The problem of correlated trial-by-trial parameter estimates in fMRI decoding – solved

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Introduction:

Techniques of multivariate pattern analysis (MVPA) can be used to decode the discrete experimental condition or a continuous modulator variable from measured brain activity during a particular trial. In functional magnetic resonance imaging (fMRI), trial-wise response amplitudes are sometimes regressed out of the BOLD signal using a general linear model (GLM) with one onset regressor for each trial [1]. When using rapid event-related designs with trials closely spaced in time, those estimates are highly variable and serially correlated due to the delayed shape of the hemodynamic response function (HRF) [2,3,4]. Here, we describe inverted transformation encoding models (ITEM), a principled approach of accounting for those serial correlations and decoding from the resulting estimates.

Methods:

The standard GLM for first-level fMRI data analysis is given by:

$$y = X\beta + \varepsilon, \varepsilon \sim \mathrm{N}(0, \sigma^2 V)$$

The first-level GLM for estimating trial-wise responses is given by:

$$y = X_t\gamma + \varepsilon_t, \varepsilon_t \sim \mathrm{N}(0, \sigma_t^2 V)$$

The crucial step of an ITEM analysis is finding a transformation matrix T $(t \times p)$ that maps from the trial-wise design matrix X_t $(n \times t)$ to the standard design matrix X $(n \times p)$:

$$X = X_t\, T$$

(see Figure 1). The trial-wise response amplitudes γ (the "gammas") can be estimated as

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

and it can be shown that they are distributed as

$$\hat{\gamma} = T\beta + \eta, \eta \sim \mathrm{N}(0, \sigma^2 U)$$

where the uncorrelation matrix U $(t \times t)$ is given by

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

This is called a transformation encoding model (TEM), because it uses T to encode a transformed version of the data ($\hat{\gamma}$). Switching the explanatory direction in the TEM, i.e. predicting the transformation matrix T from trial-wise response amplitudes $\hat{\gamma}$ [5], gives rise to the inverted transformation encoding model (ITEM). The ITEM is estimated in a multivariate (over voxels) and cross-validated (over sessions) fashion and decoding accuracy is obtained as proportion correct for discrete classification and via correlation coefficients for continuous reconstruction.

Results:

Simulation validation: We repeat the simulation described by Mumford and colleagues [2] which investigates the effect of different trial-wise estimation methods on the accuracy of classification between two experimental conditions. We find that, depending on the exact noise variance and the distribution of inter-stimulus intervals, ITEM decoding accuracies are up to 8% higher than the original simulation's best approach (see Figure 2A).

Empirical validation: We re-analyze data from a continuous visual stimulation experiment [6] 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, subjects were looking at a stimulus consisting of 48 sectors randomly changing their illumination intensity from trial to trial. Data were converted to the BIDS format [7], preprocessed using SPM12 [8] and further analyzed using the MACS toolbox [9]. Using the ITEM approach, visual contrast in almost all parts of the visual field could be reliably decoded from fMRI signals in left and right V1 (see Figure 2B).

Discussion:

The problem of correlated trial-by-trial parameter estimates has been discussed several times in the fMRI/MVPA literature [2,3,4]. Whereas the previous contributions have suggested ad-hoc solutions, e.g. estimating each trial using a separate design matrix [2], the present work provides a principled approach, based on the actual distribution of the trial-wise parameter estimates, as implied by the trial-wise design matrix. However, ITEMs are not only applicable to rapid event-related designs, but generally useful when trial-wise linear decoding by classification or reconstruction is the goal. We hope that the ITEM approach – available as an SPM plug-in on GitHub [10] – will increase the power of fMRI-based MVPA.

