Social Feature Enhanced Group-based Routing for Wireless Delay Tolerant Networks

Fan Li* Chao Zhang* Zhenmin Gao* Lunan Zhao* Yu Wang†
* School of Computer Science, Beijing Institute of Technology, Beijing, 100081, China.
† Department of Computer Science, University of North Carolina at Charlotte, Charlotte, NC 28223, USA.

***Abstract*—Mobile devices in delay tolerant networks (DTNs) are used and carried by people, whose behaviors could be described by social models. Understanding social behaviors and characteristics of mobile users can greatly help the routing decision in DTN routing protocols. However, to obtain the stable and accurate social characteristics in dynamic DTNs is very challenging. To achieve efficient delivery of messages at low costs, in this paper, we propose a novel enhanced social group-based routing protocol in which the relay node is selected based on multi-level cross-community social group information. We apply a simple group formation method with both historical encounters (social relationships in physical world) and social features of mobile users (social relationships in social world) and build multi-level cross-community social groups, which summarize the wide range of social relationships among all mobile participants. Our simulations over a real-life data set demonstrate the efficiency and effectiveness of the proposed method by comparing it with several existing DTN routing schemes.**

***Index Terms*—routing, relay selection, social features, multi-level, delay tolerant networks**

I. Introduction

In wireless *Delay Tolerant Networks* (DTNs) [1], mobile devices are moving around and contact each other opportunistically in cooperative way to deliver data in challenging environments. The possible applications of wireless DTNs include vehicular networks [2]–[4], space communications [5]–[7], pocket switched networks [8]–[10], and mobile social networks [11], [12]. Intermittent connectivity in these DTNs results in lack of instantaneous end-to-end paths, large transmission delays and unstable network topology. Therefore, the classical ad hoc routing protocols, which request the existence of end-to-end paths between the source and the destination during the route discovery and data delivery phases, are not applicable or perform poorly in DTNs.

Many opportunity-based routing protocols [13]–[19] have been proposed for delay tolerant networks to handle intermittent connectivity. Most of these DTN routing methods share the same principle, *store and forward*, which is described as follows. If there is no connection available at a particular time, the node with the packet can store and carry the packet until it encounters other nodes. When the node has such a forwarding opportunity, it needs to decide which encountered node to be the relay of this packet towards the final destination. Various DTN routing methods adopt different forwarding strategies to select such relay nodes based on certain routing metrics, such as estimated delivery probability, historical contact frequency, available network resources, or estimated delay.

In many delay tolerant networks, especially pocket switched networks or mobile social networks, a multitude of mobile devices are used and carried by people, whose behaviors could be described or modeled by social models. If social characteristics of the mobile users or devices can be obtained or learned, they can be used to improve the DTN forwarding decision. Notice that social relationships and behaviors among users are usually long term characteristics and less volatile than node mobility. This inspires a new type of DTN routing: *social-based* DTN routing [20]. These social-based approaches [8], [10], [21]–[23] exploit various social characteristics in DTNs (such as community and centrality) to assist the relay selections. For example, nodes with higher social centrality (more popular) are selected as relay nodes (such as in *SimBet* [21], *Bubble Rap* [8], and *friendship based* routing [22]); or nodes within the same community (or social group) with the destination are preferred as relay nodes (such as in *Label* routing [10], *Bubble Rap* [8], *group based* routing [23] and *friendship based* routing [22]).

Social-based DTN routing methods have been proved more promising than pure opportunity-based routing protocols for certain DTNs since they take advantages of relatively stable characteristics (social properties) to predict and deal with the dynamics of DTNs. However, to obtain the stable and accurate social characteristics in dynamic DTNs is a very challenging task. Most of the existing social-based approaches obtain social metrics (such as community and centrality) from the trajectory and/or the contact history of mobile users. This information is dynamic and usually has to be collected globally through a long-term process. Recently, both [24] and [25] found that certain social features (such as occupation, personal interest, age) can be used to improve the performance of DTN routing if they are available. These social features are relatively static and can be obtained before the deployment of the network. Routing methods based on these social features do not need to maintain any dynamic states except for these static social features. Thus, sometime, they are called stateless protocols.

