Chapter 6

Neuroinformatics

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6.1 Introduction

Neuroinformatics 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 new tools, the fields of application include often the analysis and modelling of neuronal behaviour, as well as the efficient handling and mining of scientific databases. The group aims at proposing algorithmic and methodological solutions for the analysis of elements and networks of functional brain activity, addressing several forms of communication mechanisms. Motivation and application areas include the understanding of ongoing brain activity and the neuronal responses to complex natural stimulation.

From a methodological viewpoint, the neuroinformatics group has studied properties of source separation methods, such as their reliability and extensions to subspaces. We have also assessed the suitability of such methods to the analysis of electrophysiological recordings (EEG and MEG), and functional magnetic resonance images (fMRI). We proposed also methods for the study of phase synchrony within the central nervous system, and between this and the peripheral nervous system. We have also developed methods for the analysis of neural responses of natural stimulation, based on a novel approach of capturing statistical dependencies between brain activity and the stimulus itself.

In addition to the analysis of fMRI recordings from natural stimulation, we have been also involved in the analysis of single trial event-related MEG data. Albeit its significantly higher temporal resolution, the signal-to-noise ratios are typically very poor, and averaging across hundreds of stimuli is often required. We currently search as well for efficient tissue segmentation of structural MRI.

In addition to these ongoing but stable research topics, we have made a pilot study in document mining. The goal is to extract, in a semi-automatic manner, functional information from neuroscience journals, hence reducing the dependence on curator intervention. We have also continued our research on approaches for segmentation of tissues in multi-spectral magnetic resonance images, with particular interest to the automatic detection and delineation of degenerative pathologies.

Research reported in this section has been carried out in collaboration with experts in neuroscience and cardiology. In the following, we highlight some of the results attained in the reported years.

References

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6.2 Natural stimuli and decoding

Natural stimuli are increasingly being used in neuroscientific experiments in order to study more complex brain activity, such as the brain's response to viewing movies, listening to free-flowing speech, or even being engaged in a discussion. New computational methods are needed for analysis of such experiments, since it is no longer feasible to assume single features of the experimental design to alone account for the brain activity. Instead, the stimulus itself becomes another source of data with rich features.

We have developed novel machine learning models (see Chapter 4 for more details) for analysis of MEG and fMRI response to natural stimuli. The models find latent representations that describe functional patterns in the brain data that correlate with rich feature representations of the stimuli. Besides providing interpretable components, the models are useful for decoding brain activity [9]. Given a brain measurement (for example, one TR in fMRI or a small time-window in MEG) the goal is to tell what kind of a stimulus the subject was exposed to. As a practical example, in [5] we used Bayesian Canonical Correlation Analysis (CCA) to model the MEG response to natural speech, and managed to identify which short segment of speech the subject was hearing with high accuracy even for segments lasting only for a few seconds (Fig. 6.1).

We also organized a PASCAL2 challenge on MEG decoding [4], to demonstrate the feasibility of single-trial MEG decoding and to provide public benchmark data. The task was to identify which of five types of video the subject was seeing based on just two seconds of data, and the best teams reached almost 70% accuracy (chance level 23%).

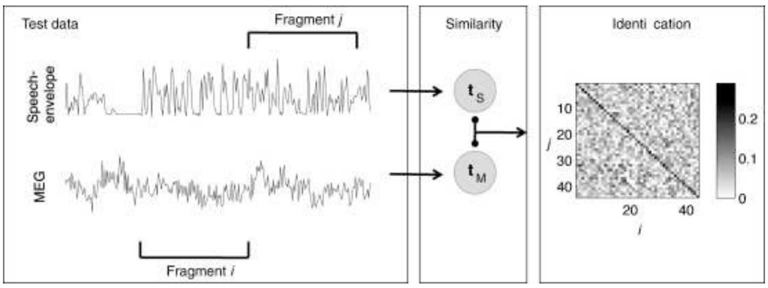

Figure 6.1: Bayesian CCA decodes speech by representing the speech fragments (left) in a joint latent space which enables directly comparing the MEG samples with speech envelopes (middle). The image is reproduced from [5] with permission.

6.3 Phase synchrony

Interest in phase synchronization phenomena has a long history, when studying the interaction of complex, natural or artificial, dynamic systems. Although not completely adopted, synchronization was attributed a role in the interplay between different parts of the central nervous system as well as across central and peripheral nervous systems. Such phenomena can be quantified by the phase locking factor, which requires knowledge of the instantaneous phase of an observed signal. Yet, observations are often mixtures of underlying phenomena, which destroys sources' phases.

Algorithms for Synchrony Source Separation
During the reported years, we extended the set of algorithmic tools for the identification of phase synchronous phenomena. And studied these tools in terms of deviations from the ideal modelled situations, when synchrony is affected by significant amounts of noise. Our earlier methods dealt with the extraction of sources phase-locked to a reference signal, the clustering of a population of oscillators into synchronous sub-populations, as well as the extraction of phase-locked subspaces, following an approach akin to the underlying considerations in independent component analysis. A summary of the said methods appeared in [2].

