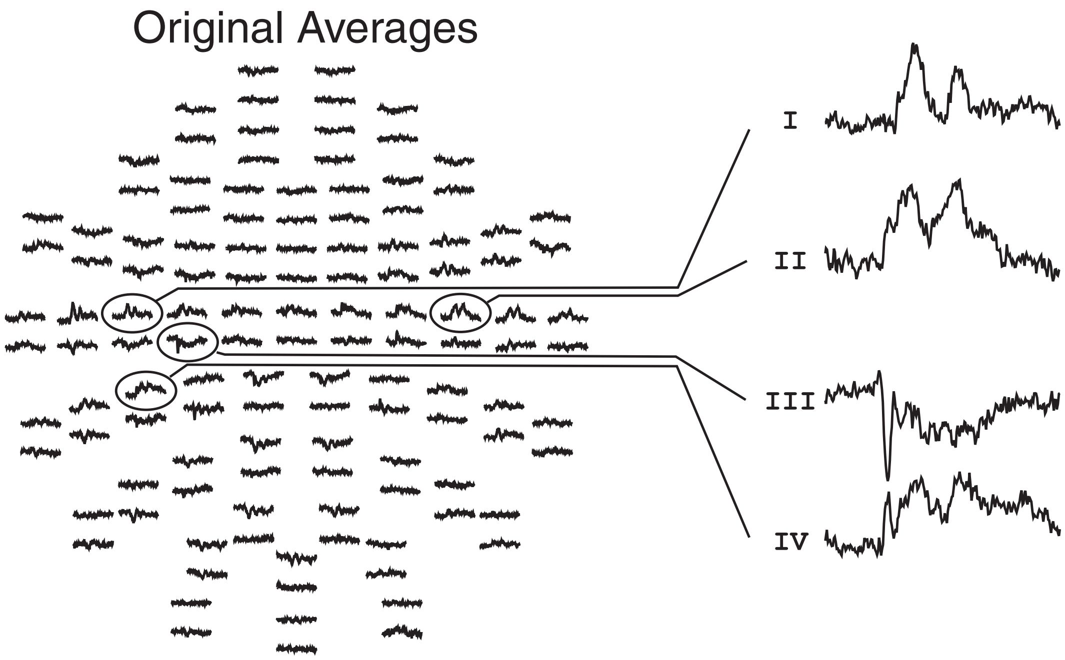


Figure 6.1: Average evoked MEG recordings to concomitant vibrotactile and auditory stimulation. Onsets show the maximum responses for the stimulation.

Both the original (Or) and the dipole modeled (Dm) ICA approaches give good results in the decomposition of the evoked responses, as can be seen, in Fig. 6.2, for DmICA. Note that each component corresponds to only the auditory or the somatosensory brain responses. Yet, we can see as well that the newly introduced algorithm requires a much simpler neural modeling to justify each one of its components (c.f. [2] for details on the goodness of fit values). In Fig. 6.3a) are plotted the same 4 signals seen in Fig. 6.1. Underneath are the remaining of these signals once the first, second, third and fourth original independent components are removed. Fig. 6.3b) present the same type of results for the