To achieve efficient delivery of messages at low costs, in this

The work of F. Li is partially supported by the National Natural Science Foundation of China under Grant 60903151, Beijing Natural Science Foundation under Grant 4122070 and Scientific Research Foundation for the Returned Overseas Chinese Scholars, State Education Ministry. The work of Y. Wang is supported in part by the US National Science Foundation under Grant No. CNS-0915331 and CNS-1050398. F. Li (fli@bit.edu.cn) and Y. Wang (yu.wang@uncc.edu) are co-corresponding authors.

paper, we propose an enhanced group-based routing protocol for delay tolerant networks, in which the relay node is selected based on social group information obtained from both historical encounters (social relationships in physical world) and *social features* of mobile users (social relationships in social world). We adopt a simple but efficient formation method [23] to build multi-level cross-community social groups, which summarizes the wide range of social relationships among all mobile participants. Our group-based routing method forwards the packet greedily toward the destination's social groups. Simulation results on a real life tracing data [26] demonstrate the efficiency and effectiveness of our social feature enhanced group-based routing method, comparing with several existing methods.

The rest of the paper is organized as follows. Section II briefly reviews the group-based routing and its group formation method from our recent work [23]. Section III provides our detailed design of social feature enhanced group-based routing for wireless delay tolerant networks. Section IV presents our simulation results over a real-life mobile tracing data [26]. Finally, Section V concludes the paper.

II. Group-based Routing

Our social feature enhanced group-based routing is based on a multi-level social graph based routing from our previous work [23]. Social group (or community), an important concept from sociology [27], is usually defined as a group of interacting people living in a common location. It has been 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 [27], [28]. Therefore, social groups may reflect possible encounter patterns among mobile users in DTNs and our social group-based routing [23] uses social group information obtained from historical encountered data (a contact graph) to make its forwarding decision .

Many methods [29]–[32] can construct social groups or communities from the encountered data. However, most of them are relatively complex. Instead, 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 are more than t encounters between them 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 inside a group. Assume that G is the contact graph including all past encounter relationships among nodes, 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_t with all "strong" contact history. 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.

Since it is believed that devices within the same social group have higher chances to encounter with each other, our multi-level group-based forwarding method mGroup intends

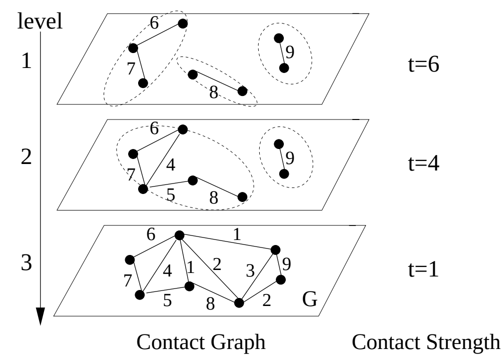

Fig. 1. *Multi-level social groups* formed from contact graph with different values of t. The number labeled on each link is the number of past encounters between two endpoints. When $t = 1$, G_t is the original contact graph G.

Algorithm 1 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 $g_{t_1}(), g_{t_2}(), \cdots, g_{t_m}()$ is available, where $t_1 > t_2 > \cdots, t_m$.

if $v_d \in R$ **then**
  Forward M to v_d
else
  $k = 1$
  while $k < m$ **do**
    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**
      Let v_k be the node in $R \cap g_{t_k}(v_d)$ which has contacted v_d most recently
      Forward M to v_k
      return
    else
      $k = k + 1$
    end if
  end while
  Hold M
end if

to choose the members of the destination's social group as the preferred relay nodes. Algorithm 1 shows the details of mGroup. In mGroup, we consider m-level social groups $g_{t_1}(), g_{t_2}(), \cdots, g_{t_m}()$ formed by different thresholds. We assume that $t_1 > t_2 > \cdots, t_m$, thus the first level group (top level) requires the strongest social tie among its members while the m level group has the weakest social tie. The current node v_i with a message M destined to v_d encounters a set of nodes R which includes all possible relay nodes at this particular time. If the destination v_d of M is in R, v_i simply delivers the message to v_d. Otherwise, mGroup starts its exploration with the top-level social group (with threshold t_1). 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, mGroup 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* [17]. If no node locates in the same group with the destination at this level, mGroup will check with the second level social group. This procedure continues until either it finds a relay node within the same group of the destination or m-level groups are all explored. In the latter case, v_i continues holding M. In mGroup, multi-level 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. If only one-level social group is used, we denote the routing method as Group. In [23], simulation results show that mGroup can achieve better performance than Group, by taking the full advantages of wide ranges of social relationships at all levels.

