

Routing with Multi-Level Social Groups in Mobile Opportunistic Networks

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Abstract—Mobile Opportunistic Networks (MONs) are intermittently connected networks, such as pocket switched networks formed by human-carried mobile devices. Routing in MONs is very challenging as it must handle network partitioning, long delays, and dynamic topology. Flooding is a possible solution but with high costs. Most existing routing methods for MONs avoid the costly flooding by selecting one or multiple relays to deliver data during each encounter. How to pick the “good” relay from all encounters is a non-trivial task. To achieve efficient delivery of messages at low costs, in this paper, we propose a new group-based routing protocol in which the relay node is selected based on social group information obtained from historical encounters. We apply a simple formation method to build multi-level social groups, which summarizes the wide range of social relationships among all mobile participants. Our simulations demonstrate the efficiency and effectiveness of the proposed method by comparing it with several existing MON routing schemes.

I. INTRODUCTION

Mobile Opportunistic Network (MON) is one of the emerging communication paradigms in wireless mobile communications. MONs are commonly defined as a type of mobile networks where communication is challenged by sporadic and intermittent contacts as well as frequent disconnections and reconnections, and where the assumption of the existence of an end-to-end path between the source and the destination is relinquished. Examples include pocket switched networks [1], [2], which are comprised of human-carried mobile devices moving in a restricted physical space and use occasional contact opportunities to deliver data. Intermittent connectivity in MONs results in lack of instantaneous end-to-end paths, large transmission delays and unstable network topology. These characteristics make the classical mobile ad hoc routing protocols not applicable for MONs, therefore, many opportunity-based routing protocols [2]–[9] are proposed recently for MONs.

Most of existing opportunity-based routing methods for MONs share the same principle, “store and forward”, to handle intermittent connectivity. If there is no connection available at a particular time, the current node can store and carry the data until it encounters other nodes. When the node has such

a forwarding opportunity, all encountered nodes could be the candidates to relay the data. Therefore, relaying selection and forwarding decision need to be made by the current node based on certain forwarding strategy.

The simplest routing method is *epidemic routing* [3], in which a node forwards copies of message to any nodes it encounters. This flooding-based method can guarantee the best delivery ratio, but with possibly huge message overheads. To reduce the overheads, many routing methods restrict the number of message replicas in the network to a certain constant (such as in *Spray and Wait* [4]) or just one (such as in *SimBet* [6]) or a small one by only replicating the message when certain condition is met (such as in *delegation forwarding* [5]). We call the method which allows multiple replicas and the method which allows a single replica as multi-copy routing and single-copy routing, respectively.

Forwarding decision (or replicating decision) and relay selection in these routing protocols usually rely on comparisons between per-node metrics. For example, in *FRESH* [7] the current node forwards if it encounters another node which has met the destination more recently than it does, and if multiple nodes satisfy such a condition during encounter it just selects the one which has met the destination most recently as the relay; in *Greedy-Total* [8] the node forwards if it meets nodes with a higher contact frequency, it picks the one with highest frequency as the relay. In addition to these metrics which aim to estimate the delivery probability or expected delay to the destination node, there are also certain social metrics (such as community and centrality) which can be used to assist forwarding decision and relay selection in recent *social-based* approaches [2], [6], [10]–[12]. For example, in *SimBet* [6] the current node forwards if it encounters a node with higher social centrality and has more common neighbors with the destination; in *Bubble Rap* [2] the current node forwards data to the node with higher centrality following a hierarchical community structure. These social-based methods take the advantages of understanding of social relationships among nodes to make smarter forwarding decisions.

In this paper, we propose a new group-based routing protocol for mobile opportunistic networks, in which the relay node is selected based on social group information obtained from historical encounters. We introduce a simple formation method to build multi-level social groups, which summarizes the wide range of social relationships among all mobile participants. Notice that social relations and behaviors among mobile users

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are usually long-term characteristics and less volatile than node mobility. Our group-based routing method forwards the packet greedily toward the destination's social groups. We conduct extensive simulations using real life tracing data [13], [14] to compare the proposed method with several existing methods. Our simulation results demonstrate the efficiency and effectiveness of the proposed method.

