MODELING FUNCTIONAL NETWORK DYNAMICS VIA MULTI-SCALE DICTIONARY LEARNING AND NETWORK CONTINUUMS

Xiang Li[1], Binbin Lin[2], Jinglei Lv[1], Jieping Ye[2], Tianming Liu[1]

[1]Cortical Architecture Imaging and Discovery Lab, Department of Computer Science and Bioimaging Research Center, the University of Georgia, Athens, GA. [2]Department of Computational Medicine and Bioinformatics, University of Michigan, Ann Arbor, MI

ABSTRACT

Although there is growing recognition and interest in the dynamic organization of the brain's functional architecture, the characterization and systematic analysis of such dynamic patterns are still largely under-investigated. In this work, we proposed a novel multi-scale dynamic dictionary learning framework which decomposes the input fMRI signals into functional networks via sliding/growing time window network analysis approach based on a fast dictionary learning method. As the functional networks are obtained at every possible temporal position and multiple scales within the framework, links across functional networks are then defined by the direct or indirect correlations between their temporal variation patterns. The identified links between networks are then concatenated into network continuums, which are the dynamic combinations of functional networks at various temporal segments. By applying the proposed framework on the task fMRI data from the Human Connectome Project (HCP) Q1 release, we have found that the network continuum has the capability of capturing the dynamic transition patterns of functional networks and providing an intuitive characterization of the network stationarity across time scales.

***Index Terms*—**fMRI, dynamic functional network, dictionary learning.

1. INTRODUCTION

In the field of functional magnetic resonance imaging (fMRI) analysis, there has been growing recognition and interest in discovering and modeling the dynamic organization patterns of the brain's functional architectures from various perspectives, including studies on dynamic spatial/temporal patterns of fMRI signals [1] and on the dynamics of functional connectivity [2-4], as well as resting-state functional networks [13]. In addition, previous successes in applying component-based analysis on fMRI data, including spatial independent component analysis (sICA) [5], temporal independent component analysis (tICA) [6] and network decomposition by dictionary learning methods [7-9], have enabled us to analyze functional brain dynamics based on the temporal variation/organization pattern of the components identified from those methods. As such functional networks have been shown to have the capability of revealing the underlying functional brain behavior and organization patterns [6, 9], an intuitive yet largely unresolved question is whether the networks are consistent across different time periods and/or on different time scales. Specifically, in most of current studies, the networks were identified from the whole fMRI time series, which imposes an implicit assumption that the networks' spatial distributions are constant over time [10]. However, as indicated by the simultaneous spatial/temporal partitioning results on fMRI data [2], as well as in the sliding-time window sICA study [11], functional networks including the well-known default mode network (DMN) have time-varying spatial distribution patterns.

In order to address the above questions, in this work we have proposed a multi-scale dynamic dictionary learning framework to identify functional networks from input fMRI signal at various temporal positions and scales. Then based on the obtained functional networks at discrete temporal segments, we have developed a generalized correlation measurement to define the network continuum, which aims at collecting the persistent yet evolving networks over different temporal positions and scales. By applying the proposed framework on the motor task fMRI (tfMRI) dataset from the Human Connectome Project (HCP) Q1 release, we have found that certain functional networks will maintain a relatively stable spatial and temporal pattern across different time scales/positions, while other networks were more transient, quickly diminishing in other temporal segments. In general, the proposed framework offers a breakdown of the fMRI signals into a series of functional networks at various temporal positions/scales, while network emerged at any temporal segments will be tracked throughout the time to obtain its transition map.

2. MATERIALS AND METHODS

2.1. Data acquisition, preprocessing and model overview

In this study we used the tfMRI dataset consisting of 68 subjects from the HCP Q1 release during the motor task for testing and validation. Each individual dataset contains 284 volumes of tfMRI data defined on around 140k volumetric voxels. The details of image acquisition parameters, preprocessing steps and reports from behavior studies of the HCP Q1 release dataset can be refereed to [12]. An overview of the proposed framework is shown in Fig. 1, where the fMRI data will be first temporally segmented at each possible temporal position/scale (a), followed by dictionary learning on each temporal segment (b), then dictionary learning results (i.e. identified functional networks) will be linked to networks at other segments by generalized correlation (d), and the linked networks will finally be collected into the network continuum (e).

