Coarse Graining for Synchronization in Directed Networks

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Coarse graining model is a promising way to analyze and visualize large-scale networks. The coarse-grained networks are required to preserve statistical properties as well as the dynamic behaviors of the initial networks. Some methods have been proposed and found effective in undirected networks, while the study on coarse graining directed networks lacks of consideration. In this paper, we proposed a Path-based Coarse Graining (PCG) method to coarse grain the directed networks. Performing the linear stability analysis of synchronization and numerical simulation of the Kuramoto model on four kinds of directed networks, including tree networks and variants of Barabási-Albert networks, Watts-Strogatz networks and Erdös-Rényi networks, we find our method can effectively preserve the network synchronizability.

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I. INTRODUCTION.

Complex networks have become a key approach to understanding many social, biological, chemical, physical and information systems, where nodes represent individuals and links denote the relations or interactions between nodes. In this sense, to study the dynamics of such systems is actually to investigate the dynamical behaviors on the networks. In particular, the network synchronization as an important emerging phenomenon of a population of dynamically interacting units in various fields of science has attracted much attention [1–12]. Most works focused on studying the relation between network topology and the synchronization [3–7], enhancing the synchronizability by designing the weighting strategies [8–12]. Moreover, some efforts have been made to study the synchronization in directed networks [13–17]. It has been pointed out that the optimal structure for synchronizability is a directed tree [13, 14] and the convergence time is strongly related to the depth of the tree [15, 16]. Most of the experiments on investigating the dynamic behaviors are implemented on small-size networks. However, when the networks contains very large number of nodes, it becomes sometimes impossible to model the dynamic process. For example, to investigate the synchronization, extrapolating the coupled differential equations model of a single node to this large system is too complicated to be carried out.

A promising way to address this problem is to coarse grain the network, namely to reduce the network complexity by means of mapping the large network into a smaller one. The coarse graining techniques have been successfully applied to model large genetic networks [18] and extract the slowest motions in protein networks [19]. Essentially, the coarse graining process is very similar to the problem of cluster finding or community detection in networks (see Ref. [20–23] for some popular methods).

The coarse-grained network is obtained by merging the nodes in the same cluster or community. However, the coarse graining model is far beyond the clustering techniques, since it requires the coarse-grained networks keep the same topological properties or dynamic behaviors as the initial networks, such as preserving the degree distribution, cluster coefficient, assortativity correlation [24], the properties of random walk on the network [25], synchronization [26] and critical phenomena [27]. Most of the former works on coarse graining consider undirected networks. However, in many real systems, the interactions between individuals are not reciprocal. For example, the food web, gene regulation system, metabolic system and neural system are usually represented by directed networks where the nodes are affected by their upstream nodes. In directed networks, of course we can ignore link directions and apply methods developed for undirected networks, but this approach discarding potentially useful information contained in the link directions may lead to dramatically change of the key organizational features when coarse graining the networks [28]. In addition, some prominent methods may confront problems when applied to directed networks. Among all these existing coarse graining methods for undirected networks, the spectral coarse graining (SCG) method is a very general method which can be applied in many dynamic processes such as synchronization, random walk and epidemic spread [29–31]. In order to preserve a typical eigenvalue, the SCG method coarse grains the nodes with similar elements in the corresponding eigenvectors. For different dynamic processes, different eigenvalues should be considered. Therefore the choice of the eigenvectors is indeed problem dependent. As the synchronizability is mainly related to the largest and smallest nonzero eigenvalue, the SCG method for synchronization takes the $p_2$ and $p_N$ into consideration ($p_2$ and $p_N$ are respectively the eigenvectors for the smallest nonzero and the largest eigenvalue). However, this method may not provide good performance in directed networks since the eigenvector elements cannot successfully characterize the nodes’ dynamic role. For instance, the nodes in different layers...
may have exactly the same eigenvector elements in directed acyclic networks while the nodes with exactly the same topology may have totally different eigenvector elements in directed networks with cycles. In a word, to design an effective coarse graining method for directed networks is still challenging.

