Searchlight-based trial-wise fMRI decoding in the presence of trial-by-trial correlations

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Introduction:

In multivariate pattern analysis (MVPA) for functional magnetic resonance imaging (fMRI), trial-wise response amplitudes are sometimes estimated using a general linear model (GLM) with one onset regressor for each trial [2,3]. When using rapid event-related designs with trials closely spaced in time, those estimates can be highly correlated due to the temporally smoothed shape of the hemodynamic response function (HRF) [3,4]. Inverse transformed encoding modelling (ITEM) is a principled approach for trial-wise decoding from task-based fMRI signals in the presence of trial-by-trial correlations [1,2]. So far, ITEMs have only been validated for decoding from signals in a region of interest (ROI), but not for decoding from signals in a moving searchlight [5,6]. Here, we present searchlight-based ITEM analysis which allows to predict a variable of interest from the vicinity of each voxel in the brain. We empirically validate the approach by confirming *a priori* plausible hypotheses about the well-understood visual system.

Methods:

ITEM is based on (i) estimating trial-wise response amplitudes using a design matrix with one HRF regressor for each trial [2, eq. 4] (see Figure 1A); (ii) calculating the covariance of those parameter estimates from the trial-wise design matrix [2, eq. 7] (see Figure 1B); and (ii) incorporating this covariance matrix into an inverse multivariate GLM for cross-validated prediction of a given experimental design variable [2, eq. 11] (see Figure 1C).
Here, instead of decoding from all voxels within a predefined ROI [2], we create searchlights, i.e. spherical volumes containing all voxels within a given radius (e.g. 6 mm) from a given center voxel, where each in-mask voxels serves as the center voxel once. Then, the above estimation procedure is carried out to decode from all signals near the current voxel, and the searchlight is moved from one voxel to the next [5] (see Figure 1C). At each voxel, a performance measure is calculated (decoding accuracy for classification; correlation coefficient for regression), giving one map for each reconstructed variable.