II. RELATED WORKS

Mobile opportunistic networks are special cases of *Delay/Disruption Tolerant Networks* (DTNs) [15]. The major difference of DTNs from MONs is that mobility is often predictable or the future contact information is known. Irregularity of mobility pattern in MONs poses great challenges in the design of routing protocols. Here, we mainly focus on *opportunity-based routing* where messages are forwarded using available communication opportunities when nodes meet at the same place. By taking the advantages of mobility of intermediate nodes, it is expected to deliver the messages eventually, but with no guarantees.

Epidemic routing [3] floods copies of message to any nodes it encounters, thus can guarantee the delivery. However, it suffers from huge message overheads. Spyropoulos *et al.* [4] then proposed *Spray-and-Wait* routing which limits the total number of replicas of a message in the network by a constant x . The source of the message initially creates x replicas of the message. If a node u has $k > 1$ replicas and meets a node v with no replicas, u forwards half of its replicas to v and keeps the other half. Erramilli *et al.* [5] also proposed another way to reduce the total number of replicas, called *delegation forwarding*, in which the current node only forwards a replica to encountering nodes with highest-quality metric so far. In other words a node will forward a message only if it encounters another node whose quality metric is greater than any nodes the message has yet met. Here, the quality metric can be defined in different ways as we will discuss it in the next paragraph for single-copy routing. All these three methods allow multiple replicas propagated in the network which can clearly improve the chance of delivery.

There are also many forwarding schemes which only allow one single copy of each message in the network, *i.e.*, after forwarding the message to a single selected encountered node the current node will not forward anymore. Forwarding decision usually relies on certain type of quality metric and the message is only forwarded to a node with higher quality metric. If during an encounter, there are multiple nodes with higher quality metric, only the one with highest quality metric is selected as the relay. Examples include *FRESH* [7] (picking the node which has met the destination more recently), *Greedy-Total* [8] (picking the node with a higher encounter frequency to all other nodes), or *MobySpace* [16] (picking the node which has more location similarity with the destination).

Mobile devices in MONs are used and carried by people, whose behaviors are better described by social models. This opens the new possibilities of social-based routing [12] for MONs, in which the knowledge of social characteristics is

used for making better forwarding decisions. For example, nodes with higher social centrality (more popular) are selected as relay nodes (such as in *SimBet* [6], *Bubble Rap* [2], and *friendship based* routing [11]); or nodes within the same community (or social group) with the destination is preferred as relay nodes (such as in *Label* routing [10], *Bubble Rap* [2], and *friendship based* routing [11]). Our proposed group-based method belongs to this category and uses the concept of social groups to extract underlying social relationships among all nodes. However, it is different from the community-based method (such as *Bubble Rap* [2]) by using a much simpler social group formation method.

III. GROUP BASED FORWARDING

In this section we introduce our group-based routing protocol for mobile opportunistic networks in details. We start with a simple social group formation and then follows with two versions of the proposed group-based routing. Here, we assume that a set of n mobile nodes $V = \{v_1, v_2, \dots, v_n\}$ and each possible data forwarding happens when two mobile nodes are in contact (*i.e.*, move within transmission range of each other). By recording contacts seen in the past, a *contact graph* G can be generated where each vertex denotes a mobile node (device or person who carries the device) and each edge represents one or more past meetings between two nodes. An edge in this contact graph conveys the information that two nodes encountered each other in the past. Such existence of an edge intends to have predictive capacity for future contacts. The contact graph can be constructed to record the encounters in a specific period of time by recording the time, the frequency and the duration of all encounters.

