Journal of Universal Computer Science, vol. 20, no. 13 (2014), 1829-1854
submitted: 26/1/14, accepted: 6/9/14, appeared: 28/11/14 © *J.UCS*

A Utility-Oriented Routing Scheme for Interest-Driven Community-Based Opportunistic Networks

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Abstract: Opportunistic networks, as representative networks evolved from social networks and Ad-hoc networks, have been on cutting edges in recent years. Many research efforts have focused on realistic mobility models and cost-effective routing schemes. The concept of *"community"*, as one of the most inherent attributes of opportunistic networks, has been proved to be very helpful in simulating mobility traces of human society and selecting suitable message forwarders. This paper proposes an interest-driven community-based mobility model by considering location preference and time variance in human behavior patterns. Based on this enhanced mobility model, a novel two-layer routing algorithm, named *InterCom*, is presented by jointly considering utilities generated by users' activity degree and social relationships. The results, obtained throughout an intensive simulation analysis, show that the proposed routing scheme is able to improve delivery ratio while keeping the routing overhead and transmission delay within a reasonable range with respect to well-known routing schemes for opportunistic networks.

Keywords: Opportunistic Networks, Mobility Model, Routing Algorithm, Community, Simulation Analysis, Performance Evaluation
Categories: H.3.1, H.3.2, H.3.3, H.3.7, H.5.1

1 Introduction

In the context of Mobile Ad-hoc Networks (MANETs) that in recent years have evolved towards a social perspective, there is always an assumption: nodes are well-connected and capable of organizing themselves arbitrarily most of the time [Han, 12]. In addition, an end-to-end path between the source and the destination is always expected to exist in the network. Despite the fact that MANETs present promising results in the network environment with high density (e.g. conference environment), their performance are far from satisfactory in sparse settings where an end-to-end connected path rarely or never exists [Daly, 07]. For this reason, opportunistic networks as an evolutionary version of MANETs, are well researched. Unlike in MANETs, in opportunistic networks the operating mechanism of message forwarding is to let nodes with messages (to be forwarded) wait for an appropriate forwarding opportunity rather than deliver messages through a pre-computed path. To this end, mobility is seen as a resource to bridge disconnections, rather than a problem to deal with. According to the *store-ferry-forward* paradigm, nodes opportunistically exploit any contact with other peers to exchange messages, if such peers are deemed good candidates to bring such messages closer to the appropriate destinations.

Since opportunistic networking often deals with network of mobile handheld devices, it is easy to understand how these networks have many features in common with the social activities of human beings [Costa, 08]. Community as one of the most inherent and natural social features is also represented clearly in the operating process of opportunistic networks. In sociology, community is usually defined as a group of interacting people living in a common location (e.g. home, hospital, restaurant, mall, sky resort, beach, park, etc.). Community ecologists and sociologists study the interactions between species/people in communities at several spatial and temporal scales [Rhee, 11]. It has been shown that a member of a given community is more likely to interact with another member of the same community than with a randomly chosen member of the population [Musolesi, 06]. Therefore, community naturally reflects social relations among people. Since social relations and behaviors among mobile users are usually long-term characteristics and less volatile than node mobility, it is worth observing that the knowledge of the community of mobile users allows making better forwarding decisions.

According to this modern vision, the current research about community-based opportunistic networks mainly focuses on two aspects: 1) community-based mobility model; 2) community-based routing protocol.

Regarding the mobility model, even though there already exist many mobility models to simulate the human traces, their definition is based on the assumption that the users' mobility is driven by the social relationships among users. Despite the fact that social relationships can be conceived as an influential factor to affect the users' behavior, it is not the only factor influencing human mobility behavior. Users also could visit communities with less social connection due to their functional demand. This is the case, e.g. when citizens want to have dinner outside, it is highly possible that they visit communities connected to restaurants even though they do not have friends belonging to that community. Based on this simple consideration, we propose an *interest-driven community-based (InterCom) mobility model*. In the proposed model, the movement of users is affected by social relationships and by their own

interests. The model allows users to have higher probability to visit the communities with intimate social ties and maintain a certain level of probability to visit functional communities due to their own interest-based demand. Besides that, aiming to make the proposed model close enough to the reality, we introduce the time and speed variance feature into the model by enhancing existing mobility models. We define time periods in which the nodes move differently to introduce periodical behavior and associate the moving speed of the users to the current interest-driven behavior they perform. To the best of our knowledge, this is the first mobility model that is driven by interests and social relationships and also considers patterns of time and speed variance. Based on the InterCom mobility model, we present a utility-oriented routing protocol named InterCom routing protocol. The idea behind the InterCom routing protocol is that each node exploits two different utility functions for intra-community and inter-community routing.

