Research Article

Synchronization of Neuronal Networks via Control Rank Pinning Scheme

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Received 11 January 2013; Accepted 26 January 2013

Academic Editor: Yang Tang

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Recent studies have proposed the controlling regions in the corticocortical network of cats' brain at different scales. Here we study pinning control using a simple model of coupled oscillators assigned to cortical areas in the corticocortical network of cats' brain. We analyze control rank (CR) values of areas in the cortical network. It is found that most of the hubs have bigger CR values than other nodes in the same functional community. Moreover, we analyze the synchrony state of the functional communities in the cortical network, revealing that a community with a larger percentage of pinned nodes inside will be conducive to synchronization.

1. Introduction

Over the last years, the complex networks approach has been widely applied in the field of neuroscience. The study changes from the topological structure of the global neuronal networks to the segregation and the integration of different subnetworks. The analysis of the anatomical connectivity of the mammalian cortex has uncovered that large-scale neuronal networks display high clustering and short path length [1, 2]. The cortical network also shows a hierarchy of complex connectivity and a hierarchy of interacting elements on different levels: the microscopic level of interacting neurons, the mesoscopic level of local neural circuits, and the macroscopic level of large-scale organization of the brain areas [3–6]. The understanding of the topological structure in different levels of neural networks help in studying the dynamical process on such networks.

Synchronization is widely observed in many fields such as coupled nonlinear systems and neural networks, which closely relates to neural information processing [7–12]. It is found that the synchronization phenomena, over a wide range of spatial and temporal scales, reflect the relevance for cognitive dysfunctions and pathophysiology [13]. The

process of synchronization is from partial nodes to the global network, and it also reflects the underlying topology of interactions [14]. Pinning control is an effective method to attain synchronization of networks [15–25]. By injecting feedback control action on part of the nodes, the network is synchronized to equilibrium state or nonlinear dynamical orbits. Utilizing control theory and master stability function (MSF) method, the concept of controllability was proposed to evaluate how easily a network is controllable [21]. The Eigenratio R and the maximum imaginary part σ of an extended matrix were proposed to evaluate the network's controllability. Both the number of pinned nodes and control gains influence the network's synchronization. The detection of controlling regions was converted into a constrained optimization problem, where the objective function R was minimized and σ was regarded as a constraint [22–24]. By utilizing control theory and assuming linear dynamics in each vertex, the results of structure controllability $\pm$ revealed that, in both model and real systems, the driver nodes tend to avoid the high-degree nodes [25, 26]. The concept of control rank (CR) was defined and used to control a scale-free (SF) directed dynamical network to an equilibrium state [27].

In this work, we study synchronization in the cortical network of cats' brain. Each cortical area is modeled by a nonlinear dynamical system with different initial states. The coupling between areas is modeled using the inner state coupling of the systems' state variables. Based on the network model, we analyze CR values of each area in the cortical network. Then we study CR pinning scheme in terms of the number and the distributions of the pinned nodes. Moreover, we analyze global synchronization and community synchronization in the cortical network.

The remainder of this paper is organized as follows. In Section 2, the topic of pinning control is introduced. Then, we introduce CR pinning scheme in Section 3. In Section 4, we present CR values of each area in the cortical network. In Section 5, we analyze synchronization under CR pinning scheme. Conclusions are given in Section 6.

2. Overview of Pinning Control

Notations. Throughout this paper, define a graph by $\mathcal{G} = [\mathcal{V}, \mathcal{E}]$, where $\mathcal{V} = \{1, \dots, N\}$ denotes the vertex set and $\mathcal{E} = \{e(i, j)\}$ denotes the edge set.

