#OHBM2022
@JoramSoch

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

Abstract #2588
Poster #WTh594

Joram Soch[1,2,9,•], John-Dylan Haynes[1–8]

Bernstein Center for Computational Neuroscience Berlin

[1] Bernstein Center for Computational Neuroscience, [2] Berlin Center for Advanced Neuroimaging, [3] Berlin School of Mind and Brain, Berlin, Germany
[4] Clinic for Neurology, Charité – Universitätsmedizin Berlin, Germany, [5] Department of Psychology, Humboldt-Universität zu Berlin, Germany
[6] EXC NeuroCure, Charité Berlin, [7] EXC Science of Intelligence, TU Berlin, [8] CRC Volition and Cognitive Control, TU Dresden, Germany
[9] German Center for Neurodegenerative Diseases, Göttingen, Germany, • BCCN Berlin, Philippstraße 13, Haus 6, 10115 Berlin, Germany;
e-mail address: **joram.soch@bccn-berlin.de**.

CHARITÉ UNIVERSITÄTSMEDIZIN BERLIN

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 regions of interest, 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.

Theory

Inverse transformed encoding modelling (ITEM) is based on
(i) estimating trial-wise response amplitudes using a design matrix with one HRF regressor for each trial (see Figure 1A):

$$\hat{\gamma} = (X_t^T V^{-1} X_t)^{-1} X_t^T V^{-1} y$$

(ii) calculating the covariance of those parameter estimates from the trial-wise design matrix (see Figure 1B):

$$U = (X_t^T V^{-1} X_t)^{-1}$$

(ii) and incorporating this covariance matrix into an inverse multivariate GLM for cross-validated prediction of a given experimental design variable (see Figure 1C):

$$T = YW + N, N \sim \mathcal{MN}(0, U, \Sigma_x)$$

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:

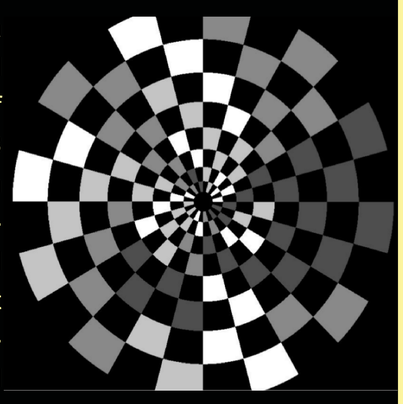
$$\mathrm{Perf} = \mathrm{Acc}(T, \hat{T})$$

$$\mathrm{Perf} = \mathrm{corr}(T, \hat{T})$$

Analysis

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. N = 4 subjects were looking at a stimulus consisting of 48 sectors randomly changing their illumination intensity from trial to trial (see below). These 48 sectors could be categorized with respect to 12 angles and 4 eccentricity levels (see Figure 2A).

For ITEM analysis, we used a searchlight radius of 6 mm and decoded contrast levels in each of the 48 sectors, 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).



