Abstract— We consider the problem of identifying large-scale effective connectivity of brain networks from fMRI data. Standard vector autoregressive (VAR) models fail to estimate reliably networks with large number of nodes. We propose a new method based on factor modeling for reliable and efficient high-dimensional VAR analysis of large networks. We develop a subspace VAR (SVAR) model from a factor model (FM), where observations are driven by a lower-dimensional subspace of common latent factors with an AR dynamics. We consider two variants of principal components (PC) methods that provide consistent estimates for the FM hence the implied SVAR model, even of large dimensions. Information criterion is used to select the optimal subspace dimension. We established asymptotic normality and convergence rates for the estimated SVAR coefficients matrix. Evaluation on simulated resting-state fMRI shows that the SVAR models are more robust and produce better connectivity estimates than the classical model for a moderately-large network analysis. Results on real data by varying the subspace dimensions identify strong connections in the default mode network and reveal hierarchical connectivity of resting-state networks with distinct functional relevance.

Index Terms— Vector autoregressive model, factor model, brain effective connectivity, fMRI.

I. INTRODUCTION

Brain connectivity can provide useful information on sensory and cognitive functions. Vector autoregressive (VAR) models have been widely used for inferring effective connectivity [1]-[7], the causal interactions between different regions or nodes of a brain network, from EEG or fMRI time series. The VAR coefficients matrix and the various derived connectivity measures [4] can characterize not only the functional inter-regional dependence but the temporal precedence of one neuronal region influencing the others. The challenge is that the dimension of the time series, \( N \) corresponding to the number of nodes can be very large, often larger or comparable to the sample size \( T \), \( N > T \) with \( N \to \infty \), especially in the full-brain network analysis [5] where the number of voxel-wise (fMRI) time series is of order of hundred thousands, but with only hundreds of time points. This makes reliable inference in the standard VAR modeling for such high-dimensional networks difficult, even for a moderately large \( N \), due to huge number of fitted parameters, \( qN^2 \) with \( q \) the model order[8]. Many studies focused only on small-scale specialized networks of a few aggregated regions of interest (ROIs) related to particular brain processes [9]-[11].

In this paper, we develop a novel statistical method based on a dimension-reduction approach using factor modeling to achieve a reliable and efficient high-dimensional VAR analysis of large-scale effective brain connectivity. Factor models (FMs) have been applied rather successfully for analyzing large number of macroeconomic variables, relying on the rationale that the co-dynamics of the high-dimensional time series are mainly driven by only a few unobserved dynamic factors in the common components with \( r \ll N \), plus the idiosyncratic noise components. The observation space lies approximately on a lower-dimensional factor subspace spanned by a factor loading matrix. These latent factors are commonly assumed to follow a VAR process.

We propose a new VAR modeling framework based on the FM to facilitate reliable inference on the high-dimensional settings. Precisely, by assuming an orthogonal factor loading matrix, we show that a VAR process can be derived for the observation space, by embedding into the FM its underlying VAR factor process. The VAR coefficients matrix for the observation space is then only an orthogonal transformation of that for the lower-dimensional factor space, by the factor loadings. We call this model subspace VAR (SVAR) model, since it spans a subspace of the total parameter space of a usual VAR model. The uniqueness of this formulation is that the causal inter-dependences in the large-dimensional observations can then be achieved through the VAR dynamics of the few common factors. It enables a more reliable and computationally more efficient parameter estimation than the standard VAR under the large \( N \) settings, hence a robust way of estimating large-scale directed brain networks. It involves only a simple reconstruction from the estimates of the FM, and thus can benefit from various efficient and consistent estimation methods developed for FMs of large \( N \). Moreover, one only needs to fit the VAR model on the lower-dimensional factors instead of the observations directly. Our method allows reliable estimation of a full arbitrary connectivity matrix without the needs of imposing the restrictive sparsity assumption as in [2]-[3].