Experimental results show that InterCom can achieve important global performances and a significant tradeoff between data delivery ratio and resource consumption in opportunistic networks.

The proposed mobility model and routing scheme have been partially introduced in [Fu, 13]. With respect to such preliminary paper, many aspects have been revised and extended: *(i)* the concept of "interest-driven" is introduced into the mobility model; *(ii)* the double-layered routing scheme has been completely re-designed and tested throughout intensive simulation campaigns.

The rest of this paper is structured as follows. We first discuss the related work in Section 2, and then we describe a novel mobility model well-suited for opportunistic networks in Section 3. In Section 4, we propose the InterCom routing protocol whilst its performance evaluation, in terms of the main network performance indices, is carried out in Section 5. Section 6 discusses some issues and looks into future work. Finally, we conclude the paper with a brief summary of contributions.

2 Related Work

2.1 Mobility Models

Many mobility models have been presented to analyze protocols and algorithms for opportunistic networks. A comprehensive review of the most popular mobility models can be found in [Mota, 14].

Mobility models attempt to realistically represent the behaviors of mobile hosts without the use of traces. The most widely use of such models is based on random individual movement; the simplest one is the RW (Random Walk) mobility model that is used to represent pure random movements of the entities of a system [McGuire, 05]. A slight enhancement of RW is the RWP (Random Way-Point) mobility model [Gowrishankar, 07], in which pauses are introduced between changes in direction or speed.

Mobile devices are commonly carried by humans, so the movement of such devices is necessarily based on human decisions and socialization behaviors. Community, as a significant characteristic observed from social behavior, has been proved much helpful in building a realistic mobility model with wide suitability. CMM (Community-based Mobility Model) presented by Musolesi et al. [Musolesi, 06]

is one of the first models taking into account community features. In CMM, nodes move between the communities based on node attraction features. Afterwards, Boldrini et al. [Boldrini, 07] have highlighted the shortcomings of CMM which are mainly based on the fact that the nodes belonging to the same community are more likely to follow the first node that has decided to leave the community. Aiming at solving this issue, HCMM (Home Cell Mobility Model) [Boldrini, 07] is proposed which considers both node and location attraction. HCMM maintains the social model of CMM but nodes have also location-preference towards some grids on the map. Simulation results indicate that the traces generated by HCMM are more close to reality than those of CMM.

Besides community feature, time-variance and location-preference are also considered as two influential factors to the reality of mobility model. Time-variance indicates that human activity shows various mobility patterns during different time period. TVMM (Time-Variant Mobility Model) [Hsu, 07] is one of the first models that take into account this important characteristic. In TVMM, nodes move to different squares at different day times in a periodic manner and their movements are homogeneous, i.e. every node follows the same instructions. Based on TVMM, Ekman et al. [Ekman, 08] proposed TDMM (Working Day Movement Model) which combines three major human activities, being home, working and evening activities. Location-preference indicates that human is more willing to visit some interest sites than other places. In fact, since in community-based model, the node has higher probability to visit the community with closer relationship, the community-based model can be considered as a representative class of location-preference model. However, all synthetic movement models do not fully conform to the real human mobility because it is quite difficult to assess in which way they can map the reality.

Our goal in this paper is twofold: from one hand, the design of a mobility model more realistic than the existing synthetic mobility models, by addressing characteristics observed from human mobility traces; on the other hand, the definition of such model should be simple enough to allow in-depth theoretical analysis, and flexible enough to have a wider applicability than the currently available models.

2.2 Routing Protocols

Many new routing schemes have been proposed for opportunistic networks. However, the unpredictable mobility and restricted resource in opportunistic networks significantly obstruct us from finding an ideal forwarding mechanism. Lately, the consideration of social characteristics provides a new angle of view in the design of routing protocols for opportunistic networks. Furthermore, it is worth noting that social relations and behaviors among mobile users are usually long-term characteristics and less volatile than node mobility. Based on this consideration and taking into account the recent advances in social network analysis, several social-based routing methods have been recently proposed to exploit the various social characteristics in opportunistic networks to support the relay selection.