We consider a general complex network model composed of N identical nodes with diffusively coupling. The model is described as follows:

$$\dot{x}_i = f(x_i) - c \sum_{j=1}^N g_{ij} \Gamma x_j, \quad i \in \mathcal{V}, \quad (1)$$

where $x_i = (x_{i1}, x_{i2}, \dots, x_{in})^T$ is the state variable of the i th node; $f(x_i)$ is a continuous vector function; the positive constant $c > 0$ is the overall coupling strength; $\Gamma = \text{diag}(r_1, r_2, \dots, r_n)$ is the inner coupling matrix and reveals the coupling terms of two connected nodes. Connection matrix $G = (g_{ij}) \in \mathbb{R}^{N \times N}$ is related to the topology of the network and represents the coupling configuration of the network. If there is a directed link from node j to i ($i \neq j$) and the weight of the link is w_{ij} , then $g_{ij} = w_{ij}$, otherwise $g_{ij} = 0$. Let $\text{OD}(i)$ and $\text{ID}(i)$ denote the output degree (outdegree) and input degree (indegree) of the i th node, respectively. The outdegree $\text{OD}(i) = \sum_{j=1, j \neq i}^N g_{ji}$, $i \in \mathcal{V}$ of a node i is the number of efferent connections that it projects to other nodes, and its indegree $\text{ID}(i) = \sum_{j=1, j \neq i}^N g_{ij}$, $i \in \mathcal{V}$, is the number of the afferent connections it receives. In this paper, the matrix G is asymmetric, and it has complex eigenvalues. Assume, the eigenvalues set of matrix G is $\mu_i = \mu_i^r + j\mu_i^m$ ($j = \sqrt{-1}$), $i \in \mathcal{V}$, and they are ordered in such a way that $\mu_1^r \leq \mu_2^r \leq \dots \leq \mu_N^r$. The Laplacian matrix of the directed network (1) can be defined as $L = -G$, $L_{ii} = \sum_{j=1, j \neq i}^N L_{ij}$, $i \in \mathcal{V}$. Thus, the matrix has $\sum_{j=1}^N L_{ij} = 0$, $i \in \mathcal{V}$.

Assume, $s(t)$ is the desired target trajectory and satisfies

$$\dot{s}(t) = f(s(t)). \quad (2)$$

Applying pinning control to (1) to control the network to desired reference evolution $s(t)$, we get the following expression:

$$\begin{aligned} \dot{x}_i &= f(x_i) - c \sum_{j=1}^N g_{ij} \Gamma(x_j) + u_i, \quad i = 1, 2, \dots, l, \\ \dot{x}_i &= f(x_i) - c \sum_{j=1}^N g_{ij} \Gamma(x_j), \quad i = l+1, l+2, \dots, N, \end{aligned} \quad (3)$$

where $u_i = -k_i \Gamma(x_i - s)$, $k_i > 0$, $i = 1, 2, \dots, l$. k_i are control gains and assumed to be constant here, for example, $k_i = k$, $i = 1, 2, \dots, l$. Let p denote the ratio of the pinned nodes over all nodes of the network ($0 \leq p \leq 1$), then the pinned nodes set $I = \{i_1, i_2, \dots, i_l\}$, where $l = \lfloor p \times N \rfloor$. Here, assume that for any node i ($i \in [1, N]$), we can always find a node j in the pinned nodes set I such that there is a directed path from the pinned node j to node i ($i \neq j$).

Assume that $s(t)$ is a virtual system and by setting $y_i(t) = x_i(t)$, $i \in \mathcal{V}$, and $y_{N+1}(t) = s(t)$, we obtain a network with $N+1$ dynamical systems as follows [21]:

$$\dot{y}_i = f(y_i) - c \sum_{j=1}^{N+1} M_{ij} \Gamma(y_j), \quad i = 1, 2, \dots, N+1, \quad (4)$$

where $M = \{M_{ij}\}$ is an $(N+1)$ -dimensional squared matrix defined by

$$M = \begin{pmatrix} L_{11} + \delta_1 k_1 & L_{12} & \dots & L_{1N} & -\delta_1 k_1 \\ L_{21} & L_{22} + \delta_2 k_2 & \dots & L_{2N} & -\delta_2 k_2 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ L_{N1} & L_{N2} & \dots & L_{NN} + \delta_N k_N & -\delta_N k_N \\ 0 & 0 & \dots & 0 & 0 \end{pmatrix}, \quad (5)$$