III. Social Feature Enhanced Group-based Routing for DTNs

In [23], we build the multi-level social groups purely from the contact graph obtained based on historical encounters, which exploit possible physical contacts between pairs of devices in the physical world. However, the multi-level social group techniques mGroup can be applied to other types of social graphs, if those information are available. In this paper, by introducing social groups defined by social features, we propose an enhanced group-based routing for DTNs. We begin with discussions of possible social features.

A. Social Features

Social features of a mobile user could include nationality, affiliation, speaking language, and so on. These social features can represent either physical features (such as gender and height) or logical ones (such as membership in an organization). These information could reflect certain level of social relationships among users in a virtual social world. Using these social features of each individual, it is possible to measure the social similarities between individuals and generate social groups with common social features.

Social features are available and have been used in DTNs for routing guidance [24], [25]. For example, the data set of Infocom 2006 [26] includes answers from each participant to a questionnaire with a number of social information about this person, such as nationality, affiliation and speaking language. In [25], Wu and Wang showed that in this data set the total contact times and contact durations between two individuals reduce when the social feature differences between them increase. The individuals with only one different social feature have about 36.5% more contact times and 32.6% longer contact durations than the individuals with two different features. Similarly, in [24], Mei *et al.* also found that individuals with similar social features tend to contact more often in DTNs. Therefore, it is also possible to consider the social features or relationships among mobile users to improve the performance of DTN routing. Both [24] and [25] directly use social features as routing metrics, however, this paper considers how to use social features to discover social groups so that social group-based routing can be applied.

One advantage of using social features for routing guidance is that social-feature based routing does not need to collect and maintain routing state information. Social features are static internal features of each mobile node and usually can be obtained before the deployment of the network or during user registration phase.

In this paper, we also use the Infocom 2006 trace data [26], which includes Bluetooth sightings by groups of users (*i.e.*, 79 participants) carrying iMotes for four days during Infocom 2006 conference in Barcelona, Spain. In addition to the Bluetooth contact information among participants, it also has social features of each participant, which are the statistics of participants' information returned from a questionnaire form. Since some social features in participants' questionnaire forms are blank, we extract eight social features from the original data set: *nationality*, *graduated school*, *languages*, *current affiliation*, *current position*, *city of residence*, *country of residence*, and *interested topics*.

TABLE I
Entropy of social features for Infocom 2006 Dataset

Social Feature	Entropy
Graduated School	5.223
Topics	4.864
Affiliation	4.618
City	4.379
Nationality	4.333
Country	3.928
Languages	3.524
Position	1.390

Among multiple social features, some are more important than others for either routing or group formation purposes. One way to measure the importance of a social feature is to calculate its entropy value over the data set, as did in [25]. In information theory, Shannon entropy is a measure of the uncertainty associated with a random variable. We use entropy to quantify the value of the information contained in the social features. Specifically, there are n mobile users in the network, and each user has N social features, denoted as f_1, f_2, ..., f_N. For a social feature f_j with M_j possible outcomes, $\{x_i : i = 1, \dots M_j\}$, its Shannon entropy, denoted by $E(f_j)$ is defined as

$$E(f_j) = -\sum_{i=1}^{M_j} p(x_i) log_2 p(x_i), \quad j = 1, \dots, N$$

where $p(x_i)$ is the probability of outcome x_i in the data set. Table I shows the entropy of each social feature listed in the descending order for Infocom 2006 data set. It is clear that a social feature with larger entropy means better distinction among mobile users. But if we use common values of social features to form social groups (*i.e.* two users are in the same group if they share the same values of certain social features), using only social features with largest entropy may lead to small or isolate groups. This is not good for group-based routing. On the other hand, using social features with lowest entropy may lead to a huge social group, since everyone have the same values. This is also useless for routing purpose. In our

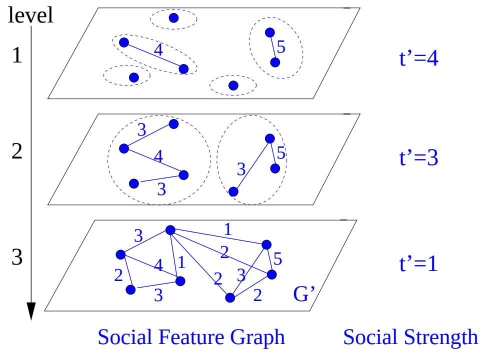

Fig. 2. Multi-level social groups based on common social features.