Hui et al. [Hui, 07] introduced a routing method based on community labels in Pocket Switched Networks (PSNs). Label routing takes the advantage of the knowledge of social community. It assumes that people from the same community tend to meet each other more often than people from different communities, and hence they can be good forwarders to relay messages destined to other members in

the same community (with the same label). In label routing, the message forwarding from the source to the destination is purely via the members within the same destination community. This may significantly increase the delay or even fail to deliver the message. Bubble Rap [Hui, 11] is a social-based protocol using two centrality values that are associated to each node based on the node global popularity in the whole network and local popularity within its own community or communities. The forwarding scheme uses these centrality values so that a message is transferred to nodes with higher global centrality values until the carrier node meets a node with the same community label of the destination node. A message is forwarded to nodes with higher local rankings until successful delivery. The protocol named Habit [Mashhadi, 09] realizes data dissemination in a selection-based manner by exploiting node physical proximity and user social ties. It makes use of both a regularity graph, to keep trace of when and how often two nodes come into contact, and an interest graph, to build dissemination paths based on node's interest on the data. In [Ahmed, 11], the popularity of a node in opportunistic networks is exploited for message forwarding. In the former, popular nodes (called hubs) are connected with most of the other nodes in opportunistic networks and are characterized by analyzing the history of encounters. In the latter, a destination-unaware message-forwarding strategy that takes into consideration both the popularity of a node in opportunistic networks and the contact durations is proposed. Looking at the scenario of urban searching and rescuing in [Ochoa, 13] and [Santos, 11], the authors introduced a new opportunistic network infrastructure named HWSN (Human-centric Wireless Sensor Networks). The basic idea of HWSN is to use the movement of rescuers to retrieve the monitoring data from wireless sensor networks deployed in various isolated disaster zones and the encountering of rescuers to accelerate the speed of data spreading.

3 Mobility Model Design

In this section we design a mobility model that is able to capture human mobility behavior in real life. The description of the mobility model is organized as follows:

- Firstly, we describe the design details of the proposed mobility model. We are aiming to address the following points: 1) how to select the destination; 2) how long the node will stop after arriving at the destination; 3) what speed the node should follow when moving.
- Secondly, after proposing the mobility model, we provide simulation-based evaluation of the proposed model.

3.1 Design of the *InterCom* Mobility Model

This section describes the design of a novel mobility model named *InterCom* well-suited for the analysis of opportunistic networks.

3.1.1 Event-based Location preference

With reference to a generic squared map, we model communities by dividing the map into a given number of grids. Each grid represents one community, which is a squared geographical area. In order to meet the periodical feature of human mobility traces,

we classify the human mobility behavior into two main types (see Figure 1): local event and global event. Both kinds of events are processed as follows: 1) select the destination community; 2) move to the selected community (i.e., arriving at a random point within the selected community); 3) stay at the community for a while. The fundamental difference with respect to previous approaches lies in how to select the destination. For local events, the selected destination is constrained within the node community, whilst for global events, nodes are allowed to visit any target point on the map, which means that they are capable of visiting any communities. In order to capture periodical re-appearance at the same location, we establish a specific event order which sets that events occur in a cyclic way (see Figure 2). A similar idea of modeling periodical features of human mobility traces has also been suggested in [Hsu, 07]. After defining the mobility model by introducing local and global events, we need to focus on the following issues: 1) how to calculate the selection probability of destination communities; 2) how long will the node rest once arrived to the target point; 3) what speed will the node follow during the moving stage. It is worthy to note that, since in the local event the selected points is always within the node community, the probability of visiting each community is only considered when a global event occurs.

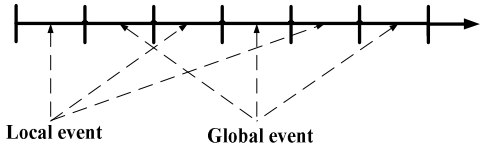


Figure 1: The distribution of local event and global events in the InterCom model

