Chapter 3

Neuroinformatics

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3.1 Setup of the group

In the period spanned by this report, a neuroinformatics group was formally established. This field of research has been defined as *the combination of neuroscience and information sciences to develop and apply advanced tools and approaches essential for a major advancement in understanding the structure and function of the brain.* Aside from the development of the tools, this often means that the fields of application include the analysis and modelling of neuronal behaviour, as well as the efficient handling and mining of scientific databases.

From a methodological viewpoint, the neuroinformatics group has been involved in studying certain properties of ICA, such as its reliability and applicability to the analysis of electrophysiological brain data (namely electroencephalograms, EEGs and magnetoencephalograms, MEG). Also the denoising source separation framework (DSS) was introduced, in the more general context of linear source separation and feature extraction (see Sec.2.4). From a biomedical signal processing viewpoint, we have shown the usability of DSS to study MEG signals, as is illustrated in Sec.3.3. Also using DSS, we investigated different possible origins for high- and low-amplitude alpha-activity in EEG (see Sec.3.2).

Several other topics have been researched in the field of biomedical signal processing, which are not thoroughly reported here. These lines of research will only have a visible outcome in the next biennial report. They include the analysis of synchronous activity in the brain; a more thorough study on the applicability of ICA to MEG; as well as the application of our methods of tissue segmentation in magnetic resonance imaging (MRI), to the detection of brain lesions. We also continued our research on technical aspects of the analysis of functional magnetic resonance imaging (fMRI), and progress towards the analysis of more natural stimuli.

References

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3.2 Source localization of low- and high-amplitude alpha activity

In this work, we addressed the question of whether low- and high-amplitude alpha activities have common brain activation sources. Due to the well-documented nonstationary nature of electroencephalograms (EEG), we could not apply our methods directly to the complete data set. Yet, in practice, it can be considered as a sequence of quasi-stationary segments. Therefore, we used a segmental analysis in all our processing. This was used to segregate between the higher and lower alpha amplitude segments. In addition, we used the denoising source separation (DSS) method to isolate EEG components in the alpha range.

We analyzed EEGs of 9 healthy subjects. We used 16 electrodes, in the standard 10/20 configuration. Subjects were asked to rest with their eyes closed. The segmentation analysis of alpha activity was performed for each subject separately. Then, segmented EEGs were divided in two sequences, comprising the 50% high- and 50% low-amplitude segments, respectively (see Fig. 3.1).

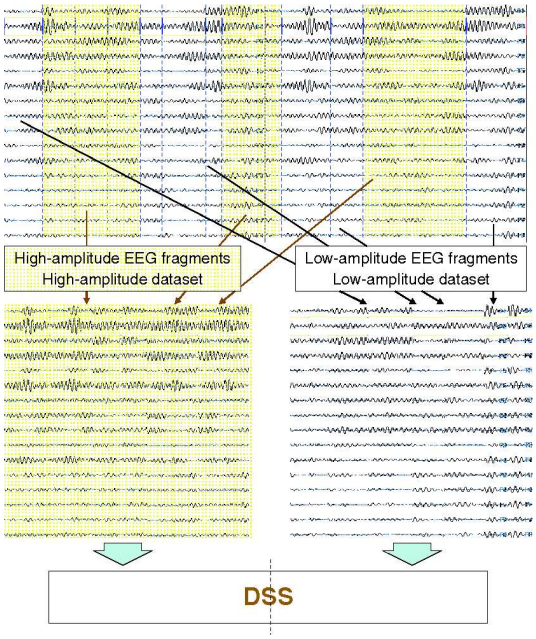

Figure 3.1: Original EEG data for one subject. Pre-processing segmentation of the high- and low-amplitude alpha activity, based on a reference channel over the occipital area.