where if $i \in I$, $\delta_i = 1$, else $\delta_i = 0$. Through the above transformation from (1) to (6), the problem of controllability of complex networks is converted into synchronizability of networks. Let $\lambda_i^r + j\lambda_i^m$ ($j = \sqrt{-1}$) be the eigenvalues of the matrix M and in the order of $0 = \lambda_1^r \leq \lambda_2^r \leq \dots \leq \lambda_{N+1}^r$. Similar to the analysis method of synchronizability of the networks, the bounded systems' controllability can be evaluated by eigenvalues ratio

$$R = \frac{\lambda_{N+1}^r}{\lambda_2^r}, \quad (6)$$

$$\sigma = \max \{\lambda_i^m\}, \quad i = 1, 2, \dots, N+1.$$

The smaller the R and σ are, the easier the network is controllable. It is evident that the values of control gains k and the number of pinned nodes l will influence the eigenvalues of matrix M .

3. CR Pinning Scheme

Usually, two kinds of pinning control strategies are considered on general network model. (i) Random pinning: the pinned nodes are randomly selected with uniform probability. (ii) Selective pinning: the nodes are sorted according to a certain property of the nodes, for instance, the nodes' degree, betweenness, or closeness centrality, then the pinned nodes are chosen according to the order. It is mentioned that random pinning scheme cannot guarantee synchronization of the directed networks [20]. It is verified that synchronization can be achieved if and only if forcing is applied to the roots of trees in a spanning-directed forest of the interaction graph of connection matrix G .

Supposing that each node with indegree has contribution to the nodes point to it, so the nodes which have more children and grandchildren and such as this will have larger CR values than others. According to CR values of each node, the concept of CR pinning scheme was defined and utilized to deal with pinning control of the directed networks [27].

Supposing that $[CR^0]_{N \times 1}$ is a row vector composed of initial CR values of each node. After k times iteration, the final stable CR values CR^k are calculated as follows:

$$CR^k = CR^{k-1} \times ID^{-1} \times L, \quad (7)$$

where $ID = \text{diag}(ID_1, ID_2, \dots, ID_N)$. At each iteration in (7), vertex j will contribute with $CR_j \times (1/ID_j)$ to each of its indegree neighbors, which is in direct proportion to $1/ID_j$. If there is a path from vertex p to j through vertex i , j will contribute with $CR_j \times (1/ID_i) \times (1/ID_j)$ to the CR value of vertex p . Hence, the contribution of CR value from vertex j to vertex p attenuates with increment of the path length from p to j . The CR values have an obvious positive correlation with the nodes' outdegree. It is also related to the largest distance from it to all the other vertices. Considering both the property of outdegree and the distance from the pinned nodes to the others in the network, pinning a vertex according to its CR value will be an effective strategy in dealing with control of directed networks.

4. The Cortical Network of Cats' Brain

The cortical network of cats' brain can be divided into 53 cortical areas, linked by about 830 fibres of different densities into a weighted and directed complex network. Here we use a data set from [28]. The cerebral cortex consists of four topological interconnected communities that agree with four functional cortical subdivisions: visual cortex (V, 16 areas), Auditory (A, 7 areas), somatomotor (SM, 16 areas), and frontolimbic (FL, 14 areas). The auditory community is sparsely connected, while the visual, somatomotor, and frontolimbic are densely connected among each other.

In the cortical network, the hub areas (Hubs) are densely interconnected at the top of the cortical hierarchy. Here we consider the case that the Hubs comprise 11 nodes from four functional communities, 20a, 7, and AES from visual cortex, EPp from auditory, 6 m and 5AI from somatosensory-motor, and Ia, Ig, CGp, 35, and 36 from frontolimbic [29].

TABLE 1: CR value of areas of the cortical network with size $N = 53$.