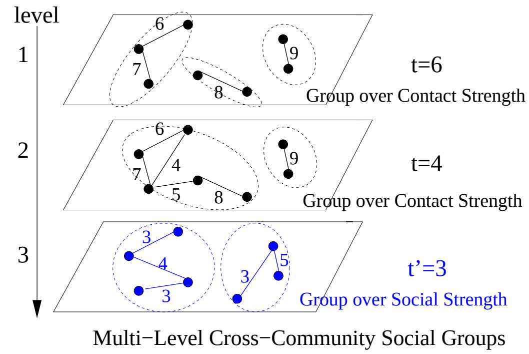

Fig. 3. Multi-level social groups based on different social graphs from heterogeneous sources for the same network.

simulations (Section IV), we will study the trade off among different social features.

B. Group-based Routing with Social Features

Motivated from the fact that people come in contact with each other more frequently if they have more social features in common, we apply social features to divide mobile users into different social groups. Recall that in [23] we use different values of contact strength threshold t to form multi-level social groups based on encounter frequencies in contact graph (as shown in Figure 1). The same approach can be easily adopted to form social groups using the social features.

As illustrated in Figure 2, we can define the social feature strength between any two nodes as the number of common identical social features. For example, if nodes v_i and v_j only share the same nationality and affiliation, we give their social strength weight of 2. Large social strength implicitly implies strong social tie. By defining social strength among nodes, we can have a weighted social feature graph G'. Using different value of threshold t', we can then define multi-level social groups among mobile users. In addition, based on different sets of social features where the common social features are considered, we can have different ways to define various multi-level social groups.

Our multi-level group-based forwarding method mGroup still works on this multi-level social groups. Since people come in contact with each other more frequently if they have more social features in common, we can prefer the nodes in the same social group with the destination as possible relay nodes. If multiple social groups co-exist, the one with strongest social strength (highest in the multi-level structure) can be picked. To distinguish this method from the method using historical encounters, we use mGroup-CG and mGroup-SF to represent group-based routing purely using encounter frequencies from contact graph and the one purely using common social features, respectively. Once again, if only one level social group is used, we denote the method as Group-CG or Group-SF.

C. Social Feature Enhanced Hybrid Group-based Routing

Notice that the social groups based on social features are distinct from the social groups based on historical encounters. The first ones are in the virtual world irrespective of physical distance among mobile users while the second ones are in the physical world which depend on the physical proximity of users. However, both types of social groups are complementary. One of the advantages using social features is that they can be obtained before the deployment of DTNs and there is no need to maintain any states during the routing except the static social graph. On the other hand, the encounter-based social groups reflect the dynamic way people exchange information through direct, face-to-face contacts. Therefore, both types of social groups can be combined and used as a hybrid cross-community multi-level social graph, as shown in Figure 3. We denote the group-based routing over these hybrid social graphs as mGroup-H. This approach actually makes more sense for DTNs, since modern people are living in a cross-space and multi-community co-existed world. Our simulation results in Section IV will verify this conclusion.

IV. Simulations

In this section we conduct extensive simulations of our proposed method with realistic contact traces [26], *i.e.*, Infocom 2006 trace data, which is publicly available at Crawdad [33]. This data set includes Bluetooth sightings by groups of users (*i.e.*, 79 participants) carrying iMotes for four days during Infocom 2006 conference in Barcelona, Spain. We use all 79 users in our simulations. There are $74,981$ contacts between 79 participants over a period of $337,418$ seconds. We divide the period using time slot with length of one hour and test the routing performance over randomly chosen 120 time slots. We use the first 40 hours data as historical data to obtain social group information and then evaluate the performance of routing tasks over the remaining 80 hours. For each simulation, we try all possible routing pairs in the network, *i.e.*, each mobile user tries to send messages to other 78 users. The number of message replicas allowed is set to 10 except for epidemic routing. As described in Section III-A, we use eight social features from the original data set, which are summarized in Table I, to generate the social groups used by our group-based routing.

