Optimising Searchlight Representational Similarity Analysis (RSA) for EMEG

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Introduction

Multivariate Pattern Analysis (**MVPA**) has been applied in many areas of neuroimaging, including fMRI, EEG and recently MEG. A notoriously difficult problem with MVPA of neuroimaging data is the **curse of dimensionality**, which reflects the difficulty in fitting models with very large number of dimensions (voxels) to imaging datasets, which have very few training examplars (volumes).

To overcome this, a critical step in MVPA is **dimension reduction**, which can be achieved, for example, through principal component analysis or preselecting data according to existing priors. Another useful approach is the searchlight algorithm that uses anatomically local multivariate patterns to assess the neural population code (1). By moving the position of the searchlight in space, one can derive a whole brain map. The searchlight algorithm was originally derived for fMRI, and we have now applied it to spatio-temporal patterns in source space estimates of combined MEG and EEG (EMEG) data (2). To account for the temporal dimension in these data, in addition to moving the searchlight in space, a sliding temporal window is applied to cover different time points.

Here, we investigated the **optimal spatio-temporal parameters** for the searchlight of Representational Similarity Analysis (**RSA**). We did this in an EMEG experiment, in which participants listened passively to short phrases.

Methods and Materials

Regular	Irregular	Music Rain (MR) regular	Music Rain (MR) irregular
I walk	I fall	MR (I walk)	MR (I fall)
he walks	he falls	MR (he walks)	MR (he falls)
he walked	he fell	MR (he walked)	MR (he fell)

Experimental Conditions
We selected 20 verbs (10 regular & 10 irregular) with -s, -ed inflected and uninflected forms. We also created acoustic baseline (MR) forms of each phrase, sharing the complex auditory properties of speech (e.g. overall envelope) but are not perceived as speech.

Participants
20 healthy, right-handed native English speakers

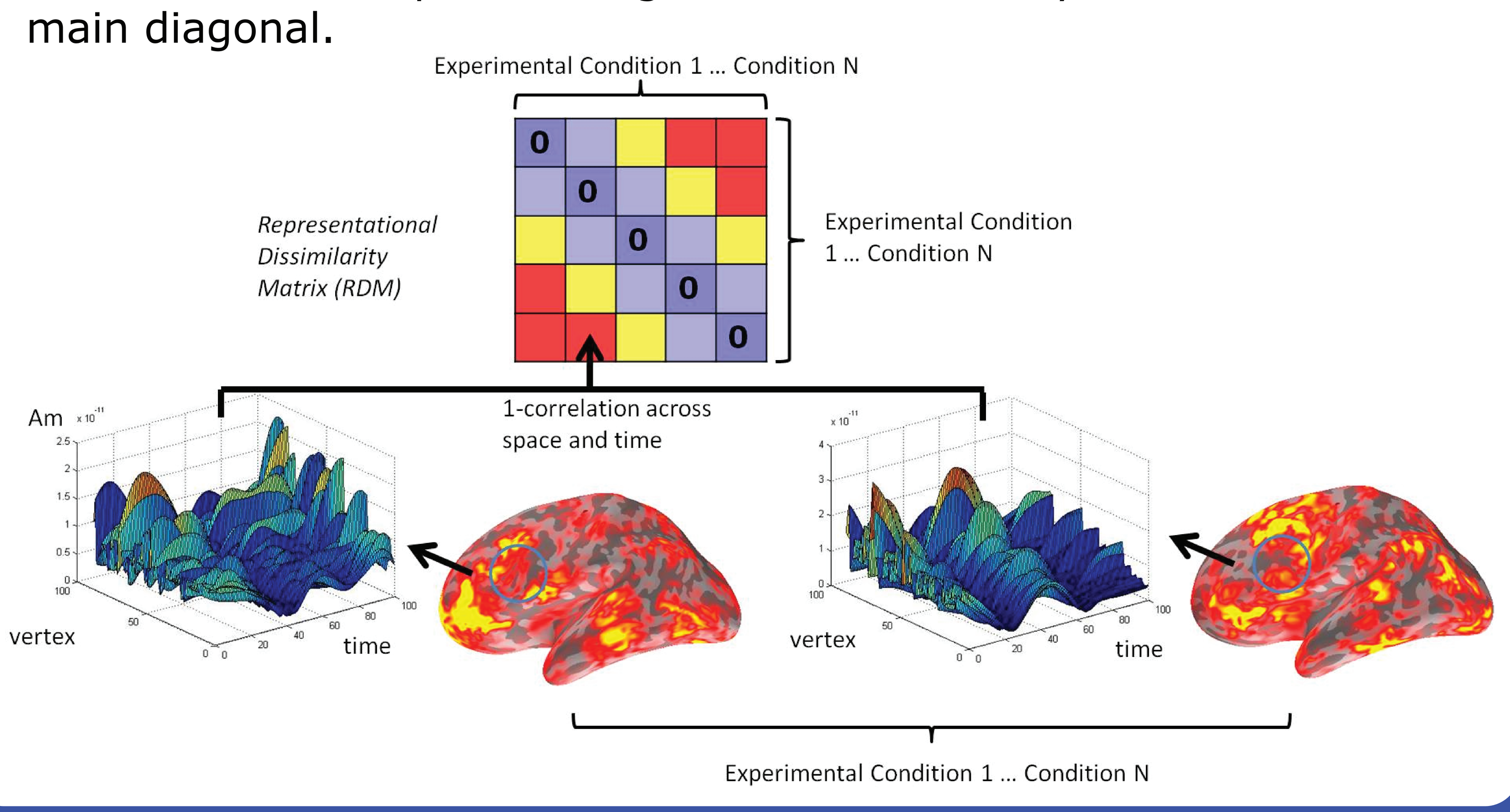
Procedure
Participants listened to short English phrases and occasionally performed a 1-back semantic completion task. Each stimulus was repeated 12 times in a pseudo-random order.