In this paper, we propose a Path-based Coarse Grain-ing (PCG) method to coarse grain directed networks for synchronization. The basic idea is that the nodes who obtain the same impacts from other nodes are similar to each other, and thus can be merged. The impacts that one node receives from other nodes are calculated via tracing the origin of the source in the directed networks (i.e., along the opposite direction of links). It has been pointed out that the dynamical correlation can be predicted from such topological similarity [29]. Therefore, coarse graining in this way will most naturally merge the nodes according to their functional performance and likely preserve the dynamical properties. The linear stability analysis of synchronization and numerical simulation of the Kuramoto model on four kinds of directed networks, including tree networks and variants of Barabási-Albert networks, Watts-Strogatz networks and Erdös-Rényi networks, show that our method can effectively preserve the synchronizability of the initial directed networks. Additionally, we find the far sources play more important roles when identifying the nodes’ roles in directed networks with obvious hierarchy structure, while the near sources are more important in the directed networks with many loops.

II. PATH-BASED COARSE GRAINING (PCG) METHOD

A. Definition of node’s impact-vector

Many structural-based similarity indices have been proposed to quantify the nodes’ similarity [30-32], most of which only work for undirected networks. How to define the nodes’ similarity in directed networks is still a challenge. Here we propose a method via tracing the origin of impacts in directed network. The basic assumption is that two nodes are structural-similar if they obtain the same impacts from other nodes, and thus they are more likely to be merged during the coarse graining process. Given a directed network \( G(V, E) \), where \( V \) and \( E \) denote the set of nodes and directed links respectively. Multiple links and self-connections are not allowed. The impact of node \( x \) on node \( y \) is defined by summing over the collection of directed paths from \( x \) to \( y \) with exponential weights by length. The mathematical expression reads

\[
f_{x \rightarrow y} = \sum_{l=1}^{l_{\text{max}}} \beta^l |\text{path}_{x \rightarrow y}^{<l>}|,
\]

where \( |\text{path}_{x \rightarrow y}^{<l>}| \) is the set of all directed paths with length \( l \) starting from node \( x \) to node \( y \). Mathematically, \( |\text{path}_{x \rightarrow y}^{<l>}| = (A^l)_{xy} \), where \( A \) is the adjacency matrix: if \( x \) points to \( y \) \( A_{xy} = 1 \), otherwise \( A_{xy} = 0 \). \( \beta \) is a free parameter that controls the weights of the paths. Smaller \( \beta \) indicates assigning more weights on the short paths, and vice versa. Here the paths whose lengths are not larger than \( l_{\text{max}} \) are considered. If \( l_{\text{max}} = \infty \), namely considering all directed paths from \( x \) to \( y \), Eq. (1) is similar to the Katz index [33]. However, the significant difference is twofold: On one hand, the adjacency matrix in Katz index is symmetrical while asymmetrical in Eq. (1); On the other hand, the parameter \( \beta \) is usually smaller than unit in Katz index, namely assigning more weights to the short paths, while in Eq. (1) \( \beta \) has no limitation. Since counting all paths between every pair of nodes is very time-consuming especially in large networks, we here set \( l_{\text{max}} \) equal to the length of the longest path among all the shortest paths between two nodes. Note that when \( l_{\text{max}} = \infty \) and \( \beta \) is smaller than the reciprocal of the largest eigenvalue of \( A \) (i.e., ensure the convergence), the impact matrix \( F \) with element \( f_{xy} \) defined in Eq. (1) can be directly calculated by \( F = (I - \beta A)^{-1} - I \).

B. Group partition via k-means clustering

We assign each node \( x \) a \( N \) dimensional impact-vector which is equal to the \( x \)th column of matrix \( F \), namely \( \vec{f}_x = (f_{1x}, f_{2x}, f_{3x}, \ldots, f_{Nx})^T \), where \( N = |V| \) is the number of nodes. Clearly, if two nodes receive the same impacts from their ancestors (i.e., upstream nodes), they tend to have the same phase in synchronization, and thus are more likely to be merged during coarse graining. Suppose we are going to coarse grain a network containing \( N \) nodes to a smaller one with \( K \) nodes. We adopt the k-means clustering method [34] to partition the \( N \) nodes into \( K \) groups. The nodes in the same group will be merged. The k-means clustering technique aims at minimizing the within-cluster sum of squares:

\[
E = \sum_{i=1}^{K} \sum_{x \in V(i)} ||\vec{f}_x - \vec{c}(i)||^2, \quad (2)
\]

where \( V(i) \) is the set of nodes in cluster \( i \) (\( i = 1, 2, \ldots, K \)), and \( \vec{c}(i) \) is the centroid of cluster \( i \) which is equal to the mean of points in cluster \( i \), namely

\[
c_k(i) = \frac{1}{|V(i)|} \sum_{x \in V(i)} f_{kx}. \quad (3)
\]