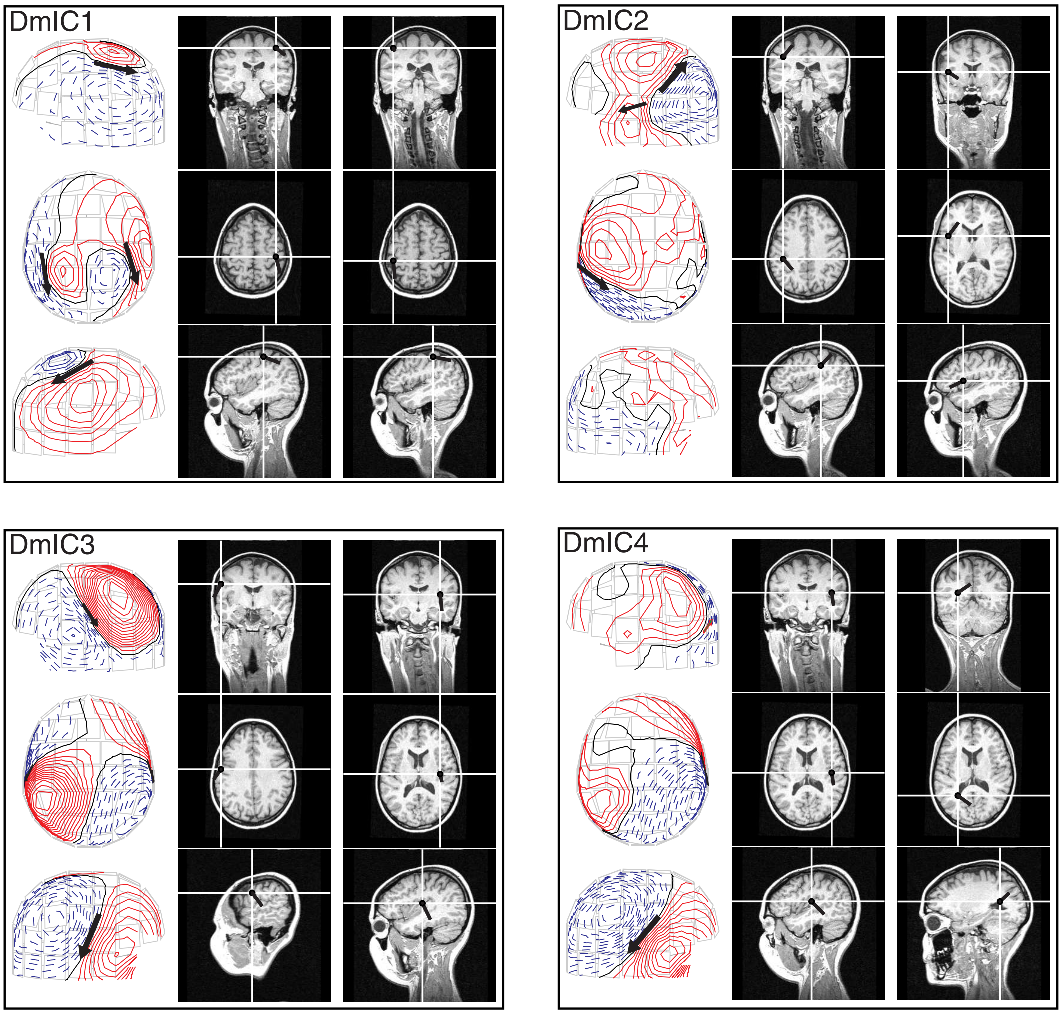


Figure 6.2: Field patterns and localizations of the independent components found by the dipole modeled ICA method.

dipole modeled algorithm. In OrICA, the extraction of the first component removes all auditory responses, whereas DmICA discriminates between the left and the right responses, after removal of the third and fourth components, respectively.

References

[1] R. N. Vigário. Dipole modeling in FastICA decomposition of evoked responses. Proceedings of the 2nd Int. Workshop on Independent Component Analysis and Blind Separation of Signals, ICA'00 (Helsinki, Finland), 2000.

[2] R. Vigário and E. Oja. Independence: a new criterion for the analysis of the electromagnetic fields in the global brain? Neural Networks, 13:891–907, 2000.

