Compressive Sensing Over Graphs Based Inter-Community Detection Scheme in Mobile Social Networks

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***Abstract*—Recently, mobile social networks (MSNs) has been playing an increasingly large proportion in people's daily life, and consequently attracted enormous amount of researches in this area, including network data collection, user behavior analysis and so on. Many of them are based on the community structure of the MSNs, the detection of which has attracted academic attention. In this paper, we propose an inter-community detection scheme under the framework of the emerging compressive sensing (CS) over graphs. Firstly, we extract the social structure among users by calculating the probability of two users encountering with each other. Then, the proposed scheme utilizes the encounter probability and the edge-clustering coefficient to define a novel additive property to make the CS algorithm applicable. Simulation results demonstrate that the proposed detection scheme can detect inter-community links more accurately than the conventional random walk based method.**

***Index Terms*—mobile social network, compressive sensing over graphs, edge clustering coefficient, encounter probability.**

I. Introduction

With the development of the production techniques, the mobile devices, such as cellphones and tablets, have walked into people's daily life and significantly changed the way we live [1]. As a result, more social activities are carried out on emerging networks, i.e., mobile social networks (MSNs). Recently MSNs have attracted academic researches in many aspects, including network generating and organizing [2][3], excavating new kinds of services [4][5], improving communication quality [6], and reducing the load on the network infrastructures [7].

In practice, it is very important to have the accurate detection of the community structure in order to fully exploit MSNs and obtain more inherent information. The MSNs of users in physical wireless networks have been studied by using their friendship and mobility to form interest-induced or locality-induced social groups. By retrieving the hidden structure behind users, we can increase the efficiency of data forwarding among users. The structure of the social network can be derived by the inter-community links, which refers to the links between node groups.

Thus, the detection of inter-community links in MSNs deserves further research and it was firstly investigated in the field of conventional social networks. Girvan and Newman (GN) have introduced a divisive algorithm in which the edges are selected and removed one-by-one based on the value of their edges. The order of the removal process reveals the community structure of a network [8]. Filippo and Claudio proposed a method based on the edge-clustering coefficient [9]. From then on, the edge-clustering coefficient has been used in many other community detection schemes to enhance the performance [10][11].

Compressive sensing (CS) over graphs has provided another approach in community detection. As an emerging paradigm in signal processing, CS has brought new solutions to many conventional problems, including the channel estimation [12][13], interference elimination [14] and so on [15][16]. As a branch of CS, CS over graphs, which takes advantage of the sparsity over the network, can be used to detect the sparse value in a graph [17][18]. The compressive sensing approach for inter-community detection (CS-ComDet) [19] constructs an additive value via the edge-clustering coefficient to resolve this problem in the traditional social networks and achieves good performance. However, to our best knowledge, there is no relevant work in MSNs and the direct application of CS over graphs based methods

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cannot achieve ideal performance.

In this paper, an efficient detection method based on CS over graphs is proposed for the inter-community detection problem in MSNs. A novel metric based on the edge-clustering coefficient and the encounter probability in MSNs is investigated to construct the measurement matrix better. And a two-step detection method is proposed based on the CS over graphs algorithms. Moreover, the edge-clustering coefficient is investigated to improve the recovery performance. Simulations are carried out on the MSNs and the traditional social networks, and the results demonstrate that the proposed method achieves higher recovery probability than the random walk based method.

The rest of the paper is organized as follows. In Section II, the system model, the traditional random walk method based on CS over graphs and the edge-clustering coefficient are explained respectively. In Section III, the proposed inter-community detection method and the necessary analysis is addressed. The numerical stimulation results are provided in Section IV. Finally, conclusions are drawn in Section V.

II. System Model

In this section, we will briefly introduce the encounter probability in the MSNs, the traditional random walk based CS over graphs detection and the edge-clustering coefficient.

A. Encounter Probability

According to [7], the encounter durations of users in a mobile social network follow a gamma distribution

$$X \sim \Gamma(k,\theta) = \Gamma\left(\frac{M_{i,j}^2}{I_{i,j}}, \frac{I_{i,j}}{M_{i,j}}\right), \tag{1}$$

where $k = M_{i,j}^2/I_{i,j}$, $\theta = I_{i,j}/M_{i,j}$, $M_{i,j}$ and $I_{i,j}$ denote the mean and the variance of the encounter duration between user i and j, respectively.