The detailed steps of k-means clustering are shown as follows: (i) Choose \( K \) vectors as the initial centroid of each cluster. (ii) Randomly choose a node \( x \) from the set \( V \). This node will belong to the cluster \( i \) if the distance between its vector \( \vec{f}_x \) and the centroid of cluster \( i \), namely \( \vec{c}(i) \), is the minimum among all the centroids of \( K \) clusters. (iii) Update the centroid of each cluster according to Eq. (3) (iv) Repeat steps (ii) and (iii) until all the centroids cannot be modified. Note that for a given
$K$, clusters will depend heavily on the initial configuration of the set of centroids, thus making interpretation of the clusters rather uncertain. Different initialization may lead to different solutions which may trapped in the local minimum. Clusters should be, as much as possible, compact, well separated, and interpretable, possibly with the help of some additional variables, such as the $F$-statistic. Here we only focus on whether the clusters are compact, namely the vectors (nodes) within one cluster are close (similar) enough, while neglect if the clusters are well separated. Therefore we will finally choose the clustering result subject to the lowest $E$ among $L$-possible solutions (we set $L = 20$ in this paper).

C. Weighting strategy for the coarse-grained networks

Another crucial problem in the process of coarse graining is how to update the links’ weights after merging the nodes so that the resulting network is truly representative of the initial one. An effective weighting strategy was proposed by Gfeller et al. [26]. Here we apply it to directed networks. Specifically, when we merge the nodes in cluster $i$ to form a new node labeled by $m_i$, the weights of the merged links update according to the following principle:

$$
\begin{align*}
    & w_{x \rightarrow m_i} = \frac{\sum_{y \in \partial_i} w_{x \rightarrow y}}{|\partial_i|}, \text{ for } m_i's \text{ in-links} \\
    & w_{m_i \rightarrow x} = \sum_{y \in \partial_i} w_{x \rightarrow y}, \text{ for } m_i's \text{ out-links}
\end{align*}
$$

where $w_{x \rightarrow y}$ indicates the weight of the directed link from $x$ to $y$, which can also be interpreted as the coupling strength. A simple illustration is shown in Fig. 1. The initial network as shown in Fig. 1(a) is constituted of seven nodes and eight directed links. Assuming the initial links’ weights are all equal to unit. After merging the three nodes $a$, $b$, and $c$, a new node $m$ is generated, and according to Eq. (4) the links weights in the reduced network are drawn as in Fig. 1(b). Indeed, since the three nodes in total receive three in-links from node $d$, while two from node $e$, the weights of $m$’s two in-links are respectively $w_{d \rightarrow m} = 3/3 = 1$ and $w_{e \rightarrow m} = 2/3$. For $m$’s out-links, since the three nodes have two out-links to node $f$ and one to $g$, the weight are respectively $w_{m \rightarrow f} = 1 + 1 = 2$ and $w_{m \rightarrow g} = 1$.

