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

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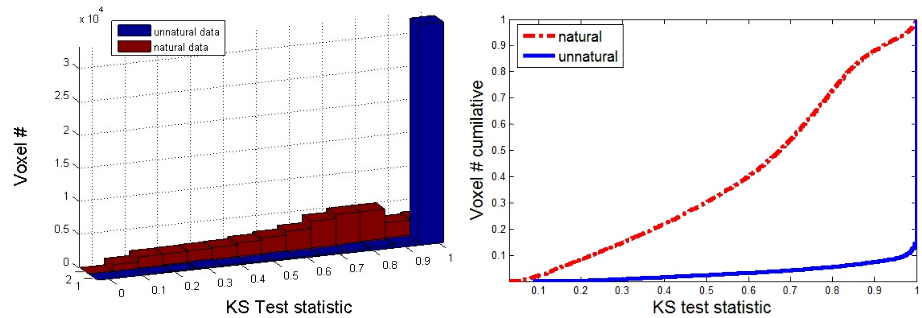
Introduction and Motivation: fMRI is a natural source of high-dimensional time series data. Recordings are typically acquired in several hour sessions, with processing and analysis done offline. Due to the short amount of recording time available from any session, there is an imbalance between the comparatively small number of time slices and the high dimensionality of the data at each slice. Additionally, low spatial variation in the activation across voxels may imply the need for a spatial regularizer. Classical statistical tests, such as the Kolmogorov-Smirnov test of independence work on univariate data samples [5]. Recent extensions to high-dimensional non-parametric testing typically do not assume spatial or temporal dependence [3]. While these statistical tests are nevertheless commonly applied to fMRI recordings, the underlying generating process clearly violates the assumptions inherent in the design of the statistical tests.

Resting state activity is the activation in brain arising in the absence of any task, and is usually measured in awake subjects during prolonged fMRI scanning sessions where the only instruction given is to close the eyes and do nothing. Data-driven analyses of resting state activity reveals a similar functional architecture [4, 2]. In addition to the difficulties in characterizing fMRI data due to the high-dimensionality, characterization of resting state data faces particular challenges given that it is not feature-driven. Recently, resting state data has been successfully used in a semi-supervised learning framework in order to augment feature-driven fMRI analyses [1]. Specifically, the use of resting state data in semi-supervised regression analyses not only improves the predictive performance and generalizability of the model, but also reveals previously identified functional areas of the brain from purely feature-driven studies. These results strongly suggest similarities between the distributions of resting state data and of natural viewing data.

We would therefore like to test the hypothesis that fMRI data acquired in a resting state is statistically similar to feature-driven activity from natural, complex stimuli. We approach this by non-parametrically assessing the statistical similarities of these two types of time-series data, as well as the dissimilarities between resting state data and feature-driven data from unnatural stimuli. However, classical tests only allow comparisons of one-voxel (one-dimensional) regions of the brain at a time, which cannot exploit the information contained in the higher dimensionality of the data. In order to get at the distribution information contained in the higher dimensions, we also use a new two-sample non-parametric kernel test [3]. 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.



(a) Histograms of the KS statistics.

(b) CDFs of the KS statistics.

Figure 1: Visualizations for resting state data with both natural and unnatural data.

Methods and Results: Data were collected from human volunteers in three distinct settings: (a) resting state (eyes closed, no task); (b) natural vision: free viewing of a feature movie (James Bond and Star Wars); (c) task-execution in a block-paradigm: subjects were exposed to several distinct random dot displays (each lasting 12s) containing flow, random motion, static dots, hemi-field stimulation and blank screen while they performed a central distractor task requiring button-press whenever a centrally presented char was presented twice in a row. All data were acquired using a 3T Siemens fMRI scanner, with (TR of 2.3-3s, echo time of 40ms, 33 slices, resolution: 3x3x3 mm).

Formally, the brain volumes at each time slice corresponds to data in a vector space $(x_1, \ldots, x_n) \in \mathbb{R}^{d \times n}$, where each voxel corresponds to a dimension of the vector space. The experiments consisted of running two-sample non-parametric tests on the data sets, considering different voxel-sized regions of the brain, in the entire brain (i.e. region size of one voxel until regions of 1000). Thus for a region size of one voxel, or one dimension, we used the two-sample Kolmogorov-Smirnov test [5] on the two data sets. When the region contained more than one dimension, we used the two-sample kernel test [3].

We compare voxel similarities across the different stimulation conditions in the entire brain. See Figures 1 for an illustration of the results from the Kolmogorov-Smirnov tests, the one-dimensional case. When we considered more dimensions in the case of the two-sample kernel test, the results were highly insignificant for both comparisons and no meaningful similarities could be detirmined from any of the comparisons.

Discussion: Classical one-dimensional statistical tests, namely the Kolmogorov-Smirnov test, firmly show the expected similarities and dissimilarities in the sets of high-dimensional time-series data. The voxels behave more similar during free viewing of a movie compared with rest, and less similar during unnatural viewing (of task-driven paradigm) compared to resting state. However, these classical tests can only consider one-dimensional regions of the brain at a time, thereby cannot capture the information inherent to the higher dimensionality. Unfortunately experiments with higher dimensional non-parametric kernel tests yielded negative results. We beleive this is due the the fact that these tests cannot consider the temporal and spatial dependencies inherent in the data. Thus, as current methods in time-series data analysis cannot extract the similarities in high dimensions, we beleive task specific models which can consider these dependencies are needed in order to extract the similarities that are strongly suggested by the classical statistical tests.

References

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