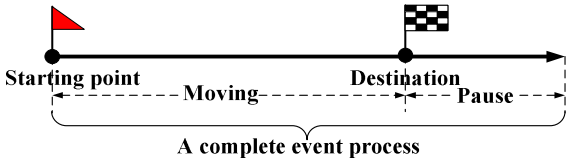


Figure 2: Schema of a complete event process

3.1.2 Community selection

The community selection mechanism is defined as follows. A certain number of nodes (zero or more) are associated to each community C_p at a given time. Each community exerts a certain social attraction for a given node. The social attraction of a square region is a measure of its importance in terms of the social relationships for the node taken into consideration. The social importance is calculated by evaluating the strength of the relationships with the nodes that are moving towards that particular square (i.e., with the nodes that have a current goal inside that particular community). More formally, given $\mathbf{S}_{C_p}$ (i.e., the set of the nodes associated to community C_p), we define the social attraction of community C_p towards the node i, $SA_{C_p}(i)$ as follows:

$$SA_{C_p}(i) = \frac{\sum_{j \in \mathbf{S}_{C_p}} RS_{i,j}}{\omega} \quad (1)$$

where ω is the cardinality of $\mathbf{S}_{C_p}$ (i.e., the number of nodes associated to the community C_p) and $RS_{i,j} \in \{0,1\}$ is the strength of social relationship between nodes i and j. In other words, the social attraction of a community towards a node i is defined as the sum of the degrees of social relationships between i and the other nodes belonging to the community C_p, divided by the total number of nodes associated to that community. If $\omega = 0$ (i.e., the square region is empty), the value of $SA_{C_p}(i)$ is set to 0. The next step is to determine the probability distribution of nodes moving to each community without considering the impact of interests and the related equation is shown as follows:

$$PA_{C_p} = \frac{SA_{C_p}(i)}{\sum_{C_x \in \mathbf{C}} SA_{C_x}(i)} \tag{2}$$

where $PA_{C_p}(i)$ denotes the probability of node i moving to community C_p and $\mathbf{C}$ is the set of all communities.

If we only take into account the impact of social attraction of communities, we might find that the communities with few members have low probabilities to be visited by nodes coming from other communities. However, in people's daily life some "functional" communities (e.g. supermarkets, hospitals), which have very few citizens but often receive visits from other communities, exist. Therefore, in order to improve the realism of the mobility model, in the following, we describe the visiting behavior propelled by functional demands as interest-driven behavior.

Since human interest-driven behavior can be categorized into several activities such as having rest at home, going to work, shopping and so on, we can reasonably define a finite, non-empty set $\mathbf{A} = \{A_1, A_2, \dots, A_n\}$ as the general interest set, where A_i $(1 \leq i \leq n)$ represents one type of interest-driven behavior. The quite general interest set $\mathbf{A}$ incorporates all potential interest activities. Since for each node, every community can only provide several kinds of services to meet interest demands and the service capabilities are also different, here we propose a *satisfaction degree* ST representing the ability of a community to satisfy a specific interest. For the generic node i, the ability provided by the community C_p to meet the interest A_j, is defined as $ST_{C_p,A_j}(i)$. We set the value of ST within the range$[0,1]$. To better understand the definition of satisfaction degree, let us assume that the interest activity A_1 refers to "having rest at home" and nodes p and q live in community C_1 and C_2 respectively. The community C_2, being the location of q's home, has the highest probability to receive q's visit when q wants to have a rest at home. So we can reasonably set $ST_{C_2,A_1}(q)$ to 1. But for p, since its home is not in community C_2, $ST_{C_2,A_1}(p)$ can be set to 0. As a consequence, we can easily define the node p's interest matrix $\mathbf{IM}(p)$:

$$\mathbf{IM}(p) = [ST_{C_m,A_n}(p)]_{m \times n} \tag{3}$$

where the cardinality of community set $\mathbf{C}$ and interest set $\mathbf{A}$ correspond to the row and column number of the matrix, respectively. For the node p, $ST_{C_m,A_n}(p)$ represents the ability that community C_m can provide a service to meet the interest A_n. After defining the interest matrix, the satisfaction degree can be easily computed. As mentioned before, we use the encounter times of nodes p and q to evaluate their degree of social relationship, similarly we choose the times that the node performs an

interest activity in a given community in order to represent the satisfaction degree.