CR Order	Name	CR Value	Community
1	CGp	0.04478	Frontolimbic
2	5AI	0.03849	Somato-Motor
3	CGa	0.03760	Frontolimbic
4	Ia	0.03692	Frontolimbic
5	6m	0.03499	Somato-Motor
6	7	0.03319	Visual
7	5Bm	0.03234	Somato-Motor
8	5Am	0.03125	Somato-Motor
9	PFCMd	0.03114	Frontolimbic
10	5Bl	0.02990	Somato-Motor
11	35	0.02973	Frontolimbic
12	PFCL	0.02952	Frontolimbic
13	20a	0.02939	Visual
14	Ig	0.02919	Frontolimbic
15	SSAo	0.02887	Somato-Motor
16	AES	0.02766	Visual
17	4g	0.02667	Somato-Motor
18	6l	0.02564	Somato-Motor
19	EPp	0.02558	Auditory
20	SSSAi	0.02450	Somato-Motor
21	36	0.02136	Frontolimbic
22	SIV	0.02131	Somato-Motor
23	PFCMil	0.02091	Frontolimbic
24	20b	0.01867	Visual
25	SII	0.01847	Somato-Motor
26	4	0.01825	Somato-Motor
27	19	0.01732	Visual
28	RS	0.01680	Frontolimbic
29	Enr	0.01608	Frontolimbic
30	PLLS	0.01329	Visual
31	PMLS	0.01307	Visual
32	3b	0.01297	Somato-Motor
33	PS	0.01292	Visual
34	18	0.01070	Visual
35	P	0.01064	Auditory
36	21a	0.01059	Visual
37	3a	0.01018	Somato-Motor
38	17	0.00997	Visual
39	AII	0.00952	Auditory
40	2	0.00887	Somato-Motor
41	AMLS	0.00881	Visual
42	1	0.00881	Somato-Motor
43	AI	0.00840	Auditory
44	21b	0.00796	Visual
45	VLS	0.00751	Visual
46	ALLS	0.00618	Visual
47	DLS	0.00598	Visual
48	pSb	0.00594	Frontolimbic
49	Sb	0.00550	Frontolimbic
50	VP(ctx)	0.00438	Auditory
51	Tem	0.00430	Auditory
52	AAF	0.00381	Auditory
53	Hipp	0.00318	Frontolimbic

FIGURE 1: Time evolution of pinning control error E for the cortical network with $N = 53$. The coupling strength $c = 0.3$, and the feedback gains $k = 30$. (a) $p = 0.2$. Red line is used in the case of pinning the Hubs, and blue line is used in the case of descending CR value pinning scheme. (b) $p = 0.03$. Red line is used in the case that Ig and 36 are pinned, and blue line is used in the case that CGa and PFCMd are pinned.

We present the CR values of 53 areas of the cortical network in Table 1. The CR values are sorted in a descending way. The area named CGp in frontolimbic has the biggest CR value. It is impressive that most areas in auditory have smaller CR values. Taking an analysis of the CR values of the Hubs, we find that the Hubs in visual, auditory, somatosensory-motor communities have bigger CR values than the others in the same community. But for frontolimbic, the hub areas are Ig and 36 other than CGa and PFCMd, which have bigger CR values than the two areas mentioned before.

From the viewpoint of a control scheme design, we compare the effect of pinning the Hubs and the nodes based on descending CR values. As shown in Figures 1(a) and 1(b), the pinning scheme according to descending the CR value has an advantage at the beginning of pinning control, then it becomes consistent with pinning the Hubs till all nodes synchronize to $s(t)$. Moreover, a further analysis between CGa, PFCMd, Ig, and 36 in frontolimbic is presented. We study the dynamics via pinning only two nodes of CGa and PFCMd or Ig and 36. From Figure 1(b), it is evident that CGa and PFCMd have better property in controlling the network.

5. Analysis of CR Pinning Scheme

In this section, we analyze the descending CR pinning scheme based on the cortical network described in Section 4. The dynamics of each area are modeled by Rössler's system. The Rössler system is given by the following differential equations:

$$\begin{aligned}\dot{x}_1 &= -x_2 - x_3, \\ \dot{x}_2 &= x_1 + ax_2, \\ \dot{x}_3 &= b + x_3(x_1 - c),\end{aligned}\tag{8}$$

where a , b , and c are constants. In this study, $a = 0.165$, $b = 0.2$, and $c = 10$ are used. The output function $\Gamma = ((1 \ 0 \ 0), (0 \ 1 \ 0), (0 \ 0 \ 1))$ indicates that the systems are coupled through the variables x_{i1} , x_{i2} , and x_{i3} . Here we evaluate the effects of n pinned nodes with feedback gains $k_1 = k_2 = \dots = k_n$ on the control error E . The control error is denoted by $E = (1/(\Delta T)N) \sum_{i=1}^N \int_T^{T+\Delta T} \|x_i(t) - s(t)\| dt$, in which $\|x_i\| = |x_{i1}| + |x_{i2}| + |x_{i3}|$.

