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Reconstruction of continuous motion direction from fMRI data

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Introduction

The neural representation of motion perception has been extensively studied in cognitive neuroscience. Functional magnetic resonance imaging (fMRI) and multivariate pattern analysis (MVPA) are often used to identify brain areas associated with motion perception [1,2]. The rationale behind this is that certain voxels are sensitive to motion direction, and the resulting activity pattern can be exploited by a *classifier* to discriminate between possible motion directions based on previously unseen data.

An alternative approach, *inverted encoding modelling* (IEM), consists in specifying a forward model describing the mapping between motion direction and voxel activity. Then, this model is inverted to perform stimulus reconstruction from new data [3,4]. IEMs seek the optimal response profile of motion-selective neuronal populations tuned to different directions, but the choice of basis functions is often difficult, as cells tuned to motion direction can exhibit a variety of response profiles [5].

Here, we test a novel non-parametric approach to reconstruction of continuous motion direction. This method uses a cyclic version of *Gaussian process regression* (GPR) [6] to obtain a continuous estimate of trial-wise direction of motion.

Experiment

N = 23, S = 10, T = 480, t = 160

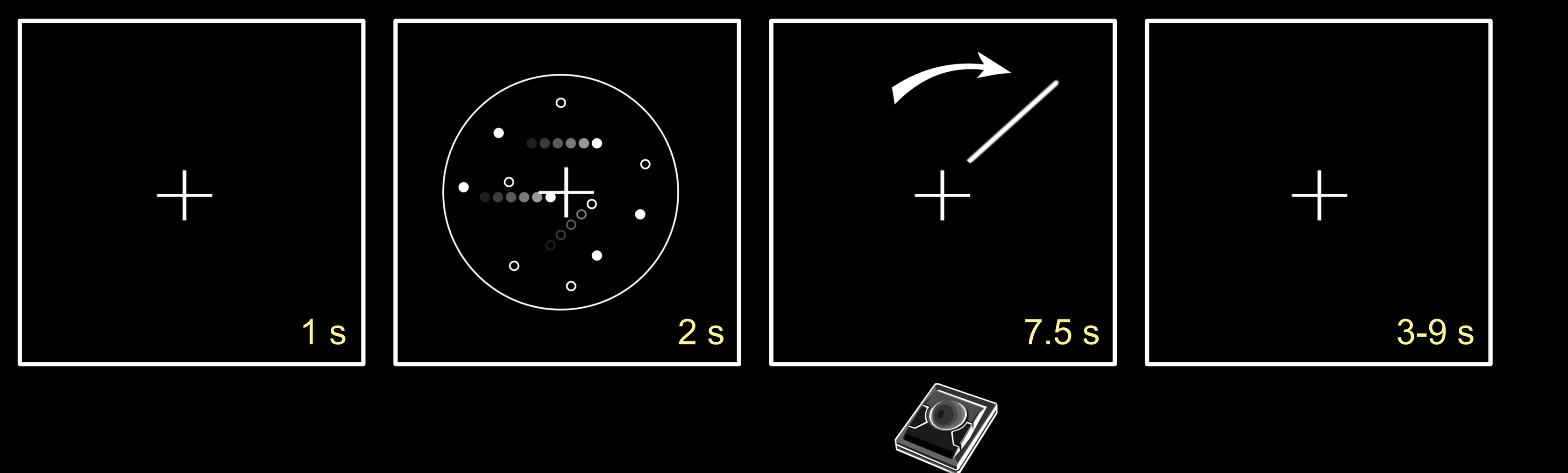

Figure 1. *Feature-continuous task.* Each trial started with the presentation of a fixation cross for 1s. This was followed by a 2s random dot kinematogram (RDK) shown at 0%, 100% or a medium coherence level, estimated from a behavioral training phase. Immediately after the stimulus offset, a moving bar appeared, rotating clockwise or counter-clockwise. Subjects were asked to report the net motion direction by pressing a button when the bar orientation matched the perceived direction of motion.