Under the framework of master stability analysis, the synchronizability of an undirected network can be quantified by the ratio between the largest and the smallest non-zero eigenvalues of the Laplacian matrix of this network, namely $R = \lambda_N/\lambda_2$, where $\lambda_N$ and $\lambda_2$ are respectively the largest and the smallest non-zero eigenvalues of the Laplacian matrix. In directed networks, since the Laplacian matrix, defined as $L_{ij} = k_i^m \delta_{ij} - a_{ij}$, is asymmetric with zero rowsum, it has complex eigenvalues. In order to achieve the synchronizability condition, every eigenvalue is entirely contained in the region of negative Lyapunov exponent for the particular master stability function. Once the stability zone is bounded and the imaginary part of complex eigenvalue is small enough, the network synchronizability can be approximately measured by the real part of eigenvalue ratio $R = \lambda_N/\lambda_2$, where $\lambda_N$ and $\lambda_2$ are respectively the largest and the second smallest real parts of eigenvalues. Generally speaking, the stronger the synchronizability, the smaller the ratio $R$. Note that an accurate index for measuring the synchronizability in directed networks has not yet been proposed and asks for further studies. Here, we use the approximate index $R = \lambda_k^r/\lambda_k^s$ as an indicator to see whether the synchronizability of a directed network changes after coarse graining. Usually $\lambda_N$ is proportional to the largest degree $k_{\text{max}}$ (i.e., largest node’s strength in weighted network) of the network and $\lambda_2$ corresponds to the lowest degree $k_{\text{min}}$ (i.e., lowest node’s strength in weighted network). Therefore, keeping the $k_{\text{max}}$ and $k_{\text{min}}$ unchanged can effectively help to maintain the synchronizability after coarse graining. Thus, in the coarse graining process, the nodes with largest and smallest in-degrees can only be merged if the $k_{\text{max}}$ and $k_{\text{min}}$ of the coarse-grained network are respectively equal to that of the initial network. Otherwise, we will randomly select two nodes, one with largest in-degree and the other with the smallest in-degree, before group partition. Then the rest $N - 2$ nodes will be classified into $K - 2$ groups according to k-means clustering. Note that, unless stated otherwise, $k$ always refers to the in-degree. In appendix, we further discuss the effect of the constraint of keeping $k_{\text{max}}$ and $k_{\text{min}}$ on coarse graining results. It shows that the eigenvalue ratio $R$ is sensitive to $k_{\text{max}}$ and $k_{\text{min}}$, while the order parameter of Kuramoto model does not.

Finally, for the aspect of computational complexity, the k-means clustering algorithm is of $O(N^2)$, and the time complexity of calculating the impact-vector $F$ is $O(N^3)$. Likewise, the calculation of eigenvectors in SCG method also takes $O(N^3)$. However, with the develop-
III. RESULTS

A. Coarse graining on modeled networks

We apply the Path-based Coarse Graining (PCG) approach to four kinds of directed networks: (i) Directed tree network. A tree with $N$ nodes and $L$ layers is generated starting from a directed train with length $L$, in which each node represents a layer. Then rest $N - L$ nodes are added one by one. Each new added node is connected by a directed link starting from one of its ancestors which are not located in the layer $L$. (ii) A variant of Barabási-Albert networks [41]: Directed BA network. An acyclic directed BA network is generated by using the mechanism for undirected BA network and assuming the link direction can only from older node to younger node. (iii) A variant of Watts-Strogatz networks [42]: Directed WS network. The model starts from a completely regular (iii) A variant of Watts-Strogatz networks [42]: Directed WS network. The model starts from a completely regular network which is initially connected by a directed link starting from one of its ancestors. (iv) A variant of Erdős-Rényi networks [43]: Directed ER random network. The directed ER random networks can be generated by setting $q = 1$.

Firstly, we investigate the performance of PCG on above four kinds of networks. The synchronizability of the coarse-grained network $R$ in the $(\beta, K)$ plane is shown in Fig. 2, where $K$ is the size of the coarse-grained network. Interestingly, we find that in tree network and acyclic BA network larger $\beta$ in average provides better results than smaller $\beta$. Especially, in tree network there is an obvious line at $\beta \approx 1$. In the BA network, with $\beta > 1$ the coarse-grained network can keep the synchronizability exactly the same as the initial network. In the cyclic WS network the $\beta$ that best preserves the synchronizability is around 0.1. It seems that networks with more loops tend to obtain better coarse graining with smaller $\beta$ (see subsection C for detailed discussion of the relationship between the optimal parameter $\beta^*$ and the number of loops in network). The result in Fig. 2(d) shows that the synchronizability of the coarse-grained ER network is not sensitive to $\beta$ regardless of $K$, since the total fluctuation is smaller than 0.07.

