Reconstruction of continuous motion direction from fMRI data

Poster No:

3904

Submission Type:

Abstract Submission

Authors:

Riccardo Barbieri[1], Felix Töpfer[1,2], Joram Soch[1,3], Carsten Bogler[1,3], John-Dylan Haynes[1,3,4,5,6,2,7,8]

Institutions:

[1]Bernstein Center for Computational Neuroscience, Berlin, Germany, [2]EXC NeuroCure, Charité – Universitätsmedizin, Berlin, Germany, [3]Berlin Center for Advanced Neuroimaging, Berlin, Germany, [4]Berlin School of Mind and Brain, Berlin, Germany, [5]Clinic for Neurology, Charité – Universitätsmedizin, Berlin, Germany, [6]Department of Psychology, Humboldt University, Berlin, Germany, [7]EXC Science of Intelligence, Technical University, Berlin, Germany, [8]CRC Volition and Cognitive Control, Technical University, Berlin, Germany

Introduction:

The neural representation of motion perception has been extensively studied in cognitive neuroscience. Functional magnetic resonance imaging (fMRI) is often used in combination with multivariate pattern analysis (MVPA) 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 from previously unseen data.
An alternative approach, inverted encoding modelling (IEM), consists in specifying a forward model describing the mapping between changes in motion direction and the expected voxel activity. Then, this model is inverted to perform stimulus reconstruction from new data [3,4]. IEMs typically seek the ideal 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 the 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.

Methods:

Experimental paradigm: 24 participants performed a feature-continuous perceptual decision-making task during an fMRI experiment (see Figure 1). In each trial, they viewed a 2s random dot kinematogram (RDK) with different coherence (0%, 100% and a medium level) and direction (randomly varying from 0° to 360°). After the stimulus presentation, they indicated the perceived motion direction (see Figure 1).
fMRI data analysis: For each subject, we estimated a trial-wise general linear model (GLM), convolving each 2s RDK period with the canonical hemodynamic response function (cHRF), to obtain trial-by-trial fMRI response

amplitudes. Then, responses within each coherence condition were subjected to a GPR against presented motion direction [6], accounting for the cyclic nature of the independent variable, to obtain a continuous response profile for each individual voxel. Finally, the estimated response profiles within a searchlight were combined to obtain a reconstructed direction of motion.