The DSS algorithm was then applied to both sequences separately, yielding two sets of sources. The spatial patterns associated with these sources, for both high- and low-amplitude segments, were analyzed using standard k-means cluster analysis. We observe that most clustering procedures displayed similar spatial patterns of sources across different subjects, suggesting the existence of reliable sets of neural sources of alpha activity across subjects. Also we see (Fig. 3.2), that some clusters discriminate between high- and low-amplitude segments. This suggests that each neuronal source is mostly involved in either high or low amplitude activity (respectively depicted as yellow and clear frames).

According to the results, it is possible to assume that both low- and high-amplitude alpha activity may have both common and distinctive bioelectrical sources in the brain.

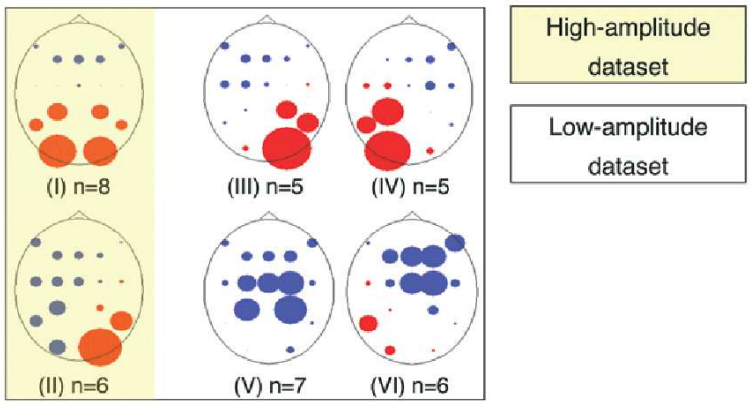

Figure 3.2: Averaged spatial patterns of the sources within the clusters. n is the number of sources in the clusters. All sources within the same cluster belong to different subjects (of 9). Frame I and II correspond to high-amplitude alpha, whereas the others display low.

The different spatial patterns of sources found for low- and high-amplitude may suggest that these populations of alpha-activity have their own nature and could perform different physiological functions.

3.3 DSS extraction of the cardiac subspace in MEG

In this section, we demonstrate the capability of the denoising source separation framework (DSS, see Sec.2.4) to extract some very weak cardiac signals, using detailed prior information in an adaptive manner.

Denoising of the cardiac subspace

A clear QRS complex, which is the main electromagnetic pulse in the cardiac cycle, can be extracted from the MEG data using standard BSS methods, such as kurtosis- or tanh-based denoising. Due to its sparse nature, this QRS signal can be used to estimate the places of the heart beats. With the places known, we can guide further search using the averaging DSS, discussed below.

Consider the source estimate in Fig. 3.3a. Let us assume to be known beforehand that the signal has a repetitive structure and that the average repetition rate is known. The quasi-periodicity of the signal can be used to perform DSS to get a better estimate. The denoising proceeds as follows:

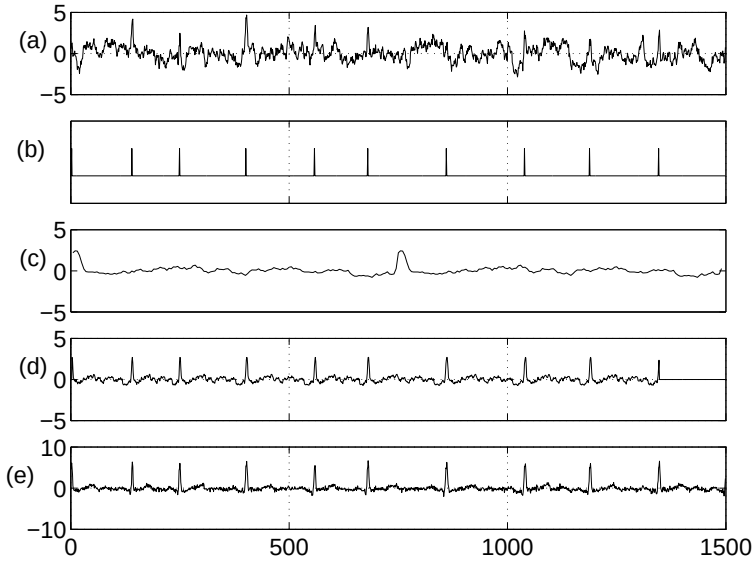

Figure 3.3: *a) Current source estimate of a quasiperiodic signal b) Peak estimates c) Average signal (two periods are shown for clarity). d) Denoised source estimate. e) Source estimate corresponding to the re-estimated.*