We compare the PCG method with other two methods, namely Random Coarse Graining (RCG) and Spectral Coarse Graining (SCG) [26]. In RCG, the $N$ elements of each nodes’ vector are randomly selected in the range of $(0,1)$. Then the nodes will be classified into $K$ groups by using k-means clustering. In directed networks, the eigenvalues and eigenvectors of their laplacian matrices have complex values. When we apply SCG to directed networks, we consider only the real parts of the values in this paper. In practice, we define $I$ equally distributed intervals between the maximum and minimum of $p_2$ ($p_N$), where $p_2$ and $p_N$ are the eigenvectors corresponding to the second smallest and the largest real-part-eigenvalues of the laplacian matrix, respectively. The nodes whose eigentopic components in $p_2$ ($p_N$) fall in the same interval are merged. Specifically, if the elements in both $p_2$ and $p_N$ are identical, we will randomly divide the nodes into $K$ groups. Actually, the relation between $I$ and $K$ strongly depends on the network structure (i.e., the distribution of the elements in $p_2$ and $p_N$). For instance, considering the initial WS and ER network shown in Fig. 2 when $I = 800$ the size of the coarse-grained WS network is 951, while the reduced ER network only contains 281 clusters. Note that there are many potential ways to apply the SCG method to directed networks making use of the imaginary part of the elements in eigenvectors. For example, the vectors ($p_2$ ($p_N$)) can be generated by combining the real part and the imaginary part (such as $\sqrt{(p_2^2) + (p_N^2)}$, $p_2 + p_N$, $p_2p_N$, et al.). Another way is grouping the nodes according to four vectors, namely ($p_2$, $p_2$, $p_N$, $p_N$). If the imaginary parts are appropriately considered, the performance of SCG can be improved. However, how to find the right way to make use of the imaginary parts is a tough problem and inappropriately involving the imaginary parts in SCG method may lead to even worse results.

Figure 2 shows how the indicator $R$ changes with $K$ on the above four kinds of directed networks with typical
\( \beta \). Overall speaking, PCG outperforms SCG, and RCG performs worst. As shown in Fig. 3(a) (b) and (c), with SCG and RCG, the synchronizability changes even only a few nodes have been merged, while the PCG displays a large stable range. In a directed tree network, most of the elements in eigenvectors corresponding to the smallest and the largest eigenvalues are identical. Thus it is impossible to distinguish the role of nodes by the analysis on the eigenvectors as suggested in Ref. [26]. In the tree networks, the most effective coarse graining strategy is to merge the nodes in the same layer. PCG can indeed performs worst. As shown in Fig. 3(a) (b) and (c), with \( K \) see that when \( L \) in acyclic directed tree network. From Fig. 3(a), one can parameter to merge the nodes in the same layer. PCG can indeed on the eigenvectors as suggested in Ref. [26]. In the tree impossible to distinguish the role of nodes by the analysis est and the largest eigenvalues are identical. Thus it is a large stable range. In a directed tree network, most of a few nodes have been merged, while the PCG displays impossible to distinguish the role of nodes by the analysis in different layers and thus leading to a smaller \( k_{\min} \) according to the weighting strategy in Eq. [4]. In this case, if we artificially set \( k_{\min} \) of the reduced network equal to that of the initial network, the synchronizability can be well preserved (exactly equal to 1). Similar phenomenon exists in acyclic BA network where the hierarchical structure is clear.

It has been demonstrated that the synchronizability of the directed BA network with average in-degree \( \bar{k} = 3 \) is exactly 3 [11]. Figure 3(b) shows that PCG with parameter \( \beta = 5 \) can guarantee \( R = 3 \) by keeping the network acyclic and \( k_{\max} \) and \( k_{\min} \) unchanged, even the network is reduced to 30 clusters (i.e., \( K = 30 \)). When \( K < 30 \), merging may generate some loops and decrease \( k_{\min} \), and thus lead to a sharp increase of \( R \). It can not be perfectly avoided by artificially keeping \( k_{\min} \) as what we did in the tree network, instead \( R \) can effectively reduce to around 3, since here the loops also play a role. On the contrary, the SCG method may induce loops even merging a few nodes (i.e., for a larger \( K \)). For example, when \( K = 600 \), the synchronizability of the reduced SCG network is \( R = 3.77 \), while synchronizability of the reduced PCG network is exactly equal to 3.

In the networks with cycles including directed WS networks and directed ER networks, there are no clear hierarchical structures, thus the local information (i.e., short paths) plays more important role to quantify the node’s impact during the coarse graining process, and thus a relative small \( \beta \) is required. Here we use \( \beta = 0.1 \). The results show that the PCG method performs as well as SCG method in directed ER networks while much better than SCG and RCG in directed WS networks.

