Social-Greedy: A Socially-Based Greedy Routing Algorithm for Delay Tolerant Networks

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ABSTRACT

Efficient routing in mobile opportunistic networks and Delay Tolerant Networks (DTNs) in particular, is a challenging task because human mobility patterns are hard to predict. Several recent work have shown the importance of communities in efficient routing of messages in DTNs. However, real time community detection in DTNs is a complex and time consuming process. In this paper, we propose a simple and cost effective method for bootstrapping wireless devices by employing available social profiles. Moreover, we propose a simple greedy routing algorithm called Social-Greedy which uses a social distance derived from people's social profiles to route messages in DTNs.

Categories and Subject Descriptors

C.2.1 [**Computer-Communication Networks**]: Network Architecture and Design—*Store and forward networks*

General Terms

Algorithms, Measurement, Performance

Keywords

Delay Tolerant Networks, Mobile Opportunistic Networks, Routing Algorithms, Social Profile, Social Distance

1. INTRODUCTION

The appearance of smart phones has created a new opening for pervasive computing. People who are carrying these devices form a DTN in the sense that senders opportunistically forward messages to other mobile nodes in order to reach the destinations of the messages. These opportunistic wireless networks have two dimensions. One relates to the properties of wireless networks while the second dimension has a social network component based on human mobility pattern and people's social profiles. Unlike the legacy MANETs for which the existence of an end-to-end path between source and destination nodes is assumed, opportunistic networks have a more dynamic nature. Thus, routing in mobile opportunistic networks becomes a challenging task.

Milgram's experiment [9] shows that people use their local information to find short paths to destinations in which a message holder forwards its message to one of its neighbors which is in the closest social distance to the destination of the message. Kleinberg has used a d-dimensional lattice as the underlying structure for his small-world network to model routing in social networks [8]. He has shown that there does exist an efficient routing algorithm if there is a correlation between the underlying lattice structure and the length of long range contacts.

Recent work have shown the importance of communities for routing information in DTNs [3, 5]. Hui et al. have proposed three distributed algorithms for community detection in DTNs [6]. The high cost of information exchange and calculations, and the complexity of adjusting several threshold parameters required by distributed community detection algorithms have led us to consider static programming of mobile devices with pre-existing social profiles instead of running a dynamic method for detecting communities in contact graphs [1]. In this work, we are assuming that the social profiles of all participants are known in advance. Our contributions may be summarized as follows:

- Based on our results, we suggest a new low cost and simple method for bootstrapping mobile wireless devices with already available social information.
- Using social profiles collected from Infocom 2006's participants, we define a social distance and introduce three greedy routing algorithms for DTNs inspired by Kleinberg's small-world network model which are more cost effective than Epidemic routing [13] and have higher delivery ratio than Waiting routing [5].
- To our knowledge, this is the first empirical evaluation of Kleinberg's greedy strategy for a mobile network, and the first empirical evaluation for a routing strat-

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[1]A contact graph is a dynamic graph in which nodes are people and the edges between nodes are the encounters from human mobility traces.

egy which uses social distance rather than geographic distance to determine each move.

2. RELATED WORK

By using human mobility traces, researchers have found a close connection between people's social profiles and their mobility patterns. Eagle et al. inferred friendships from observational collected data from cell phones [11]. Mtibaa et al. have also shown that there is a strong correlation between properties of social and contact graphs [10].

Hui et al. have proposed a routing algorithm called LABEL which takes advantage of communities for routing messages [3]. LABEL partitions nodes into communities based on only affiliation information. However, our Social-Greedy algorithms obtain multi-dimensional social profiles to assign a real valued social distance between pairs of nodes. Hui et al. have also observed the variation in degree of nodes in contact graphs [4]. They have proposed the Bubble rap routing which utilizes the nodes' centralities to reach the community of destination node more quickly [5]. When a message reaches the community of destination node, Bubble rap limits the message forwarding range to nodes with the same community. While Bubble rap utilizes only nodes' centrality and communities, our Social-Greedy algorithms utilize several social dimensions.