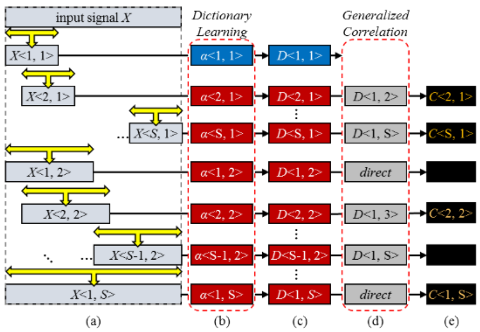

Figure 1. Illustration of the algorithmic flow of the proposed framework. (a): Segmentation of the input signal X into multi-scale temporal segments. (b): Dictionary learning applied on each temporal segment *X*, with results *α* (loading coefficients) and *D* (dictionaries). (c): Learned dictionaries used for the continuum inference, targeting the first temporal segment *D*<1, 1> (blue). (d): Generalized correlation calculated between the target network and all other networks. Carrier network used during the correlation are shown as grey blocks. (e): Network continuum *C* summarized from the generalized correlation. Blocks with highlighted text indicate the presence of linked networks associated with the target network.

2.2. Nested dictionary learning on fMRI time series data

Similar to the previous works of utilizing dictionary learning methods for fMRI data analysis [7-9], in this study, we aim to learn a set of dictionaries *D* with sparsity-constrained loading coefficients *α* from the input signal matrix *X* consisting of *N* number of time series with the length *T*:

$$\min_{D_{i,j}\in\mathbb{R}^{T\times K},\alpha_{i,j}\in\mathbb{R}^{K\times N}} \frac{1}{2}||X_{i,j}-D_{i,j}\alpha_{i,j}||_F+\lambda||\alpha_{i,j}||_1$$

where *K* is the predefined dictionary size, and *λ* is the parameter used to tune the balance between regression accuracy and loading sparseness. In this work, *K* and *λ* were determined experimentally (*K*=400, *λ*=0.08), which are the same across all subjects and temporal segments. The optimization is regularized by the *l*-1 norm (i.e. sum of the absolute value of all elements) of matrix *α*, thus adding the sparsity constraint on the number of dictionaries used to represent the input signal. Within the proposed framework, the dictionary learning results are termed as “functional networks”, where the learned dictionary characterizes the temporal variability pattern of the network and the corresponding loading coefficients characterize the spatial distribution of the network. An example of applying the dictionary learning method on the whole time series of an individual’s motor tfMRI data is shown in Fig. 2.

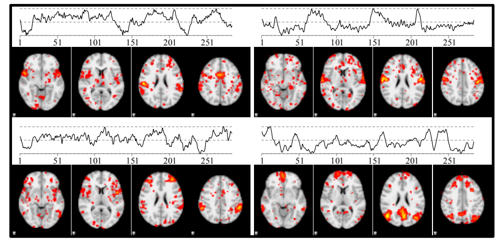

Figure 2. Four functional networks obtained by performing dictionary learning method on the whole time series of motor tfMRI data of the sample subject. The time series (from *D* matrix) of each network is shown on the top, with four slices of its spatial distribution pattern (from *α* matrix) shown at the bottom.

Different from most of previous static component-based analysis methods [5-9], in this work, we have applied the dictionary learning method on temporal segments of the fMRI data with various positions and scales over the whole time span, essentially applying a sliding/growing window approach for the dictionary learning method. Specifically, for the input data *X* with length of *T*, we will define two window size parameters b_0 and b_1, where b_0 is the minimal length for all segments, and b_1 is the size for window sliding/growing. Then a series of temporal segments with unique identifier tuple <*s*, *w*> will be extracted:

$$\forall s\in\left[1,\frac{(T-b_0)}{b_1}\right],\forall w\in\left[1,\frac{(T-b_0)}{b_1}\right]:$$

$$X\langle s,w\rangle = X[(s-1)*b_1+1,\dots,(s-1)*b_1+1+b_0+(w-1)*b_1],$$

$$\text{subject to: } (s-1)*b_1+1+b_0+(w-1)*b_1\le T$$

In this way, we can completely break down the input data into temporal segments with every possible positions/scales combination. For example, *X*<1, 1> is the temporal segment at the starting point of the input data with minimal scale (b_0). Then for each temporal segment *X*<*s*, *w*>, we will obtain the functional network with temporal pattern *D*<*s*, *w*> and spatial distribution *α*<*s*, *w*> by the dictionary learning method introduced above, which solely represents the major functional variation patterns of the brain at the specific time period identified by the tuple <*s*, *w*>. It should be noted that as each set of functional networks were learned individually, there is no correspondence between networks learned from different temporal segments, even though these segments are consecutive or enfolding. In this way, we can transform the original fMRI time series defined on volumetric space into a series of dynamic combination of functional networks. In this work, b_0 is set to 50 and b_1 is set to 20 based on the paradigm design of the motor task. The dynamic transition pattern of each functional network emerged at a given period will then be tracked.