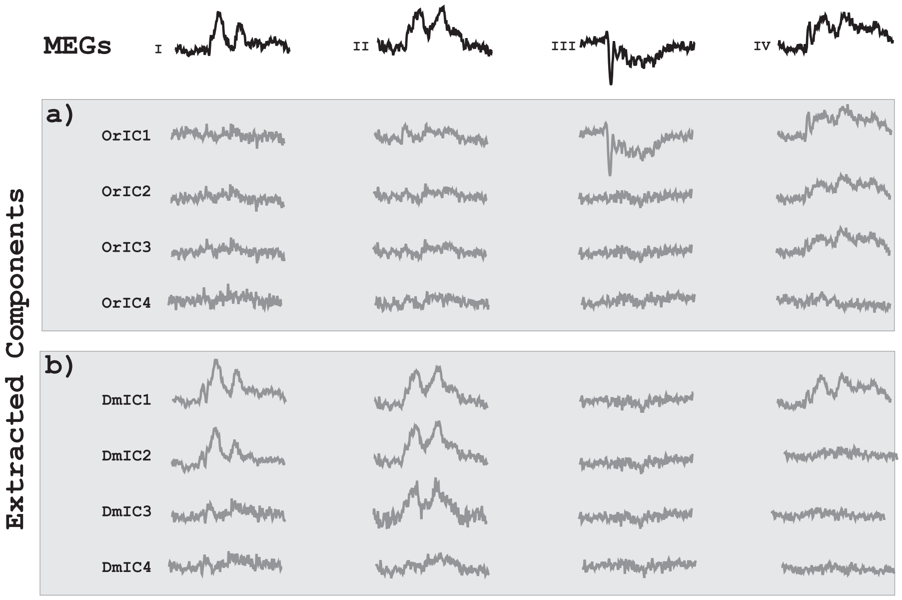


Figure 6.3: Original four MEG averages (see Fig. 6.1), and the result of extracting each of the first four independent components, using the original ICA algorithm (a) or the dipole modeled one (b).

6.3 Analysis of rhythmic electromagnetical brain activity

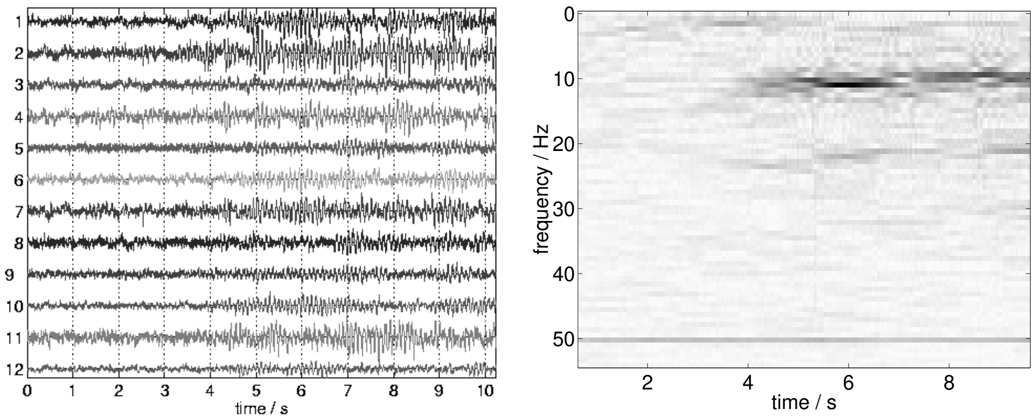
Periodicity information in extraction of cardiac artefacts

In [1], we propose an algorithm, based on the deflationary version of the FastICA, which uses prior information to find the periodic and quasi-periodic signals of interest out of a number of MEG recordings. This algorithm joins some advantages of high-order statistics methods to the ones of the temporally based ones. It has been used to extract, very accurately, the cardiac artifact present in some MEG data, without the need for any additional electrical measurements

Dynamical factor analysis of rhythmic MEG signals

In dynamical factor analysis (DFA) [2], the dynamics of the underlying sources are modelled using a state-space model. The state transitions themselves are modelled by nonlinear feedforward networks with one hidden layer. The underlying sources are observed through a linear process as in ICA. DFA is learned using *ensemble learning*, which is a full distribution approximation of correct Bayesian treatment (for a more detailed description see Chapter 4).