A. Simple Social Group Formation

Since wireless devices are usually carried by people, it is natural to explore the social interactions among wireless devices in mobile opportunistic networks to design better forwarding strategy. *Social group* (or community) is an important concept from sociology [17], [18]. A social group is usually defined as a group of interacting people living in a common location. Sociologists have studied the interactions between people in groups on many spatial and temporal scales [17]–[20] and shown that a member of a given social group is more likely to interact with another member of the same group than with a randomly chosen member of the population [19]. Therefore, social groups naturally reflect social relationships among people in social networks and implicitly define encounter patterns among wireless devices in mobile opportunistic networks. Our proposed group-based routing protocol hence uses social group information obtained from historical encountered data (a contact graph) to make its forwarding decision.

Constructing social groups from the encountered data could be done by using different methods. For example, there are several community detection algorithms [21]–[24] available for identifying social communities from the underlying contact graphs. However, most of these methods are relatively complex

and not suitable for real-time executions in MONs. Instead, in this paper, we adopt a very simple social group formation method based on the number of past encounters among nodes. For any two nodes v_i and v_j , if there is more than t encounters between v_i and v_j in the past, they will be placed into the same group. Here t is an adjustable threshold which defines how strong the social tie between two members is. In other words, given the contact graph G in the past, we only keep an edge between v_i and v_j when the number of their encounters is larger than or equal to t . For the graph G_t formed by all remaining edges, we treat each connected component as one social group. If two nodes are within the same group, there must be a path connecting them in G with all “strong” contact history. Another way to form the social group is letting each completed subgraph of G_t be a social group. This requires a much stronger tie among group members, *i.e.*, any two members must directly have a “strong” contact history. In our simulations, we use the first method to define social groups. Notice that by defining different values of t , we can construct multi-level social groups. Larger t leads to smaller groups with stronger ties. See Figure 1 for illustration.

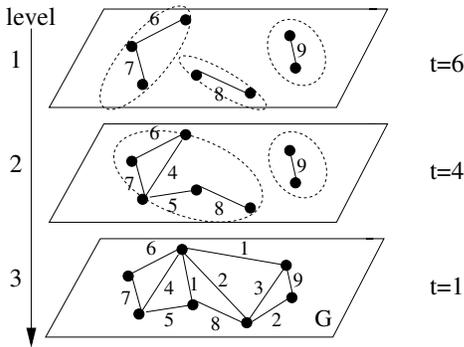


Fig. 1. Multi-level social groups formed from different values of t . The number labeled on each link is the number of past encounters between two endpoints. When $t = 1$, G_t is the original contact graph G .

Note that our group-based forwarding algorithm does not rely on particular social group formation method. Social group information from other group/community detection algorithms or specified by users could be adopted in our model.

B. Routing with Single-Level Social Group

Having the knowledge of social groups could help routing protocol to choose better forwarding relays for particular destinations, and hence improve the chance of delivery. Since it is believed that devices within the same social group have higher chances to encounter with each other, our group-based forwarding method intends to choose the member of social group of the destination as the preferred relay nodes.

Our group-based forwarding method (denoted by **Group** hereafter) works as follows. The current node v_i with a message M destined to v_d meets a set of nodes which means that they are capable to exchange messages. Assume that R is the set of nodes among them which do not hold message M , *i.e.*, all possible relay nodes at this particular time. If

the destination v_d of message M is in R , v_i simply delivers the message to v_d . Otherwise, v_i looks for nodes within the same group of v_d (we use $g(v_d)$ to denote the member set of social group of v_d) as possible relay nodes. If there exists multiple such nodes, our method picks the one which has met the destination most recently as the relay node and forwards M to it. This is similar to the idea of *FRESH* [7]. If there is no any member of $g(v_d)$ in R , v_i continues holding M . Algorithm 1 shows the detailed description. In **Group**, social group information is used to increase the chance of meeting the destination while the *FRESH* pick tries to deliver the message to destination as soon as possible.

