An Effective Routing Algorithm Based on Social Community for Mobile Opportunistic Networks*

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ABSTRACT

An important application scenario of mobile opportunistic networks is social contact networks, in which nodes are composed of mobile devices carried by human beings, and social relations among nodes should be considered when we design routing algorithm for mobile opportunistic networks. In this paper, we focus on social relations among nodes and node movement prediction, and propose a novel social community-based routing algorithm. We introduce the social relations as the key metrics for community dividing, and semi-Markov process is used to model movement of nodes based on the community structure. Based on the result of prediction, the next-hop nodes can be appropriately chose for message forwarding. Simulation is done, and the result shows that the proposed algorithm outperforms the other three classic routing algorithms.

CCS CONCEPTS

• **Networks** → **Network algorithms**;

KEYWORDS

mobile opportunistic network, social relations, social mobility, routing algorithm

ACM Reference format:
Nan Zhao, Feng Zeng, and Wenjia Li. 2017. An Effective Routing Algorithm Based on Social Community for Mobile Opportunistic Networks. In *Proceedings of ACM conference, , (MOBIMEDIA2017),* 6 pages.
DOI: 10.475/123_4

1 INTRODUCTION

Mobile Opportunistic Network (MONs) is a new kind of wireless self-organized network, in which there does not exist the permanent path between any two nodes, and the communication depends on the opportunity of node meeting [1]. This kind of network solves the problem of communication difficulties in traditional Ad hoc networks due to the changing network topology. The MON technology uses the "storage-carry-forward" working mechanism to complete the message forwarding, thus the traditional routing algorithm is no longer applicable [2], and effective routing design becomes a hot research issue in MONs.

The MONs have wide range of applications in challenging environments such as rural communications [3], wildlife tracking [4, 5], vehicular ad hoc networks(VANETs) [6, 7] and social contact networks [8–10]. In social contact networks, nodes are composed of mobile devices carried by human beings, the contacts and mobile behavior of nodes thus show certain social attributes. Although the network topology is dynamically changing, social relations among nodes are relatively stable. Based on this feature, it is reasonable to use social relations to design the routing algorithm.Just like in real life, individuals with close social relations are often clustered into a community, then the complex network will be divided into a number of high-cohesive communities based on the intensity of social relationship. In the same community, the contacts between nodes are frequently and stable [11], the social relations of nodes between the communities are loose.The close social relations of the nodes contribute to message forwarding. In addition, messages only need to be forwarded in a limited number of communities to reduce the number of messages copies in the network and decrease network overhead. Therefore, taking advantage of the community structure in the routing algorithm can effectively improve the routing performance [12].

In MONs, the movement of nodes has a great impact on the routing algorithm [13]. How to accurately predict the movement of nodes becomes a key issue. In this paper, we combine the structure of the community with the Markov chain. Because the movement of node from a community to another community is only related to the current time rather than history, this characteristic coincides with Markovian memoryless property, it is reasonable that use Markov chain to model nodes movement process. We regard communities in the networks as the states of Markov chain and compute the transition probability of nodes between communities, then design community-based routing algorithm by transition probability to find the appropriate forwarding node.

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*Drs. Feng Zeng and Wenjia Li are both corresponding authors for this paper. This work is supported by the Fundamental Research Funds for Central Universities of the Central South University(Grant No.2016zzts384)

MOBIMEDIA 2017, July 13-14, Chongqing, People's Republic of China

The rest of this paper is organized as follows. Section 2 shows a brief overview of the related works. In section 3, we give the system model. The design of the proposed algorithm are discussed in Section 4. Section5 focuses on the performance evaluation of the proposed algorithm. At last, a summary of our proposed methods and future works are discussed in Section 6.

2 RELATED WORK

Routing in MONs is concerned recently and continues to be a challenging issue [14]. There are several works have been specifically devoted to the research of routing algorithm. A number of routing strategies and algorithms were proposed based on "storage-carry-forward" data transmission mechanism with the goal of improving the data delivery rate, reducing the transmission delay and routing overhead [15, 16].

