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Dynamic pattern decoding of source-reconstructed MEG or EEG data: Perspective of multivariate pattern analysis and signal leakage

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ABSTRACT

Recently, an increasing number of studies have employed multivariate pattern analysis (MVPA) rather than univariate analysis for the dynamic pattern decoding of event-related responses recorded with a MEG/EEG sensor. The use of the MVPA approach for source-reconstructed MEG/EEG data is uncommon. For these data, we need to consider the source orientation information and the signal leakage among brain regions. In the present study, we evaluate the perspective of the MVPA approach in the context of source orientation information and signal leakage in source-reconstructed MEG data. We perform face vs. tool object category decoding (FvsT-OCD) of event-related responses from single or multiple voxels from a brain region using a univariate analysis approach and/or the MVPA approach. We also propose and perform symmetric signal leakage correction of source-reconstructed data using an independent component analysis-based approach. FvsT-OCD using single voxel information shows higher sensitivity for the MVPA approach than univariate analysis, as the MVPA approach efficiently utilizes information on all three dipole orientations and is less affected by inter-subject variability. The MVPA approach shows higher sensitivity for FvsT-OCD when considering information from multiple voxels than for a single voxel in a brain region. This finding suggests that the MVPA approach captures the latent multivoxel distributed pattern. However, the results may be partly or entirely attributable to signal leakage between brain regions, as the sensitivity is substantially reduced after signal leakage correction. A consideration of signal leakage is therefore essential during the evaluation of MVPA outcomes.

1. Introduction

One of the goals of functional neuroimaging studies is to determine when, where and how brain regions are involved in a particular cognitive process. To make this determination, the researcher often performs hypothesis testing to identify an association between recorded brain activity and behavioral or perceptual parameters. One commonly used approach is univariate analysis (UVA), in which mass univariate hypothesis testing is performed across channels or voxels (independent variables). Recently, an increasing number of studies have employed a multivariate pattern analysis (MVPA) approach for evoked activity recorded from various neuroimaging modalities, such as fMRI, MEG and EEG [1–3]. The MVPA approach involves the single-trial classification of labeled (behavioral or perceptual parameters) and distributed brain responses across these channels or voxels, using a machine learning technique. In contrast to the UVA approach, the MVPA approach enables the investigator to evaluate whether the distributed pattern of brain responses at multiple voxels or channels is associated with an experimental variable [1,2,4]. In general, the MVPA approach is more sensitive than the UVA approach in detecting the difference between two brain states, for two reasons [2,4,5]. Firstly, the MVPA approach is able to capture a distributed multi-dimensional effect in which multiple variables (voxels or sensors) carry non-identical information about an experimental condition, which cannot be captured by a single variable. Secondly, the performance of the UVA approach is more susceptible than that of MVPA to functional and spatial inter-subject variability in brain activity.

Multi-voxel pattern analysis using the MVPA approach have changed the way of fMRI data analysis and their neural underpinnings [1,3,4]. Recently, MEG/EEG-based cognitive studies have also employed the MVPA approach, considering the scalp distribution of event-related

Abbreviations: EEG, Electro-encephalogram; MEG, Magneto-encephalogram; fMRI, Functional magnetic resonance imaging; ICA, Independent component analysis; ROI, Brain region of interest; MVPA, Multivariate pattern analysis; UVA, Univariate analysis; FvsT-OCD, Face vs. tool object category decoding; WoutSLC, Without signal leakage correction; WithSLC, With signal leakage correction.

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potential (for EEG modality) or field (for MEG modality) as a multivariate distributed pattern to address the experimental question, particularly detection of differences between mental states [2,6,7]. The extension of the MVPA approach to source-reconstructed MEG/EEG data can also provide a source localization of the effect in the brain. However, the use of the MVPA approach to source-reconstructed MEG/EEG is uncommon. Few studies have applied the MVPA approach to source-reconstructed MEG or EEG data considering the distribution of the current density of voxels from an entire cortex or a brain region of interest [8–10]. In an analysis of fMRI data using the MVPA approach, researchers have meant to find -an association between the multi-voxel distributed pattern of activation in a brain region and the experimental variables [1,3,4]. Each voxel has a single attribute (BOLD amplitude response), and BOLD activity is independent across the voxels (due to the higher spatial resolution). Source-reconstructed MEG/EEG data have different physical properties from fMRI neuroimaging data; for example, (i) each voxel or source location has three attributes (source orientations) per voxel, and (ii) spatial resolution is limited. This should therefore be considered when performing analyses using the MVPA approach on source-reconstructed MEG/EEG data.

In source-reconstructed data, each source location has three time series or attributes; that is, one for each of the three x-, y- and z-orthogonal dipole orientations. In the UVA approach, these three time series or variables are reduced to one, either by constraining the source orientation to a single optimal direction (normal to the cortical surface or source direction with maximum variance) or by taking the norm of all three variables (refer to http://neuroimage.usc.edu/brainstorm/Tutorials/SourceEstimation). These dimensionality reduction steps are likely to cause information loss. In contrast, the MVPA approach can utilize information from all three orientations, which is not straightforward in the UVA approach.