In addition, we point out that grouping the nodes aiming at preserving the dynamics cannot maintain the topological properties at the same time, although the grouping is according to the topological similarity. Generally, the average degree of the coarse-grained network is larger than that of the initial network. For comparison, we generate a group of modeled networks which have the same topological properties as the initial network and same size as the coarse-grained network. It is shown that the average number of reachable nodes and loop number of the coarse-grained networks are always higher than that of the modeled networks, while the average shortest distance of the coarse-grained networks is always smaller than the modeled networks. Moreover, the coarse graining procedure may change the degree distribution of the initial networks. However, the topological properties of the PCG networks are relatively closer to the initial networks than the SCG networks especially in the acyclic networks (not so obvious in directed networks with cycles). For example, the PCG method can prevent the producing of loops and keep the coarse-grained networks still partial reachable.

**B. Kuramoto model on coarse-grained networks**

Since the Laplacian matrixes for directed networks are asymmetric, the eigenvalues \( \lambda_2 \) and \( \lambda_N \) are complex. In this case, the indicator \( R \) can not exactly represent the synchronizability of a network. Hence, we further test our method with the Kuramoto model [44, 45], which is a classical model to investigate the phase synchronization phenomena. The coupled Kuramoto model in the
network can be written as

$$\dot{\theta}_i = \omega_i + A \sum_{j=1}^{N} A_{ij} \sin(\theta_j - \theta_i), \quad i = 1, 2, ..., N \quad (5)$$

where $\omega_i$ and $\theta_i$ are the natural frequency and the phase of oscillator $i$ respectively, and $A$ is the adjacency matrix. The collective dynamics of the whole population is measured by the macroscopic complex order parameter,

$$r(t)e^{i\phi(t)} = \frac{1}{N} \sum_{j=1}^{N} e^{i\theta_j(t)}, \quad (6)$$

where the modulus $r(t)$ ($\in [0, 1]$) measures the phase coherence of the population and $\phi(t)$ is the average phase. $r(t) \simeq 1$ and $r(t) \simeq 0$ describe the limits in which all oscillators are respectively phase locked and moving incoherently. By studying the behavior of the order parameter $r(t)$, we are able to investigate whether the topology of the coarse-grained network is representative of the initial one. The initial network is a tree network as shown in Fig. 4(a), which contains 100 nodes and has 10 layers. After the PCG procedure, we obtain a train-like network with depth equal to 10, see Fig. 4(b). With the SCG method, a cyclic network will be generated as shown in Fig. 4(c). The result of how the order parameter $r(t)$ of Kuramoto model performs in these three networks is shown in Fig. 4(d). It is obvious that $r(t)$ of the PCG network converges with almost the same speed as the initial one, while in the SCG network it converges faster. Moreover, the results of directed WS network and BA network are respectively shown in Fig. 4(e) and (f). Their coarse-grained networks all contain 25 clusters. It is clearly that the PCG method can preserve the synchronizability more effectively than SCG.

C. The optimal parameter $\beta^*$ for different networks

In different networks, the optimal parameters $\beta^*$ corresponding to the best performance on coarse graining are different. Empirically, the $\beta^*$ of acyclic networks is larger than that of those containing loops. To investigate whether $\beta^*$ is affected by the cycles in networks, we carry out an experiment based on directed BA networks, on which loops are generated by reshuffling some links. Specifically, we randomly select two directed links from the network, for example, one is from node $A$ to $B$ and the other is from node $C$ to $D$. Then we rewired these two links as $A$ to $D$ and $C$ to $B$. In this way, the degree of these nodes will not be changed during the reshuffling procedure. In average, reshuffling more links leads to more loops, see an example in Fig. 5(a) where the numbers of loops with length 3, 4 and 5 all increase with the increasing of reshuffling steps. Now, we would like to find the optimal parameters for the reshuffled networks. For a given network, $\beta^*$ might be different with different $K$ as we have shown in Fig. 2. However, in practice, checking the optimal parameter for different $K$ in advance is sometimes impossible. Thus, we here ignore the relationship between $\beta$ and $K$, and consider the general performances of one parameter on the coarse-grained networks with the possible sizes we concerned. The $\beta^*$ is thus correspond-
ing to the $\beta$ that yields the minimum synchronizability difference between the coarse-grained networks and the initial networks, which can be mathematically expressed by:

$$d = \sum_{K=n}^{N} |R_K - R_0|$$

(7)