Epidemic Routing [17] flooded the message to all nodes without consideration to routing overhead. Theoretically, Epidemic Routing had the highest success rate of data delivery, but at the price of highest routing overhead. Direct Transmission [18] required that the source stored the data to be sent, and did not forward the data to any nodes but the destination. Direct Transmission had lowest overhead among all routing algorithms, but also had the lowest success rate of data delivery. Zhao et al. [19] studied the routing based on two-hop forwarding, the source node forwarded the data to the mobile node that encountered it, and then the mobile node was responsible for forwarding the data to the target node. By limiting backups of data within two-hop range, the mechanism reduced the forwarding cost compared to the Epidemic algorithm and accelerated the transmission process in a certain extent, but it is necessary to improve the success rate of data delivery. Unlike Epidemic algorithm and Two-hop forwarding mechanism with unlimited data backups, in [20, 21], the authors reached the purpose of reducing routing overhead by spreading a certain data backups through the network. However, these routing algorithms achieved the balance of the ratio of delivery, transmission delay and overhead.

In recent years, many scholars focus on information-aided forwarding strategy research, and the social relations of nodes is the key information for routing in MONs. Chen et al. [22] found that the friend relationship between two users is stable, and they proposed a routing algorithm based on user social graph with the calculation of the node's contact probability executed on the sender side, reducing the time of information exchanging between nodes. In [23], the authors presented a community-based message forwarding scheme for MONs, which divided the network into a number of communities on the basis of the frequency of contacts between nodes and adaptively controlled the number of message duplication. The algorithm improved delivery rate and reduced routing overhead. Li et al. [24] proposed a message transmission labeling scheme based on social structure. Each node owned a label which is used to mark the community they belong to. The main idea of the algorithm is that the message did not be forwarded to any nodes but the destination node or nodes with the same label as destination node. The algorithm can reduce the number of messages duplication in network, but have a long transmission delay and low transmission success rate.

Different from the existing works, in this paper, we consider both the node contact frequency and encounter duration for community dividing. In addition, we use homogeneous semi-Markov process to model the node mobility pattern, which accurately reveals the movement and encounter characteristics of nodes in MONs. At the same time, in our routing algorithm, according to the prediction of the nodes movement between the communities, the appropriate nodes will be selected to forward message.

3 SYSTEM MODEL

As discussed above, we firstly divide the networks into some communities according to the social relationship between nodes. Then we make use of the semi-Markov to accurately predict the movement of nodes between communities, and design the routing algorithm based on the transition probability of the nodes between communities in section 4.

3.1 Community division

In real life, the more times and the longer time of contact between individuals , the stronger social relation individuals have. On the contrary, weak social relation among people means they have few encounter times and short encounter duration. In general, we call the group with strong social relation as community. Individuals in the same community are more closely than in different communities and all of them in same community can communicate with each other in direct or indirect way.

When we use the strength of social relations to divide the community, firstly we should get a reasonable way to measure the strength of social relations among nodes.It is well known that individuals with higher contact frequency and longer contact duration are more closely, more cooperative, and the social relations even stronger. So, contact frequency is often used to measure the strength of social relations. In addition to, contact frequency should be associated with the duration of the contact when quantifying social relationships, since only the encounter state occurring over a longer period of time is firm and reliable .

Definition 1 Degree of Affinity

The degree of affinity between node i and node j is defined as the formula(1).$A_{ij}(t)$ denotes the strength of social relation between node i and node j at the current time t.

$$A_{ij}(t) = \frac{\sum_{\varepsilon=1}^{n}(t_{\varepsilon}^{e} - t_{\varepsilon}^{s})}{T} + \frac{E_{ij}}{E_i} \tag{1}$$

Where the encounter of node i and j is recorded as $R_{ij} = \{(t_{\varepsilon}^{s}, t_{\varepsilon}^{e})\}$,$\varepsilon = 1, 2, ..., n$, E_{ij} denotes the total number of times the node i and node j encounter. E_i denotes the total number of encounters between node i and the other nodes. t_{ε}^{s} represents the start time of the ε-th encounter between node i and j. t^e_ε represents the end time of the ε-th encounter between node i and j. T is the collection time.