Spatial filters used for inverse solutions induce linear interactions between reconstructed source activity from nearby source locations; this is often referred to as a signal leakage phenomenon [11,12]. The performance of the MVPA approach for a particular brain region can be attributable to activity within a single or a few voxels, rather than a distributed multi-voxel pattern. Consequently, the performance of the dynamic pattern decoding of that brain region can be partly or entirely attributable to signal leakage from nearby brain regions. A consideration of signal leakage is therefore essential, particularly when employing the MVPA approach involving information from multiple voxels in a brain region. It is also important to analyze whether a multi-voxel dimensionality effect exists across the voxels sensitive enough to detect the difference between conditions than a single-voxel-level analysis in such practical scenario. Signal leakage induces linear and stationary interactions between nearby source locations. The ICA algorithm can therefore be used to attenuate the signal leakage between source locations in source-reconstructed MEG data, as shown in our earlier studies [12,13]. In the present study, we extend this algorithm to perform symmetric signal leakage correction of source-reconstructed MEG/EEG data.

In the present study, we evaluate the perspective of MVPA analysis for source-reconstructed MEG data in relation to source orientation information, the multi-voxel dimensionality effect, and inter-subject variability. We also evaluate the extent to which signal leakage and its correction can influence the sensitivity of MVPA outcomes.

2. Materials and methods

2.1. Dataset and preprocessing

We used a publicly available dataset from the WU-Minn Human Connectome Project [14], and the terms of use were followed for open access data, as provided by the Human Connectome Project. This study used preprocessed and artifact-removed working memory (WM) experimental MEG recordings from 82 subjects. For detailed information regarding the experimental paradigm and data preprocessing, please refer to the Human Connectome Project (HCP) web portal (http://www.humanconnectome.org/storage/app/media/documentation/meg1/MEG1_Release_Reference_Manual.pdf). In brief, MEG data were recorded from the subject performing a 0-back or 2-back WM task in the visual sensory modality. There were two sessions; in each of these, there were eight blocks for both the 0-back and 2-back WM tasks. We used data from the second session for this study since the participants became familiar with the WM task (particularly for the 2-back WM task) after the first session, and behavior performance was higher for the second session than for the first. In a single block of the 0-back WM task, a target image of either a face or tool was displayed at the beginning of the block; then, a sequence of 10 sample images of the same object category was displayed, interspaced with a fixation cross. The participant was asked to press a button if the sample image matched the target image. The task was slightly different for the 2-back WM task block; here, the target image was not displayed, but the participant had to press a button when the sample image matched the image from the previous 2-position task. Irrespective of the task, the image and fixation cross were displayed for 2 s and 0.5 s, respectively. Moreover, the button press response was performed during when the fixation cross was presented. There were a total of 160 trials in a session, i.e. 40 trials for each of the 0-back-face, 0-back-tool, 2-back-face, and 2-back-tool WM tasks. The face and tool object category stimuli used in this dataset provided an opportunity for the analysis of object category decoding utilized in the present study. We selected an equal number of trials from the 0-back-face, 0-back-tool, 2-back-face, and 2-back-tool WM tasks for this analysis. Consequently, we had 50 to 80 (median: 70) trials for the subjects, for each of the face and tool object stimulus categories in this analysis. When necessary, we considered the baseline period to range from 1.4 s to 1.9 s onset time latency instead of the pre-stimulus period, since the presence of an offset response from previous visual stimuli made the pre-stimulus period (i.e. 0.5 s–0 s) unsuitable.

MEG data were recorded at a sampling rate of 2034.5101 Hz with 248 channels, using a 3600 MEG system (4D Neuroimaging, San Diego, CA). Next, the data sampling frequency was down-sampled to 508.6275 Hz. For each participant, fiducial points and head surface anatomy were digitized, and structural MRI was also scanned. The HCP portal provides a pre-computed headmodel (single-shell) and sourcemodel (a cortical sheet with 8004 source grid point locations, nonlinearly pre-registered to the standard template). The headmodel, sourcemodel and MEG sensor data were registered (registration was refined using the iterative closest point algorithm) to a common three-dimensional space (BTi coordinate system).

2.2. Reconstruction of source signals

Source (voxel) time series were reconstructed from sensor MEG data using an unconstrained weighted minimum norm estimate (wMNE) inverse solution [15]. For computation of the inverse solution, lead fields were pre-whitened, the signal-to-noise ratio (SNR) value was set to three, and the normalization parameter value was set to 0.8. Due to the unconstrained condition, each source location had three source time series corresponding to three orthogonal dipole orientations (x-, y-, and z-orientations) (V_{xyz}, Eq. (1)). We also computed a single-source time series from three source time series (i.e. we reduced the source orientation dimension) in two ways: (i) we projected all three source time series onto their strongest orientation, which meant computing the first principal component of three source time series using a singular value decomposition (SVD) approach (V_{svd}, Eq. (2)); and (ii) we computed the norm of amplitude from three dipole orientations at each time sample (V_{norm}, Eq. (3)).

$$V_{xyz}(t) = \left[V_x(t);\ V_y(t);\ V_z(t)\right] \tag{1}$$