Similarities in resting state and feature-driven activity: Non-parametric evaluation of human fMRI

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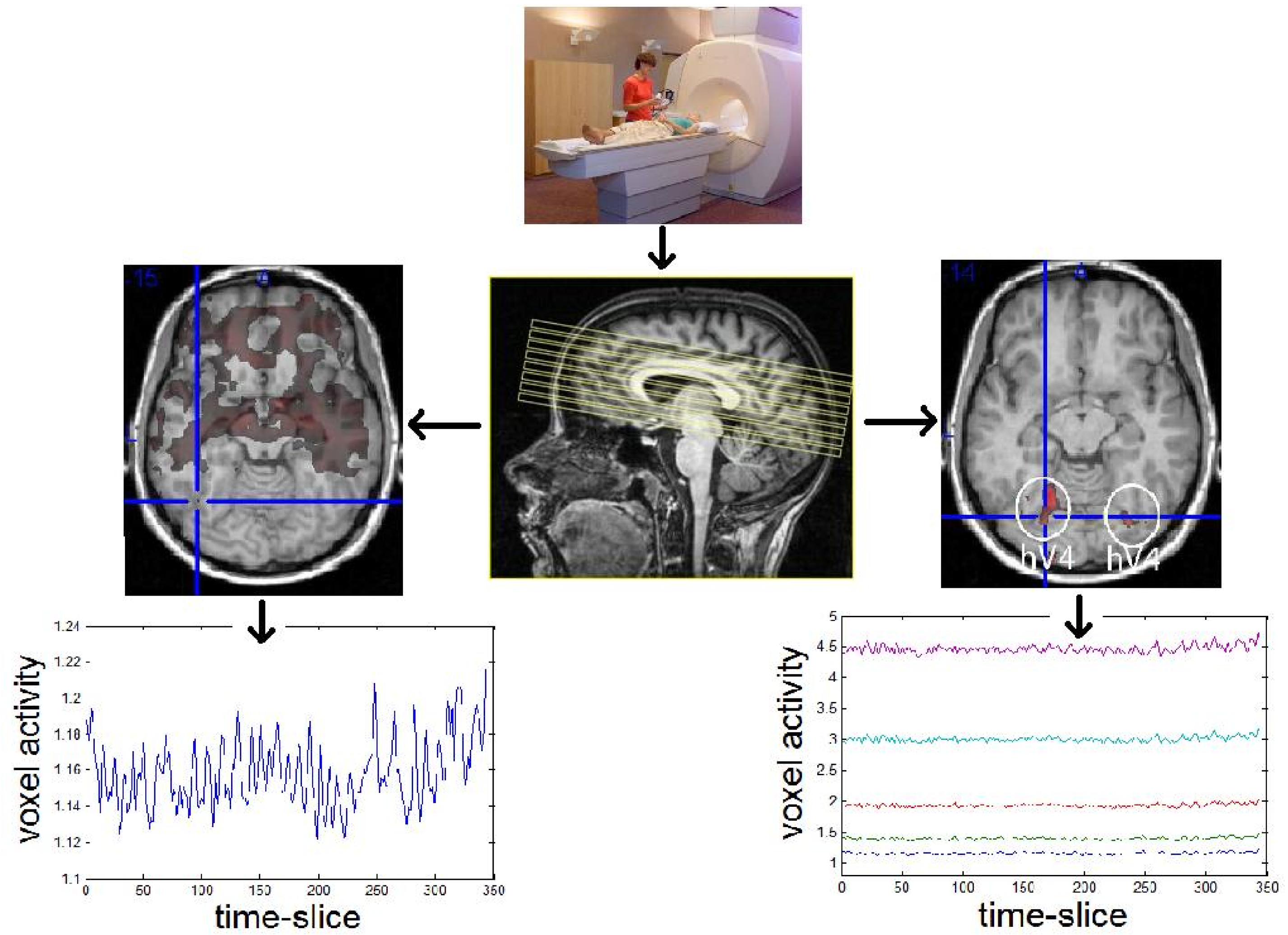
Motivation

- **fMRI: natural source of high-dimensional time series data**
- **Want: characterize brain activity in various feature-driven scenarios and in the absence of any task (resting state)**
- **Aim: test the hypothesis that fMRI data acquired in resting state is statistically similar to feature-driven activity from natural, complex stimuli**
- **Challenges: fMRI data has strong imbalance in high-dimensionality versus sample size, and difficult temporal and spatial dependencies in the data**

1 Introduction



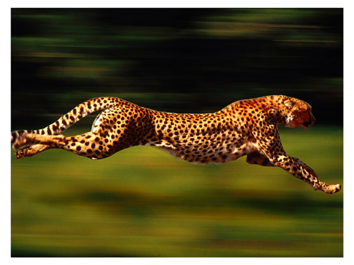
Acquisition of fMRI time-series data.