According to the formula (1), we can compute the degree of affinity of any two nodes. In order to avoid the whole network will form one big community, we will give a threshold ϕ. When the degree of affinity exceeds the given ϕ, it shows that the social relations between nodes are strong and can be divided into the same community, so that the whole network can be divided into a number of high cohesive communities. Let $C(t) = \{C_1(t), C_2(t), ..., C_m(t)\}$ denote a collection of disjoint community.

3.2 Node movement prediction

In this paper, we use homogeneous semi-Markov process to model the movement of nodes between communities. There is no relationship between the probability of node moving from one community to another and the probability of the community which it was located in the previous. The movement of the nodes between communities is random and irregular, which is consistent with the Markovian memoryless property. So we suppose communities in the network as the state of Markov chain, the process of a node movement can be defined as follows:

$$\begin{aligned} P^i_{ab} = P(X_i(t+1) = b | X_i(t) = a, X_i(t-1) = 1,\\ X_i(t-2) = 2, ..., X_i(t-k) = k,\\ ..., X_i(t-n) = m\\ = P(X_i(t+1) = b | X_i(t) = a) \end{aligned} \tag{2}$$

Where P^i_{ab} denotes transition probability of node i from community a to community b. $X_i(t+1) = b$ means the node i is in community b at time $t+1$. $X_i(t) = a$ means the node i is in community a at time t. Formula (3) is the state transition probability matrix, which represents the probability that node i will be transferred between communities, every node will own a state transition probability matrix. In theory, if the node can move to every communities, then $\sum_{a=1}^{m} P^i_{ab} = 1$.But in reality, because of the individual's social behavior, there are some special case that some nodes never transfer from community d to community e, so $\sum_{a=1}^{m} P^i_{ab} < 1$ is reasonable.

$$P_i = \begin{pmatrix} p^i_{11} & p^i_{11} & \cdots & p^i_{11} \\ p^i_{11} & p^i_{11} & \cdots & p^i_{11} \\ \cdots & \cdots & \cdots & \cdots \\ p^i_{11} & p^i_{11} & \cdots & p^i_{11} \end{pmatrix} \tag{3}$$

Definition 2 Transition Probability of nodes

$$P^i_{ab} = \frac{N^i_{ab}}{N^i_a} \tag{4}$$

As discussed above, P^i_{ab} is the transition probability of node i. N^i_{ab} represents the number of times node i transferred from community a to community b, N^i_a represents the total number of times node i has moved from community a to other communities. According to the transition probability of nodes among communities, we can predict the next transfer of nodes.

Table 1: Node Information Table

Node_id	Community_id	transition probability matrix

Table 2: Encounter Information Table

Encounter node_id	Encounter records	Degree of Affinity

4 ROUTING ALGORITHM

In this section, we will introduce a community-based routing algorithm. In the last section, we divide the network into several communities, nodes with close social relationships and stable links are clustered into the same community, while the contacts of nodes in different communities are sparse.Therefore there are high cohesion within the community and low cohesion among communities. Based on this characteristic, we propose a community-based routing algorithm(SCRA) to improve routing performance.The main idea of the algorithm is that close social relations and frequent contacts between nodes is beneficial to forward the message in the same community ,and messages can be forwarded through the appropriate forwarding nodes when the source node and destination node in the different communities.This method can effectively improve the data forwarding rate. At the same time, the message is only forwarded in a limited number of communities, which can reduce the number of copies of the message in the network to achieve the purpose of reducing routing overhead.

4.1 Table structure

Each node maintains two tables, node information table and encounter information table. The node information table records which community the node belongs to and transition probability of node between communities. When two nodes encounter, they will update the encounter information table respectively. The encounter information table contains contact records between the node and encountered nodes. According to encounter records and the formula (1), the degree of affinity between the two nodes can be calculated for community division. Specially, the nodes transition probability matrix is updated after each period of time.

4.2 Forwarding strategy

Suppose the source node s needs to forward the message to the destination node d. There are two cases for node s to forward message, the one is source node s and destination node d are in the same community, the other one is source node s and destination node d are in the different communities.

Table 3: Forwading Messages Algorithm

Algorithm1 Forwarding messages

Input: s, d, $C(t)$

1.Suppose the source node s attemps to forward messages to the destination node d

2.**If** s and d in the same community

3. s directly forward message to d

4.**Else**

5. execute FAFN algorithm

6. s forward message to forwarding nodes

7. forwarding nodes directly forward massage to d

8.**END**

These two cases correspond to two forwarding strategies, as follows.