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

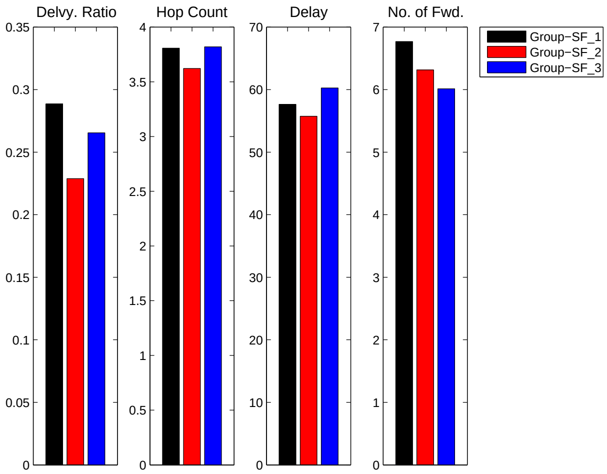

Fig. 4. Performance of single-level group-based routing with social features.

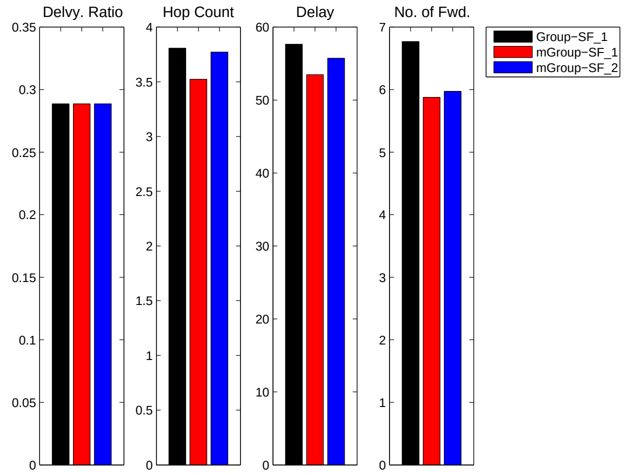

Fig. 5. Performance of 3-level group-based routing with social features.

- **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.

A. Single-Level Group-based Routing with Social Features: Grouping with Two Common Features

In the first set of simulations, we test a single-level group-based routing based on social features Group-SF. Here, we set $t' = 2$, *i.e.*, two nodes belong to the same social group if they have identical values of two or more social features. We implement three different versions:

- Group-SF_1: All eight social features listed in Table I are considered.
- Group-SF_2: Only the top four social features listed in Table I (*graduated school*, *interested topics*, *current affiliation* and *city of residence*) are considered.
- Group-SF_3: Only the middle four social features listed in Table I (*current affiliation*, *city of residence*, *nationality*, and *country of residence*) are considered.

Figure 4 shows the simulation results. It is clear that Group-SF_1 can achieve best delivery ratio. Thus considering more social features is helpful. Compared with Group-SF_2, Group-SF_3 has better performances though they both consider four social features. This shows that it does not necessarily lead to better performance using social features with higher entropy. Notice that if the entropy of a social feature is very large, it is hard to find common values of that social feature among users.

B. Multi-Level Group-based Routing with Social Features: Grouping with Two Common Features

In the second set of simulations, we test a multi-level group-based routing with social features mGroup-SF. Here, we again set the social strength threshold $t' = 2$. We implement two 3-level mGroup-SF methods:

- mGroup-SF_1: The first level considers the top four social features listed in Table I; the second level considers the top six social features; while the third level considers all eight features.
- mGroup-SF_2: The first level considers the middle four social features listed in Table I; the second level considers the middle six social features; while the third level considers all eight features.

Figure 5 shows the simulation results. In order to compare the performance of multi-level group-based routing with single-level group-based routing, we also plot Group-SF_1 in Figure 5. Though there is no much difference between mGroup-SF and single-level Group-SF_1 in term of their delivery ratios, it is clear that using multiple levels of social groups can improve the performances (smaller hop counts, delay and number of forwarding). Since mGroup-SF already uses multiple levels of social groups generated from different sets of social features, how to choose among social features becomes not such important.

