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Decoding magnetoencephalographic rhythmic activity using spectrospatial information

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A B S T R A C T

We propose a new data-driven decoding method called Spectral Linear Discriminant Analysis (Spectral LDA) for the analysis of magnetoencephalography (MEG). The method allows investigation of changes in rhythmic neural activity as a result of different stimuli and tasks. The introduced classification model only assumes that each "brain state" can be characterized as a combination of neural sources, each of which shows rhythmic activity at one or several frequency bands. Furthermore, the model allows the oscillation frequencies to be different for each such state. We present decoding results from 9 subjects in a four-category classification problem defined by an experiment involving randomly alternating epochs of auditory, visual and tactile stimuli interspersed with rest periods. The performance of Spectral LDA was very competitive compared with four alternative classifiers based on different assumptions concerning the organization of rhythmic brain activity. In addition, the spectral and spatial patterns extracted automatically on the basis of trained classifiers showed that Spectral LDA offers a novel and interesting way of analyzing spectrospatial oscillatory neural activity across the brain. All the presented classification methods and visualization tools are freely available as a Matlab toolbox.

Introduction

Unveiling neuronal information processing in the human brain during real-world experiences is a central challenge in cognitive neuroscience (Spiers and Maguire, 2007). Conventionally, functional neuroimaging studies have been applied using relatively simple patterns of sensory stimuli, and little is known about how the human brain operates with real-world sensory input. More recently, the neuroimaging community has started to introduce more naturalistic experimental conditions (Hasson et al., 2004, 2008; Hejnar et al., 2007; Kauppi et al., 2010; Lahnakoski et al., 2012; Wolf et al., 2010), and even "two-person neuroscience" has been advocated to record brain activity simultaneously from two interacting subjects (for a review, see Hari and Kujala (2009)).

Due to the diversity of the stimuli and/or the complexity of the experimental settings mimicking real-world conditions, it may be necessary to use data-driven analysis methods that allow investigation of brain function without stringent assumptions about the underlying brain mechanisms (Spiers and Maguire, 2007). One of the most promising data-driven approaches to analyze complex brain-imaging signals is "decoding", which gathers information from multiple brain imaging signals to deduce the task, stimuli or brain state during the measurement. Most commonly, multivariate classifiers are used to discriminate between categories (Blankertz et al., 2011; Cox and Savoy, 2003; Kamitani and Tong, 2005; Mitchell et al., 2004; Murphy et al., 2011) but decoding can also be performed using regression in more complex experimental settings (Carroll et al., 2009; Kauppi et al., 2011).[1]

Brain-function decoding can advance our knowledge in different ways. For instance, above-chance classification performance for an independent test data set implies the presence of mutual information between the measured signals and the categories of interest (Kriegeskorte, 2011). Thus, decoding can be used to test for the presence of specific stimulus information in the region of interest or across the whole brain. Additionally, investigating how the trained models are fitted to the brain-imaging signals tells where and how information is processed and represented in the brain. For instance, the coefficients of the linear classifier may provide hints of brain regions involved in the processing and discrimination of the stimuli (see e.g. Rasmussen et al. (2012)). It is also possible to construct several decoders based on different neuroscientific hypotheses and compare their performances. *A priori* knowledge can be incorporated to the decoder design for instance in the form of neuroscientifically inspired feature transformations (see e.g. Richiardi

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[1] Hence, the terms "decoder" or "decoding model" may refer either to a classifier or a regression model.

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et al. (2011)) or it can be embedded more directly to the model design (see e.g. Tomioka and Müller (2010)).

So far, most decoding studies in neuroscience have used functional magnetic resonance imaging (fMRI) signals to demonstrate spatial patterns related to different tasks or stimulus categories (Haynes and Rees, 2006; Tong and Pratte, 2012). However, the poor temporal resolution of fMRI makes it inherently unsuitable for investigating the fine spectral and temporal signatures of information encoding. Instead, the brain's oscillatory electrical activity has been suggested to have a central role in information processing, and distinct oscillation frequencies and amplitudes even in the same neuronal structure reflect different brain states (Singer, 1993). Large neuronal populations can generate synchronized oscillatory electrical activity that can be enhanced or suppressed by tasks and stimuli, and the dynamics of brain oscillations associated with distinct brain states forms complex spatiotemporal patterns (Buzsáki and Draguhn, 2004). Thus, to understand brain function during real-world experiences, it seems necessary to interpret at the same time the spatial, temporal and spectral signatures of brain activity.

Magnetoencephalography (MEG) has a millisecond-range temporal resolution and has therefore potential to reveal detailed spectral and temporal characteristics of distinct brain states induced by specific tasks or stimuli. Nevertheless, decoding on the basis of MEG signals cannot be expected to be an easy task. Several factors, including the low signal-to-noise ratio (SNR) of single-epoch measurements and the high dimensionality of whole-scalp recordings, make the decoding based on MEG signals very challenging. In addition, MEG signals do not vary only between different individuals under the same experimental condition, but to some extent also within the same subject between repeated identical sessions, which makes it complicated to construct a highly generalizable classifier across sessions and/or individuals. However, training of the multivariate model based on single-epochs provides inevitable advantages over a univariate analysis based on averaged epochs. For instance, a decoding approach allows finding combinations of the most discriminative features (or sensors) among a high number of initial features, and provides a principled way of assessing the goodness of the discrimination in terms of the estimated generalization accuracy.