where $R_K$ is the synchronizability of the coarse-grained network with $K$ nodes, $R_0$ is the synchronizability of the initial network and $n$ is the minimum size of the coarse-grained network that we considered. Since too small $K$ may lead to dramatic change of $R$, here we choose $n = 10$ in the example shown in Fig. 5. We obtain $\beta^*$ subject to the minimum $d$. The dependence of $\beta^*$ on the number of reshuffling steps is shown in Fig. 5(b). Instead of considering all possible $\beta$ which is very time consuming, we test the parameter $\beta$ in the range of $[0.01,10]$ with step 0.01, 0.1 and 1 respectively in $[0.01,0.1], [0.1,1]$ and $[1,10]$. It is clear that $\beta^*$ decreases with the increasing of reshuffling steps. Actually, if directed networks have obvious hierarchical structure and rare loops, PCG can perform better with a relatively large $\beta$ since it emphasizes on long path to detect the hierarchical structure. However, in directed networks with many loops, the hierarchical structure is not clear. As a path involved in loops can be regarded as an infinite long path, its effect on the impact-vector will be enormously amplified with a large $\beta$, and thus leading to noise when characterizing the dynamic role of a node. In this case, it is better to pay more attention to the impacts from local structure, namely emphasize the effects of short paths by using small $\beta$.

IV. CONCLUSION

Coarse graining is an effective way to analyze and visualize large networks. Many methods and models have been proposed to reduce the size of the networks and preserve main properties such as degree distribution, cluster coefficient, degree correlation, as well as some dynamic behaviors such as random walks, synchronizability and critical phenomena. However, most of these works take into account the undirected networks, while the study on coarse graining of directed networks lacks of attention. In this paper, we introduce a Path-based Coarse Graining (PCG) method which assumes that two nodes are structural-similar if they obtain the same impacts from other nodes, and thus they are more likely to be merged during the coarse graining process. The impacts that a node obtained from other nodes are calculated via tracing the origin of impacts in directed network. Specifically, the impact of node $x$ on node $y$ is defined by summing over the collection of directed paths from $x$ to $y$ with exponential weights by length, which are controlled by a parameter $\beta$. Larger $\beta$ indicates the long paths are more important (i.e., assign more weights to the long paths). Numerical analysis on four kinds of directed networks, including tree-like networks and variants of Barabási-Albert networks, Watts-Strogatz networks and Erdös-Rényi networks, shows that our method can effectively preserve the synchronizability during the coarse graining process. This result is further demonstrated by the Kuramoto model. In addition, we find that the long paths play more important roles on the coarse graining in the tree-like networks, while in the cyclic networks, the long paths that involve the loops usually have negative effects on quantifying the impacts of one node on the other nodes during the coarse graining process, and thus a smaller parameter $\beta$ gives better performance.

Finally, we claim that the idea for merging nodes which receive the same impacts from the network is quite general for coarse graining directed networks. For example, for random walk, two nodes in a directed network having exactly the same upstream neighbors should be grouped together since their random walker probabilities come from the same sources. In this sense, coarse graining directed networks for other dynamics can be interesting extensions.

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Appendix A: PCG method without degree constraint

In the paper, we assumed that the nodes with largest and smallest in-degrees can only be merged if the $k_{\text{max}}$ and $k_{\text{min}}$ of the coarse-grained network are respectively equal to that of the initial network. In order to investigate the effect of keeping the maximum and minimum in-degree on the coarse graining result, we remove the constraint of $k_{\text{max}}$ and $k_{\text{min}}$ in PCG and see the performance of the modified PCG method. As we mainly consider synchronization, the indicator $R$ is shown to be sensitive to the $k_{\text{max}}$ and $k_{\text{min}}$, see Fig. 6. It is obvious that the PCG with constraint performs better than that without constraint. However, as shown in Fig. 7 the order parameter $r(t)$ of the Kuramoto model does not show obvious differences. Moreover, we compared the RCG with and without the in-degree constraint. The result shows that the degree constraint cannot prominently improve the performance of RCG.
FIG. 6: (Color online) Comparison of the PCG with and without the constraint of $k_{\text{max}}$ and $k_{\text{min}}$. All the parameters in this figure are the same to the ones in Fig. [2]

FIG. 7: (Color online) The order parameter of Kuramoto model on four networks. All the parameters in this figure are the same to the ones in Fig. [3]

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