Analysis

Using SPM, we specified a trial-wise general linear model (GLM) and estimated trial-wise response amplitudes using weighted least squares (WLS) parameter estimates:

$$y = X_t \gamma + \varepsilon, \; \varepsilon \sim \mathcal{N}(0, \sigma^2 V)$$

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

Given trial-wise response amplitudes γ_j (in one voxel **j**) and associated directions of motion $\boldsymbol{\theta}$ (actual or reported), we used Gaussian process regression (GPR) to estimate a circular function $\mathbf{f_j}$ characterized by kernel parameters $\mathbf{k_j}$ mapping from direction $\boldsymbol{\theta_i}$ to activation γ_{ji} (in one trial **i**) :

$$\hat{\gamma}_j = [\hat{\gamma}_{j1}, \ldots, \hat{\gamma}_{jt}]^\mathrm{T}, \quad \theta = [\theta_1, \ldots, \theta_t]^\mathrm{T}, \quad \theta_i \in \Theta = (0, 2\pi]$$

$$\hat{\gamma}_{ji} = f_j(\theta_i, k_j) + \varepsilon_{ji}, \quad \varepsilon_{ji} \sim \mathcal{N}(0, \sigma_j^2), \quad f_j : \Theta \rightarrow \mathbb{R}$$

This can then be extended to a model for responses across voxels, e.g. a region of interest (ROI) or searchlight (SL), for which voxel-wise parameter estimates γ_j and GPR predictions $\mathbf{f_j(\theta_i)}$ are horizontally concatenated into **v x t** matrices (numer of voxels **v**, numer of trials **t**):

$$\hat{\Gamma} = \begin{bmatrix} \hat{\gamma}_{11} & \cdots & \hat{\gamma}_{v1} \\ \vdots & \ddots & \vdots \\ \hat{\gamma}_{1t} & \cdots & \hat{\gamma}_{vt} \end{bmatrix}, \quad f(\theta, k) = \begin{bmatrix} f_1(\theta_1, k_1) & \cdots & f_v(\theta_1, k_v) \\ \vdots & \ddots & \vdots \\ f_1(\theta_t, k_1) & \cdots & f_v(\theta_t, k_v) \end{bmatrix}$$

Data are partitioned into training and test set and the covariance within a searchlight is estimated from the residuals of the trained GPR model, plus some diagonal regularization:

$$\hat{R} = \hat{\Gamma}_\mathrm{train} - f(\theta_\mathrm{train}, \hat{k})$$

$$\hat{\Sigma} = (1 - r) \cdot \frac{1}{t} \hat{R}^\mathrm{T} \hat{R} + r \cdot \mathrm{diag}\left([\hat{\sigma}_1^2, \ldots, \hat{\sigma}_v^2] \right)$$

Reconstructed directions are obtained via maximum likelihood estimation (MLE), i.e. by searching for the direction $\boldsymbol{\theta}$ which best fits with the estimated voxel-wise responses **f** and across-voxel covariance $\boldsymbol{\Sigma}$:

$$\hat{\theta}_i = \underset{\theta \in \Theta}{\arg\max} \; \mathrm{LL}(\theta) = \underset{\theta \in \Theta}{\arg\max} \left[\log \mathcal{N}(\hat{\Gamma}_\mathrm{test}^{(i)}; f(\theta, \hat{k}), \hat{\Sigma}) \right]$$

Finally, reconstructed and actual direction of motion are compaired using a trial-wise precision measure:

$$\mathrm{Prec}(\theta_i, \hat{\theta}_i) = \left(180^\circ - |(\theta_i - \hat{\theta}_i)_\mathrm{circ}| \right) / 180^\circ \cdot 100\%$$

Results

Figure 4. *Exemplary tuning functions* This figure is based on 16 direction-responsive voxels from the early visual areas of a single subject. Each plot shows estimated trial-wise response amplitudes (white dots), voxel tuning predictions (white lines) and variance (white shades), as a function of direction of motion (x-axis), estimated using cyclic Gaussian process regression (GPR), cross-validated over fMRI recording sessions. As one can see, GPR allows for flexible estimation of arbitrary tuning functions, varying in precision and smoothness.