1. Estimate the locations of the peaks of the current source estimate (Fig. 3.3b).
2. Chop each period from peak to peak.
3. Dilate each period to a fixed length L (linearly or nonlinearly).
4. Average the dilated periods (Fig. 3.3c).
5. Let the denoised source estimate be a signal where each period has been replaced by the averaged period dilated back to its original length (Fig. 3.3d).

The re-estimated signal in Fig. 3.3e, based on the denoised signal, shows significantly better SNR compared to the original source estimate, in Fig. 3.3a.

When the estimation of the QRS locations has been stabilised, a subspace that is composed of signals having activity phase-locked to the QRS complexes can be extracted.

Separation results

Figure 3.4 depicts five signals averaged around the QRS complexes, found using the procedure above[1]. The first signal presents a very clear QRS complex, whereas the second one contains the small P and the T waves. An interesting phenomenon is found in the third signal: there is a clear peak at the QRS onset, which is followed by a slow attenuation phase. We presume that it originates from some kind of relaxing state.

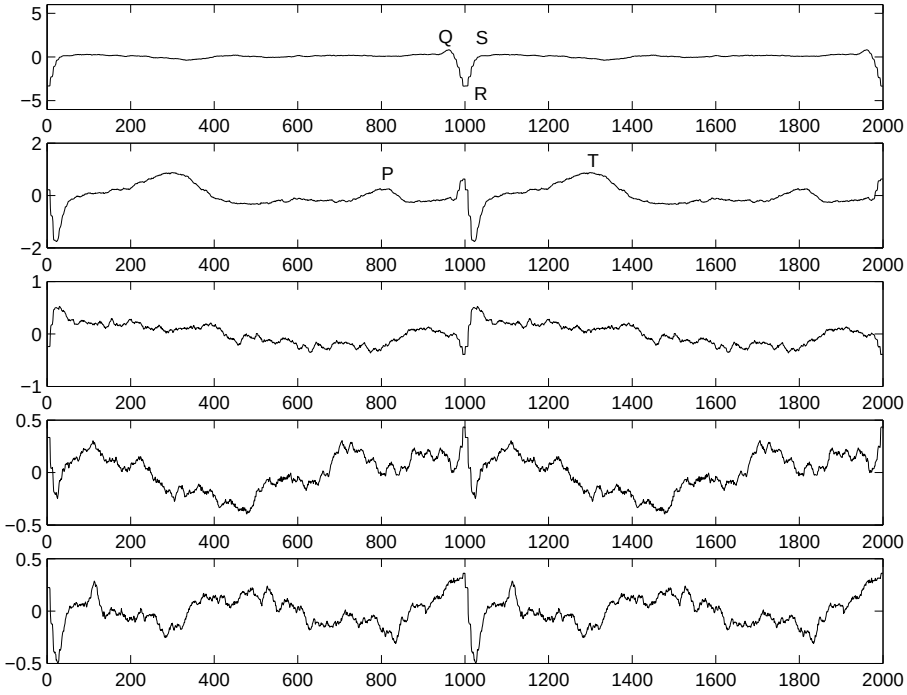

Figure 3.4: *Averages of three heart-related signals and presumably two overfitting results.*

Two other heart-related signals were also extracted. They both show a clear deflection during the QRS complex, but have as well significant activity elsewhere. These two signals might present a case of overfitting. It is worth noticing that even the strongest component of the cardiac subspace is rather weakly present in the original data. The other components of the subspace are hardly detectable without advanced methods beyond blind source separation. This clearly demonstrates the power that DSS can provide for an exploring researcher.

[1]For clarity, two identical cycles of averaged heart beats are always shown.