Previously, Besserve et al. (2007) used band-limited power and phase synchrony features to classify between MEG data recorded during a visuomotor task and rest condition. Rieger et al. (2008) used temporal features and wavelet coefficients to predict the recognition of natural scenes from single-trial MEG recordings. Ramkumar et al. (2013) used both time-resolved and time-insensitive classifiers to decode from single-epoch MEG low-level visual features in the early visual cortex. Zhdanov et al. (2007) used temporal features together with the regularized linear discriminant analysis (regularized LDA) to classify between two different visual categories (faces and houses) on the basis of MEG signals. In the “Mind Reading from MEG” challenge organized in conjunction with the International Conference on Artificial Neural Networks (ICANN 2011), the task was to design a classifier to distinguish between different movie categories on the basis of 204-channel gradiometer MEG data (Klami et al., 2011). The data were recorded from a single subject who was shown five different movie clips. The winners of the competition extracted statistical features from time-domain signals and applied sparse logistic regression for classification (Huttunen et al., 2012).

Decoding has also been applied to electroencephalographic (EEG) signals. For instance, Murphy et al. (2011) and Simanova et al. (2010) successfully decoded abstract semantic categories from EEG data. Moreover, Chan et al. (2011) used temporal features in the classification of MEG and EEG data recorded simultaneously while the subjects performed visual and auditory language tasks.

Classification on the basis of MEG signals has also been studied in the context of brain–computer interfaces (BCIs), communication pathways between brains and external devices (Bahramisharif et al., 2010; Mellinger et al., 2007; Santana et al., 2012; van Gerven and Jensen, 2009). A successful BCI has to distinguish between brain signatures of the users intentions, and both temporal and spectral features have been applied, often selected based on specific *a priori* knowledge of the brain function. For instance, preparation to move a hand is associated with a brief suppression of the Rolandic mu rhythm that comprises 7–13 Hz and 15–25 Hz frequency bands. The power estimates characterizing these specific oscillations originating from the sensorimotor cortex have been successfully applied to decode motor-imagery tasks, where an individual mentally simulates different motor actions, such as hand movements (Pfurtscheller and Neuper, 2001). Even though most of the BCI literature has concentrated on classification on the basis of EEG, many technical advances in this field may also benefit MEG-based decoding; see for instance Lemm et al. (2011), Tomioka and Müller (2010), Dyrholm et al. (2007a), Liu et al. (2010), Blankertz et al. (2011), Mellinger et al. (2007), Suk and Lee (2013). On the other hand, the existing best BCI methods are not directly applicable to our setting because the goals of the analyses and experimental conditions are different. In BCI, the only goal is maximum classification accuracy, while in brain-function decoding, it is important to obtain a decoder with a meaningful interpretation to advance understanding of brain function. Consequently, many recent neuroimaging studies have concentrated on the interpretation of the decoding models (Carroll et al., 2009; de Brecht and Yamagishi, 2012; De Martino et al., 2008; Grosenick et al., 2013; Rasmussen et al., 2012; Ryali et al., 2012; van Gerven et al., 2009; van Gerven et al., 2010; Yamashita et al., 2008).

Here, we constructed a brain decoding system for MEG with the explicit goal of providing an easily interpretable decoder, as well as a general-purpose decoding toolbox for neuroscientific research. As an example of this approach, we analyzed MEG data from an experiment where the subjects were exposed to blocks of auditory, visual and tactile stimuli interspersed with rest blocks (Malinen et al., 2007; Ramkumar et al., 2012). We aimed to decode four distinct brain states, that is, “auditory”, “visual”, “tactile”, and “rest”.

The stimuli were complex, comprising video clips of people and urban scenes, speech sounds and tone beeps, as well as tactile stimuli to finger tips, all presented in brief blocks of varying duration within the same session. Because sensory stimuli are known to activate discrete projection areas, we considered this experiment well-suited for the validation of our method. However, the applied complex stimuli (speech and videos) may also activate higher-order processing. For instance, although it is plausible that variations in oscillatory activity in the visual cortex are mainly responsible for discriminating the visual category from the other categories, higher-order brain processes may involve additional neural activity in other brain regions, thereby complicating the decoding task. On the other hand, the diversity of the stimuli makes the decoding problem also more interesting, advocating the use of data-driven approaches based on relatively weak *a priori* information. As our goal was to build a classifier to infer brain function in an exploratory manner, we did not impose strong assumptions on spectral contents or spatial locations of the underlying neural activity; instead, we tried to capture the most relevant spectrospatial features automatically from a large number ($L = 204$) of MEG channels across a relatively wide frequency band (5–30 Hz).

Materials and methods

Naturalistic stimulation

We analyzed MEG data (306-channel Elekta Neuromag MEG system (Elekta Oy, Helsinki, Finland), filtered to 0–200 Hz and digitized at 600 Hz) from a previous experiment (Ramkumar et al., 2012). Eleven healthy adults (6 females, 5 males; mean age 30 years, range 23–41 years) were exposed to 6–33 s blocks of auditory, visual and tactile stimuli. Similar to Ramkumar et al. (2012), data of only nine of the eleven subjects were used in the analysis; data from two subjects were discarded due to improper delivery of auditory stimuli.