- Data-driven analyses – reveal similar functional architecture [4, 2] of resting state activity and feature-driven activity.
- Activation in brain arising in the **absence of any task**
- Not feature-driven – characterization of data faces particular challenges
- **Semi-supervised framework** results shows [1]:
  - Resting state data can **increase generalizability of model** in feature-driven fMRI analyses
  - Learning with resting state data **reveals previously identified functional areas** of the brain from purely feature-driven studies
- **Strong indications that resting state data is similar to natural feature-driven data**

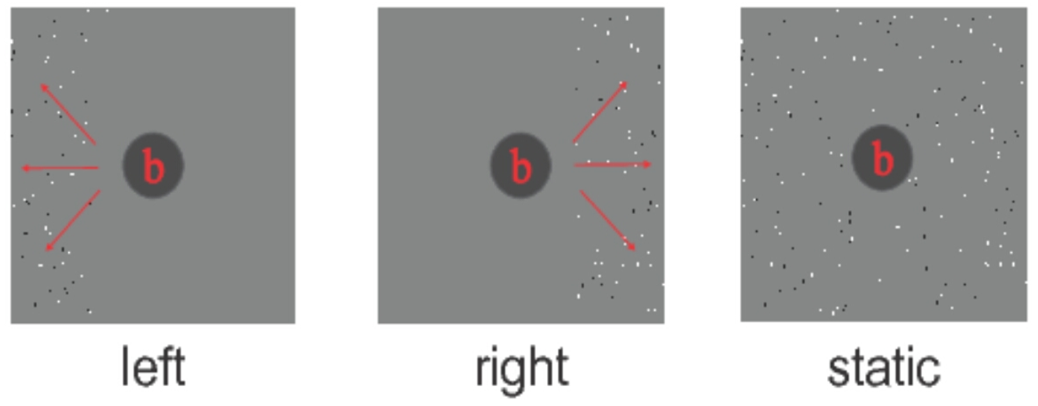
2 Methods and Materials

- **3D fMRI brain volumes** in vector space $(x_1, \ldots, x_n) \in \mathbb{R}^{d \times n}$ acquired with a Siemens 3T TIM scanner, separated by 2.3 or 3 seconds (TR), 40ms echo time, 3x3x3 mm spatial resolution.
- Pre-processed: Statistical Parametric Mapping (SPM) toolbox [6].

- **fMRI data** of one human volunteer in 3 conditions:
  (a) **resting state**: eyes closed, no task ($n = 344$ time-slices)
  (b) viewing of **natural video stimuli** ($n = 344$ time-slices)



  (c) viewing of **unnatural stimuli** ($n = 209$ time-slices)



→ Task-execution in block-paradigm: subject exposed to several distinct random dot displays (12s each) containing flow, random motion, static dots, hemi-field stimulation and blank screen.
→ During exposure, subject performed a central distractor task requiring button-press when a centrally presented char was presented twice in a row.

Non-parametric two-sample tests [3, 5]

Analysis of 1-voxel regions

- **Kolmogorov-Smirnov Statistic [5]:**

$$D_{s_1,s_2} = sup_x |F_{s_1}(x) - F_{s_2}(x)| \qquad (1)$$

F_{s_1}, F_{s_2}: **CDFs for the 2 samples,** s_1, $s_2 \in \mathbb{R}^{n \times 1}$