Algorithm 1 Group-based Forwarding (**Group**)

Node v_i with a message M destined to v_d meets a set of nodes R which do not hold M .

- 1: **if** $v_d \in R$ **then**
 - 2: Forward M to v_d
 - 3: **else**
 - 4: **if** there exists $v_j \in R$ within the same group with v_d ,
i.e., $\exists v_j \in R \cap g(v_d)$ **then**
 - 5: Let v_k be the node in $R \cap g(v_d)$ which has contacted
 v_d most recently
 - 6: Forward M to v_k
 - 7: **end if**
 - 8: **end if**
-

C. Routing with Multi-Level Social Groups

In **Group**, we only use one-level of social group information to make forwarding decision. However, the choice of threshold t could affect the routing performance significantly. If t is too large, the constructed group could be too small and none relay nodes could be found in **Group**. If t is too small, the constructed group will include everyone and **Group** will regress to *FRESH*. Therefore, it makes great sense to take the advantages of wide spectrum of social relationships by considering multi-level social group information into our group-based forwarding method. We call this version of our method **mGroup**.

In **mGroup**, we consider m -level social groups $g_{t_1}(), g_{t_2}(), \dots, g_{t_m}()$ formed by different thresholds. We assume that $t_1 > t_2 > \dots, t_m$, thus the first level group (we called top level) requires the strongest social tie among its members while the m level group has the weakest social ties. During a round of encounter, **mGroup** starts with the top-level group with threshold t_1 . If no node locates in the same group with the destination, **mGroup** will check with the second level group of the destination. This procedure continues until either it finds a relay node within the same group of the destination or m -level groups are all explored. By taking the full advantages of social groups at all levels, **mGroup** intends to achieve better performance than **Group**. Algorithm 2 shows the details of **mGroup**.

Algorithm 2 Multi-level-Group-based Forwarding (mGroup)

Node v_i with a message M destined to v_d meets a set of nodes R which do not hold M . Information of m -level social groups $g_{t_1}(), g_{t_2}(), \dots, g_{t_m}()$ is available, where $t_1 > t_2 > \dots, t_m$.

```
1: if  $v_d \in R$  then
2:   Forward  $M$  to  $v_d$ 
3: else
4:    $k = 1$ 
5:   while  $k < m$  do
6:     if there exists  $v_j \in R$  within the same group at level
        $k$  with  $v_d$ , i.e.,  $\exists v_j \in R \cap g_{t_k}(v_d)$  then
7:       Let  $v_k$  be the node in  $R \cap g_{t_k}(v_d)$  which has
       contacted  $v_d$  most recently
8:       Forward  $M$  to  $v_k$  and  $k = m + 1$ 
9:     else
10:       $k = k + 1$ 
11:     end if
12:   end while
13: end if
```

IV. SIMULATIONS

In this section we conduct extensive simulations with realistic contact traces to evaluate our proposed method and compare it with existing opportunity-based routing schemes.

A. Compared Routing Methods

We implement our algorithm mGroup and compare it with five other existing routing methods which are listed below.

- **Epidemic** [3]: during any encounter, the message is forwarded to all encountered nodes.
- **Spray and Wait** [4]: when node v_i has $k > 1$ message replicas and meets node v_j , it gives v_j half of its replicas and keeps the other half. Initially, the source have x copies of the message. The default value of x is 10 in our simulations. If there are multiple nodes during the encounters, v_i randomly picks one of them to share its copies.
- **FRESH** [7]: the message is only forwarded from node v_i to node v_j if v_j has met the destination more recently than v_i does. If there are multiple nodes satisfying such a condition during the encounters, v_i forwards the message to the one who has met the destination most recently.
- **Destination Frequency** [5]: the message is only forwarded from v_i to v_j if v_j has met the destination more often than v_i does. If there are multiple nodes satisfying such a condition during the encounters, v_i forwards the message to the one who has met the destination most often.
- **Greedy-Total** [8]: the message is only forwarded from v_i to v_j if v_j has more total contacts with all other nodes than v_i does. If there are multiple nodes satisfying such a condition during the encounters, v_i forwards the message to the one who has most contacts.