C. Single/Multi-Level Group-based Routing with Social Features: Grouping with Multiple Common Features

In the third set of simulations, we test our Group-SF and mGroup-SF by changing the values of social strength threshold t'. In other words, we now consider different strengths over multiple social features to form the social graphs. We implement the following new methods.

- Group-SF_4: We set $t' = 4$ and consider all eight social features. In other words, it requests that two group members share at least 4 common social features.
- Group-SF_5: We set $t' = 6$ and consider all eight social features.
- mGroup-SF_3: A 3-level social groups where each level has different t'. The first level uses social groups from Group-SF_5 ($t' = 6$); the second level considers social

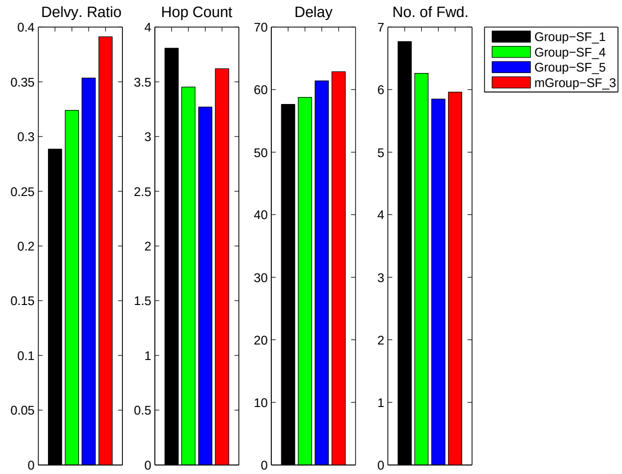

Fig. 6. Performance of single/3-level group-based routing with social features using different t' values.

groups from Group-SF_4 ($t' = 4$); while the third level considers social groups from Group-SF_1 ($t' = 2$).

Figure 6 shows the results. For Group-SF with single-level social groups, larger threshold t' leads to higher delivery ratio since it provides the information of stronger social ties. However, overall mGroup-SF_3 with 3-level social groups has the highest delivery ratio. This confirms our original conjecture of better performance with more information.

D. Social Feature Enhanced Hybrid Group-based Routing: Combining Social Features with Contact Graphs

So far we only test our group-based routing with social groups generated based on social features. Via simulations, we can find that the delivery ratio of these methods is still not high compared with some existing DTN routing methods. Therefore, in the last set of simulations, we test our proposed *social feature enhanced hybrid group-based routing* mGroup-H which combines both social groups from contact graphs and social groups from social features. We implement the following mGroup-H and mGroup-CG.

- mGroup-CG [23]: It is the group-based routing with a 3-level social group structure built from historical encounters. The threshold values of encounters t are $100, 50, 10$ from the upper level to the lower level, respectively. We use this as a baseline method for all mGroup-H methods.
- mGroup-H_1: We use a hybrid 4-level cross-community social groups, where the top three levels are from mGroup-CG and the last level is from Group-SF_1 with 2 common social features.
- mGroup-H_2: We use a hybrid 4-level cross-community social groups, where the top three levels are from mGroup-CG and the last level is from Group-SF_4 with 4 common social features.
- mGroup-H_3: We use a hybrid 4-level cross-community social groups, where the top three levels are from mGroup-CG and the last level is from Group-SF_5 with 6 common social features.
- mGroup-H_4: We use a hybrid 6-level cross-community social groups, where the top three levels are from mGroup-CG and the last three levels are from mGroup-SF_3 with $t' = 2, 4, 6$.

We compare our mGroup-H methods with five other existing opportunity-based routing methods which are listed below.

- Epidemic [14]: During any encounter, the message is forwarded to all encountered nodes.
- Spray and Wait [15]: 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 10 copies of the message. If there are multiple nodes during the encounters, v_i randomly picks one to share its copies.
- FRESH [17]: 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, v_i forwards the message to the one who has met the destination most recently.
- Destination Frequency [18]: 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, v_i forwards the message to the one who has met the destination most often.
- Greedy-Total [19]: 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, v_i forwards the message to the one who has most contacts.

Table II shows all simulation results. First, it is clear that our social group based routing method can achieve better performances than most of existing opportunity-based DTN routing methods 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. Notice that even though epidemic routing has the best delivery ratio, it costs extremely large amount of forwarding. It is also clear that with new additional information from social features our hybrid multi-level social group method mGroup-H can further improve the delivery ratio while maintaining similar level of other metrics. This confirms the complementary properties of two types of social groups obtained from both physical and virtual worlds and the benefits of combining useful social information cross-space/community.