Classical factor analysis typically faces the issues of identifiability and consistency especially when \( N \to \infty \). To overcome these limitations, we apply the principal components (PC) methods [12]-[13] to estimate the high-dimensional FM. The PC method can produce consistent estimators for both the latent factors and their loadings, under more general conditions than the classical one that both \( NT \to \infty \), and is robust to (weak) serial and cross-sectional correlations in the idiosyncratic errors. [12] proved the uniform consistency of the estimated factors, under these weak conditions. [13] established the convergence rate and asymptotic normality for the estimated factors and factor loadings. Moreover, the PC-based estimation involves only a simple eigenanalysis of the sample covariance matrix of the data. In addition, by varying the eigensubspace dimension \( r \), SVAR model can be useful for hierarchical connectivity analysis. Coefficient matrix reconstructed based on main principal eigenvectors can capture dominant information of a network and reveal global connectivity pattern between greater regions. In contrast with previous studies using PCA merely for dimension-reduction with connectivity analysis performed on the reduced PCs [14]-[15], we re-project the connectivity matrix from the factor-space back to the high-dimensional observation space.

We extend the preliminary work of our method [16] by developing an asymptotic theory and comparing different PC estimators. We consider further an alternative PC estimator developed recently by Lam [17] who decomposes the FM into a common component and a white noise instead of a correlated one as in [12]-[13]. Such simpler decomposition leads to identifiability of both factor and loading space for any finite \( N \), which is arguably more difficult under the of
serial-correlation assumption on the idiosyncratic noise. Moreover, it enables the eigenanalysis to be performed on a matrix function of several autocovariance matrices of non-zero lags, instead of a variance-covariance matrix [12]-[13], and thus can accumulate more information on the dynamics along different time-lags. To determine the unknown number of factors \( r \), we use the Bayesian information criterion (BIC) suggested by [18]. We establish the asymptotic properties of the SVAR model-based estimators, relying on that of the conventional VAR model. We derive the limiting distribution and convergence-rate for the estimated coefficient matrix of the SVAR model as \( T \to \infty \), from that of the latent VAR factor generating process scaled by the factor loadings. We extend the simulated evaluation of [16] on identifying effective connectivity of moderately-large brain networks from resting-state fMRI, by including a real dataset of 90 ROI based signals.

II. METHODS

A. Factor Model

Let \( y_t = (y_{1t}, \ldots, y_{Mt})^T \) be a \( N \times 1 \) vector of fMRI time series measured from \( N \) voxels or ROIs (defining the nodes of a brain network) at time \( t \), for \( t = 1, \ldots, T \). The dimension of time series \( N \) is usually large, larger or comparable to the sample size \( T \). Consider a FM defined by the decomposition [12]-[13]

\[
y_t = Q f_t + \epsilon_t
\]

where \( f_t \) is a \( r \times 1 \) vector of unobserved common factors, with \( r \leq N \) the number of factors assumed fixed and unknown, \( Q \) is a \( N \times r \) unknown constant factor loading matrix and \( \epsilon_t \) is a \( N \times 1 \) vector of idiosyncratic noise components that can represent measurement errors. The term \( Q f_t \) is referred as common components. Dimension-reduction is achieved in (1) where the serial-dependence of the observation process \( y_t \) is driven by a much lower-dimensional factor process \( f_t \). (1) is a latent subspace model where \( y_t \) lies approximately on a subspace of lower dimension \( r \), spanned by the columns of \( Q \).

The dynamics of the latent factors \( f_t \) are commonly modeled as a VAR process, assumed here of order one

\[
f_t = A_r f_{t-r} + \eta_t, \quad \eta_t \sim N(0, \Sigma_\eta)
\]

where \( A_r \) is the \( r \times r \) AR coefficients matrix and \( \eta_t \) is a \( r \times 1 \) Gaussian white noise with mean zero and covariance matrix \( \Sigma_\eta \). \((Q, f_t)\) are not separately identifiable since, for any invertible \( r \times r \) matrix \( H \), \( Q H^{-1} f_t = Q H^{-1} f_t \), where \( Q = QH \) and \( f_t = H f_t \). (1) is observationally equivalent to \( y_t = Q f_t + \epsilon_t \).

B. PC Estimation

We use PC methods to estimate the \( Q \) and \( f_t \) of FM with large \( N \). The following condition together with a diagonal \( \Gamma = \text{diag}(\Gamma_t) \) restrict \( H \), to identify \( f_t \) and \( Q \) up to a sign change.

**Condition 1:** \( Q \) is orthonormal i.e. \( Q^T Q = I_r \), where \( I_r \) denotes a \( r \times r \) identity matrix.