Methods: *searchlight-based ITEM analysis*

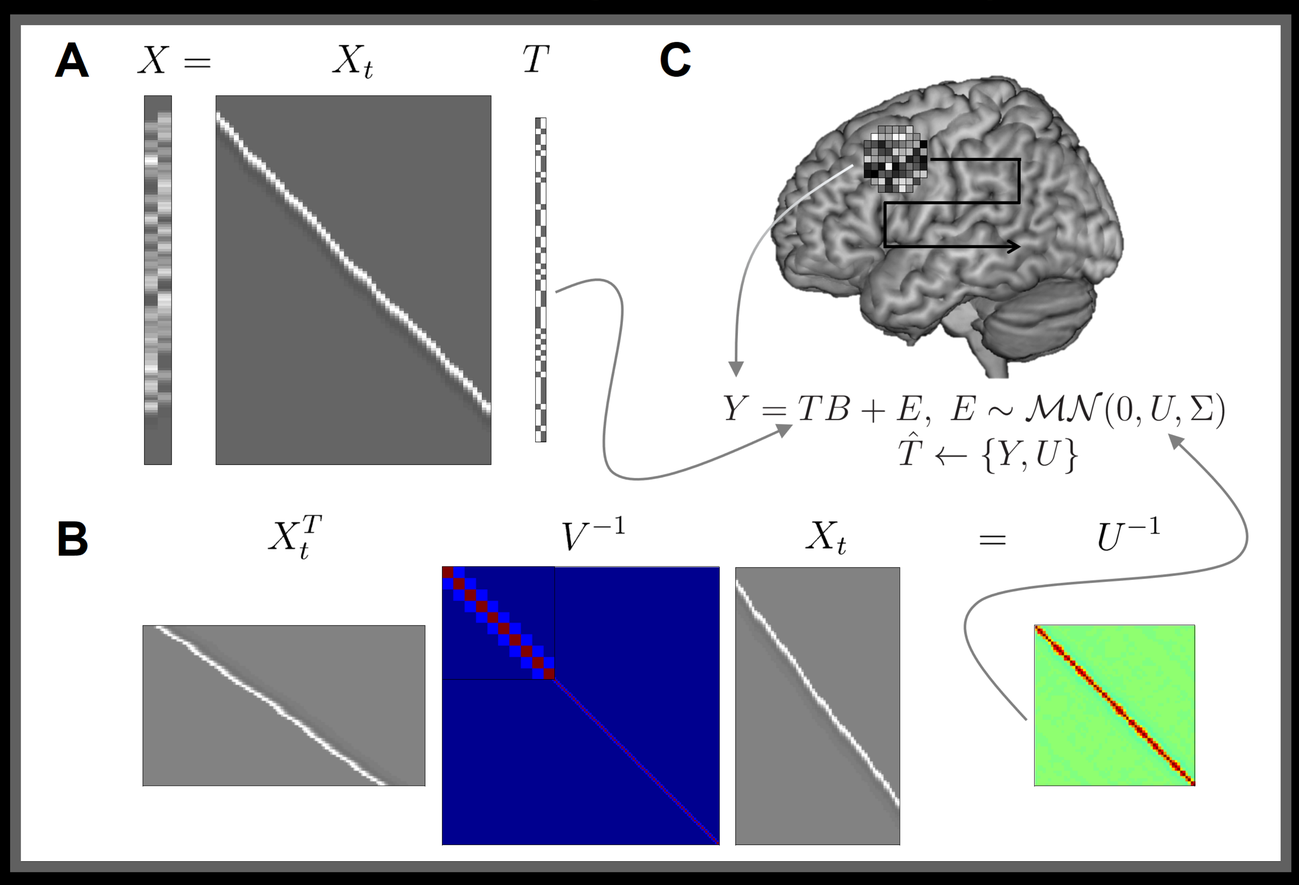


Figure 1. *Mathematical basics of searchlight-based ITEM analysis.* **(A)** The trial-wise design matrix X_t can be related to the standard design matrix X using a trial-level specification matrix T. **(B)** Under this assumption, the trial-by-trial covariance matrix U is a function of the trial-wise 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.

