A Multimodal Approach to Representational Similarity Analysis

Li Su, Cai Wingfield, Mirjana Bozic, Elisabeth Fonteneau,
William Marslen-Wilson and Nikolaus Kriegeskorte

Li.Su@mrc-cbu.cam.ac.uk
MRC Cognition and Brain Sciences Unit, Cambridge, UK

MRC Cognition and Brain Sciences Unit

European Research Council erc

Introduction

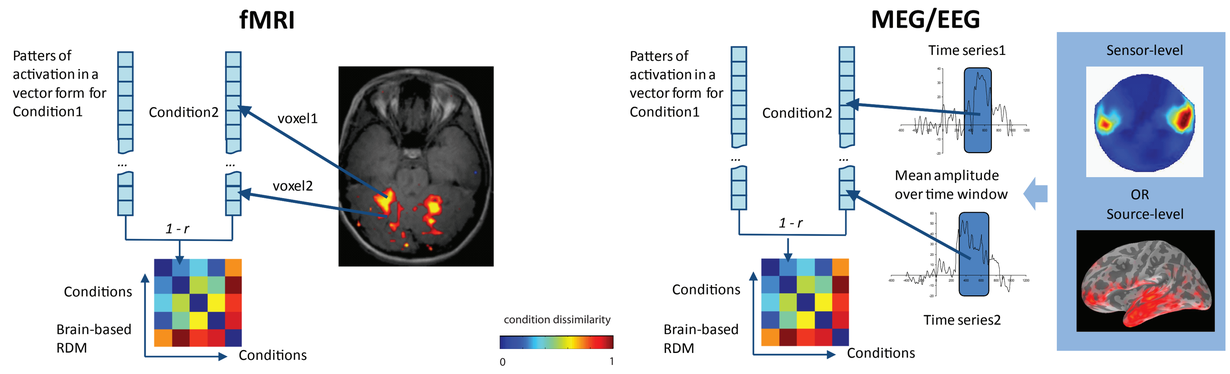
Multivariate Pattern Analysis (MVPA) has been successfully applied to fMRI (e.g. [1,2,3]) and (quasi) time series data [4]. The particular approach of Representational Similarity Analysis (RSA) [5] has also demonstrated the potential to integrate neuroscientific data from different modalities, experimental designs, or even species. For instance, RSA has been used to relate cell-recording from monkey Inferior Temporal cortex (IT) to the blood-oxygen-level dependent responses from human IT [6].

Unlike mass-univariate approaches such as SPM [7], 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.

Representational Similarity Analysis

First Level Analysis: Construct Representational Dissimilarity Matrix (RDM) for Individuals

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 (e.g. one minus the correlation value) between activation patterns elicited by a pair of experimental conditions within a specific experimental setup.



For fMRI, we used individual unsmoothed and unnormalised beta images. For scalp (sensor) MEG/EEG, we used individual participants' time series data after having removed artefacts such as eye blinks. For the source estimation of MEG/EEG data, we pre-processed the data with minimum-norm estimation [8], which computes a distributed-source solution combining both MEG and EEG scalp information. The result of the first level analysis is a set of brain-based RDMs for each participants at each spatial location and each time point.

Second Level Analysis: Compare Brain-based RDMs to Theoretical Models and Group Statistics

Theoretical models can also be represented by RDMs, as shown below. So, in the second level of analysis, the resulting brain-based RDMs from both modalities are compared to model RDMs.

A "searchlight" algorithm [2] is used to localise pattern information by searching across the entire brain using a moving sphere/patch. For time series, e.g. MEG/EEG, it combines with a temporal sliding-window to separate effects in time. The output indicates when and where in the brain, each model fits best to the pattern of neural activation.

Group statistics can be achieved by either Statistical Parametric Mapping (SPM) or nonparametric methods, such as permutation tests.