4.2.1 Intra-community message forwarding. If the destination node d and the source node s are in the same community, because the social relationship among the nodes in the same community is strong and the possibility of contact is large, a direct forwarding algorithm can be used to forward the message, namely, the source node s will not forward the data to any encounter nodes but the destination node d.

4.2.2 Inter-community message forwarding . In this paper, the appropriate forwarding nodes refer to the node in the same community as the destination node d and the node will be in the same community as the destination node d through the next movement. According to the above node movement prediction method, we can find the nodes that will move to the community where the destination node d is located. The algorithm of finding appropriate forwarding nodes(FAFN) is shown in table 4. Source node s will send message duplication to appropriate forwarding nodes. When appropriate forwarding nodes is located in the same community with destination node d, it will use intra-community message forwarding strategy, as show in 4.2.1.

Table 4: Finding Appropriate Forwarding Nodes Algorithm

Algorithm2 Finding appropriate forwarding nodes(FAFN)

Input: s, d, $C(t)$, P_n

Output:φ {forwarding set}

1.**For all** encounter node e **do**

2. **If** e in the same community with d

3. $\varphi = \varphi \cup e$

4. Search for f such that

$$f = \arg\max \left\{ \sum_{a=C(t);b=1}^{b=m} p_{ab}^{f} * \sum_{a'=1,\forall a' \neq a; \forall b' \neq b}^{a'=m} p_{a'b'}^{d} \right\} \tag{5}$$

5.$\varphi = \varphi \cup f$

6.**End for**

7.**Return** φ

5 SIMULATIONS

We implement the proposed scheme of Social-base Clustering and Routing (SCRA) in ONE simulator [25], and evaluate SCRA by performance comparison with Epidemic, PRoPHET and bubble algorithm . In simulation, for Epidemic, PRoPHET and bubble algorithm ,the real datasets Infocom5 are used for node activities driving, which can be downloaded from CRAWDAD (http://www.crawdad.org/). In simulation, node buffer size is set to 5M, TTL is 200 minutes, and message size is 1K. In the same simulation environment, SCRA, Epidemic, PRoPHET and bubble algorithm run respectively with 274833 seconds of total simulation time.

We compare the performance of each routing algorithm in the same simulation environment and analyze the impact of parameters on SCRA. The following metrics are used in the performance comparison.

1) **Data Delivery Rate** :

The ratio of the number of data packets successfully reached the destination node and the amount of data packets sent by the source node within a certain time.

2) **Transmission Delay** :

The delay is the average time it takes for a packet to reach the destination after it leaves the source.

3) **Routing Overhead Ratio** :

As shown in equation (6), the total number of data packets to be forwarded (relayed_number) minus the number of data packets successfully transferred to the destination node (delivered_number), and then divided the number of data packets successfully transferred to the destination node.

$$\begin{aligned} &Routing\ Overhead\ Ratio \\ &= \frac{relayed\_number - delivered\_number}{delivered\_number} \end{aligned} \tag{6}$$

5.1 Data delivery rate

With various simulation times, the result of data delivery rate is shown in Figure 1. When simulation time is less than one day, SCRA has the higher data delivery rate compare to the other three algorithms. Due to the contacts of nodes is important for data delivery in social contact networks. For Infocom5 dataset, in the one days, the less contacts of nodes have negative on the data delivery ratio. As you can see, the data delivery rate of SCRA approach the Epidemic with the increasing of simulation time. Compared with PRoPHET, the data delivery rate of SCRA has increased by 9.2%. The data delivery rate of SCRA is 17.8% higher than Bubble

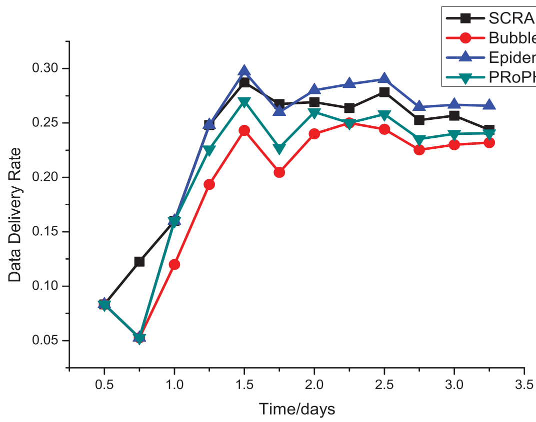

Figure 1: Data delivery rate with various simulation times.