Boldrini et al. have proposed a context-aware routing protocol for opportunistic networks where every node captures context information of its neighbours and the nodes which it has met in the past [1]. Based upon the collected information, every node calculates the delivery probabilities of encountered nodes to choose the best candidate for routing. Their work is similar to ours because we also use social information for routing, but our works differ in that we use the offline social profiles to initialize the wireless mobile devices in advance of a future meeting.

3. SOCIALLY-BASED GREEDY ROUTING

3.1 Real Data Description

In this paper, we use the actual human mobility traces collected from 79 researchers attending in Infocom 2006 conference [12]. In this experiment, they distributed 79 iMote devices among people to collect the proximity information by using Bluetooth. Participants of the experiment had also been asked to fill out a questionnaire form. The questions were about different social properties of experimentalists.

3.2 Social Closeness/Distance Definitions

Any question in questionnaire form can be considered as a social dimension. We can model a node's answer set for its questionnaire form as an n-dimensional social profile where n is the number of questions answered by participants. We use Jacard index [7] to measure the similarity between the i^{th} indices of the social profiles of two nodes u and v as $\sigma^i_{jacard}(u,v) = \dfrac{|\Gamma^i_u \bigcap \Gamma^i_v|}{|\Gamma^i_u \bigcup \Gamma^i_v|}$ where Γ^i_u is the answer set of the user u for the question i and $|\Gamma^i_u|$ is the cardinality of the set Γ^i_u. The σ^i_{jacard} is a real number between 0 and 1 which represents the closeness of nodes u and v in terms of the social dimension i.

Here, we consider 7 questions of the questionnaire forms as: (1) nationality, (2) graduate school, (3) languages, (4) affiliation, (5) city of residence, (6) country of residence, (7) topics of interests. Averaging over all dimensions, we can calculate the total social closeness between a pair of nodes. Thus, we can define the social distance between two nodes u and v as $dist(u,v) = (\sum_{i=1}^{d} \dfrac{\sigma^i_{jacard}(u,v)}{d})^{-1}$. We say that u is socially closer to v than w if $dist(u,v) < dist(u,w)$.

Table 1: Correlation Coefficient

Variable Pairs	Correlation
$r_{nc_{u,v}cd_{u,v}}$	0.369
$r_{cdu,vsdu,v}$	0.253
$r_{ncu,vsdu,v}$	0.182

3.3 Human Network Mobility Model

Our main hypothesis is that in a conference people who are interested in the same research area or speak the same language have a higher probability to meet each other for a longer time than others. Therefore, we expect that for a given node u, the probability of meeting other nodes is influenced by u's social distance from other nodes. We have found a close relationship between number of contacts and contact duration in the hman mobility traces collected in Infocom 2006 which is in agreement with previous work [4]. We have also calculated the correlation coefficients between the number of contacts, the average contact duration time, and the social distance as shown in Table 1.

3.4 Social-Greedy Routing Algorithm

In the previous section we have found a distinctive relationship between social distances among people and their mobility patterns. This motivates us to employ a greedy mechanism similar to Milgram's to route messages to their destinations. We assume that every node has information about the social profile of the destination as well as its neighbours'. We have implemented three versions for Social-Greedy routing as listed below:

- Social-Greedy I: If node u has a message for the destination v and encounters node$w$ which is socially closer to v than u, u hands off that message to w. Node u does not remove the message from its buffer unless it encounters node v or the TTL of the message expires.

- Social-Greedy II: When node u, which is carrying message M for node v, encounters node w at time t_0, u hands off M to w if it is socially closer to v than u. However, for any $t > t_0$, u can only pass the message M to an encountered node if it is socially closer to v than w (the closest node to v which u has met so far).

- Social-Greedy III: When node u hands off the message M to w as in the first version, it deletes M from its own buffer.