B. Routing Metrics

In all experiments, we compare each algorithm using the following routing metrics.

- **Delivery ratio**: the average percentage of successfully delivered messages from the sources to the destinations.
- **Hop count**: the average number of hops during each successful delivery from the sources to the destinations.
- **Delay**: the average time duration of successfully delivered messages from the sources to the destinations.
- **Number of forwarding**: the average number of messages forwarding in the network during the whole period.

C. Simulation Results on NUS Contact Trace Data

In order to test our proposed forwarding method in realistic mobile opportunistic networks, we first use the NUS student contact trace [13], which was collected during the Sprint semester of 2005/2006 in National University of Singapore. There are total 22,341 students who enroll in 4,885 sessions and last for 77 session hours in this dataset, which is publicly available at Crowdad [25].

As different sessions have various start and end time and may last more than one hour, we split all sessions into unit time slot size (one hour). Therefore, there will be total 77 time slots. If two students share the same session at a particular time slot, we consider they have contact in that time slot. We use the same method used in [9] to select a subset of students for our simulations. Contacts related to the non-selected students are ignored. The selection method works as follows. The first student is randomly selected. If we already have k students, we randomly split them into two groups V_1 and V_2 . Then we select the next student as the one who has highest connection to students in V_1 and the lowest connection to students in V_2 among the students that are not yet selected. Here the level of connection is the average number of shared sessions. We put the selected student in group V_1 . This procedure is repeated until we have the required number of students.

For routing tasks, we randomly choose 50 pairs of selected students as the sources and destinations. All results are reported as the average of these 50 tasks. We test both single-copy and multiple-copy routing versions of all methods. For the multi-copy case, we allow the number of replicas at the source at either 10 or 20. Table I summaries the parameters used in our experiments.

TABLE I
PARAMETERS USED FOR NUS DATASET

Parameter	Value or Range
Total Number of Students / Sessions	22341 / 4885
Total Number of Time Slot	77
Number of Selected Students	100 – 600
Number of Routing Tasks	50
Number of Message Replicas Allowed	1,10 or 20
Number of Levels of Social Graph	1 or 4

In total, we have conducted three sets of simulations. In all simulations, we increase the number of selected students from 100 to 600 and perform 50 routing tasks in each setting. For all

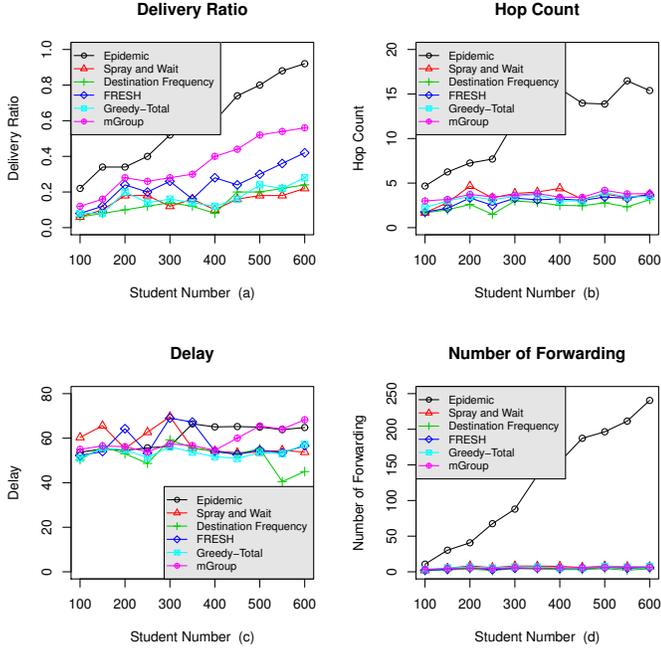


Fig. 2. Simulation results of all different routing algorithms.

methods, we use the first 40 sessions data as historical data to obtain statistics (such as social groups or encounter counts), and routing tasks are performed for the last 37 sessions to evaluate the routing performances.