Next, we present numerical results of the descending CR pinning scheme under variations of the coupling strength c and the pinning probability p on the cortical network.

Control error E has been calculated in Figures 2(a) and 2(b) on networks with $c = 0.1, 0.2, 0.3$, and 0.5 (pinning ratio $p = 0.1$ and $p = 0.3$, resp.). A strong coupling strength will be conducive to control of the network, which is profound when the pinning ratio is large such as $p = 0.3$ and above. Moreover, we take a further research on the network with coupling $c = 0.1$ and $c = 0.3$. From Figures 3(a) and 3(b), it can be seen that increasing the number of pinned nodes will help to synchronize the network. It is very prominent in the network with coupling strength $c = 0.3$ that the network is stabilized on orbit $s(t)$ when $p = 0.4$ and above. In Figure 3(a), especially a large number of pinned nodes are needed to stabilize the network with $c = 0.1$ or with even smaller coupling strength. Hence, it is easier to control a strong coupling network, and only a small number of pinned nodes can synchronize the network to target orbit.

In the following, the effect of the descending CR pinning scheme on synchronization of the cortical network and the four communities is analyzed. The nodes which attain synchronization are calculated by $\sum_{i=1}^N \|x_i(t) - s(t)\| < 0.01$, in which $\|x_i\| = |x_{i1}| + |x_{i2}| + |x_{i3}|$. The results are shown in Figures 4(a) and 4(b). Note that somatomotor community is

FIGURE 2: Time evolution of pinning control error E for the cortical network with $N = 53$, feedback gains $k = 30$. With pinning ratio (a) $p = 0.1$ and (b) $p = 0.3$.

FIGURE 3: Control error E as a function of time t with different pinning ratios $p = 0.1, 0.4, 0.7, 1.0$. For the cortical network with $N = 53$, the feedback gains $k = 30$, and the coupling strength (a) $c = 0.1$ and (b) $c = 0.3$.

firstly synchronized and then visual community, frontolimbic community, and auditory community, successively. The distributions of the pinned nodes among communities are listed in Table 2. It is found that the distributions of the pinned nodes influence the dynamics of the communities. A community with a larger percentage of pinned nodes in it is easier to synchronize, for example, somatomotor community in the cortical network. Without pinned nodes inside it, the auditory is the last community to attain synchronization.

6. Conclusions

In this paper, the problem of pinning control of the weighted and directed cortical network has been studied. Firstly, the CR values of different areas in the cortical network are listed and then applied to analyze the hub areas in the cortical network. It is found that most of the hubs have bigger CR values than the others in the same functional community. Next, we studied the control effect of CR pinning scheme.

FIGURE 4: The CR pinning scheme of the cortical network with $N = 53$, the coupling strength $c = 0.3$, the pinning ratio $p = 0.25$, and the feedback gains $k = 30$. (a) Control error E as a function of time t . (b) The nodes synchronized to the orbit $S(t)$ with function of time t . In all the plots, the legend is as follows: red (blue, green, black, and pink) lines are used in the case of the cortical network (visual community, auditory community, somatomotor community, and frontolimbic community).

TABLE 2: Pinned nodes percentage in communities with $p = 0.25$.

Pinned nodes number	Pinned nodes percentage in community	Community
6	43%	Frontolimbic
5	31%	Somato-Motor
2	13%	Visual
0	0	Auditory

It is found that the coupling strength and the pinned nodes demonstrate mutual complement in controlling the network to the desired dynamics. Finally, we analyzed the global synchronization and community synchronization from the viewpoint of pinning control. We pointed out that community's synchronization is positively correlated with the number of pinned nodes inside it.

Acknowledgments

The authors acknowledge the support from German Academic Exchange Service (DAAD), the Major State Basic Research Development Program of China (973 Program, Grant no. 2010CB731400), the Key Creative Project of Shanghai Education Community (Grant no. 13ZZ050), and, the Key Foundation Project of Shanghai (Grant no. 12JC1400400).

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