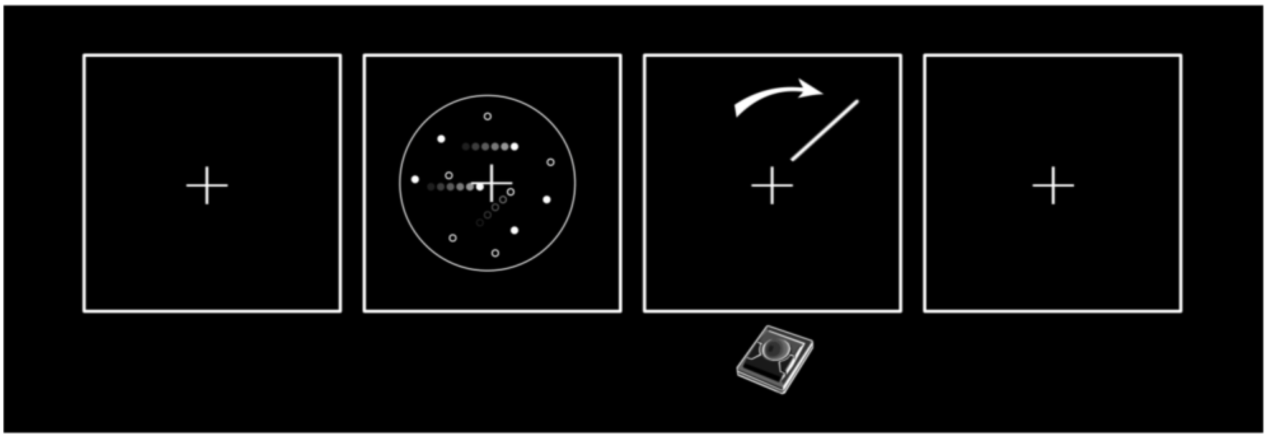

Figure 1. *Feature-continuous task.* Each trial started with the presentation of a fixation bullseye for 1s. This was followed by a 2s random dot kinematogram (RDK) shown at three coherence level: 0%, 100% and a medium coherence, estimated from a behavioral training phase. Immediately after the stimulus offset, an arrow appeared and rotated clockwise or counter-clockwise around the central fixation, starting from a random position. Subjects were asked to report the net motion direction by pressing a button when the orientation of the arrow matched the perceived direction of motion. The total duration of the arrow rotation was fixed to 7.5s. Every trial was interleaved by an inter-trial-interval of variable length (3-9s). 24 participants performed 10 runs for a total of 480 trials (160 trials per coherence level) over the course of 2 days.

Results:

Behavioral data: We found that subjects' response deviation decreased with increasing coherence (see Figure 2A), in line with previous studies employing continuous report [7,8,9]. Participants were unable to identify motion direction in the 0% coherence condition.
fMRI results: We found that reconstruction of motion direction becomes more precise with increasing coherence (see Figure 2B) and that it is impossible in the 0% coherence condition. At the group level, there was a main effect of coherence condition on reconstruction performance ($F_{2,46} = 12.72$, $p < 0.001$), according to a repeated-measures ANOVA of reconstruction precision in motion-sensitive areas, as defined by an independent localizer task.

