A Multimodal Approach to Representational Similarity Analysis

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Introduction: Multivariate Pattern Analysis (MVPA) has been successfully applied to fMRI (e.g. Haxby et al., 2001; Kriegeskorte et al., 2006; Haynes and Rees, 2006) and (quasi) time series data (Mourão-Miranda et al., 2007). The particular approach of Representational Similarity Analysis (RSA; Kriegeskorte et al., 2008a) has also demonstrated potential to integrate neuroscientific data from different modalities, experimental designs, or even species. For instance, RSA has been used to relate cell-recording from monkey Inferior Temporal cortex (IT) with the blood-oxygen-level dependent responses from human IT (Kriegeskorte et al., 2008b).

Unlike mass-univariate approaches such as SPM (Friston et al., 1995), RSA is based on the pattern-information that is naturally embedded in multi-channel recording of neural activations. Despite some previous endeavours, application of MVPA across modalities is still very limited. Here, we present recent developments in our work to extend RSA to both fMRI and MEG/EEG data in a unified framework.

Methods: The first level of RSA is the computation of similarity structures that express the dynamic patterns of neural activation over space and time. The primary data type that encodes such similarity structure is the representational dissimilarity matrix (RDM). Each entry in an RDM is the correlation-distance (one minus the correlation value) between activation patterns elicited by a pair of experimental conditions within a specific experimental setup. Neuroscientific inference can then be drawn from a second level of analysis that compares such RDMs to theoretical models, which can also be characterized by RDMs. Group analyses can also include averaging RDMs among participants. The rest of this section explains how to analyse different modalities in turn and how the results of such analyses can be combined.

For fMRI, we use individual unsmoothed and unnormalised beta images. In order to test certain hypotheses, the analysis may be focused on particular brain regions, using region of interest (ROI) masks which are either anatomically or functionally defined. Alternatively, a “searchlight” algorithm (Kriegeskorte et al., 2006) can be used to localise pattern information by searching across the entire brain.

For scalp MEG/EEG, we analyse individual participants’ time series data after having removed artefacts such as eye blinks. Unlike most sensor-level analyses, the signals from the magnetometers, gradiometers and EEG are rescaled by their own baseline noise levels (i.e. converted to SNRs) so that the data from different sensor types can be analysed together. One can then either manually select a set of sensors and time windows of interest or apply a searchlight in space, combined with a temporal sliding-window to separate effects in time.

For the source estimation of MEG/EEG data, we pre-processed the data with minimum-norm estimation (MNE; Hämäläinen and Ilmoniemi, 1994), which computes a distributed-source solution combining both MEG and EEG scalp information. As in fMRI analysis, either ROI masks or a searchlight can be applied.

In the second level of analysis, the resulting brain-based RDMs from data in all modalities are compared to model RDMs, the output indicating when and where in the brain each model fits best to the pattern of neural activation.

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Results: A significant advantage of RSA is the combination of evidence from different modalities, made possible because the second level of analysis is independent of the imaging methods. As a consequence, data collected from fMRI and MEG/EEG can be jointly analysed using RSA. As an illustration of this, we have collected two sets of data using the same experimental design but separately measured via fMRI and MEG/EEG. During these experiments, participants performed a language task on words with different levels of complexity. The results reveal that dissociable neural systems are engaged in processing different complexity levels at different points in time. In particular, the results from fMRI and sensor-level MEG/EEG highlight a left frontal network supporting the processing of inflectional complexity, e.g. the presence of the English regular pass tense '-ed'. The results of MEG/EEG source-level analysis are more distributed, possibly because a single MEG/EEG source tends to create electric or magnetic fields that have long-distance correlations. This simple application of RSA for multimodal analysis only serves as a preliminary assessment of our approach, which will be extended to more complex applications in future work.

Conclusions: To our knowledge, this is the first attempt to use RSA for both fMRI and MEG/EEG data collected from the same experimental materials. Our preliminary results show that such a multimodal approach is feasible and can provide convergent evidence for the theoretical proposal that different neural networks are engaged in processing different types of lexical complexity in different time windows. In general, our approach quantitatively combines data from different imaging modalities, potentially lending greater confidence to the conclusions than the analysis of any single modality alone.

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