In the first set of simulations, we consider all methods (using their multi-copy versions in which the total number of copies is limited by 10, except for epidemic routing). Figure 2 shows all results. It is clear that the delivery ratio is increasing as the number of students (devices) increases. This is reasonable since denser networks provide more opportunities for message delivery. As shown in Figure 2(a), our proposed mGroup algorithm achieves better delivery ratio than any others except for epidemic routing. Notice that even though epidemic routing has the best delivery ratio, it costs extremely large amount of forwarding as shown in Figure 2(d). In terms of hop count, delay and number of forwarding, mGroup is at the similar level with those of other opportunity-based methods.

In the second set of simulations, we compare the performance of our group-based methods using either a single-level social group (Group) or multi-level social groups (mGroup). For Group, we use different threshold values $t = 5, 10, 15, 20$. For mGroup, we use all these 4-level of social groups. Figure 3 shows the results in which Group $_t$ denotes Group method with threshold value t . For Group $_t$ with single-level social group, larger threshold t leads to higher delivery ratio since it provides the information of stronger social ties. However, overall mGroup with multi-level social groups has the highest delivery ratio. This confirms our original conjecture of better performance with more information.

In the last set of simulations, we consider both single-copy and multi-copy versions of our methods. We allow different

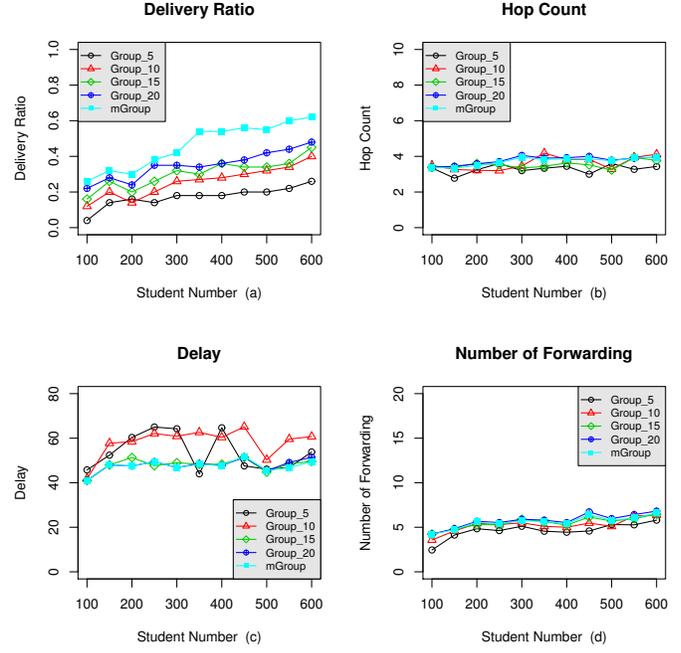


Fig. 3. Simulation results of mGroup and Group routing.