The mean of the encounter duration $M_{i,j}$ and the variance of the encounter duration $I_{i,j}$ can be derived from the encounter histories of the users in a MSN, which can be written as

$$M_{i,j} = \frac{\sum_n X_n}{N_{i,j}}, \tag{2}$$

$$I_{i,j} = \frac{\sum_n (X_n - M_{i,j})^2}{N_{i,j}}, \tag{3}$$

where X_n is the contact duration each time.

Thus, the probability density function (PDF) of the encounter duration is given by

$$f(x;k,\theta) = \frac{1}{\theta^k}\frac{1}{\Gamma(k)}x^{k-1}e^{-\frac{x}{\theta}}, \tag{4}$$

where $\Gamma(k) = \int_0^\infty t^{k-1}e^{-t}dt$.

In order to guarantee a successful data transmission, we assume that two users can be regarded as encountering with each other if and only if they have been detected by each other for at least X_{min}. Thus, the probability of any two users encountering with each other is $p_{i,j}$, which can be represented as

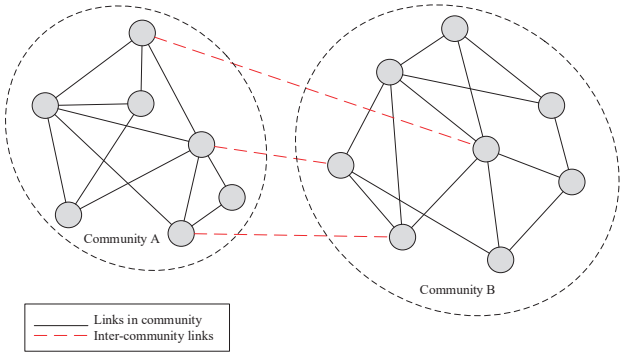


Fig. 1. The community and the inter-community links in mobile social network.

$$p_{i,j} = 1 - \int_0^{X_{min}} f(u;k,\theta)du = 1 - \frac{\gamma(k, \frac{X_{min}}{\theta})}{\Gamma(k)}, \tag{5}$$

where $\gamma(k, \frac{X_{min}}{\theta})$ is the lower incomplete gamma function, written as

$$\gamma\left(k, \frac{X_{min}}{\theta}\right) = \int_0^{\frac{X_{min}}{\theta}} t^{k-1}e^{-t}dt. \tag{6}$$

B. Compressive Sensing over Graphs Detection

Generally, the densely connected groups of nodes and sparse connections between groups define a common comprehension of the community structure in a MSN network. These groups of nodes and the links between them are called "*Community*", and the connections between groups are called "*Inter-community links*" [20]. As illustrated in Fig. 1, the dashed lines represent the inter-community links.

We consider a network which can be described by an undirected connected graph $G = (V, E)$, where V represents the set of nodes with cardinality $|V| = N$ and E represents the set of edges with cardinality $|E| = K$. The weight of each link can be 1 or any other meaningful value in a certain network and the degree of every node is denoted as $deg(V_i)$. In the graph, we consider a connected path with length L and the measurement of it is the sum of every link's weight on the path. Now, suppose we have T measurements in total over the whole graph. $\mathbf{x}$ represents a vector with length K whose j-th element is the weight of the j-th edge and $\mathbf{y}$ represents a vector with length T whose j-th element is the result of the j-th measurement. Matrix $\mathbf{A}$ with size $T \times K$ is called measurement matrix, which reflects the composition of the T measurements whose element in the i-th row and j-th column is 1 if the j-th edge is on the i-th measurement path, and 0 otherwise. Thus we have

$$\mathbf{y} = \mathbf{A}\mathbf{x}. \tag{7}$$

Fig. 2 gives an example of the construction of the measurement matrix. We consider a network with $|V| = 5$ nodes,

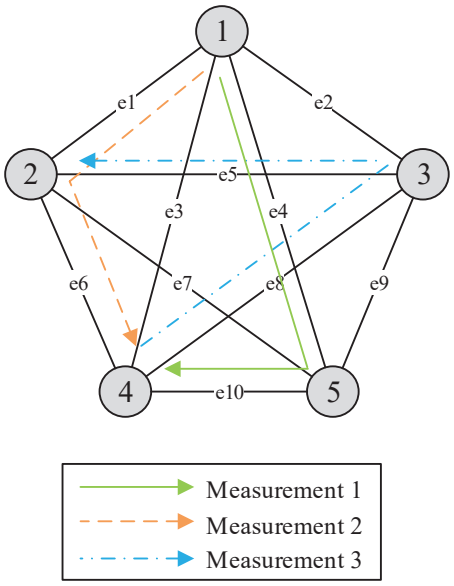


Fig. 2. The example of measurement in graph.