While Social-Greedy I hands off the message M to any encountered node which is socially closer to destination of M, Social-Greedy II acts more conservatively in the sense that at each step, it limits the range of nodes which can be recipient of the message M based on the closest node to the destination that u has met so far. Furthermore, Social-Greedy III tries to efficiently utilize nodes' buffers by removing the

Table 2: Simulation Parameters

Parameter	Value
No of nodes	79
No of unique videos	1000
No of runs	20
Starting time	Apr. 24, 9:00 AM
TTL	9 hours
Communication type	Bluetooth 2.0

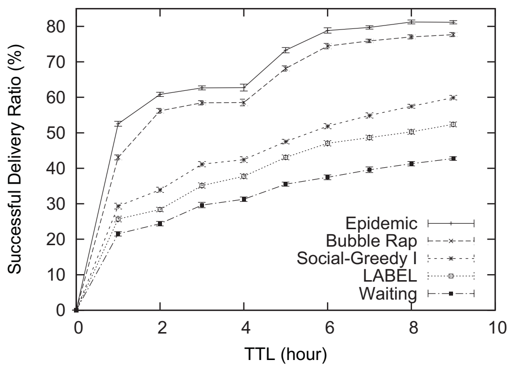

Figure 1: Successful Delivery Ratio for Different Routing Schemes (TTL=9h)

message M from the buffer of the message holder after forwarding M to the next node which is socially closer to the destination. Therefore, we expect that Social-Greedy I to have the best success delivery ratio (SDR) [2] while Social-Greedy III to have the lowest total delivery cost.

4. EVALUATION METHODOLOGY

4.1 Social-Sim Simulator

In order to evaluate our Social-Greedy routing algorithms, we have implemented a discrete event simulator called Social-Sim. Our simulator reads contact information consisting of the time of contact between two nodes and the contact duration to run the routing algorithm under study. A separate process in the simulator logs all important information including the number of delivered messages and their delivery delay as well as the number of transmissions for all messages. The simulation parameters have been shown in Table 2.

4.2 Results and Evaluations

For evaluation and comparison purposes, we have implemented five different routing algorithms including Epidemic [13], Waiting [5], LABEL [3], Bubble rap [5], and three versions of our Social-Greedy algorithms. In Waiting algorithm, a node that is carrying a message has to wait until it has a direct contact with the destination. In Epidemic, a message is given to any node that comes within the proximity of the message holder provided that the receiver does not already have the message. Hence, Epidemic has the lowest bound for delivery delay and Waiting has the lowest bound for delivery cost. While LABEL passes a message to those nodes

[2]SDR is the proportion of messages that have been successfully delivered out of the total unique messages.

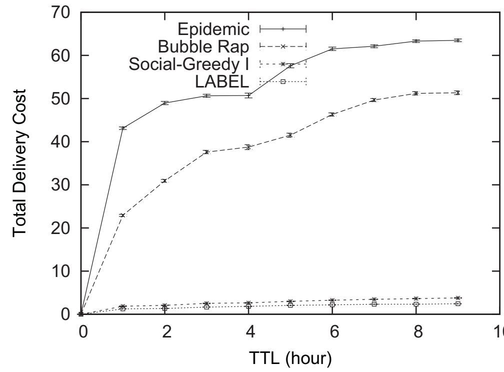

Figure 2: Total Delivery Cost for Different Routing Schemes (TTL=9h)

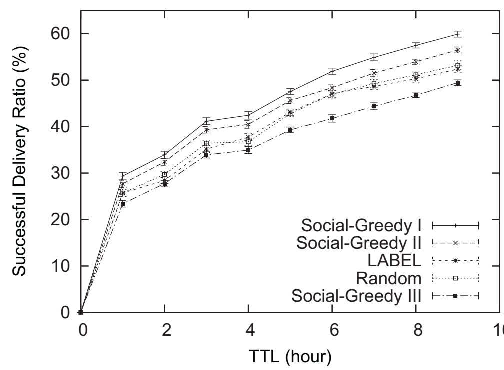

Figure 3: Successful Delivery Ratio for the three versions of Social-Greedy Algorithms (TTL=9h)

which have the same affiliation as the destination, Bubble rap uses nodes' affiliations and centralities for routing. We approximate nodes' centralities by measuring the number of unique nodes every node has met per hour [5]. We update the measured centralities every 10 minutes to adapt to the dynamic of the environment.