Analysis of higher dimensional voxel regions

- **Maximum Mean Discrepancy [3]:**

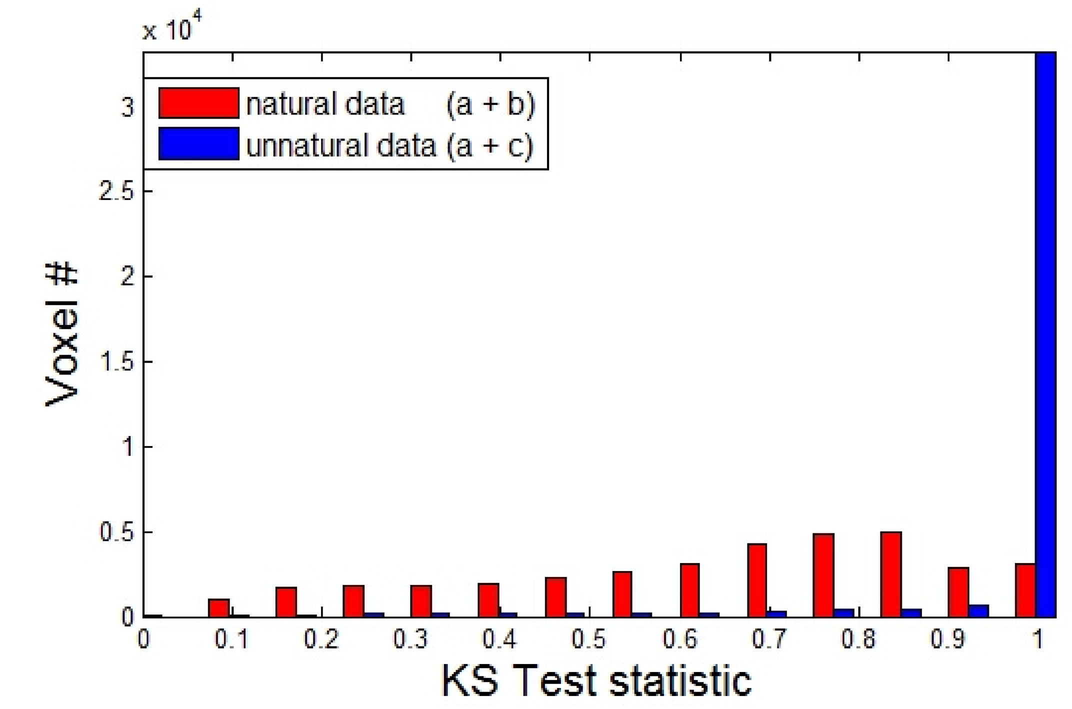
$$D_{s_1,s_2} = \|\frac{1}{m_1}\sum_i \phi(s_1^i) - \frac{1}{m_2}\sum_j \phi(s_2^j)\|^2_{\mathcal{H}} \qquad (2)$$

ϕ **maps input data** s^i, s^j **to respective Hilbert space** $\mathcal{H}$

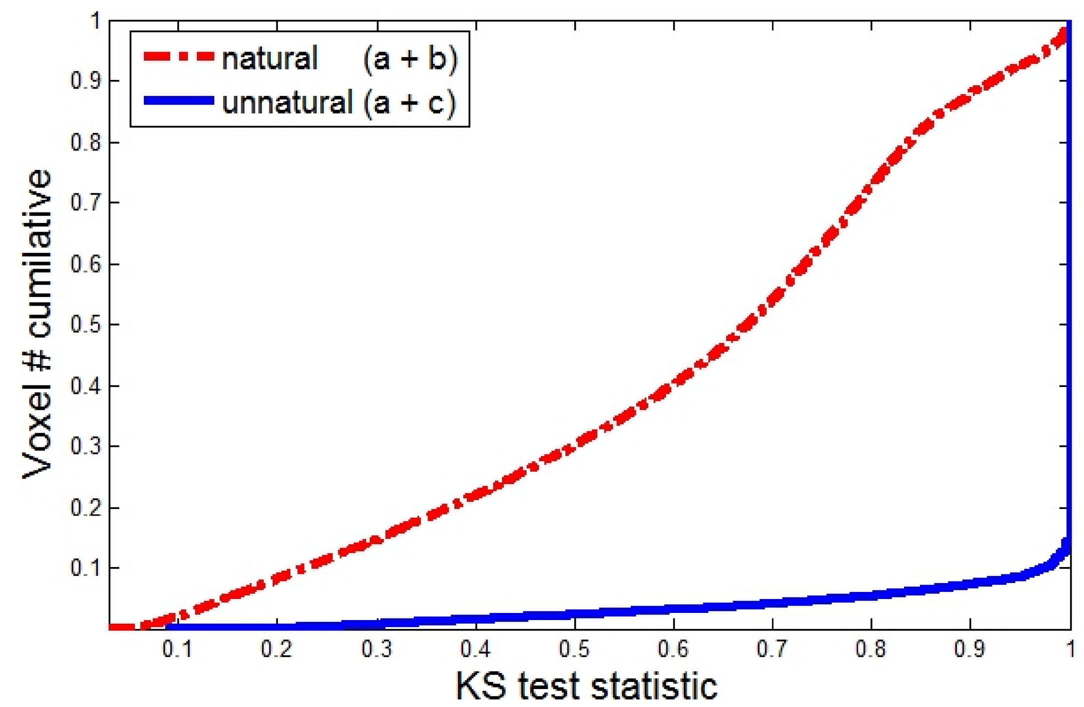
3 Results

Resting state compared with both natural and unnatural data.

Histograms of the KS statistics:



CDFs of the KS statistics:



Conclusions

- **We show that, while we are able to find meaningful dependencies in one-dimensional tests, high-dimensional non-parametric tests do not yield an interpretable result.**
- **It is our belief that modified tests that incorporate spatial and temporal dependencies would help to counter the difficulties arising from very high dimensional recordings.**

References

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[6] Friston, K., Ashburner, J., Kiebel, S., Nichols, T., Penny, W. (Eds.) *Statistical Parametric Mapping: The Analysis of Functional Brain Images*, Academic Press (2007)