$|E| = 10$ edges and 3 measurements. In measurement 2, the path goes through the e1 and e6 in order. Correspondingly, the 1-st and 6-th elements in the second row of matrix $\mathbf{A}$ are 1's. The measurement matrix $\mathbf{A}$ is

$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}. \quad (8)$$

The typical model in the CS theory has the same expression as (7) [21]. It has been proved that if T and L satisfy some constraints and the matrix $\mathbf{A}$ satisfies the restricted isometry property (RIP) condition, we can recover the *s-sparse* $\mathbf{x}$ through CS recovery algorithms with an expected accuracy, in which every measurement of matrix $\mathbf{A}$ or every connected link is generated by a 'good start' regularized random walk [17][18]. Furthermore, some prior information determined in advance can reduce the complexity and improve the accuracy of CS [22]. It is intuitive that if the weight of inter-community links are sparse, the CS over graphs can be used on detection.

C. Edge-Clustering Coefficient

The edge-clustering coefficient is one of the important coefficients in a network, which is defined as

$$\mathbf{C}_{(i,j)} = \frac{z_{(i,j)} + 1}{\min[deg(V_i) - 1, deg(V_j) - 1]}, \quad (9)$$

where $\mathbf{C}_{(i,j)}$ denotes the edge-clustering coefficient between node V_i and node V_j, $z_{(i,j)}$ denotes the number of triangles including that edge and $\min[deg(V_i)-1, deg(V_j)-1]$ denotes the maximum of possible number of the triangles.

Every edge has an edge-clustering coefficient and the possible maximum number of triangles can be calculated by the degree of two nodes linked by the edge [9]. The idea behind the coefficient is that the sparse inter-community links have a low possibility to be included in a triangle and the links in the community are on the contrary. Specifically, the inter-community links tend to have a smaller edge-clustering coefficient than the links in the community.

1) The edge-clustering coefficient indicates the intrinsic sparsity of the inter-community links to a certain degree which can be used as the weight in the method of graph detection towards CS.
2) The edge with the smallest edge-clustering coefficient has a large possibility to be an inter-community link.

Thus combining edge-clustering coefficient with the CS based inter-community detection method leads to lower complexity and higher accuracy.

III. Proposed CS over Graphs Based Method

In this section, the two-step CS over graphs based inter-community detection method is proposed and explained in detail. In the first step, a novel metric is proposed based on the encounter probability and the edge-clustering coefficient in the MSNs to construct the measurement matrix. In the second step, the CS algorithms are utilized to detect the inter-community links. The pseudo-code of our proposed method is shown in **Algorithm 1**.

A. *Step 1*: Construct Measurement Matrix

The measurement matrix is constructed based on the encounter probability and the node connections in the MSNs.

In **Phase 1**, since the inter-community links have higher probabilities to connect the nodes with large degrees and frequent encounters, a novel metric is proposed to describe the weight on a node, which is different from the random walk based method

$$\mathbf{W}_i^{\text{node}} = deg(V_i) \times \left(\sum_{j \in \Psi_i} \mathbf{U}_{(i,j)} \right). \quad (10)$$

where $deg(V_i)$ denotes the degree of the node V_i, Ψ_i denotes the neighbor nodes of V_i, and $\mathbf{U}_{(i,j)}$ denotes the encounter probability between the nodes V_i and V_j.

In **Phase 2**, $\mathbf{P}^{(0)}$ is calculated by the normalization of $\mathbf{W}^{\text{node}}$, which is utilized to choose the first node in each measurement.

In **Phase 3-18**, T measurements are constructed to form the rows of the measurement matrix $\mathbf{A}$. In each measurement, the first node is chosen according to $\mathbf{P}^{(0)}$, and then the successor nodes are chosen one-by-one according to $\mathbf{P}^{(j)}$. Once a node is chosen, the link between it and the predecessor node is deleted. After T iterations, T measurements with length L are used to form the measurement matrix $\mathbf{A}$.