MEG/EEG Acquisition
306-channel Vectorview MEG, 70-channel EEG

Source Reconstruction
Minimum-norm estimation (MNE: 3) with a three-compartment boundary-element forward model from individual structural MRIs (3T) has combined both MEG and EEG scalp information. The source data was down-sampled to 200Hz, and 10,242 vertices per hemisphere (equivalent to 5mm between adjacent vertices).

Spatio-temporal Searchlight RSA for EMEG Source Space

The Representational Dissimilarity Matrix (RDM)
Each entry in the RDM is a correlation distance (e.g. one minus the correlation value) between spatio-temporal activation patterns elicited by a pair of experimental conditions (or stimuli) within a specific experimental condition. Elements on the main diagonal of this matrix are zeros by definition. In the off-diagonal parts of the RDM, a large value indicates that the two conditions have elicited distinct spatio-temporal activation patterns, and vice versa for small values. RDMs computed using this method are symmetric about the main diagonal.



Test-retest Reliability of RDMs

Test-retest reliability was used as a measure for the amount of information in activation patterns, and to optimise the searchlight size:

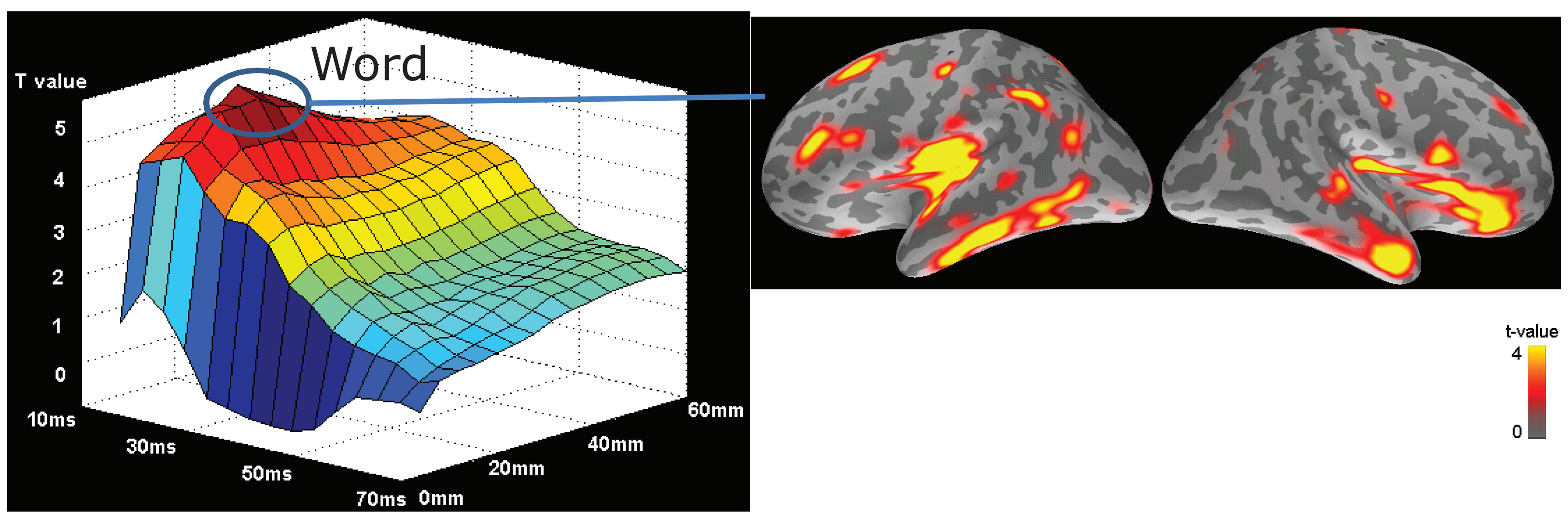
For the i th presentation of the stimuli: $P(i) = S(i) + n(i)$.
For the j th presentation of the stimuli: $P(j) = S(j) + n(j)$.