References:

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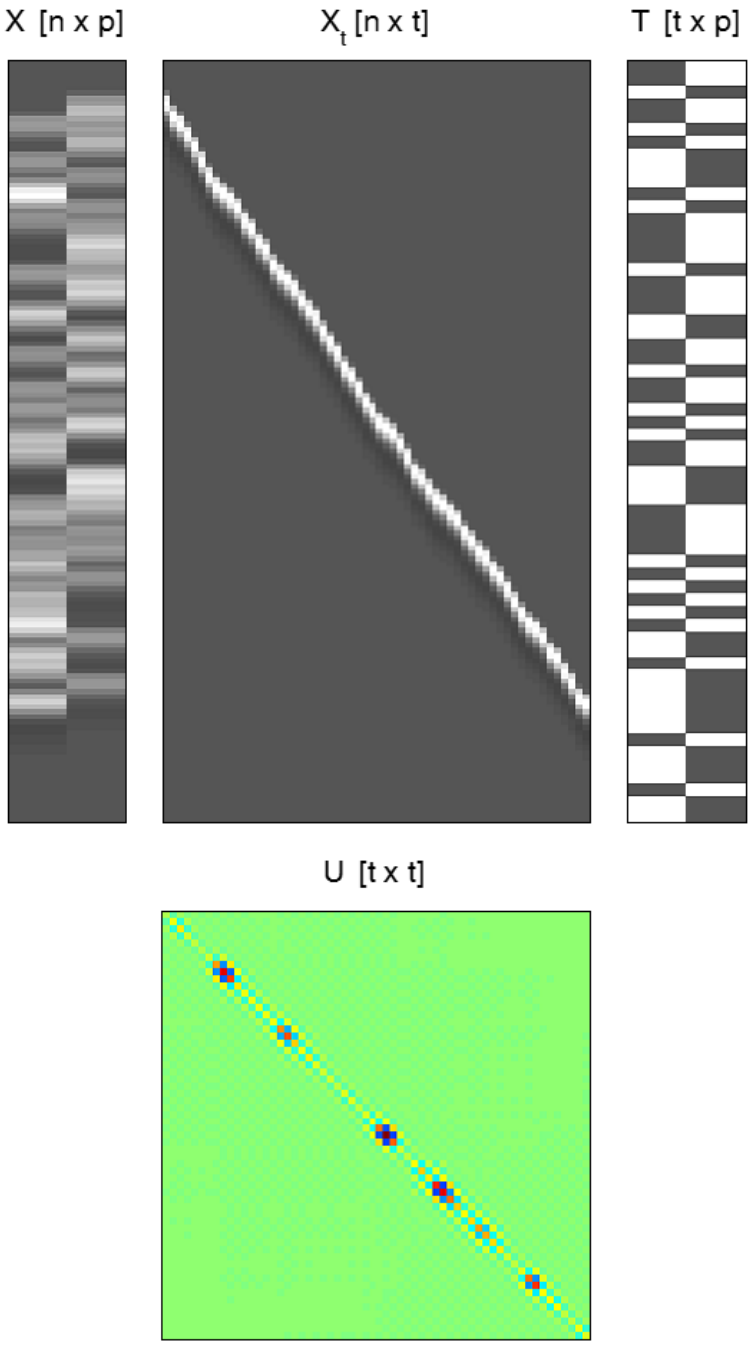

Figure 1. *Transformation encoding models.* Let there be *n* scans, *t* trials and *p* conditions. The trial-by-condition matrix *T* maps from the trial-wise design matrix X_t to the standard design matrix *X*. In this case, *T* is a just binary indicator matrix and each column simply sums up the corresponding trials from X_t into an onset regressor in *X*. The trial-by-trial matrix *U* encodes correlations between trial-wise HRFs. The closer two trials are to each other in time, the stronger they are (anti-)correlated. In the transformation encoding model, *T* takes the role of the design matrix and *U* becomes the covariance matrix (see equations in text).