A Case Study to Validate Multimodal RSA

Experimental Conditions
40 words in each condition

Condition	*Example*	*Embedded stem*	*Suffix IRP*
1. regular past tense	*played*	? (*play*)	Y
2. pseudoregulars	*trade*	Y (*tray*)	Y
3. no stem, with IRP	*trend*	N	Y
4. stem only	*claim*	Y (*clay*)	N
5. simple	*cream*	N	N

Participants
12 (fMRI), 17 (MEG/EEG), healthy, right-handed, native English speakers

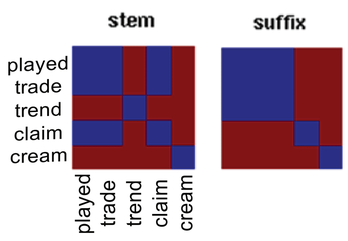
Procedure
Speach comprehension tasks with gap detection in fMRI and one-back memory in MEG/EEG to test the modulation of lexical complexity

fMRI Acquisition
3T Trio Siemens, fast sparse EPI imaging, TR=3.4s, TA=2s, TE=30ms, flip angle 78, matrix size 64x64, FOV=192x192mm, 32 oblique slices 3mm thick and 0.75mm gap

MEG/EEG Acquisition
306-channel Vectorview MEG, 70-channel EEG and three-compartment boundary-element forward model using structural MRI (3T)

Theoretical Models
Stem model for the presence of embedded stems
Suffix model for the presence of a suffix ending

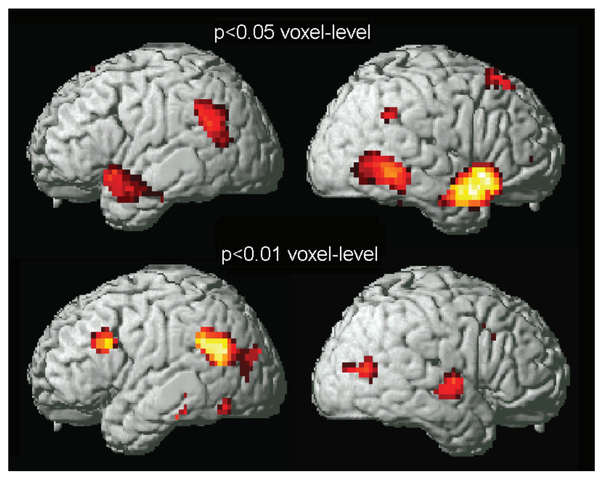
Blue squares indicate that activation patterns correlate due to a shared property. The same models are used for both fMRI and MEG/EEG.



fMRI Analysis

Stem Model shows effects, i.e. good fit between the brain-based RDMs and the model, in both anterior and posterior parts of left STG, right MTG & right IFG/STG.

Suffix Model shows effects in left IFG, posterior STG, right STG and posterior MTG.

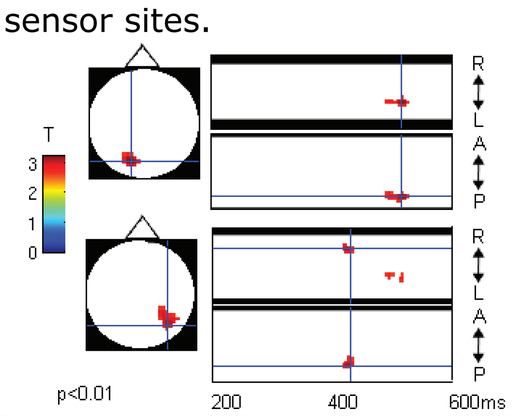


SPM5, uncorrected at whole brain level, "searchlight" radius=15mm

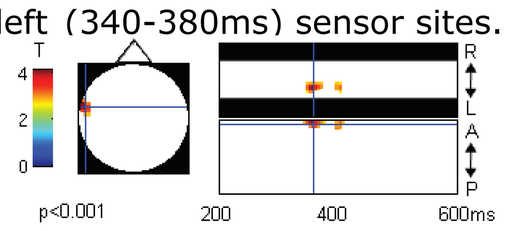
(STG, MTG and ITG = superior, middle and inferior temporal gyri respectively
IFG = inferior frontal gyrus)

MEG Sensor-level Analysis (Gradiometers)

Stem Model shows effects on both left (415-435ms) and right (485-530ms) posterior sensor sites.