P – observed patterns (sample distribution);
S – "true" neural activation patterns (signal distribution);
n – random noise (noise distribution).

Assume the unknown "true" pattern is reproducable in test-retest, i.e. $S(i) = S(j)$, but random noise $n(i) \neq n(j)$. So, $P(i)$ and $P(j)$ will be more similar if the signal-to-noise ratio (SNR = S/n) is high. This, in turn, implies that the amount of information in the sample distribution is high.

Selecting the optimal spatio-temporal searchlight parameters
We randomly split 12 repetitions into two sets of six, and computed RDMs for each set separately, and then correlated RDMs from both sets to yield a test-retest reliability metric. We performed this analysis at time windows starting from the onset of inflectional affixes, and moved the searchlight over the whole brain. We then did a t-test of the averaged correlation values over the brain against zero across participants . Finally, we selected the optimal searchlight size by maximising the test-retest reliability value among different combinations of searchlight parameters in space and in time.

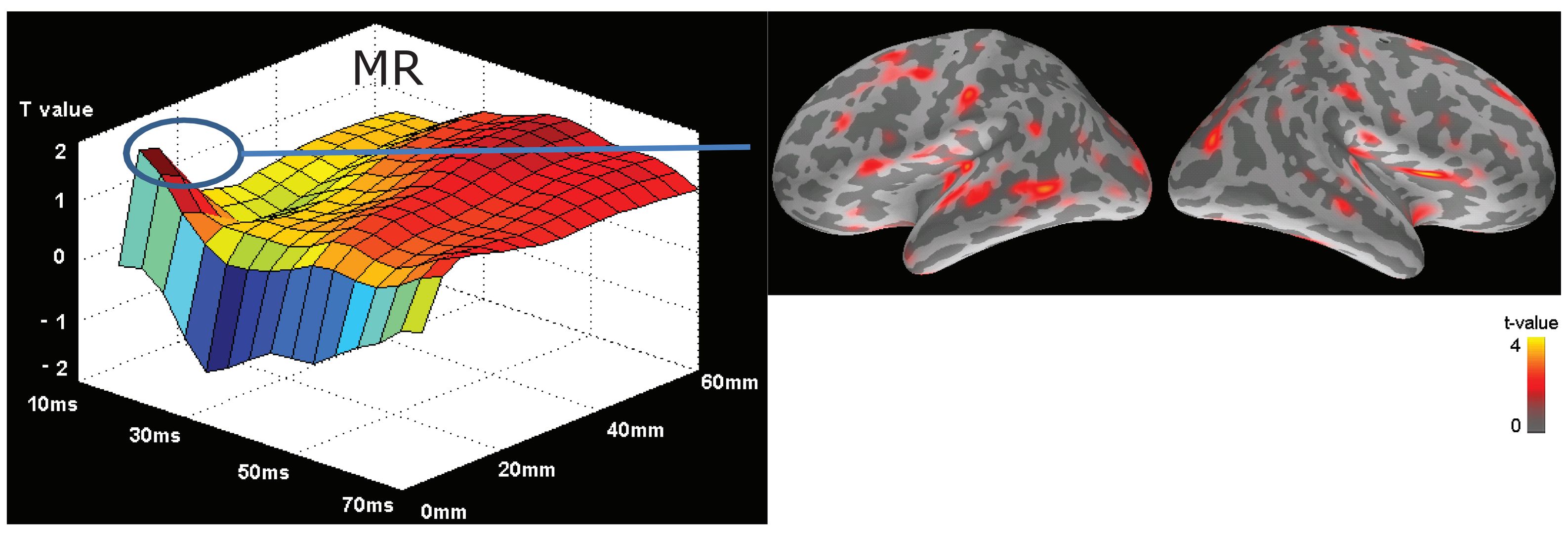
The Optimal Searchlight Size for Speech



Left: the optimal seachlight size for speech is 30mm radius in space (containing 127 vertices) and 15ms in time as shown with the largest t-value ($p < 0.05$).

Right: brain regions which show large test-retest reliability are mainly areas that support language processing. This indicates where stable neural representations of inflections are encoded in the brain.

No Optimal Searchlight for Non-speech



Left: test-retest reliability is much lower for non-speech (MR) than for speech, and not significantly above zero.

Right: t-values rendered in the brain show the reliability measures, which are weakly distributed and not specifically in language areas. This suggests that, in this time window, the brain does not have stable representations of MR stimuli, in which the information about hgih level of phonetic analysis is not present.

Conclusions

The optimal searchlight size in space is 30mm radius, which is larger than for fMRI (often on the order of 10mm). This may be because distributed source estimation using MNE has poorer spatial resolution than most high field fMRI. The optimal time window for the searchlight is 15ms, in line with the rate of information encoding in neural circuits (4). We argue that these optimal parameters are likely to be applicable beyond the current experiment because they are not only set by the physical properties of EMEG measurements, but also correlate with the speed of neural computation derived from information theory (4).

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