The PC estimators of \((f_t, Q)\) are then obtained by solving

\[
[\hat{f}_t^T, \hat{Q}] = \arg \min_{[f_t^T, Q]} \sum_{t=1}^{T} (y_t - Q f_t)^T (y_t - Q f_t)
\]

subject to \( Q^T Q = I_r \).

We consider two schemes of eigenanalysis in the PC estimation, used respectively in [12]-[13] and [17], which are based on (1) a sample variance-covariance matrix or (2) sample autocovariance matrices of the data, referred here as

Varcov-PC and Autocov-PC estimation. The two methods are based on different assumptions that the noise process \( \epsilon_t \) in (1) is either correlated or independent. [12]-[13] followed the conventional approach assuming that \( \epsilon_t \) is a general idiosyncratic process and performed the analysis on the sample variance-covariance matrix of \( y_t \), whereas [17] used a special case, the white noise that enables analysis on a matrix function of several autocovariance matrices of non-zero lags.

1) Varcov-PC Estimation with General Idiosyncratic Noise: The estimation steps for an arbitrary \( r \) are as follows

(a) Define the estimator of \( Q \) as \( \hat{Q} = (\hat{q}_1, \ldots, \hat{q}_r) \) where \( \hat{q}_1, \ldots, \hat{q}_r \) are the orthonormal eigenvectors corresponding to the \( r \) largest eigenvalues of the sample variance-covariance matrix of \( y_t \), \( \hat{\Sigma}_y = T^{-1} \sum_{t=1}^{T} y_t y_t^T \), assuming that \( y_t \) is independent.

(b) Estimate \( f_t \) by using the normalization \( Q^T Q = I_r \) and (1), which yields \( \hat{f}_t = \hat{Q}^T y_t \).

(c) Estimate \( \epsilon_t \) and its covariance matrix \( \Sigma_\eta \) by the residuals

\[
\hat{\epsilon}_t = y_t - \hat{Q} \hat{f}_t
\]

The parameters \( A_r \) and \( \Sigma_\eta \) of the latent VAR factor process in (2) can be estimated by fitting to the estimated factor series \( \hat{f}_t^T \), using the ordinary least-squares (OLS) method. In practice, the true number of factors can be estimated from the data consistently by the model selection with BIC [18]

\[
\hat{r} = \arg \min_{0 \leq r \leq \max} \{ \ln \left( \frac{1}{NT} \sum_{t=1}^{T} \| \hat{f}_t(t) \|_2^2 \right) + r \left( \frac{N+T}{NT} \right) \ln \left( \frac{NT}{N+T} \right) \}
\]

where \( \| \| \) denotes the Euclidean norm of vector \( x \). We summarize the main asymptotic results for \( \hat{f}_t \) and \( \hat{Q} \) established by [13].

**Proposition 1:** Let \( f_t^0 \) and \( q_t^0 \) be the true factors and loadings. Under general assumptions allowing weak serial and cross-sectional correlations in \( \epsilon_t \), as \( N, T \to \infty \), we have:

(i) if \( \sqrt{N/T} \to 0 \), then \( \sqrt{N/T} (\hat{f}_t - f_t^0)^T \) and \( \sqrt{T} (\hat{q}_t - q_t^0)^T \) are asymptotically normal; (ii) if \( \lim \inf \sqrt{N/T} \geq 2 \geq 0 \) then \( \sqrt{N/T} (\hat{f}_t - f_t^0)^T \) and \( \sqrt{T} (\hat{q}_t - q_t^0)^T \) are i.i.d., which imply convergence rates of \( \min(\sqrt{N/T}) \) and \( \min(\sqrt{T/N}) \) for \( \hat{f}_t \) and \( \hat{q}_t \).}

2) Autocov-PC Estimation with White Noise: An alternative model for \( \epsilon_t \) is a simple vector white-noise process with mean zero and covariance \( \Sigma_\eta, \epsilon_t \sim WN(0, \Sigma_\eta) \), which assumes no serial correlations. The idiosyncratic components are absorbed into the factors. Despite that such assumption might be unrealistic; it makes the model identification much easier and feasible for any finite \( N \). This is in distinct with the above decomposition where the serially-correlated idiosyncratic noise series may be treated as a time series itself and hence only asymptotically identifiable from the common factors as \( N \to \infty \). The estimation steps are the same as the above algorithm, except that the eigenanalysis in the step (a) is performed on, instead of \( \hat{\Sigma}_y \), a \( N \times N \) non-negative definite matrix, in sample version of