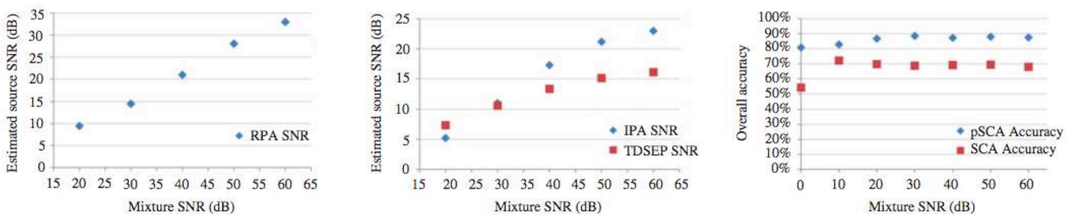

Figure 6.2: Study of noise robustness for three proposed phase-based algorithms: RPA (left), IPA and TDSEP (middle), and pSCA and SCA (right). From [2].

In [3], a new and very fast algorithm was proposed, based on a matrix factorisation approach. The separation is done through a minimisation problem involving three variables: the mixing matrix, the source time-dependent amplitudes, and their relative phases.

Phase-locked subspaces
We have further started to study the problem of blind separation of sources, when these are organized in subspaces. In this structure, sources in different subspaces have zero phase synchrony with each other, whereas sources in the same subspace exhibit full phase synchrony. Note that traditional source separation methods should fail in such generative model. The two-stage algorithm proposed in [1] performed remarkably well when in low-noise situations.

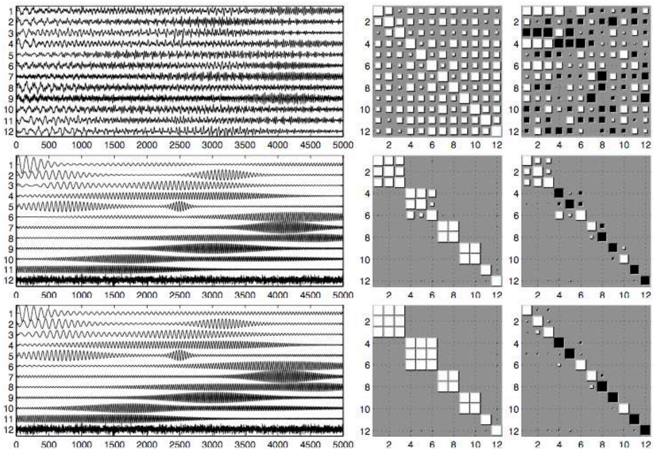

Figure 6.3: Measured (mixed) signals (first row, left); phase locking factors between those and the mixing matrix (middle); and the mixing matrix (right). (Second row) Sources resulting from TDSEP (left). Note that the inter.subspace PLFs (middle) are very close to zero, but the intra-subspace PLFs are not all close to 1. (Fourth row) Results found after the second stage of the algorithm. The estimated sources (left) are very similar to the original ones. This is corroborated by the PLFs between the estimated sources (middle) and the final unmixing matrix (right). From [1].

6.4 Document mining

There is an ever increase in the number of scientific publications in many areas in general, and in neurosciences in particular. Hundreds of articles are published each month. When comparing the results one obtains with a given experimental setup and existing information in literature, one may validate, integrate or confront different opinions and theories. The compilation of such a vast amount of information is not only crucial, but currently also rather human-intensive.

With that in mind, we have conducted a pilot study on document mining of journal publications reporting results on fMRI experiments. We have focused on the image content of the articles. The rather positive preliminary results reported in [6] suggest that a more systematic use of the methodology, and its improvement may help as well reducing the amount of curating work required for the construction of functional databases. We have been extending this research to hundreds of journal articles, and thousands of images, focusing on particular neurological conditions. The firs of our such results should appear soon.

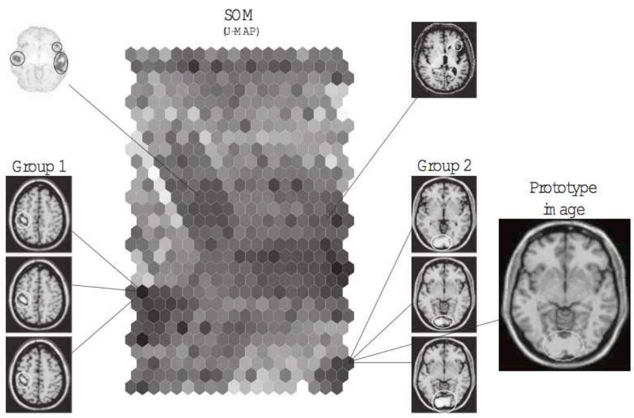

Figure 6.4: Self Organizing Map – U-matrix trained with 16 dimensional feature vectors, from a set of 100 images extracted from 11 journal papers. Two distinct cluster regions are observed at the lower left and right sides of the map. The prototype image, depicted in the upper left corner fits the expected cluster.