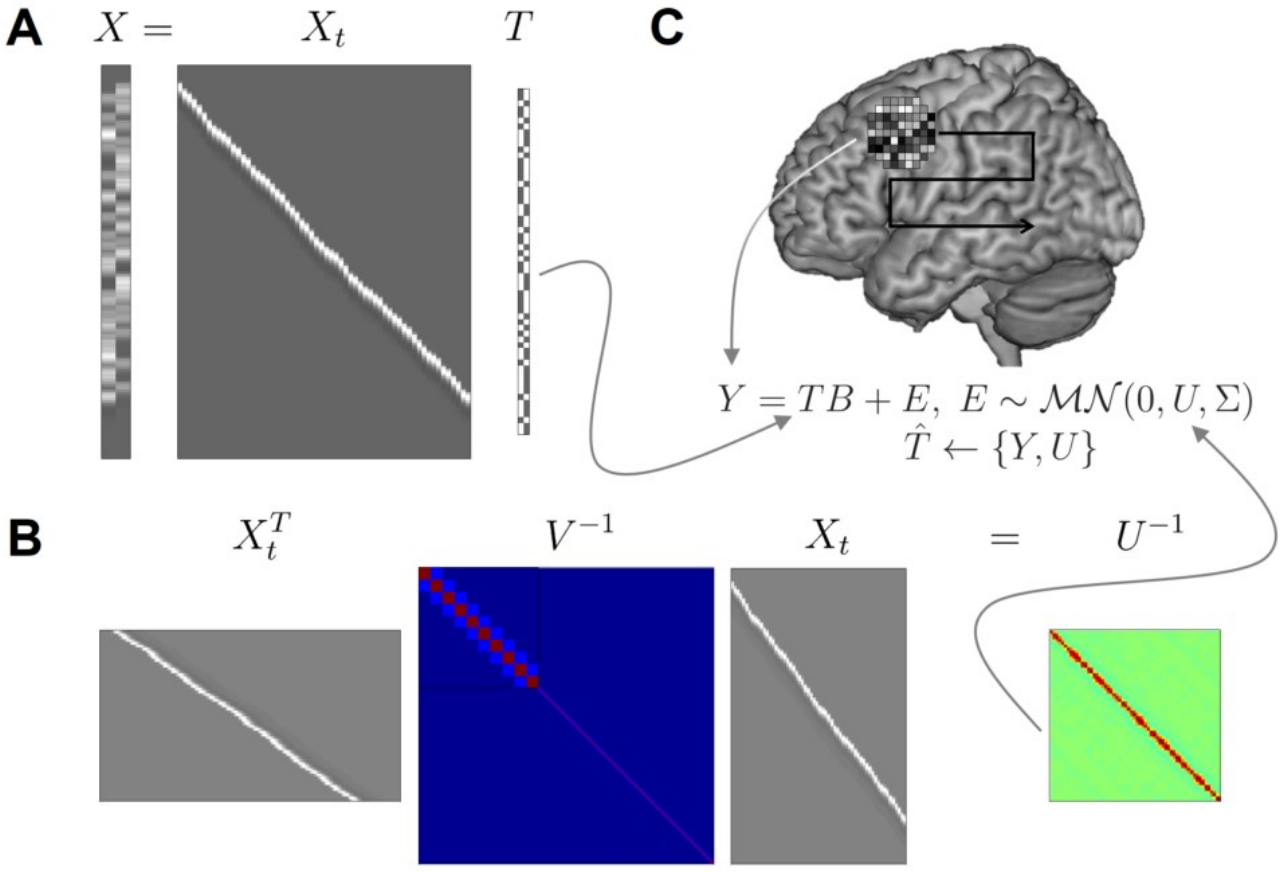

Figure 1. *Mathematical basics of searchlight-based ITEM analysis.* **(A)** The trial-wise design matrix X_t can be related to the standard design matrix X using a trial-level specification matrix T. **(B)** Under this assumption, the trial-by-trial covariance matrix U is a function of the trial-wise design matrix X_t and the scan-by-scan covariance matrix V. **(C)** In ITEM-based searchlight decoding, trial-wise responses Y from all voxels in a spherical volume are described using a multivariate GLM with design matrix T, temporal covariance U and spatial covariance Σ. Inverting this model gives rise to trial-wise predictions $\hat{T}$ of experimental design variables.

(https://files.aievolution.com/prd/hbm2201/abstracts/abs_2416/Figure_1_2021_12_17.png)

Results:

We re-analyze data from a continuous visual stimulation experiment [7,8] which is an extreme case of a rapid event-related design, using trials with a duration of 3 sec and no inter-stimulus interval. In this experiment, 4 subjects were looking at a stimulus consisting of 48 sectors randomly changing their illumination intensity from trial to trial (see Figure 2A). These 48 sectors could be categorized with respect to 12 angles and 4 eccentricity levels.
Data preprocessing was done in SPM12 and identical to the original study [2]. For ITEM analysis, we used a searchlight radius of 6 mm and decoded contrast levels in each of the 48 sectors from searchlights centered

on each voxel in the brain, yielding 48 decoding accuracy maps for each subject. We then ran a repeated-measures ANOVA with angle and eccentricity as within-subject factors. Its results matched well-known properties of early visual cortex (see Figure 2B), e.g. stimulus processing in the contralateral hemisphere as well as representation of eccentricity and angle along posterior-anterior and dorsal-ventral axes, respectively.