Algorithm 1 CS based inter-community detection with encounter probability and edge-clustering coefficient

Input:

1) Network parameters: $N = |V|, K = |E|, S$
2) Measurements parameters: T, L
3) Encounter possibility matrix $\mathbf{U}$
4) Edge-clustering coefficient matrix $\mathbf{C}$

Output:

The estimated sparse vector $\mathbf{x}$

Construct Measurement Matrix:

1: $\mathbf{W}_i^{\text{node}} \leftarrow \mathbf{U}_i$
2: $\mathbf{P}_i^{(0)} \leftarrow \dfrac{\mathbf{W}_i^{\text{node}}}{\sum_i \mathbf{W}_i^{\text{node}}}$
3: **for** $i = 1 : T$ **do**
4: Select V_1 according to $\mathbf{P}^{(0)}$
5: **for** $j = 1 : L - 1$ **do**
6: $\Psi_j \leftarrow$ neighbor of V_j
7: **if** $\Psi_j \neq \varnothing$ **then**
8: $\mathbf{P}_i^{(j)} \leftarrow \dfrac{\mathbf{W}_j^{\text{node}}}{\sum_{k \in \Psi_j} \mathbf{W}_k^{\text{node}}}$
9: Select V_{temp} according to $\mathbf{P}^{(j)}$
10: **else**
11: $V_{\text{temp}} \leftarrow$ the previous node
12: **end if**
13: Delete the link between V_{temp} and V_j
14: Update $\mathbf{W}^{\text{node}}$
15: $V_{j+1} \leftarrow V_{\text{temp}}$
16: **end for**
17: $\mathbf{A}_i^T \leftarrow [V_1, V_2, ..., V_L]$
18: **end for**

Detect with Compressive Sensing:

19: $\mathbf{W}_{(i,j)}^{\text{edge}} \leftarrow \mathbf{C}_{(i,j)}$
20: $\mathbf{w} \leftarrow \mathbf{W}^{\text{edge}}$
21: $\mathbf{y} \leftarrow \mathbf{A}\mathbf{w}$
22: $\mathbf{x} \leftarrow CS(\mathbf{A}, \mathbf{y}, S)$

B. *Step 2: Detect with Compressive Sensing*

In this step, the observation vector is constructed and the inter-community links are detected with CS algorithms.

In **Phase 19-21**, the observation vector $\mathbf{y}$ is constructed. Since the edges with larger edge-clustering coefficient have lower possibility to be inter-community links, the weight of each edge is defined as

$$\mathbf{W}_{(i,j)}^{\text{edge}} = \begin{cases} \frac{1}{\mathbf{C}_{(i,j)}} & \mathbf{C}_{(i,j)} < \varepsilon(\mathbf{C}), \\ 0 & \mathbf{C}_{(i,j)} > \varepsilon(\mathbf{C}), \end{cases} \tag{11}$$

where $\varepsilon(\mathbf{C})$ denotes the average of $\mathbf{C}_{(i,j)}$. Then the weight is transformed into vector $\mathbf{w}$, and the observation vector is derived by $\mathbf{y} = \mathbf{A}\mathbf{w}$.

In **Phase 22**, the estimated vector $\mathbf{x}$ is derived by CS algorithms. Since the measurement matrix $\mathbf{A}$ is generated with a high possibility to pass the inter-community links, we have

$$\mathbf{y} = \mathbf{A}\mathbf{w} \approx \tilde{\mathbf{y}} = \mathbf{A}\mathbf{x}. \tag{12}$$

Thus, the CS algorithm is applied to recover the vector $\mathbf{x}$, with the observation vector $\mathbf{y}$, the measurement matrix $\mathbf{A}$ and the number of inter-community links S.

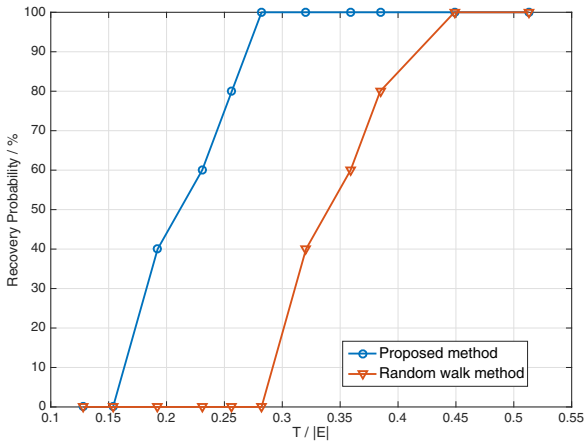


Fig. 3. The recovery probability comparison between the proposed method and the random walk method in the Karate Club network with $S = 5$.