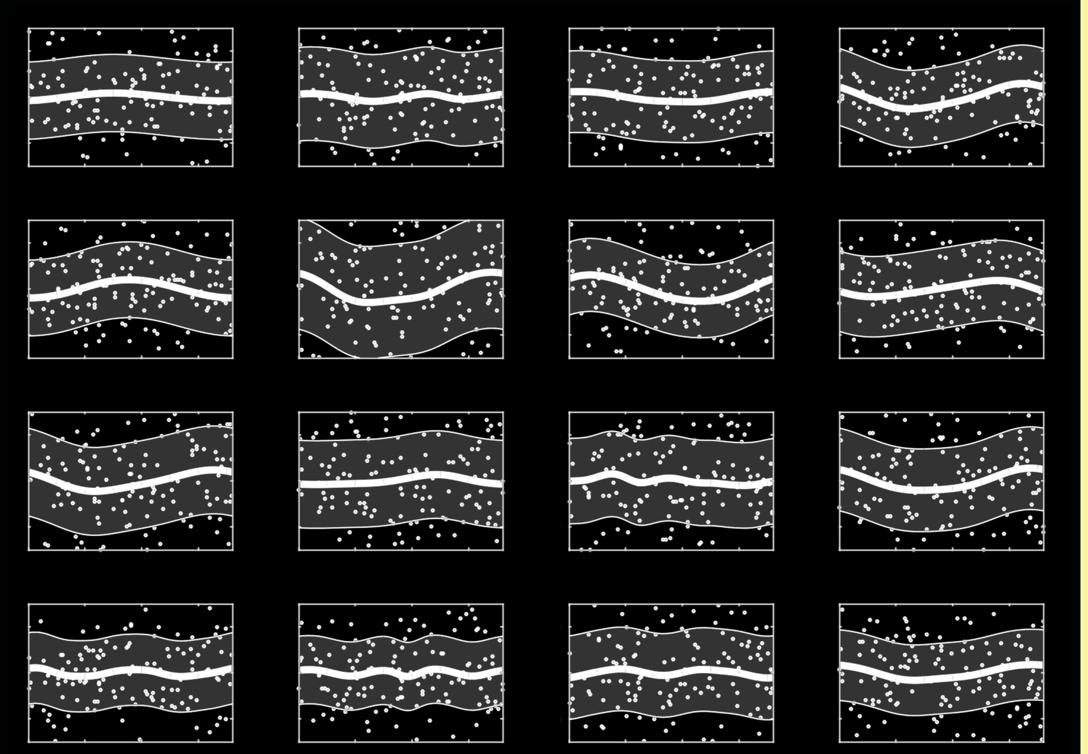

Figure 5. *Searchlight-based analyses.* Thresholded SPM from a second-level analysis of reconstruction precision for presented directions of motion in the 100% coherence condition. Red voxels indicate significant above-chance decoding precision (FWE$_c$, $p < 0.05$, $k = 732$; cluster-defining voxel threshold $p < 0.001$). The resulting map for reported directions of motion looks very similar, because presented and reported directions of motion are highly correlated at 100% coherence.