\[
\hat{L} = \sum_{l=0}^{l_0} \hat{\Sigma}_y(l) \hat{\Sigma}_y(l)^T
\]

where \( \hat{\Sigma}_y(l) \) denotes the sample autocovariance matrix of \( y_t \) at lag \( l \), \( \hat{\Sigma}_y(l) = (T-l)^{-1} \sum_{t=1}^{T-l} y_t y_t^T \) and \( l_0 \geq 1 \) is a prescribed integer. [17] suggested that the choice of \( l_0 \) is not sensitive to...
the estimation. The sum in (5) can pool together information from different time-lags, which is useful especially when \( T \) is small. They showed that, when all the factors are strong, \( \hat{Q} \) is weakly consistent with a \( \sqrt{T} \)-convergence rate which is independent of \( N \), as \( N, T \to \infty \). This implies that the curse of dimensionality is cancelled out, arguably by the increase of information from more component series, when \( N \) increases.

C. Subspace VAR Model

We derive a SVAR model for the observed time series based on a FM with an underlying lower-dimensional VAR factor dynamics. The temporal interdependence structure of \( y_t \) in (1) is achieved via that of the VAR process of \( \xi_i \) in (2).

**Theorem 1:** Suppose Condition 1 holds, a \( N \times 1 \) FM (1) with a latent \( r \times 1 \) VAR(1) factor process (2) form a \( N \times 1 \) VAR(1) process with moving-average (MA) noise for \( y_t \)

\[
y_t = \Delta_y y_{t-1} + \xi_t + \nu_t, \quad t = 1, \ldots, T
\]

which consists of an AR(1) part \( \Delta_y y_{t-1} \) with \( N \times N \) coefficients matrix defined by \( \Delta_y = \Sigma A_\gamma Q^T \), an MA(1) part \( \xi_t = e_t - \Delta_y Q^T e_{t-1} \) and a \( N \times 1 \) noise \( \nu_t = Q \eta_t \).

The proof of Theorem 1 is given in the Appendix.

(2) and (6) define two different VAR processes respectively for the latent factors \( \xi_t \) and observations \( y_t \). The SVAR model is a generalized VAR model in the sense that, by varying the subspace dimension \( r \), it allows a flexible subspace structure in the coefficients matrix. The standard VAR is a special case where \( r = N \) corresponding to the full parameter space. The estimator for \( \hat{A}_r \), which is a simple reconstruction from the consistent PC estimator of \( Q \) and the OLS estimator of the lower-dimensional \( \hat{A}_r \) by \( \hat{\Delta}_r = \hat{\Delta}_y Q^T \), is more reliable for the large \( N \) settings. The parameter space of \( \hat{\Delta}_r \) is projected onto a lower-dimensional subspace spanned by the \( r \) principal eigenvectors in \( \hat{Q} \).

**Asymptotics of \( \hat{\Delta}_r \):** We derive the limiting distribution for the estimator \( \hat{\Delta}_r \) of the SVAR model as \( T \to \infty \), while \( r \) is fixed and known. Let \( \hat{\theta} \) denotes the Kronecker product.

**Theorem 2:** Let define \( \phi_{\hat{\Delta}_r} = \text{vec}(\hat{\Delta}_r) \) and \( \phi_{\Delta} = \text{vec}(\Delta) \).

Then, \( \sqrt{T}(\phi_{\hat{\Delta}_r} - \phi_{\Delta}) \) converges in distribution to a multivariate normal random vector with mean zero, as \( T \to \infty \)

\[
\sqrt{T}(\phi_{\hat{\Delta}_r} - \phi_{\Delta}) \xrightarrow{D} N(0, G)
\]

where \( G = (\Sigma Q^T \otimes \Sigma Q^T) \otimes (Q^{-1} Q^T) \) with \( \Gamma = E(f f^T) \). The covariance matrix \( G \) can be consistently estimated from the PC estimates. The theorem implies that \( \langle \phi_{\hat{\Delta}_r} - \phi_{\Delta} \rangle = O_r((T^{-1/2}) \) with a rate of convergence of \( \sqrt{T} \), and that \( \hat{\phi}_r \) is an asymptotically unbiased estimator of \( \phi_{\Delta} \). \( E(\hat{\phi}_r) = \phi_{\Delta} \) as \( T \to \infty \).