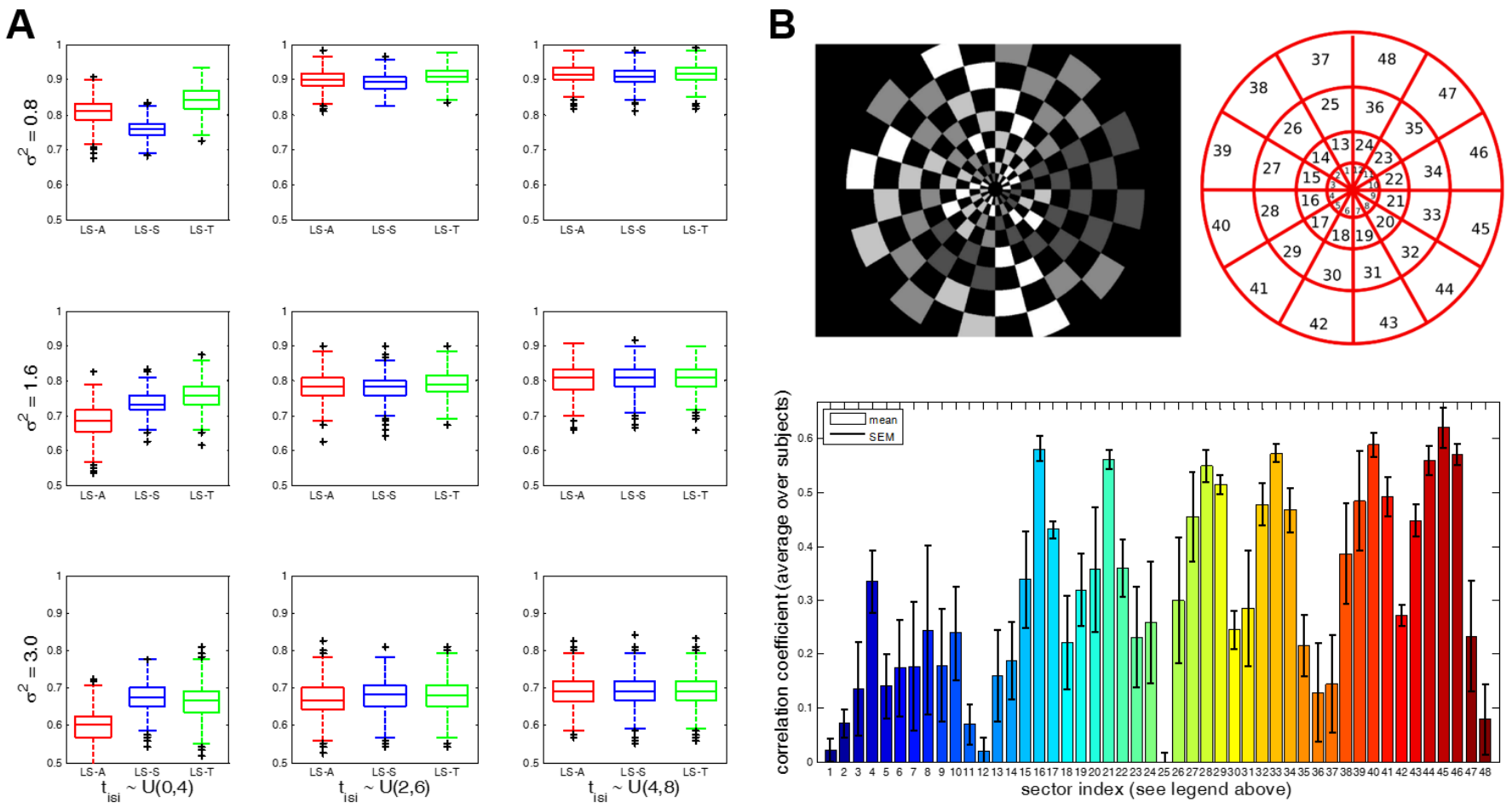

Figure 2. *Inverted transformation encoding models.* (A) Simulated data, decoding by classification. When the residual variance is high (bottom row) or the inter-stimulus interval is low (left column), the ITEM approach („least squares, transformed", LS-T, green) outperforms or at least levels with the naïve approach ignoring trial-by-trial correlations („least squares, all", LS-A, red) and the state-of-the-art approach by Mumford and colleagues („least squares, separate", LS-S, blue) [2]. (B) Empirical data, decoding by reconstruction. The visual field was partitioned into 48 individuals sectors whose illumination intensity randomly and independently varied from trial to trial (top panel) [6]. The ITEM approach allows to reliably reconstruct contrast values in almost all parts of the visual field (bottom panel). Interestingly, reconstruction performance is better for sectors which are far from the center (e.g. 45 vs. 9) and for sectors which are close to the horizontal axis (e.g. 45 vs. 48) of the visual field.