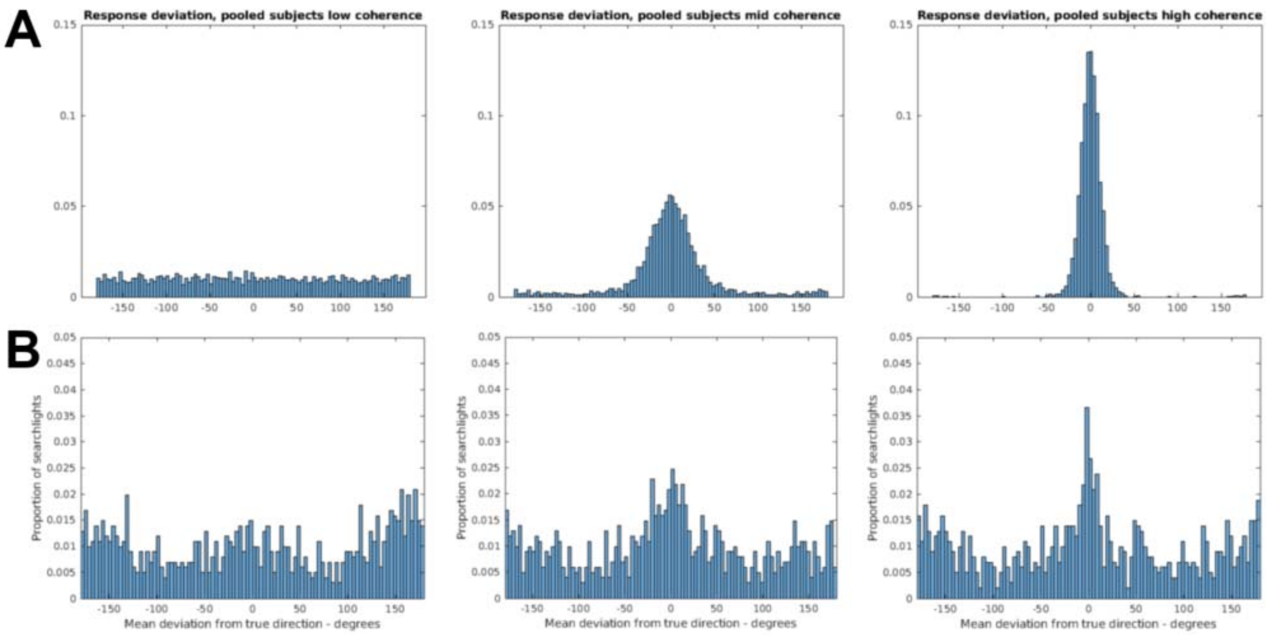

Figure 2. *Behavioral performance and motion reconstruction.* **(A)** Behavioral performance in the scanner. Each panel shows the histogram of trial-wise response deviations, i.e. circular distance between presented and reported direction, pooled from all subjects ($n = 24$), for the low coherence (left), medium coherence (middle) and high coherence (right) condition. Note that all plots use the same vertical scaling to be comparable. In the 0% coherence condition, the stimulus is carrying no information about direction of motion. With increasing coherence, participants' responses become more precise. **(B)** Motion reconstruction from neuroimaging data. Each panel shows the histogram of average reconstruction deviation, i.e. circular distance between presented and decoded direction, pooled from all searchlights in the visual areas of one participant, for the low coherence (left), medium coherence (middle) and high coherence (right) condition. Again, all plots use the same vertical scaling for comparison purposes. With increasing coherence, reconstruction performance improves.

Conclusions:

The novelty of our research consists in two aspects: First, this is one of the first neuroimaging studies employing a feature-continuous RDK, following categorical tasks almost universally applied in the past [2]. Second, this is the first application of Gaussian process regression for predicting a continuous modulator variable (here, direction of motion) from fMRI signals in the field of visual reconstruction [1]. In the future, we want to extend this work from reconstruction of *presented* to reconstruction of *reported* direction of motion and compare them across coherence levels.

Higher Cognitive Functions:

Decision Making [2]

Modeling and Analysis Methods:

Classification and Predictive Modeling
Methods Development
Multivariate Approaches

Perception, Attention and Motor Behavior:

Perception: Visual [1]

Keywords:

Data analysis
Design and Analysis

FUNCTIONAL MRI
Machine Learning
Modeling
Multivariate
Perception
Statistical Methods
Vision

[1|2]Indicates the priority used for review

My abstract is being submitted as a Software Demonstration.

No

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
Behavior
Computational modeling

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

3.0T

Which processing packages did you use for your study?

SPM

Provide references using author date format

[1] Kamitani, Y. (2006), 'Decoding seen and attended motion directions from activity in the human visual cortex', Current Biology, vol. 16, iss. 11, pp. 1096-1102.
[2] Hebart, M. (2013), 'On the Neuronal Systems Underlying Perceptual Decision-Making and

Confidence in Humans', PhD Thesis, submitted to the Humboldt University of Berlin, 24/07/2013; URL: https://edoc.hu-berlin.de/bitstream/handle/18452/17576/hebart.pdf?sequence=1.
[3] Brouwer, G.J. (2009), 'Decoding and reconstructing color from responses in human visual cortex', Journal of Neuroscience, vol. 29, iss. 44, pp. 13992-14003.
[4] Sprague, T.C. (2018), 'Inverted encoding models assay population-level stimulus representations, not single-unit neural tuning', eNeuro, vol. 5, art. 3.
[5] Albright, T.D. (1984), 'Direction and orientation selectivity of neurons in visual area MT of the macaque', Journal of Neurophysiology, vol. 52, pp. 1106-1130.
[6] Rasmussen, C.E. (2006), 'Gaussian Processes for Machine Learning', MIT Press, Cambridge, Massachusetts; London, England.
[7] Smith, P. L. (2016), 'Diffusion theory of decision making in continuous report', Psychological Review, vol. 123, iss. 4, pp. 425-451.
[8] Bae, G.-Y. (2018), 'Motion perception in 360° space: Illusory perception of opposite direction of motion', VSS 2018; URL: https://static1.squarespace.com/static/5ac114ac96d455c1a62e09e7/t/5afa60e7aa4a9925e936c33c/1526358263492/Bae%26Luck_VSS2018.pdf.
[9] Bae, G.-Y. (2019), 'Decoding motion direction using the topography of sustained ERPs and alpha oscillations', NeuroImage, vol. 184, pp. 242-255.