34 Analysis of Independent Components in EEG and MEG

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Without any doubt, the brain is among the most intriguing and complex systems ever studied by human-kind. In an attempt to give a plausible explanation to the *why's* and *how's* of human perception and cognition, many conjectures have been formulated and theories have been tested throughout centuries. In a bootstrapping (reinforced) manner, the discoveries made on the human brain are leading into the formulation of more efficient computational methods which in turn make it possible to design new signal processing tools for better extraction of information from brain data. Some of the most promising such tools are in the field of artificial neural networks, of which the independent component analysis (ICA) algorithm of this project is a good example.

The challenges presented to the signal processing community by the completely non-invasive electro- and magnetoencephalographic recordings from the human brain may be divided in two classes, one dealing with the identification and removal of artifacts from the recordings, and another the understanding of the brain signals themselves (see the Table below). The amplitude of the artifactual disturbances may well exceed that of brain signals, turning the analysis of brain activity into a very hard process. Moreover, artifacts may present strong resemblance to some physiological brain responses, bringing an erroneous interpretation of the recording.

Artifacts	*Brain signals*
Ocular artifacts	Evoked responses (e.g. auditory, somatosensory, visual, ...)
Myographic activity	Spontaneous rhythmic activity
Externally induced artifacts	Abnormal brain behavior (e.g. epileptic seizures, infarction, ...)

Over the past 3 years, combining the expert efforts from the Laboratory of Computer and Information Science, and the Brain Research Unit (both from the Helsinki University of Technology), we have shown that ICA techniques are very effective in helping to solve the problem of the extraction of artifacts from electroencephalographic and magnetoencephalographic recordings (EEG and MEG, respectively) [2,3] , enabling a better appreciation of these recordings by the physician.

Figure 54 presents a sample of the 122–channel MEG recordings, showing brain activity corrupted by a considerable amount of artifacts produced by eye saccades and blinks, head muscle activity and the cardiac cycle. The last three electrical signals were not used in the experimental setup, but are plotted for validation purposes. The artifacts, extracted using the FastICA algorithm (see section on ICA fixed-point algorithms), are shown in Fig. 55. Note that not only the strong corruptive signals (i.e. the muscle and eye activity) are correctly extracted, but even very weak artifactual signals are clearly isolated (IC4 and IC6 correspond to the cardiac cycle, and a digital watch, present in the shielded measuring room).

It is common to use event related activity as an entry level to the study of the human brain's functioning. This activity is time-locked to a particular stimulus, that may

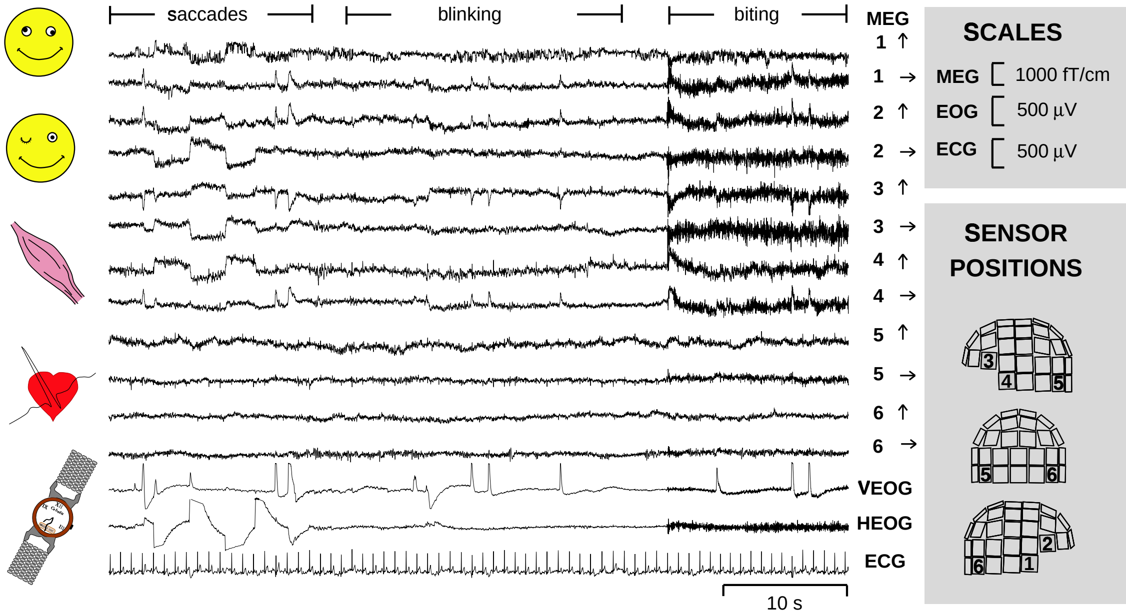

Figure 54: A sample of the 122-channel MEG recordings. For each of the 6 positions shown, the two orthogonal directions of the sensors are plotted (see [3] for further details).