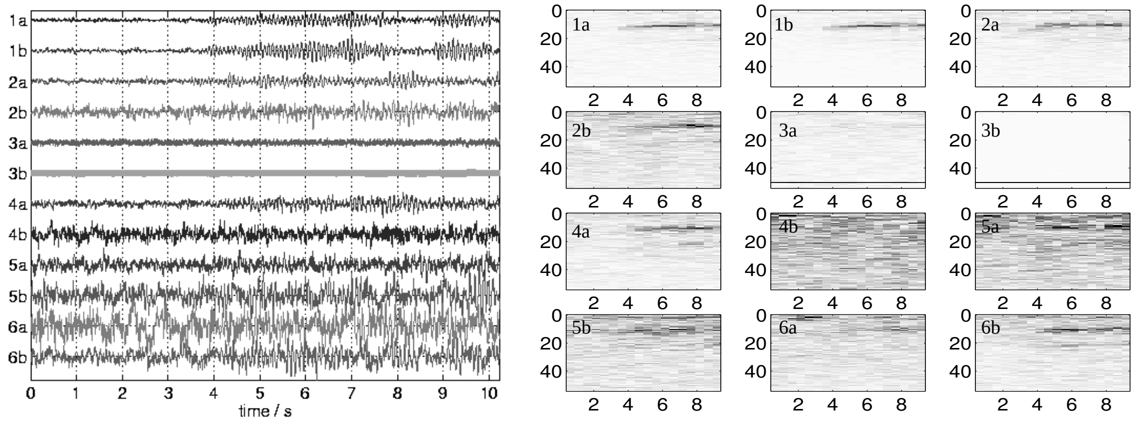
DFA can model any dynamics, given enough units in the hidden layer, but the model is at its best when modelling smooth, close to linear dynamics. In [2] DFA is used for analysis of rhythmic activity in MEG. Typically, these rhythms contain a main frequency, but also some additional harmonics, making their dynamics non-linear, but close to linear. Fig. 6.4 (a) shows a short period of time of the recordings on twelve channels and (b) shows a portion of the short time fourier transform of the first MEG channel. From both figures it is evident that there exist α-activity, characterised by a frequency around 10Hz, on the latter half, but the channels are quite noisy.



(a) (b)

Figure 6.4: (a) Short fragment of MEG recording over twelve channels. (b) Short time Fourier transform of the first channel of MEG recordings. α-rhythm is visible after 4s.

The resulting DFA decomposition, shown in Fig. 6.5, has been able to separate several α-generators (*e.g.* sources 1a, 1b, 2a, 2b and 4a) with very clear activations around 10Hz, but also some activation on the first harmonics around 20Hz, suggesting non-linear dynamics. These sources are less noisier than the sources found by traditional ICA methods using higher order statistical information or temporal correlation information. DFA also perfectly separates both phases of the 50Hz power line (sources 3a and 3b), which are both present in the measurements.



(a) (b)

Figure 6.5: (a) Resulting decomposition. (b) Short time Fourier transform of the decomposition.

DFA performs an explicit modeling of the sources. The dynamical part of DFA can determine, at each realization t of the observation $\mathbf{x}(t)$, which portion corresponds to the underlying estimated sources, $\mathbf{s}(t)$, and which corresponds to noise, $\mathbf{n}(t)$. DFA can therefore deal better with noisy signals than algorithms that are uncapable of such explicit modeling, even though they may use implicitly some temporal information.

Ensemble learning favors simpler and smoother models. Furthermore, the predictions are made over a collection of models. The probability of overfitting to a particularly strong, but very peaky, posterior is therefore very small. Because DFA uses ensemble learning to estimate the models for the factors, these are less prone to overlearning (see Section 2.2 for discussion of overlearning in ICA).

References

[1] Allan Kardec Barros, Ricardo Vigário, Veikko Jousmäki, and Noboru Ohnishi. Extraction of periodic signals from multi-channel bioelectrical measurements. IEEE Trans. Biomed. Eng., 47:583–58, 2000.

[2] J. Särelä, H. Valpola, R. Vigário, and E. Oja. Dynamical factor analysis of rhythmic magnetoencephalographic activity. Proceedings of the 3rd international workshop on independent component analysis and blind signal separation, ICA'01, (San Diego, CA, United States), 2001. Paper number 44.