By assuming a map which is divided into 4 communities $\mathbf{C} = \{C_1, C_2, C_3, C_4\}$; all of these communities are capable of offering "restaurant service (A_2)". At the initialization stage, the node p has equal willing to visit the four communities when it would like to have some food. So it is appropriate to set $ST_{C_1,A_2}(p) = ST_{C_2,A_2}(p) = ST_{C_3,A_2}(p) = ST_{C_4,A_2}(p) = 0.25$. After that, we begin to record the times of visiting certain communities when p performs the interest activity A_2 . If p visits the community C_1 by following its interest A_2, the satisfaction degree will be updated according to the formula (4) as follows, so obtaining the following values {0.625, 0.125, 0.125, 0.125}.

$$ST_{C_i,A_2}(p) = \frac{ST_{C_i,A_2}(p) + enc(i)}{2} \quad i \in \{1,2,3,4\}$$
$$\text{where} \qquad enc(i) = \begin{cases} 1 & \text{if } p \text{ visits } C_i \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

It is obvious that, if a node often visits specific communities when performing specific activities, the probability that the node will visit such communities for the same purpose will be high. The motivation behind this natural behavior comes from the real life; people always demonstrate a stronger desire to visit "old places" rather than "new places".

As mentioned before, the determination of which community should be entered is made by evaluating the mixed effects of social attraction of communities and the interests of nodes. When a node has to begin a global event, first it needs to randomly select one interest from the general interest set **A**. For the sake of simplicity, we set the interest that the node i chooses as A_j and we define the probability of the node i entering into the community as follows:

$$P_{C_p,A_j}(i) = \alpha PA_{C_p}(i) + (1-\alpha)ST_{C_p,A_j}(i) \tag{5}$$

where α is the weight coefficient to tune the influence of interest and social relationships on human mobility. If α= 1, the human behavior is only affected by its social relationships. Conversely, if α is set to 0, the human conducts moving behavior driven by social interest. Thus, the user is required to adjust the weight coefficient α to meet its expectation of mobility model.

3.1.3 Calculation of Pause Time

When people arrive at one place, they are always required to stop there for a while to finish their goal (e.g. meeting friends or having dinner). In most existing mobility models (e.g. [Ekman, 08], [Hsu, 07]), the pause time is randomly chosen from a pre-configured range $[T_{\min}, T_{\max}]$. But in real life, the pause time is closely related to the interest behavior and the strength of social relationships. In this section, aiming to connect the pause time with interests and social ties, we divide the pause time into two parts: the period T_i determined by interest behavior and the period T_s determined by social relationships.

The calculation of period T_i takes into account the differences in time costs related to the interest activity and to the activity performer. For example, the time cost of having dinner and going shopping is always different. Even for having dinner, there is also a significant difference in time cost for various people.

Given $\mathbf{A} = \{A_1, A_2, \dots, A_n\}$ the general interest set, for the node q, its personal interest set is denoted as $\mathbf{A}(q) = \{A_1(q), A_2(q), \dots, A_n(q)\}$. At the initialization phase, the default time cost of each interest is also given. Here, we use $\mathbf{T}_i(q) = \{T_1(q), T_2(q), \dots, T_n(q)\}$, where $T_i(q)$ $(1 \le i \le n)$ is the default time cost the host q will spend when performing the interest $A_i(q)$. Aiming at being compliant to the randomness of human behavior, the actual time cost t_i when performing the interest activity $A_i(q)$ follows the normal distribution as below:

$$f(t_i) = \frac{1}{\sqrt{2\pi}(T_i(q)/l_i)} e^{-\frac{t_i - T_i(q)}{2(T_i(q)/l_i)^2}} \quad (6)$$

where l_i is the variance coefficient to tune the deviation degree of $f(t_i)$.

For the period T_s, which is determined by social relationships, the node is willing to stay longer in intimate communities than in stranger communities. Thus, at the initialization phase, a standard time interval T_{unit} is given; then, the default time cost $T_s(q)$ with $(1 \le s \le n)$, can be calculated by taking into account the social attraction of community C_p towards host q as in the following:

$$T_s(q) = T_{unit} \times SA_{C_p}(q) \quad (7)$$

According to the randomness of human behavior, the actual time cost of stay t_s once arrived to the community C_p follows the normal distribution as below:

$$f(t_s) = \frac{1}{\sqrt{2\pi}(T_s(q)/l_s)} e^{-\frac{t_s - T_s(q)}{2(T_s(q)/l_s)^2}} \quad (8)$$

where l_s is the variance coefficient to tune the deviation degree of $f(t_s)$.