2.3. Construction of functional network continuum

In this work, the functional brain organization dynamics are characterized by the temporal coherence between functional networks obtained at different temporal positions and/or scales. For functional networks at the same temporal position, the coherence can be directly inferred by the correlation value between their time series. Specifically, for each functional network identified from a given temporal segment (i.e., a fixed temporal position and window length), termed "target network" in this manuscript, shown as the blue curve in Fig. 3(a), we will first iterate through all the functional networks identified from the same position but different window lengths to locate the network(s) with a similar time series to the target network, termed "linked network", shown as the red curves in Fig. 3(a). As the lengths of the time series are different between the target and the linked networks, we trimmed the longer time series to the shorter length when calculating the correlation value.

To link functional networks that are temporally away from each other (i.e., with different temporal positions), we have defined an indirect correlation measurement, called "carrier correlation", utilizing a third network identified from a longer temporal segment which covers both of the target and the linked networks. If the dictionary of the carrier network is similar to the dictionaries of both the target and the linked network at their respective temporal segments, the two networks are then regarded as indirectly correlated. In the top two panels in Fig. 3(b), the partially overlapping target (blue) and linked network (red) are joined by the carrier curve (grey dotted). In the bottom two panels in Fig. 3(b), although the target and linked networks are temporally far away, it is still possible to identify the appropriate carrier network to correlate them. The generalized correlation function Γ between the m-th atom in $D<s_i, w_j>$ and the n-th atom in $D<s_u, w_v>$ is:

$$\Gamma(m, \langle s_i, w_j\rangle, n, \langle s_u, w_v\rangle) = \begin{cases} corr\left(D\langle s_i, w_j\rangle_m, D\langle s_u, w_v\rangle_n\right), if\ S_i = S_u \\ \max\left(\forall_{p\in[1,\mathbf{k}]}, \min\begin{pmatrix} corr\left(D\langle s_i, w_j\rangle_m, D\langle s_i, s_u + w_v - s_i\rangle_p\right), \\ corr\left(D\langle s_u, w_v\rangle_n, D\langle s_i, s_u + w_v - s_i\rangle_p\right)\end{pmatrix}\right)\end{cases}$$

Note that without loss of generality, we have assumed $s_i<s_u$ and $(s_i+w_j)<(s_u+w_v)$. The Γ function tries to locate the best carrier functional network from the dictionary learned at the temporal segment with the position of S_i and window length of $S_u+W_v-S_i$, while the generalized correlation is defined by the smaller of the two correlations: correlation between carrier network and targeting network, and the correlation between the carrier network and the linked network.

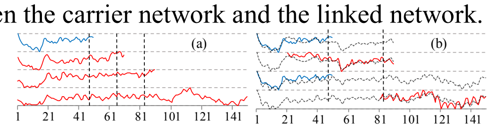

Figure 3. Illustration of the linked functional networks at the same temporal position but different window lengths by direct correlation (a), and the linked functional networks at different temporal positions and window lengths by indirect correlation (b). Carrier networks are shown as grey dotted curves.

After obtaining the generalized correlation between the targeting networks with each of the other functional networks over all possible temporal positions/scales by the multi-scale dynamic dictionary learning, we will apply a constant threshold T on the correlation values to determine the set of linked networks related to the target network. The thresholding results are then concatenated into a collection, termed "network continuum", to characterize the presence of linked networks at various temporal positions/scales with regard to the target network. An illustrative diagram of the procedure of obtaining continuum is shown in Fig. 1(d-e). For the target network at position S_i with window length w_j, its corresponding continuum collects the information of the presence of the linked network in all temporal segments as well as the carrier network to link them, where all links are effectively characterized by the generalized correlation function Γ. In this way, the quasi-stable brain state transition patterns can be captured by the continuum consisting of the functional network flows.

