Subject and Task Fingerprint using Dynamics Reconstruction from fMRI Time-series Data.

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Introduction:

Blood-oxygen-level-dependent (BOLD) signals, recorded by fMRI, can provide valuable insights for subject and task identification (ID), due to the variability in their activation patterns over different individuals and their cognitive processes [1]. To capture such variability, we present a new approach based on reconstructing a two-timescale linear state-space model [2] from fMRI time-series data. Although similar state-space models have been introduced for other purposes in causal dynamics analysis [3], the novelty of this work stems from (i) the discovery of new uses of this model to extract both temporal and spatial features from time series data and (ii) the development of an eigenspace mapping method which utilize these features for subject and task IDs. The proposed method presents improved subject ID accuracy compared with correlation-based functional connectivity (FC) measures that are commonly used in existing literature [4]. The method also shows its capability to distinguish specific fMRI tasks.

Methodology:

Data: We use Human Connectome Project (HCP) data [5], where fMRI time-series signals are collected from 391 unrelated subjects while performing resting, and 7 fMRI tasks: gambling, relational, working memory, motor, emotion, social, and language. The cortex is parcellated into 100 brain regions using Schaefer parcellation [6]. All parcellated brain regions' BOLD signals are collected in the form of time series data with a temporal resolution of 720ms.

Methods: We propose a discrete-time linear state-space model with two timescales, $x(t)=Qx(t)+Ax(t-1)+Bu(t-1)$, to capture the unique spatial-temporal features for different subjects performing various tasks. Here, $x(t)$ and $u(t)$ are system states and inputs. Matrices A, B, Q encode the spatial and temporal features of data. By two timescales, matrices A, B capture the dynamical evolution of the system from its states/inputs in the previous timestep; Q captures the interaction that happens concurrently among brain regions. To avoid a trivial concurrent self-mapping for each state, diagonal entries of Q are forced as zeros.

From the fMRI time-series data (cf. Fig. 1a), we first apply and extend generalized least squares method to compute matrices A, B, Q. Leveraged by the structural variations presented among these matrices, we developed a new approach to map unlabeled fMRI data, through its characterizing matrices, to a labeled database to identify the corresponding subject or fMRI task.

The development of this approach is based on a unique combination of a rescaled eigenspace decomposition and an orthogonal projection [7].

Results:

We employ 90 out of 100 regions as system states and the rest as input to the system. Fig. 1b shows the subject identification accuracy using resting state data for two scanning sessions (Rest1 and Rest2) and two recording orders (LR and RL). One out of 4 possible permutations is taken as labeled database and the other 3 are used as unlabeled testing sets. The ID accuracy outperforms methods in literature based on FCs. Fig. 1c shows task identification accuracy, where the method can robustly distinguish between resting state and working memory. One possible reason for the low ID accuracy on other tasks is due to the limited recording time that the data is not rich enough to capture the dynamics of the system. Apart from resting tasks, working memory has the second longest recording time.

Conclusions:

Dynamics reconstruction using a two-timescale linear state-space model is capable of exacting both temporal and spatial features from fMRI time series data. As we apply an eigenspace mapping method to utilize these features, (i) for subject ID, the proposed method outperforms correlation-based FC measures [4], which compress temporal information and only consider the concurrent spatial interactions among brain regions. (ii) for task ID, the proposed method shows robust results when distinguishing between resting state and working memory tasks based on fMRI time series data.