As mentioned before, the total pause time T is the sum of two terms: T_S and T_i. Thus, the actual total pause time t can be calculated by

$$T = \alpha T_S + (1 - \alpha) T_i \quad (9)$$

where α is the weight coefficient mentioned before to tune the influence of interest and social relationships on human mobility (see Section 3.2.2).

3.1.4 Moving Speed

In most existing mobility models, the moving speed is always the factor that is over-simplified. They always assume that the moving speed of a node in the network follows a random distribution with range $[V_{\min}, V_{\max}]$ and the moving speed is always constant before the node reaches the destination. However, the moving speed, just like the pause time and the selection of a specific community, is also closely related to the user's ongoing interest. Our more realistic assumption is that when people perform different interests, their moving speed tends to be different. For urgent situations, people tend to move faster than for normal situations (e.g. driving car rather than walking). For this reason the node q with personal interest set $\mathbf{A}(q) = \{A_1(q), A_2(q), \dots, A_n(q)\}$, is coupled to a specific default moving speed set $\mathbf{M}(q) = \{M_1(q), M_2(q), \dots, M_n(q)\}$ where $M_i(q)$ $(1 \le i \le n)$ represents the default speed the node q will keep when performing the specific interest $A_i(q)$. The moving speed of humans also exhibits a certain degree of randomness. Therefore, we model the moving speed in a time-variant way by referencing the Gauss-Markov mobility model [Meghanathan, 10]. The Gauss-Markov mobility model was designed to adapt to different levels of randomness via one tuning parameter. Initially, at each node is assigned a current speed and direction; then, at fixed intervals of time, a

movement occurs by updating the speed and direction of each node. The most obvious advancement of Gauss-Markov model is that, at each time interval, the next location is calculated based on the current location, speed and direction of movement. So the change curves of moving speed in Gauss-Markov model are smooth, which is consistent with the human mobility feature in real life. So in our model, the moving speed of node q when performing interest $A_i(q)$ is given as below:

$$M_t(q) = \beta M_{t-1}(q) + (1-\beta)\bar{M}(q) + \sqrt{(1-\beta^2)}M_{x_{t-1}}(q) \tag{10}$$

where $M_t(q)$ is the new speed of the node q at time interval t; β, where $0 \leq \beta \leq 1$, is the tuning parameter used to vary the randomness; $\bar{M}(q)$ is constant representing the mean value of speed as $t \to \infty$. In our model, we set $\bar{M}(q)$ equal to $M_i(q)$. $M_{x_{t-1}}(q)$ is a random variable independently chosen by node q from a Gaussian distribution with mean 0 and standard deviation 1. Initialized speed $M_0(q)$is equal to the default speed. It is worthy to note that, if $\beta = 0$, the moving speed tends to be constant; on the contrary, linear motion is obtained by setting $\beta = 1$.

3.1.5 Social Graph

Before calculating the social attraction of each community, we need to evaluate the social relations among people and extract their social properties to build a social graph. A social graph is a global mapping that depicts personal relations of all users within different communities. Such a graph is a weight matrix where vertices represent individual people and edges describe social ties between them. Here in our model, the social ties between two nodes are measured by the times they meet each other. We naturally think if two people are more likely to encounter with each other, they are in a closer relationship. In [Lindgren, 03], the author presented a classic algorithm to assess social graph. As a consequence, by referencing to the research work of [Lindgren, 03], we propose our calculation method of social graph as below.

Each node q in the network will maintain a social relationship strength vector $\mathbf{RS}(q)$ where $RS(p,q)$ represents the p^{th}element of $\mathbf{RS}(q)$ recording the encounter times between q and p. This value denotes the relationship strength between the two nodes. When a pair of nodes is encountered, the metric is updated according to the following relation:

$$RS(p,q) = RS(p,q)_{old} + (1 - RS(p,q)_{old}) \times RS_{init} \tag{11}$$

where $RS(p,q)$ is the relationship strength that node q has for node p, and $RS_{init} \in [0,1]$ is an initialization constant. This formula ensures that nodes often encountered have higher relationship strength. If a pair of nodes does not encounter each other in a while, they are less likely to have high relationship strength with each other, thus the relationship strength values must age according to the following equation:

$$RS(p,q) = RS(p,q)_{old} \times \gamma^k \tag{12}$$

where $\gamma \in [0,1)$ is the aging constant, and k is the number of elapsed time units since the last time the metric was aged. The time unit used may differ and should be defined based on the application and the expected delays in the targeted network.