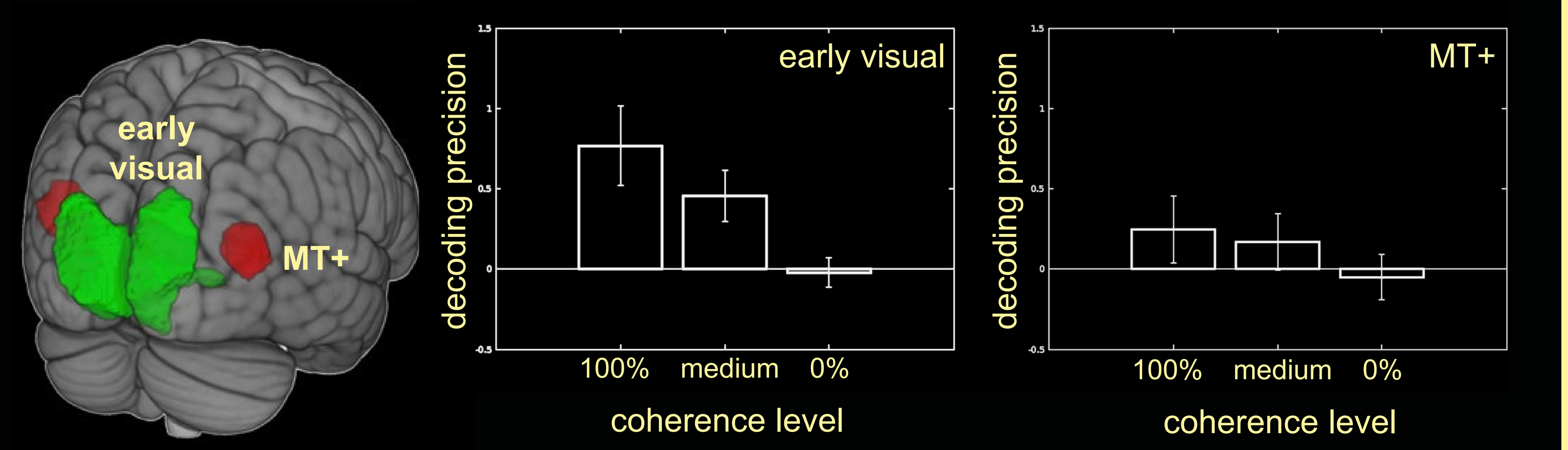

Figure 6. *ROI-based analyses.* ROIs were identified via functional localizers, additionally combined with anatomical constraints for early visual areas (V1, V2, V3). Bar plots show average precision minus chance within ROIs, averaged over subjects, as a function of coherence level. Error bars correspond to standard error of the mean (SEM). In visual areas, reconstruction precision was significantly different between 100% and 0% ($t_{22} = 4.327$, $p = 0.002$).