The proof of Theorem 2 is given in the Appendix.

D. SVAR Analysis of Large Brain Networks

We apply the proposed methods to study large-scale effective connectivity of brain networks. The VAR(1) as (6) is arguably sufficient to fit the fMRI data well [2]. The matrix \( A_r = [a_{ij}]_{N \times N} \) can characterize the network of effective connections between different brain regions. There exists a causal influence in the Granger-causality sense with direction from node \( j \) to node \( i \) if \( |a_{ij}| > 0 \) where \( |a_{ij}| \) denotes the connection strength. A high-dimensional complex network with large number of nodes \( N \) can be efficiently and reliably identified by \( \hat{\Delta}_r \). Besides, varying the eigensubspace dimension \( r \) of the SVAR model can identify a hierarchy of connectivity networks of distinct functional relevance. Reconstruction of \( \hat{\Delta}_r \) with more principal components captures detailed connectivity structures, while retaining the dominant ones reveals global connectivity between larger regions.

III. RESULTS AND DISCUSSION

We investigate the performance of the factor-analyzed SVAR model in identifying large-scale effective connectivity of resting-state brain networks, using a biophysical forward model-simulated [19] and a real BOLD fMRI dataset. We compare the two types of PC estimators for the SVAR model and the OLS estimator for the classical VAR model. Results on the simulated dataset showed, by visual inspection, that the Varcov-PC estimated SVAR model gives more accurate detection of the connections and their directionality for a large network, compared to the basic VAR [16]. Here, we use an objective measure based on estimation error between the estimated and the ground-truth synthetic connectivity matrix \( \hat{\Delta} \) defined as \( \| \hat{\Delta} - \hat{\Delta} \|_F \), where \( \| \cdot \|_F \) denotes the Frobenius norm of matrix \( M \).

Table 1 shows the performance by different methods for synthetic networks with various dimensions \( N \) and sample sizes \( T \). The results are obtained over 50 Monte-Carlo realizations corresponding to the variability across different subjects. The SVAR models estimated with both PC schemes clearly outperform the classical model, as indicated by the significantly lower estimation errors for all combinations of \( N \) and \( T \), with slightly better performance by the Varcov-PC estimators. As \( T \) increases, both means and standard deviations of the estimation errors decrease, which is consistent with the root-\( T \) convergence rate of \( \hat{\Delta}_r \) to \( \Delta \), as implied by Theorem 2. Moreover, the margin by which the estimation errors increase as \( N \) grows, is substantially larger for the basic VAR compared to the SVAR models, with particularly poorer performance at \( N=50 \). This confirms that direct estimates of full coefficient matrix in the classical specification is no longer consistent when \( N \) is comparable or larger than \( T \), due to the larger number of parameters to be estimated, relative to \( T \). In contrast, the SVAR estimates implied by the consistent estimates of the FM and the lower-dimensional factor-based VAR model are more robust to the high-dimensional setting.

We studied real resting-state fMRI data of a subject from the BS2002 database [20]. Resting-state scans were acquired on a 3-T Siemens Allegre MR scanner from subjects who are asked to remain still with their eyes fixed on a cross-hair. Each scan consisted of \( T=194 \) BOLD functional volumes with parameters TR=2.16s, TE=25ms and voxel size =4x4x4\text{mm}^3. The data were preprocessed by body-motion and slice-timing correction, removal of drift and physiological noises, and normalization to the MNI template. The voxels’ time courses were then parceled into 90 anatomical regions according to automated anatomical labeling (AAL) template [21] and averaged over these regions to obtain 90 ROI-time series. For this data, the optimal number of factors selected for the FM (1) by the BIC in (4) with \( r_{max}=20 \) is \( r=17 \).