V. Conclusion

Social features of mobile users could reflect certain level of social relationships among users in a virtual social world. By using these social features, we propose a new social-group based DTN routing protocol which forwards message based on multi-level cross-community social group information obtained both from social features and historical encounters. Our simulation results demonstrate the great performance of the proposed method and the advantages of considering diverse

TABLE II
PERFORMANCE ON SOCIAL FEATURE ENHANCED HYBRID GROUP-BASED ROUTING

	Epidemic	Spray and Wait	Dest. Frequency	FRESH	Greedy-Total
Delivery Ratio	0.70	0.38	0.25	0.46	0.39
Hop Count	3.8	4.0	1.6	3.6	3.8
Delay	54	57	56	58	56
Number of Forwarding	14.6	6.9	2.0	6.0	3.6
	mGroup-CG	mGroup-H_1	mGroup-H_2	mGroup-H_3	mGroup-H_4
Delivery Ratio	0.45	0.46	0.48	0.50	0.55
Hop Count	3.8	3.8	3.9	3.6	3.8
Delay	60	66	62	62	62
Number of Forwarding	6.9	6.0	5.3	6.2	5.9

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.

REFERENCES

[1] Z. Zhang, "Routing in intermittently connected mobile ad hoc networks and delay tolerant networks: overview and chalenges," *IEEE Communications Surveys and Tutorials*, , no. 1, pp. 24–37, 2006.

[2] J. Burgess, B. Gallagher, D. Jensen, and B.N. Levine, "Maxprop: Routing for vehicle-based disruption-tolerant networks," in *Proc. of IEEE International Conference on Computer Communications (INFOCOM 2006)*, 2006.

[3] X. Zhang, J. Kurose, B.N. Levine, D. Towsley, and H. Zhang, "Study of a bus-based disruption-tolerant network: mobility modeling and impact on routing, in *Proc. of ACM MobiCom 07*, 2007.

[4] L. Zhao, F. Li, and Y. Wang, "Hybrid position-based and DTN forwarding in vehicular ad hoc networks," in *Proc. of 2012 IEEE 76th Vehicular Technology Conference (VTC 2012-Fall)*, 2012.

[5] S. Burleigh and A. Hooke, "Delay-tolerant networking: an approach to interplanetary internet," *IEEE Commun. Mag.*, 41(6):128–136, 2003.

[6] C. Caini, H. Cruickshank, S. Farrell, and M. Marchese, "Delay- and disruption-tolerant Networking (DTN): an alternative solution for future satellite networking applications," *Proc. of the IEEE*, 99(11):1980-1997, 2011.

[7] C. Caini, P. Cornice, R. Firrincieli, and D. Lacamera, "A DTN approach to satellite communications," *IEEE J. Sel. Areas Commun.*, 26(5):820-827, 2008

[8] P. Hui, J. Crowcroft, and E. Yoneki, "Bubble rap: social-based forwarding in delay tolerant networks," in *Proc. of ACM MobiHoc*, 2008.

[9] P. Hui, A. Chaintreau, J. Scott, R. Gass, J. Crowcroft, and C. Diot, "Pocket switched networks and human mobility in conference environments," in *Proc. of ACM SIGCOMM workshop on DTN*, 2005.

[10] P. Hui and J. Crowcroft, "How small labels create big improvements," in *Proc. of International Workshop on Intermittently Connected Mobile Ad hoc Networks (ICMAN)*, 2007.

[11] A. Chaintreau, P. Fraigniaud, and E. Lebhar, "Opportunistic spatial gossip over mobile social networks," in *Proc. of ACM workshop on online social networks*, 2008.

[12] E. Miluzzo, N.D. Lane, K. Fodor, R. Peterson, H. Lu, M. Musolesi, S.B. Eisenman, X. Zheng, and A.T. Campbell, "Sensing meets mobile social networks: the design, implementation and evaluation of the CenceMe application," in *Proc. of the 6th ACM conference on Embedded network sensor systems*, 2008, SenSys '08, pp. 337–350.