Results: *ITEM analysis for visual reconstruction*

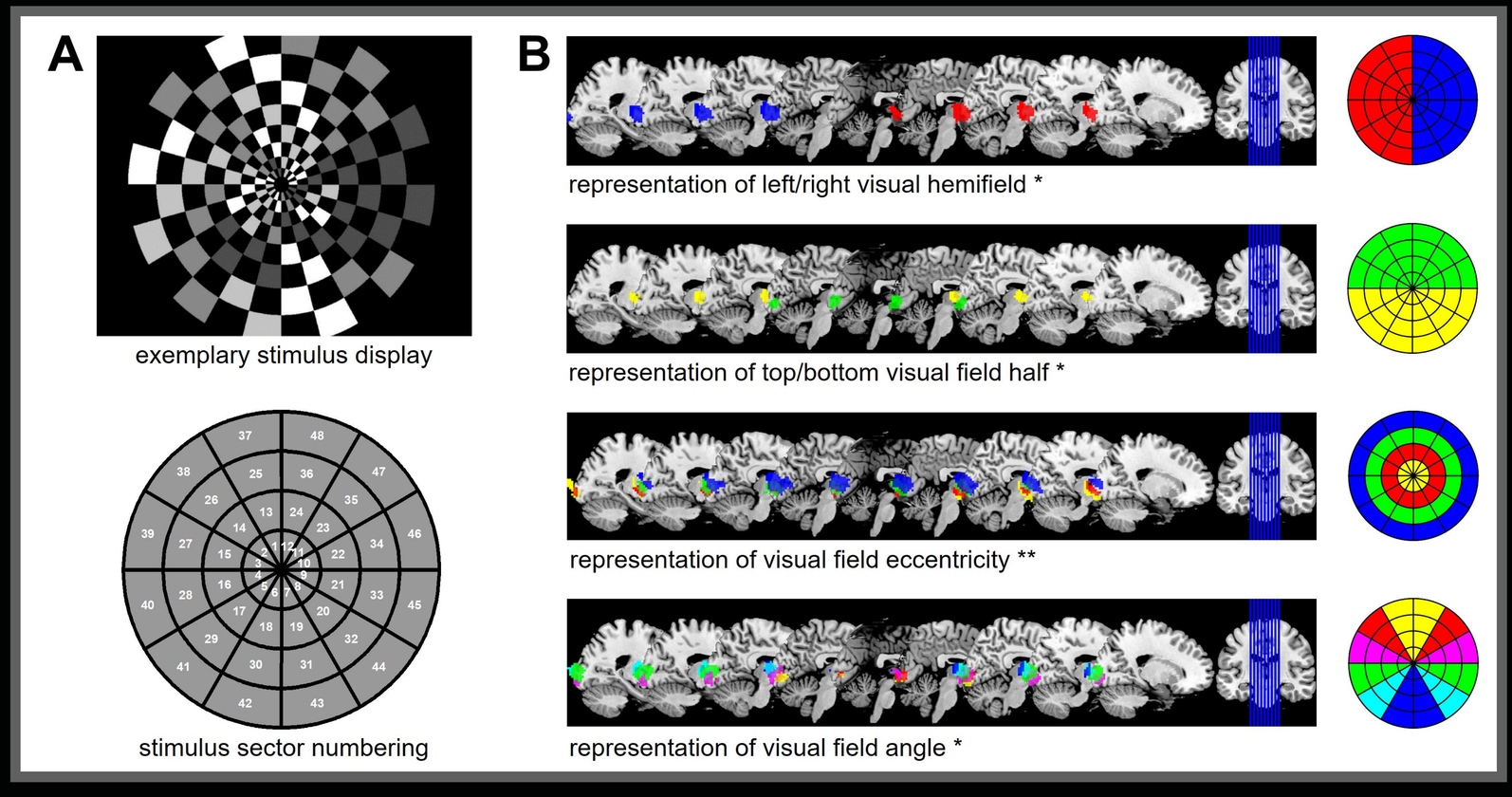


Figure 2. *Empirical validation of searchlight-based ITEM analysis.* **(A)** During fMRI scanning, subjects were stimulated with flickering checkerboard patterns (top) whose illumination intensity changed from trial to trial [7]. The visual field was partitioned into 48 sectors (bottom) organized into 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., $p < 0.001$, $k = 10$).

Discussion

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.

Toolbox

Data Set

References

[1] Soch J, Allefeld C, Haynes JD (2019). The problem of correlated trial-by-trial parameter estimates in fMRI decoding – solved. OHBM 2019, Poster #M495; URL: https://f1000research.com/posters/10-1225; DOI: 10.7490/f1000research.1118878.1.
[2] Soch J et al. (2020). Inverse transformed encoding models – a solution to the problem of correlated trial-by-trial parameter estimates in fMRI decoding. NeuroImage, 209, 116449.
[3] Mumford JA et al. (2012). Deconvolving BOLD activation in event-related designs for multivoxel pattern classification analyses. NeuroImage, 59, 2636-2643.
[4] Mumford JA, Davis T, Poldrack RA (2014). The impact of study design on pattern estimation for single-trial multivariate pattern analysis. NeuroImage, 103, 130-138.
[5] Kriegeskorte N, Goebel R, Bandettini P (2006). Information-based functional brain mapping. Proceedings of the National Academy of Sciences, 103, 3863-3868.
[6] Haynes JD, Sakai K, Rees G, Gilbert S, Frith C, Passingham RE (2007). Reading hidden intentions in the human brain. Current Biology, 17, 323-328.
[7] Heinzle J, Kahnt T, Haynes JD (2011). Topographically specific functional connectivity between visual field maps in the human brain. NeuroImage, 56, 1426-1436.
[8] Soch J, Görgen K, Heinzle J (2019). Visual receptive field mapping experiment. OpenNeuro, ds002013, first uploaded 2019-07-04; last updated 2019-10-10; URL: https://openneuro.org/datasets/ ds002013/versions/1.0.2; DOI: 10.18112/openneuro. ds002013.v1.0.2.
[9] Soch J (2018). Inverted Transformation Encoding Models. GitHub, first uploaded 2018-12-20, last updated 2021-11-30; URL: https://github.com/JoramSoch/ITEM.