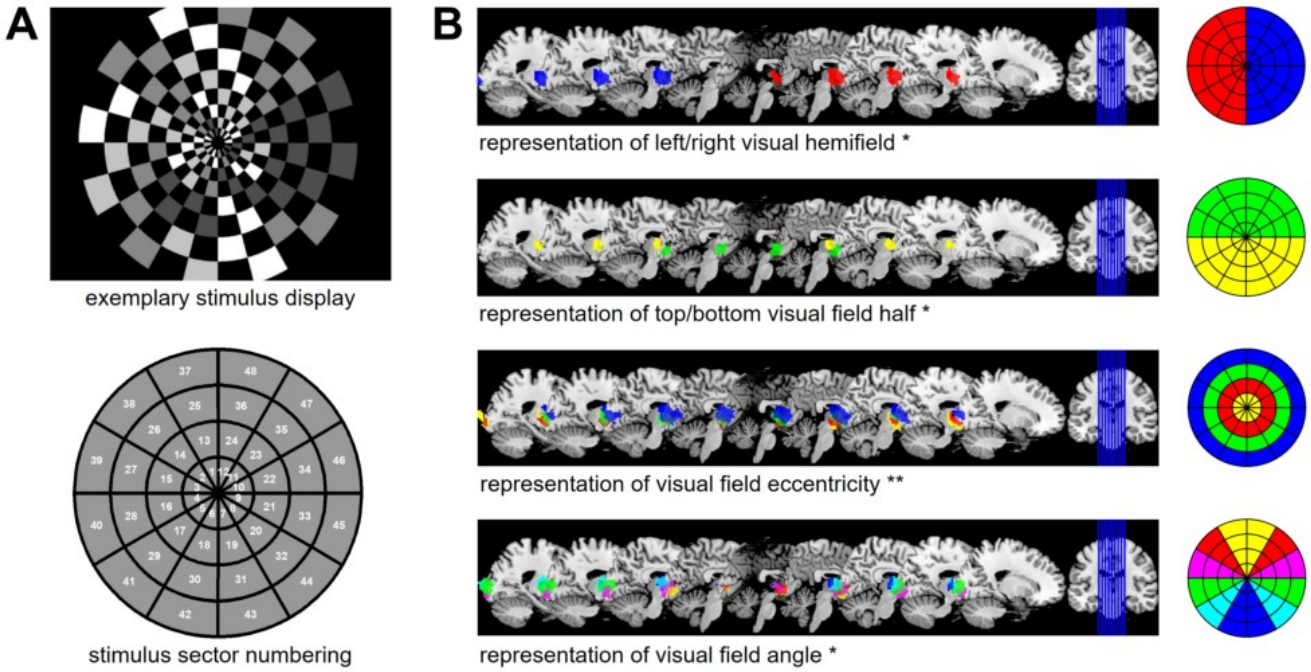

Figure 2. *Empirical validation of searchlight-based ITEM analysis.* **(A)** During fMRI scanning, subjects were stimulated with flickering checkerboard patterns (top) whose illumination intensity changed from trial to trial [7]. The visual field was partitioned into 48 sectors (bottom) organized into 4 rings and 12 segments [2]. **(B)** Trial-wise sector intensities were reconstructed using ITEM-based searchlight decoding. Colored voxels indicate searchlights from which the visual contrast in highlighted sectors could be decoded with average correlation significantly greater than zero (* FWE, $p < 0.05$, $k = 0$; ** unc., $p < 0.001$, $k = 10$).

(https://files.aievolution.com/prd/hbm2201/abstracts/abs_2416/Figure_2_2021_12_17.png)

Conclusions:

The problem of correlated trial-by-trial parameter estimates has been discussed several times in the fMRI/MVPA literature [3,4]. Whereas the previous contributions have suggested *ad-hoc* solutions, e.g. estimating each trial using a separate design matrix, ITEM provides a principled approach, based on the actual distribution of the trial-by-trial responses, as implied by the trial-wise design matrix [1,2]. Here, we have extended the ITEM methodology to searchlight decoding – available as an SPM plug-in from GitHub [9] – and shown that searchlight-based ITEM can be successfully used for information-based mapping [5] of stimulus representations in the human brain.

Modeling and Analysis Methods:

Classification and Predictive Modeling
Methods Development [2]
Multivariate Approaches [1]

Novel Imaging Acquisition Methods:

BOLD fMRI

Perception, Attention and Motor Behavior:

Perception: Visual

Keywords:

Computational Neuroscience
Data analysis
FUNCTIONAL MRI
Machine Learning
Modeling
Multivariate
Statistical Methods
Other - trial-wise decoding

[1|2]Indicates the priority used for review

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Yes

Please indicate below if your study was a "resting state" or "task-activation" study.

Task-activation

Healthy subjects only or patients (note that patient studies may also involve healthy subjects):

Healthy subjects

Was any human subjects research approved by the relevant Institutional Review Board or ethics panel? NOTE: Any human subjects studies without IRB approval will be automatically rejected.

Yes

Was any animal research approved by the relevant IACUC or other animal research panel? NOTE: Any animal studies without IACUC approval will be automatically rejected.

Not applicable

Please indicate which methods were used in your research:

Functional MRI
Structural MRI

For human MRI, what field strength scanner do you use?

3.0T

Which processing packages did you use for your study?

SPM
Other, Please list - ITEM toolbox

Provide references using author date format

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