3.2 Evaluation

In this section, aiming to better understand the model performance, we analyze two further properties of the movement patterns: *i)* the contact duration and *ii)* the inter-contact times. We adopt the same definitions used in [Musolesi, 06] in order to compare the results.

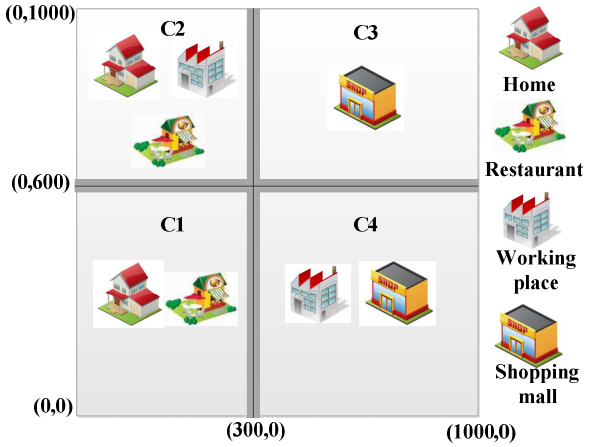


Figure 3: Layout of communities and interest sites in the simulation scenario

According to [Musolesi, 06], the contact duration is defined as the time interval in which two nodes can communicate being within the same transmission range. The number of such contacts and the distribution of contact durations is an important factor for determining the capacity of opportunistic networks. Inter-contact duration is defined as the time interval between two contacts, which describe the contact rate with other nodes in the network.

We present a simple scenario in a simulation area of 1 Km^2 and we divide such area into four communities $\mathbf{C} = \{C_1, C_2, C_3, C_4\}$ as shown in Figure 3. At the initial stage, the nodes are randomly placed in community $C_1$and C_2. As mentioned above, the node behavior is driven by local events and global events. During a local event, the node is required to return to its own community. Hence, it is reasonable to use the local event to represent the behavior "having rest at home". For global events, the movement of a node is influenced by social relationships and interests. Here, for convenience, we assume that each node share the same interest set $\mathbf{A} = \{A_1 = \text{shopping}, A_2 = \text{working}, A_3 = \text{"eating at restaurant"}\}$ that is defined by the following interest matrix:

$$\mathbf{IM}(P) = \begin{bmatrix} 0 & 0 & 0.6 & 0.4 \\ 0 & 0.5 & 0.5 & 0 \\ 0.5 & 0.5 & 0 & 0 \end{bmatrix} \tag{13}$$

It is worthy to remind that in $\mathbf{IM}(P)$, rows denote the community set $\mathbf{C} = \{C_1, C_2, C_3, C_4\}$ and columns represent the interest set $\mathbf{A} = \{A_1, A_2, A_3\}$. As an example, we can note that, by looking at the interest matrix $\mathbf{IM}(P)$, the node performing the interest A_1has the probability of visiting the community C_3 equal to

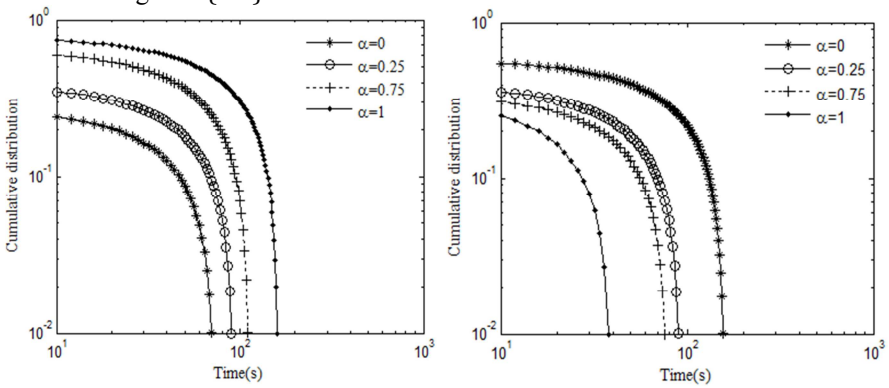
0.6 and has the possibility of entering community C_4 because the probability of visiting this community is equal to 0.4.