[13] C. Liu and J. Wu, "Scalable routing in delay tolerant networks," in *Proc. of the ACM international symposium on Mobile ad hoc networking and computing(ACM MobiHoc 2007)*, 2007.

[14] A. Vahdat and D. Becker, "Epidemic routing for partially connected ad hoc networks," Duke University, Tech. Report CS-200006, 2000.

[15] T. Spyropoulos, K. Psounis, and C. S. Raghavendra, "Spray and wait: an efficient routing scheme for intermittently connected mobile networks," in *Proc. of ACM SIGCOMM workshop on DTN*, 2005.

[16] A. Lindgren, A. Doria, and O. Schelén, "Probabilistic routing in intermittently connected networks," *SIGMOBILE Mob. Comput. Commun. Rev.*, 7(3)19–20, 2003.

[17] H. Dubois-Ferriere, M. Grossglauser, and M. Vetterli, "Age matters: efficient route discovery in mobile ad hoc networks using encounter ages," in *Proc. of ACM MobiHoc*, 2003.

[18] V. Erranmilli, M. Crovella, A. Chaintreau, and C. Diot, "Delegation forwarding," in *Proc. of ACM MobiHoc*, 2008.

[19] V. Erramilli and M. Crovella, "Diversity of forwarding paths in pocket switched networks," in *Proc. of ACM IMC*, 2007.

[20] Y. Zhu, B. Xu, X. Shi, and Y. Wang, "A survey of social-based routing in delay tolerant networks: positive and negative social effects," *IEEE Communications Surveys and Tutorials*, to apear.

[21] E.M. Daly and M. Haahr, "Social network analysis for routing in disconnected delay-tolerant MANETs," in *Proc. of the 4th ACM International Symposium on Mobile Ad Hoc Networking and Computing(ACM MobiHoc 2007)*, 2007.

[22] E. Bulut and B.K. Szymanski, "Friendship based routing in delay tolerant mobile social networks," in *Proc. of 2010 IEEE Global Communications Conference (IEEE GLOBECOM 2010)*, 2010.

[23] L. Zhao, F. Li, C. Zhang, and Y. Wang, "Routing with multi-level social groups in mobile opportunistic networks," in *Proc. of 2012 IEEE Global Communications Conference (IEEE GLOBECOM 2012)*, 2012.

[24] A. Mei, G. Morabito, P. Santi, and J. Stefa, "Social-aware stateless forwarding in pocket switched networks," in *Proc. of IEEE Infocom*, 2011.

[25] J. Wu and Y. Wang, "Social feature-based multi-path routing in delay tolerant networks," in *Proc. of The Annual IEEE International Conference on Computer Communications(IEEE INFOCOM 2012)*, 2012.

[26] J. Scott, R. Gass, J. Crowcroft, P. Hui, C. Diot, and A. Chaintreau, CRAWDAD trace cambridge/haggle/imote/infocom2006 (v.2009-05-29), Downloaded from http://crawdad.cs.dartmouth.edu/ cambridge/haggle/imote/infocom2006, May 2009.

[27] G.A. Hillery, "Definitions of community: areas of agreement," *Rural Sociology*, vol. 20, pp. 111, 1955.

[28] S. Okasha, "Altruism, group selection and correlated interaction," *British J. for the Philosophy of Science*, vol. 56, pp. 730–725, 2005.

[29] P. Hui, E. Yoneki, S.Y. Chan, and J. Crowcroft, "Distributed community detection in delay tolerant networks," in *Proc. of the ACM Int'l Workshop on Mobility in the Evolving Internet Architecture (MobiArch)*, 2007.

[30] E. Yoneki, P. Hui, and J. Crowcroft, "Visualizing community detection in opportunistic networks," in *Proc. of ACM MobiCom Workshop on Challenged Networks (CHANTS)*, 2007.

[31] P. Hui, E. Yoneki, and J. Crowcroft, "Identifying social communities in complex communications for network efficiency," in *Proc. of Int'l Conf. on Complex Sciences: Theory and Applications (Complex)*, 2009.

[32] S.Y. Chan, P. Hui, and K. Xu, "Community detection of time-varying mobile social networks," in *Proc. of Int'l Conf. on Complex Sciences: Theory and Applications (Complex)*, 2009.

[33] CRAWDAD data set, http://crawdad.cs.dartmouth.edu/.