We have chosen successful exchange of video files between nodes as a measure of their contact duration. The average video lengths has been chosen 8.4 MBytes as it has been observed from crawling Youtube website [2]. We also assume that all wireless devices have Bluetooth 2.0 which supports 3Mbit/sec data rate. Therefore, the average transmission time can be calculated as $T_{trans} = \frac{8.4 \times 8}{3} \approx 23s$. This implies that minimizing the number of video transmissions per contact is important for a video sharing application.

Figure 1 compares SDRs of different routing algorithms. It shows that Epidemic delivers around 81% of videos while Bubble rap and Social-Greedy I deliver 70% and 60%, respectively during the first 9 hours. According to Figure 1, Social-Greedy I in the worst case betters the SDR of LABEL and Waiting algorithms by 15% and 40%, respectively.

Furthermore, we compare the total delivery cost [3] of the

[3]Total delivery cost is the total number of messages (including duplications) transmitted across the network. We

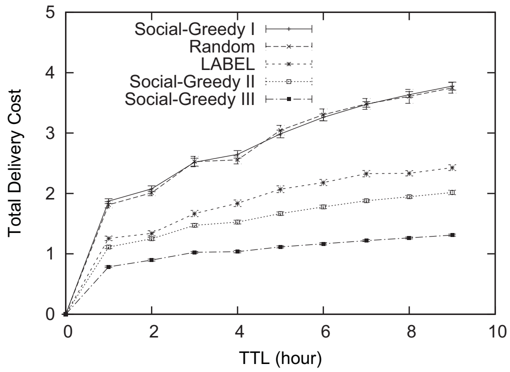

Figure 4: Total Delivery Cost for the three versions of Social-Greedy Algorithms (TTL=9h)

different routing algorithms. Figure 2 shows that Social-Greedy I forwards video files 17 times less than Epidemic and around 4.5 times less than Bubble rap. The low cost of Social-Greedy I algorithm proves that it can be considered as a power-efficient protocol for low-powered mobile devices.

To show the power of social profiling, we compare Social-Greedy routing with a Random routing. For fair comparison, first we use the same simulation parameters for both strategies. Second, in Random routing, we assign social distance in random and employ a hand off probability, which is the probability of forwarding on each encounter, to gaurantee the same average costs for both strategies. Interestingly, Figures 3 and 4 show that both Social-Greedy I and II outperform LABEL and Random in terms of SDR while Social-Greedy II and III have lower costs than LABEL.

Our results are quite impressive considering the simplicity of using already available online social profiles from conference websites or any online citation network for making forwarding decisions. For example, we can easily download the list of all submitted papers from Infocom 2006 website including the titles of papers and authors' names, schools, and city/country of residence. The titles of papers reflect the authors' topics of interests while the nationality and spoken language can be simply inferred from authors' names and their place of residence. Therefore, we are able to collect a rich social profile for each conference participant and use the collected information to initialize and bootstrap the mobile devices of the participants of the conference in advance.

5. CONCLUSIONS AND FUTURE WORK

In this paper, we have employed the social profiles collected from questionnaire forms completed by Infocom 2006 conference attendees to enhance routing in mobile opportunistic networks. We have used the Jacard measure of social profiles to define a social distance. Using defined social distance, we have proposed a greedy routing algorithm inspired by Kleinberg's model. Moreover, we have shown the effectiveness of using various social dimensions particularly for media sharing applications. Finally, we have proposed a simple method for programming mobile nodes by using available social profiles. For future work, we are planning to look into the communication costs between nodes if the initially known social profiles are augmented dynamically each time two nodes encounter each other.

normalize the total delivery cost by dividing it by the total number of unique messages.

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