Training: voxel-wise GPR

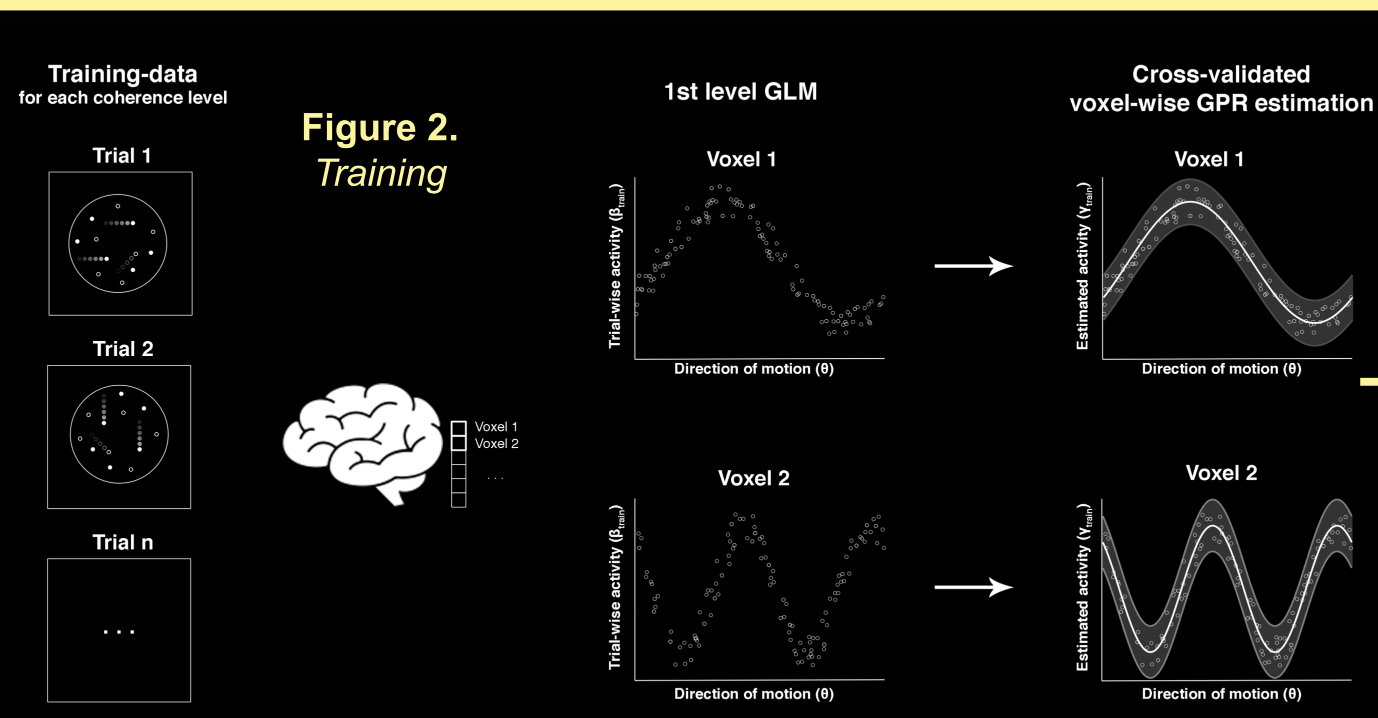

Figure 2. *Training*

Testing: searchlight-based MLE

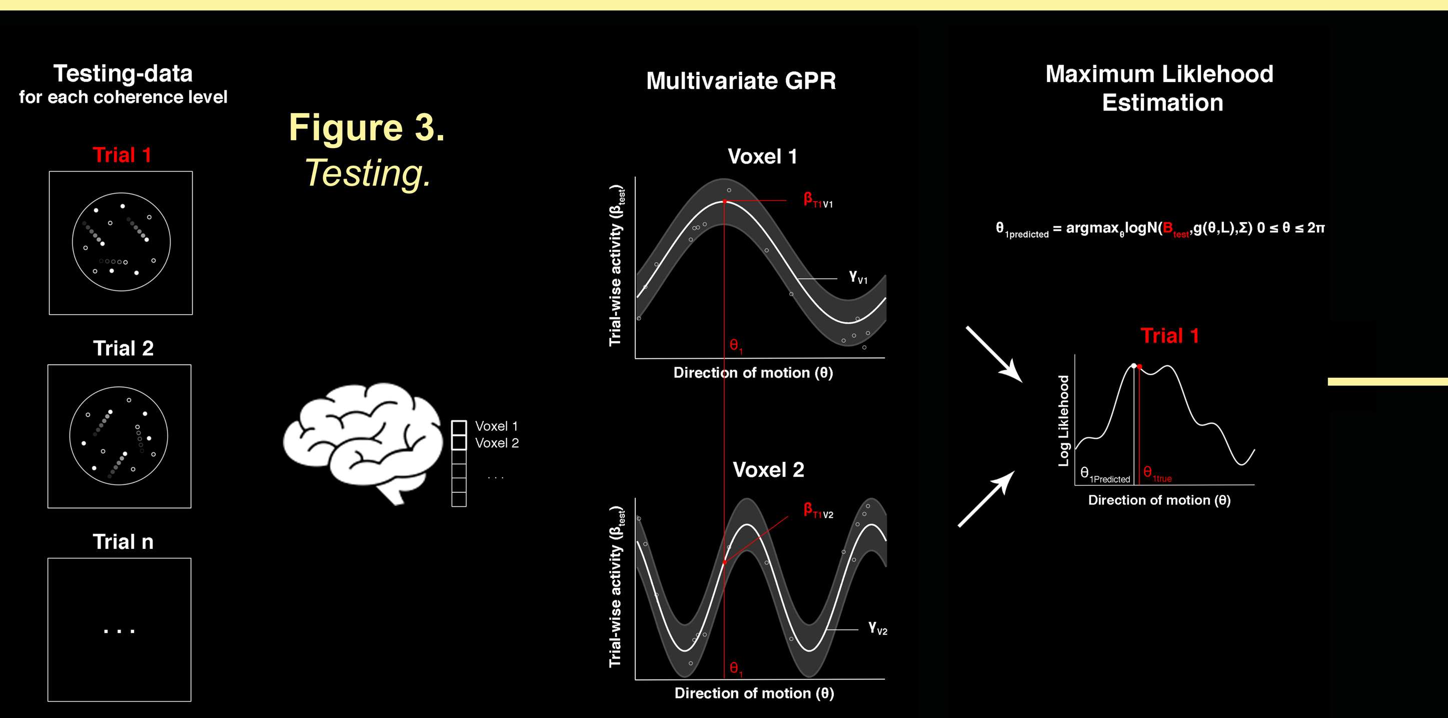

Figure 3. *Testing.*

Reporting: trial-wise precision

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Discussion

The novelty of our research consists in two aspects: First, this is one of the first neuroimaging studies employing a *feature-continuous random dot kinematogram (RDK)*, following categorical tasks almost universally applied in the past [2]. Second, this is the first application of *searchlight-based Gaussian process regression (GPR)* for predicting a continuous modulator variable (here, direction of motion) from fMRI signals in the field of visual reconstruction [1]. In the present study, this methodology allows for reconstruction of *presented* ("stimulus") as well as reconstruction of *reported* ("response") direction of motion, as a function of coherence level in the RDK stimulus.