3. RESULTS

3.1. Results from multiscale dynamic dictionary learning

By applying the multi-scale dynamic dictionary learning method introduced in 2.2 on the tfMRI dataset with motor task scan from the HCP Q1 release, for each subject we have obtained 78 sets of functional networks characterizing the functional brain activities during various temporal segments at different scales. The 78 sets were organized into 12 groups according to their temporal starting positions. As we used the constant dictionary size parameter (K=400) across all temporal segments in all subjects, each set contained 400 functional networks characterizing major temporal and spatial functional organization patterns during a specific period. Illustration of the dynamic dictionaries learned at three different positions/scales from one sample subject is shown in Fig. 4. An important premise of the results from the dictionary learning method is that the spatial/temporal characteristics of the functional networks learned from the given fMRI signals can holistically cover the major functional fluctuations of the brain within that period, as shown in literature reports such as [8] and [9]. As shown in Fig. 4, results with intriguing spatial/temporal patterns can be obtained even on very short time scales. By analyzing the temporal (correlation) and spatial (overlapping rate) similarities between the atlases obtained from the whole time series and the networks obtained from the temporal segments, we have found that over 50% of the task-evoked and over 30% of the resting-state networks are presented in the networks learned at each temporal segment.

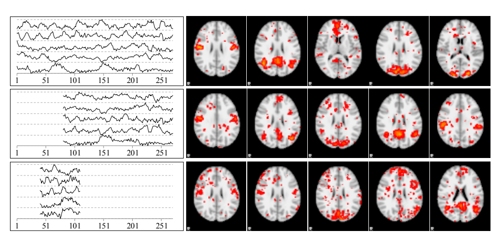

Figure 4. Time series (left) and spatial map (right) of the 5 functional networks with intriguing spatial patterns obtained at temporal position 1, window size 270 (top panel); temporal position 81, window size 190 (middle panel); temporal position 41, window size 90 (bottom panel), from the sample dataset.

3.1. Functional networks continuums

Based on the multi-scale dynamic dictionary learning results on each individual dataset, we further inferred the functional network continuums based on the method introduced in 2.3. Using all of the 400 networks at <1, 1> (i.e. start of the time) as target networks, the corresponding resulting network continuum is visualized in Fig. 5, with one sample target network with strong temporal stability (highlighted in blue) analyzed in details. It can be observed from the linked networks (b-c) within the continuum derived from the sample target network that: 1) the time series of the target, linked and the carrier networks were highly correspondent and were characterizing the same functional variation pattern, which validated the effectiveness of the generalized correlation method used in this framework; 2) The spatial patterns of the linked networks within the obtained continuum were similar yet varying with time, which cannot be detected by static component-based analysis methods, showing the necessity of a dynamic framework in this paper. Further, continuum varies significantly across columns (i.e., functional networks), indicating the considerable difference of temporal stability between functional networks.

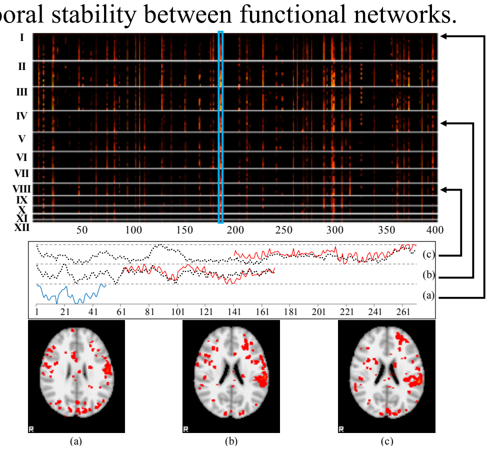

Figure 5. Top panel: visualization of the network continuum matrix from the sample individual dataset. Middle panel: Time series of the functional network highlighted by the blue block in the continuum matrix. Bottom panel: Spatial patterns of the networks.

4. CONCLUSION

In this paper we have shown that the proposed multi-scale dynamic dictionary learning framework can effectively identify and track the functional network dynamics as the network continuum. With the promising results achieved by the framework, the quantification of the time-varying network spatial patterns within the continuum and the modeling of the evolving functional activated regions will be studied in details in our future work. Also, as the current framework identifies sets of functional networks from the temporally-overlapping segments independently, another important potential algorithmic improvement is to take the possible autoregressive behavior of the network's temporal variation pattern into account, thus establishing a formalized temporal relationship across the functional networks.

5. REFERENCES

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