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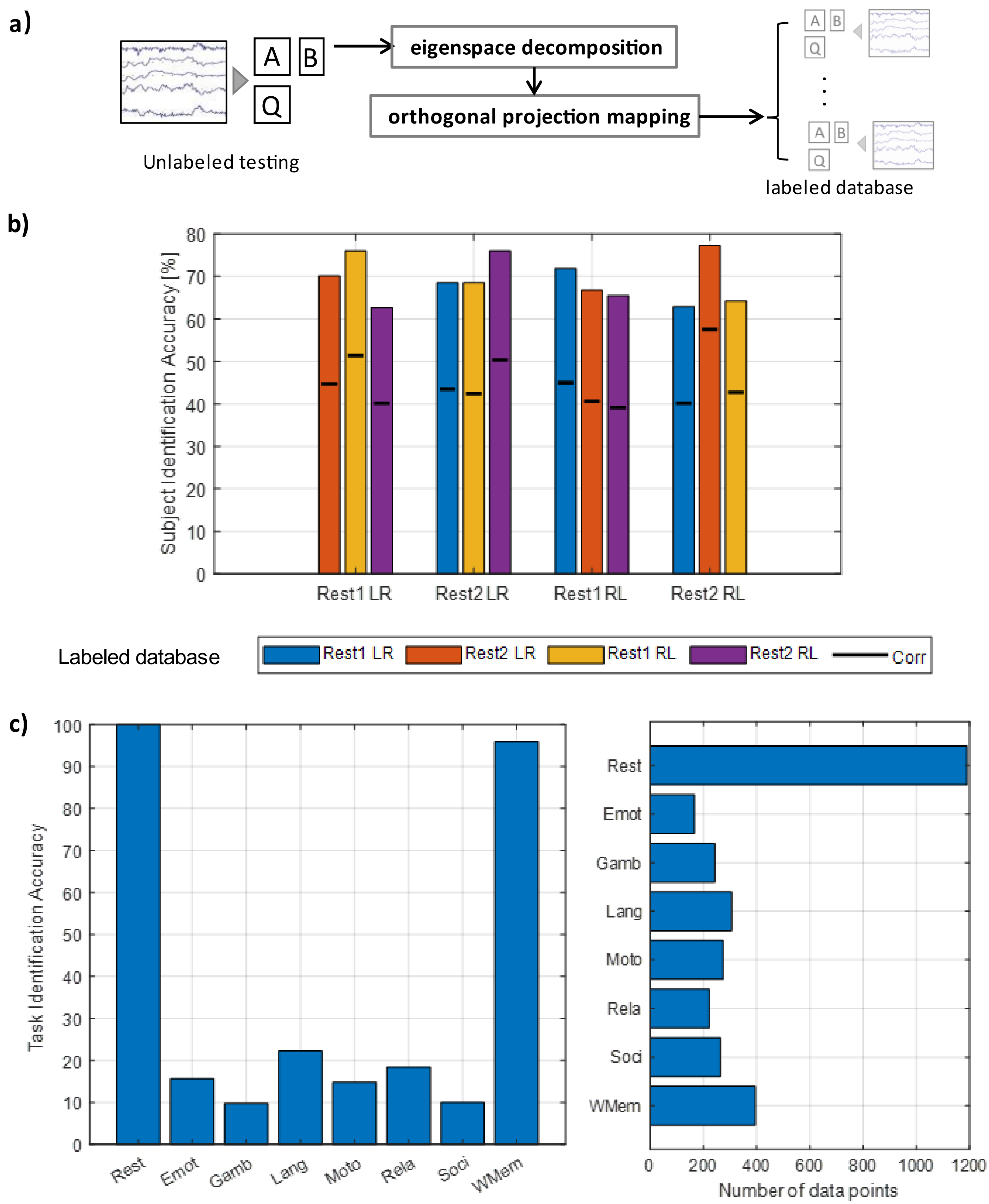

Fig. 1. Subject and task identification based on dynamics reconstruction from fMRI time-series data. (**a**) Conceptual diagram of the state-space model reconstruction and subject identification (ID) using eigenspace mapping. Interpolations [8] are used to smooth data points and improve data richness. (**b**) The identification accuracy is compared with [4] (black line) using the correlation method on time-series to compute a functional connectome (FC) matrix, then using Pearson correlation over the vectorized FC matrix for subject identification. Improved accuracy is observed on all cases. Here resting-state data is used due to its considerable variations among subjects [9]. (**c**) The task identification accuracy. Robust identification results occur on resting state and working memory task, with **all** resting state data being correctly identified. The right figure presents the data richness evaluated by the number of data points in each task.

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