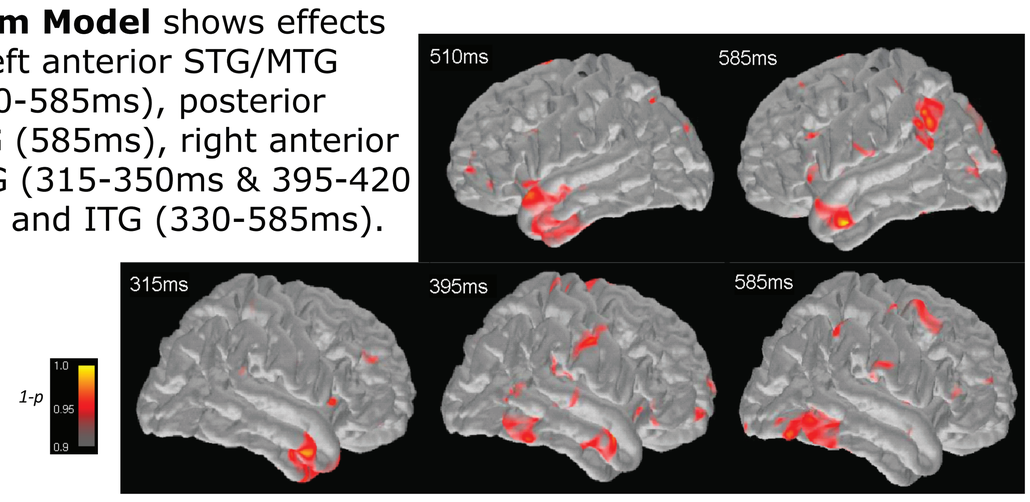
Suffix Model shows effects on left (340-380ms) sensor sites.



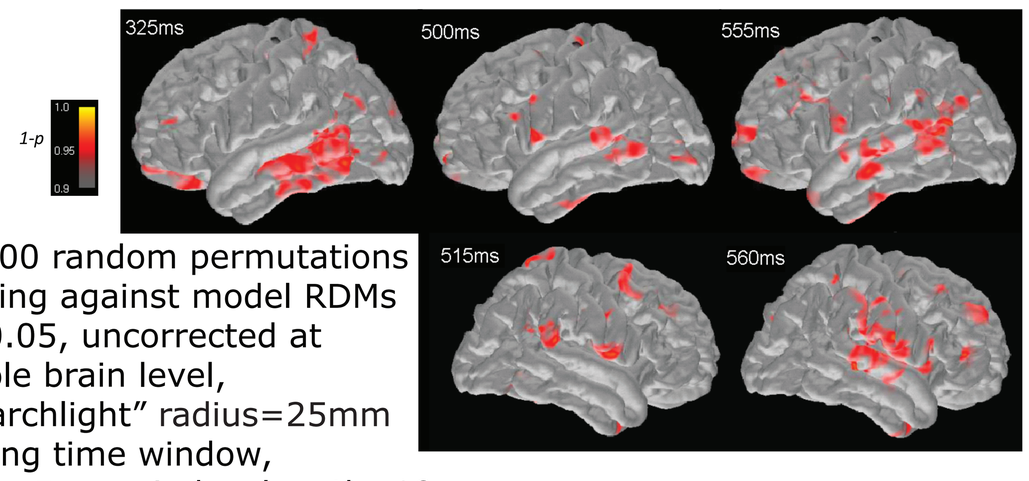
Sensor SPM, uncorrected at whole brain level, "searchlight" radius=5cm, sliding time window, step=5ms, window length=10ms

MEG/EEG Source-level Analysis

Stem Model shows effects in left anterior STG/MTG (510-585ms), posterior STG (585ms), right anterior MTG (315-350ms & 395-420 ms) and ITG (330-585ms).



Suffix Model shows effects in left MTG/ITG (325-435ms), STG/MTG (435-585ms), right ITG/MTG (305-490ms) and STG (515-560ms).



10000 random permutations testing against model RDMs p<0.05, uncorrected at whole brain level, "searchlight" radius=25mm sliding time window, step=5ms, window length=10ms

Conclusions

To our knowledge, this is the first attempt to use RSA for both fMRI and MEG/EEG data collected from the same experimental design. The sliding-window RSA is an attractive way to study the emergence of representations through recurrent processing across time. Our preliminary results show that such a multimodal approach is feasible and that it produces comparable results for each modality, which are also consistent with previously presented uni-variate analysis. It can also 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 combines data from different imaging modalities, potentially leading greater confidence to the conclusions than the analysis of any single modality alone.

References

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