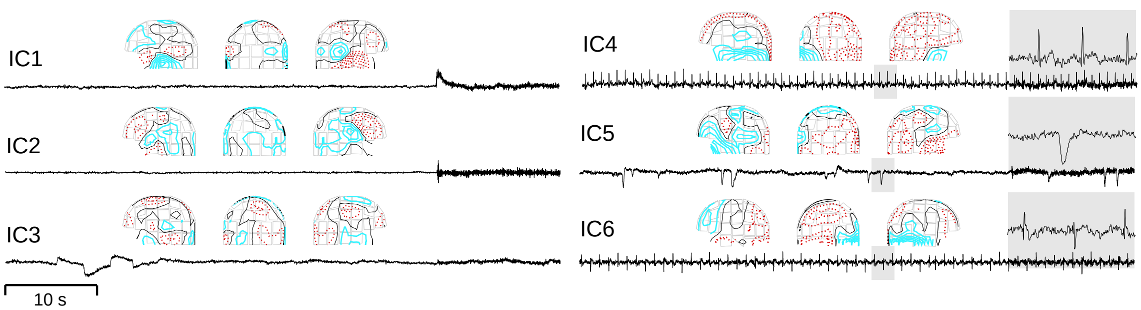

Figure 55: Six independent components extracted from the MEG data. For each component the left, back and right views of the field patterns are shown – full lines stand for magnetic flux coming from the head, and dotted lines the flux inwards. (from [3])

be of auditory, somatosensory, or visual type. Brain responses to the stimulation present minimal inter-individual differences to a particular set of stimulus parameters. In order to understand the physiological origins of the event related activity, it may be desirable to decompose the complex brain response into simpler elements, possibly easier to model and to localize their neural sources. In addition, the separation of multi-modal responses to complex stimuli, may represent a hard task to conventional methods, but is surely of capital importance, due to the diversity of stimulus modalities used in the perception of the real world.
Figure 56 shows a sample of the brain magnetic responses to a combined auditory and somatosensory stimulation a). The complex signals obtained are not resolved through PCA projection b), but rather well using an ICA approach c). The field patterns corresponding to the first two independent components (two columns of the estimated mixing matrix $\mathbf{A}$), are depicted in frame d). The different colors used stand for the different orientations of the magnetic flux on the sensor plane. Using this information, together with some dipole source modeling, we reach the

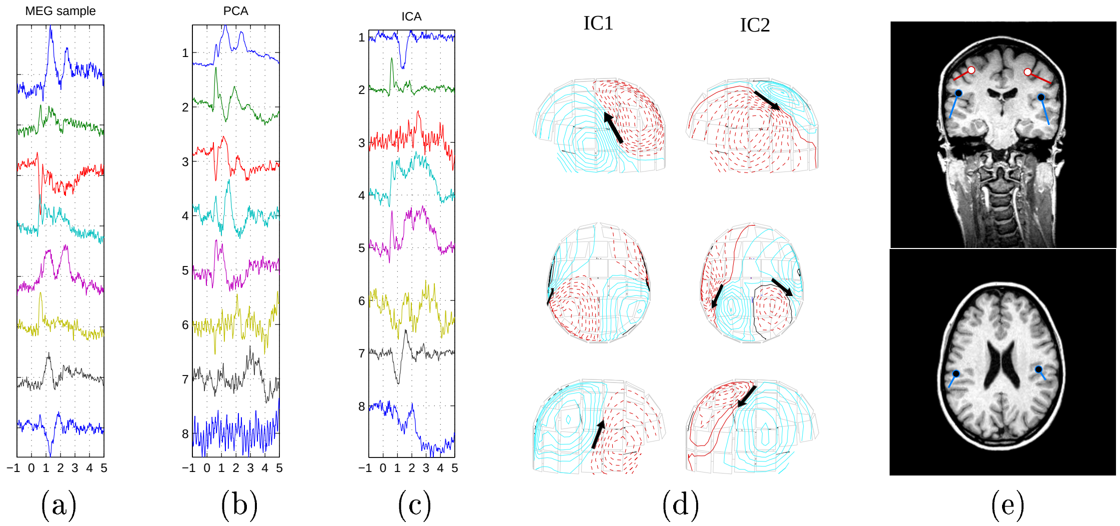

Figure 56: Results of the application of FastICA to the average brain MEG responses to a vibrotactile stimulation. The last frame show the localization of the brain sources superimposed onto an MRI scan. (adapted from [4]).

localizations present in frame *e*), superimposed onto an MRI scan of the subject. The locations found have a perfect agreement to the ones suggested by conventional neurolophysiological theories. Further information on these experiments may be seen in [4,5] . Promising results were as well obtained in the analysis of non-averaged evoked responses [1] .

The results reported in this section showed that ICA is not only a very efficient artifact removal tool both for EEG and MEG, but as well gives very promising results when dealing with the more demanding problem of extracting information from the brain's own activity. The global list of publications, at the end of this report, contains further references to this work. The ones in this section should give a good starting point to the understanding of the results achieved within the project.

References

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