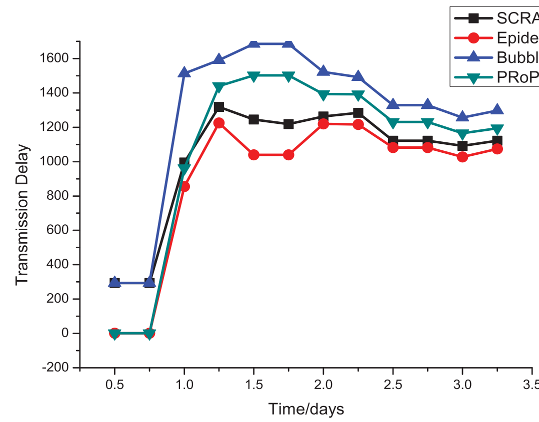

Figure 3: Transmission delay comparison.

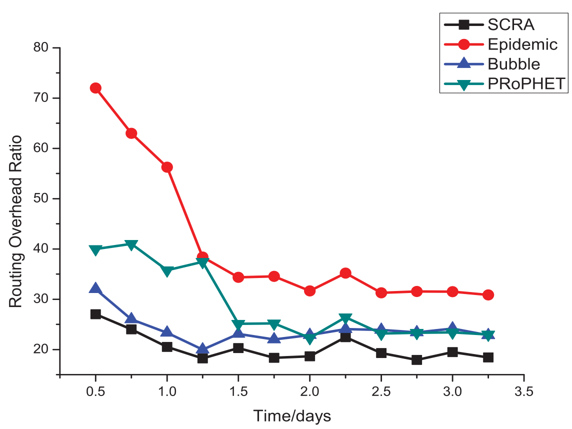

Figure 2: Routing overhead ratio comparison.

algorithm. In SCRA algorithm, we forward the data by predicting the location of the destination node to improve the data delivery rate.

5.2 Routing overhead ratio

The comparison of routing overhead is shown in Figure 2. SCRA can reduce routing overhead by about 13.4%, 23.1% respectively, compared to Bubble and PRoPHET. To Epidemic, the routing overhead of SCRA is Falling sharply, but SCRA has a close data delivery rate. Since the message is forwarded to the communities which contain the destination node and the destination node will transfer. And SCRA can predict the movement of nodes between communities.Consequently, the total number of message forwarding is reduced without negative effect on data delivery rate.

5.3 Transmission Delay

The transmission delay of each algorithm is shown in Figure 3. Compared with PRoPHET and Bubble, SCRA has the transmission delay decreased by 5.2% and 16.8% respectively. The reason why the transmission delay of SCRA is higher than Epidemic and PRoPHET in the one day is community need time to divide. As the simulation time increases, SCRA cluster the nodes with close social relations into the same community. SCRA is cluster-based routing, and cluster members have strong social relationships with each other, it can reduce unnecessary data transmission, and thereby reduce the transmission delay.

6 CONCLUSION

In this paper, we propose a novel social community-based clustering routing algorithm in MONs. To resolve the problem of data forward in mobile opportunistic networks, we study the measurement method for social relationships among nodes and introduce the node contact frequency and encounter duration as the key metrics to measure the social relation among nodes. Then, we cluster the nodes with close social relation into a community. To accurately predict the movement of nodes between communities, we use semi-Markov process to model movement of nodes based on the community structure. At the same time, we design a routing mechanism based on social community. In the same community, we use direct delivery to forward message because of the frequent and stable encounters between the members of community. Otherwise, According to the transition probability of nodes, we known the movement of nodes between communities, then we find the appropriate nodes in the same community as destination nodes currently and will be in the same community at the next transition. Simulation has done, the result shows that the proposed algorithm outperforms the other three classic routing algorithms.

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