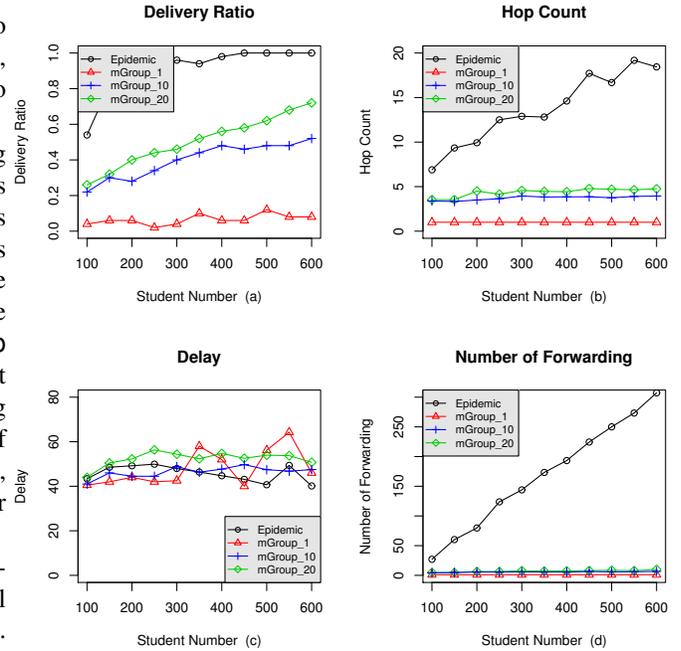


Fig. 4. Simulation results of mGroup with different number of copies.

numbers of copies (1, 10 or 20) during the routing. Figure 4 shows the comparison in which mGroup $_x$ denotes mGroup method with limitation of x numbers of copies. It is obvious that with more message copies all methods can achieve higher delivery ratio but increase the number of forwarding too. There is clearly a trade-off between number of copies and forwarding overhead.

TABLE II
SIMULATION RESULTS ON CAMBRIDGE BLUETOOTH DATASET

	Epidemic	Spray and Wait	Dest. Frequency	FRESH	Greedy-Total	Group_5	Group_10	Group_15	mGroup
Delivery Ratio	0.68	0.58	0.61	0.60	0.58	0.60	0.63	0.66	0.67
Hop Count	1.9	3.1	2.2	2.7	3.4	2.9	2.9	3.1	3.1
Delay	68	69	69	69	69	69	68	69	51
Number of Forwarding	12.6	5.6	2.9	4.4	5.0	4.0	4.0	4.4	4.2

D. Simulations Results on Cambridge Bluetooth Trace Data

We also test the performance of proposed social-group based routing protocols using a real-life Bluetooth trace dataset. The Bluetooth trace data [14] was collected from a group of mobile users (mainly students from Cambridge University) who were asked to carry iMotes with them for two months in 2005. The Bluetooth trace data consists of measurement data from 36 mobile participants and 18 fixed locations. In order to discover the social relationships among mobile users, we only use tracing contacts between 36 mobile students in this set of simulations. We split the contact time duration into unit time slot size (one hour) and test the performance of proposed single-level social group (Group) and multi-level social groups (mGroup) protocols together with other existing routing methods mentioned in Section IV-A in randomly chosen 120 time slots. For all routing protocols, we use the first 40 hours data as historical data to obtain social group information and evaluate the performance of routing tasks for the remaining 80 hours. In the simulation, each student tries to send messages to other 35 students, thus there are $36 \times 35 = 1260$ source and destination pairs in total.

The simulation results are shown in Table II which are the average of these 1260 routing tasks. The number of message replicas at the source is set to 10 except for epidemic routing. The simulation results for Bluetooth trace data are consistent with those for NUS trace data, such as for Group_t with single-level social group method, larger threshold *t* leads to higher delivery ratio; three-level social groups mGroup protocol has the highest delivery ratio among all others except for epidemic routing, but the number of message forwarding of mGroup is much less than epidemic routing and mGroup is at the similar level in terms of hop count, delay and number of forwarding with those of other opportunity-based methods.

V. CONCLUSION

Mobile opportunistic networking is a new emerging communication system which takes advantages of any possible contact opportunities to deliver data among mobile devices. Routing in such networks is a challenging problem. In this paper, we propose a new group-based routing method which forwards message based on multi-level social group information. Our simulation results demonstrate the great performance of the proposed method and the advantages of considering diverse social relationships among nodes during relay selection. We leave exploring more complex social group analysis to achieve further performance improvement as one of our future works.

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