IV. Simulation Results

In this section, we present the simulation results of the proposed inter-community detection scheme. The proposed method is simulated on both the traditional social network and the MSN scenarios. The traditional social network is simulated as a special example in which the encounter probability is 1 between each pair of users, which is collected in Zachary's Karate Club [23]. The MSN data is collected during Infocom 2005 [24]. The CoSaMP CS recovery algorithm is utilized to estimate the sparse vector in the proposed method [22]. We also implement the random walk based method as comparison.

A. *Traditional Social Networks*

The network data is from the Zachary's Karate Club [23], which has $N = 34$ nodes and $K = 78$ edges. The simulation is carried out with $S = 5$, and the recovery probability with different number of measurements is illustrated in Fig. 3.

It can be seen from Fig. 3 that the proposed method has higher recovery probability than the random walk based method with different number of measurements. The proposed method can also achieve the same recovery probability with the random walk based method with less measurements, which demonstrates the superior performance of the proposed method. The improvement benefits from the prior information based on the edge-clustering coefficient.

B. *Mobile Social Networks*

The MSN data is collected from the experiments in Infocom 2005 [24], which is conducted during Infocom 2005 for around 3 days. The traces include the encounter history of

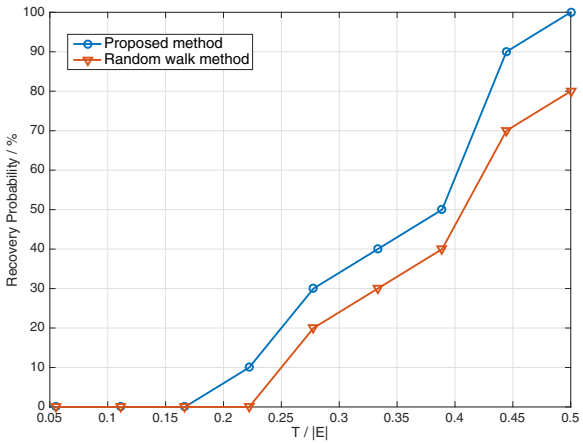


Fig. 4. The recovery probability comparison between the proposed method and the random walk method in the Infocom 2005 MSN with $S = 10$.

41 mobile iMotes with a wireless range around 30 meters, which were worn by students attending the conference. A pre-processing is applied to the network before the detection to wipe off the nodes with few connections with others and help us to concentrate on the trunk of the MSN. The encounter probability matrix $\tilde{\mathbf{U}}$ after pre-processing is given by

$$\tilde{\mathbf{U}}_{(i,j)} = \begin{cases} \mathbf{U}_{(i,j)} & \mathbf{U}_{(i,j)} > \rho, \\ 0 & \mathbf{U}_{(i,j)} < \rho, \end{cases} \tag{13}$$

where ρ is the threshold to determine the scale of the trunk of the MSN. The simulation is carried out with $S = 10$ and $\rho = 0.8$. The simulation results are shown in Fig. 4 with the random walk based method as comparison.

It can be seen from the results that the recovery probabilities of the two methods increase with the increase of the number of measurements. When the number of measurements is too small, both the proposed method and the random walk based method cannot detect the inter-community links accurately. It can also be seen that the proposed method enjoys higher recovery probability performance than the random walk based method in all range of $T/|E|$. This is because the proposed metric defined by the encounter probability and the edge-clustering coefficient exploits the inherent information in the MSN and the procedure of the measurement matrix construction makes it more likely to pass the inter-community links.

V. Conclusion

In this paper, a CS based inter-community detection method was first proposed for the MSN scenarios. In the proposed method, the algorithms of the CS over graphs are applied to detected the inter-community links. Furthermore, the encounter probability and the edge-clustering coefficient are utilized to define a novel metric and construct the measurement matrix. Simulation results show that the proposed method outperforms the traditional random walk based method in both the traditional social network and the MSN scenarios.

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