We propose a test on the significance of each estimated connection different from zero, based on the asymptotic normality in Theorem 2, with \( H_0: \hat{Q}_k=0 \) against \( H_1: \hat{Q}_k \neq 0 \) where \( \hat{Q}_k \) is the kth element of \( \hat{\phi}_r \). The test statistic \( t_k = \hat{Q}_k \sqrt{\frac{\hat{\mu}_k}{T}} \) with \( \hat{\mu}_k \) the kth diagonal entry of \( \hat{G} \), has an asymptotic distribution.
Fig. 1. Estimates of effective connectivity matrix for 90 brain regions (according to AAL template, 45 regions in each cerebral hemisphere) from resting-state fMRI data of a subject. (a) Classical VAR model and (b)-(e) SVAR models with different subspace dimensions \( r \) and PC estimators. (b) \( r=17 \), Varcov-PC (c) \( r=5 \), Varcov-PC (e) \( r=5 \), Autocov-PC. The regions are arranged with symmetrical regions across left and right hemisphere adjacent to each other and are ordered by lobe (central 1, 2, 57, 58, frontal 3 – 28, limbic 29 – 42, occipital 43 – 56, parietal 59 – 68, subcortical 71 – 76, temporal 77 – 88) [28].

**TABLE 1**

<table>
<thead>
<tr>
<th>( N )</th>
<th>( T )</th>
<th>Classical VAR Model</th>
<th>Varcov-PC</th>
<th>Autocov-PC</th>
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<tr>
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<td>20.7509 (1.2244)</td>
<td>15.8766 (0.5652)</td>
<td>16.3670 (0.6837)</td>
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<tr>
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<td>100</td>
<td>19.4967 (0.8823)</td>
<td>15.6664 (0.4796)</td>
<td>15.9743 (0.5534)</td>
</tr>
<tr>
<td>200</td>
<td>50</td>
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<td>15.5629 (0.3847)</td>
<td>15.8424 (0.4010)</td>
</tr>
<tr>
<td>50</td>
<td>28124 (131464)</td>
<td>65.2733 (0.7733)</td>
<td>66.4059 (0.9497)</td>
<td></td>
</tr>
<tr>
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<td>200</td>
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<td>65.5371 (0.8287)</td>
</tr>
<tr>
<td>200</td>
<td>110.52 (1.9816)</td>
<td>64.0306 (0.7699)</td>
<td>64.8154 (0.7698)</td>
<td></td>
</tr>
</tbody>
</table>

TABLE 1

| N(0,1), \( \phi \), \( \epsilon \). Fig. 1 shows the 90-region directed connectivity matrices estimated by SVAR models with different \( r \) and PC estimators. The results show significant connections at \( p \)-value<0.05 with false discovery rate (FDR) correction. The classical model produces very noisy estimates as in Fig. 1(a). The estimates by SVAR models using both PC methods with the optimal subspace of \( \hat{r} = 17 \) (Fig. 1(b)-(c)) are able to reveal underlying connectivity pattern between regions belonging to the default mode network (DMN) [22]-[23], one of the well-known resting-state networks (RSNs) [24]-[25], that show increased and highly correlated neuronal activity during rest and is linked to higher-order cognitive functions. It is indicated by the dark red and blue entries at nodes 23-24 (medial prefrontal cortex (MFC), 35-36 (pons), 37-38 (parietal lobe (IPL))). The Autocov-PC estimator, despite inducing somewhat noisier estimates, can capture more detailed structure that the Varcov-PC estimator fails to detect reliably, e.g. connections of the single-nodes at 24 and 65. The PCC is correctly identified as a major hub strongly connected with many other brain regions, as reported in other studies [25], and further suggested here as a source of directed information flows. Fig. 2 shows the significant causal connections (threshold at \( \hat{a}_{jk} \leq 0.08 \)) between the core regions of DMN with PCC as the hub. The results imply that our methods can identify resting-state effective connectivity of DMN, comparable to previous studies [11], [27], in a more challenging large-scale full-brain VAR analysis, instead of on a few pre-selected ROIs. Our results provide directional information to the functional connectivity estimated by the SVD-based ‘eigennetworks’ of [28]-[29] for the same 90 regions. Estimates by retaining only 5 largest principal eigenvectors (Fig. 1(d)-(e)) reveal global interactions between other RSNs of large functional clusters including the frontal, visual and parietal areas involved in attention processing. The RSNs identified by the proposed SVAR analysis may correspond with distinct functionally-linked brain regions that show hierarchical interactions among low-level sensory and high-order cognitive systems during rest. The detected connections of DMN are also consistent with reports of anatomical connectivity [30]. The PCC is associated with the heteromodal association areas that bind multiple regions into

Fig. 2. Connectivity between ROIs of DMN during rest. Edges represent connections with thickness indicate strength and arrows directionality. Blue and red represent positive and negative correlations. (a) Axial. (b) Coronal.