To analyze the proposed mobility model, we set the following simulation parameters by referencing the statistics of human mobility in [Trestian, 12]:

- The default time pause set $\mathbf{T}(p)$, corresponding to the interest set $\mathbf{A}$, is equal to $\{T_1 = 4\text{s}, T_s = 8\text{s}, T_3 = 2\text{s}\}$.
- The default moving speed set $\mathbf{M}(p)$, matching the interest set $\mathbf{A}$, is equal to $\{M_1 = 5\text{m/s}, M_2 = 10\text{m/s}, M_3 = 2\text{m/s}\}$.
- The tuning parameters β and γ are set to 0.75 and 0.98 respectively.
- The transmission range of the generic node is fixed to 100m.

Since the weighted coefficient α is the key factor to influence the performance of our mobility model, we propose two simulation cases:

- The first case is composed of 50 nodes in order to evaluate the mobility performance by varying $\alpha = \{0, 0.25, 0.75, 1\}$.
- The second scenario is designed to evaluate the impact of node density by fixing $\alpha = \{0.5\}$.



(a) cumulative distribution of inter-contact durations (b) cumulative distribution of contact durations

Figure 4: Performance of InterCom model with varying α

Figure 4(a) shows the cumulative distributions of inter-contact durations using log-log coordinates. It is easy to observe that, by decreasing α, the inter-contact durations tend to be longer. For $\alpha = 1$, only 24% of inter-contact durations last more than 10 seconds. In contrast, more than 74% of inter-contact durations are longer than 10 seconds when α is equal to 0. This behavior is mostly due to the fact that in the case of $\alpha = 0$, the movements of hosts are only determined by social relationships. Hence, the moving range of nodes is constrained within residential communities C_1 and C_2. Nodes are more likely to meet each other and maintain a relatively long inter-contact duration. Considering the case of $\alpha = 1$, nodes choose their destinations according to their own social interests and interest sites are distributed more widely than the residential communities. Hence, the moving scale of the nodes is larger, thus leading to decrease hit probability and inter-contact durations. Besides that, our

curves show an approximate power law behavior when α is 0.25 or larger. A similar pattern can also be observed in UCSD [McNett, 05].

Figure 4(b) shows the cumulative distributions of contact durations using log-log coordinates. Similar to the inter-contact duration above, the contact duration tends to be longer with the decreasing of α. In the case of $\alpha = 0$, less than 55% of contact durations can last longer than 10 seconds. On the contrary, by setting $\alpha = 1$, almost 25% of contact duration is able to achieve that result. It is easy to understand that the length of contact duration depends on the level of interest similarity of the nodes. Obviously, for $\alpha = 0$, the nodes can be seen as travelling between two residential communities (i.e., C_1 and C_2); therefore, the traces of nodes are more likely to be coincident. However, as far as the case of $\alpha = 1$ is concerned, the traces of the nodes seem to be more scattered, thus leading to the decrease of contact durations.

To sum up, we have shown that, by considering typical human characteristics such as interest-driven and social-based behaviors, our model is more similar to real human traces. Moreover, the reality of our model has been further confirmed through the evaluation of important performance indexes such as inter-contact duration and contact duration.

4 Design of Routing Protocol

In this section, we describe the main characteristics of a new routing protocol well-suited for the proposed InterCom mobility model; thus, we denote the routing scheme as InterCom either for the sake of simplicity. InterCom relies on the notion of utility for the selection of message carriers in order to enable store-ferry-forward communication. The utility of a node represents how good a carrier is for message relaying. The utility values are linked to movement patterns and co-location with other nodes. For community-based opportunistic networks, a member of a given community tends to interact with another member of the same community rather than with a randomly chosen member of the population; this makes the network heterogeneous from the perspectives of movement pattern and social property. Thus, it is reasonable to adopt two different utility measurements for intra-community and inter-community respectively. A similar idea of adopting two-layered utilities has been proposed in [Hui, 11]. In such work, each node has a global utility across the whole network and a local utility within its local community. The utility value relies on two social characteristics: community and centrality. Taking advantages of these social characteristics, the proposed Bubble Rap Forwarding mechanism, basically includes two phases: a bubble-up phase based on global centrality and a bubble-up phase based on local centrality. In both phases, the bubble-up forwarding strategy is utilized to forward messages to nodes that are more popular than the current node (i.e., with higher centrality). Although Bubble Rap, to some extent, is capable of accelerating the message forwarding from source to destination by introducing two-layer utility, it has been proven that such a strategy may fail when the destination belongs to the communities whose members are all with low global centrality values. Besides that, if the number of communities is too few or the distribution of nodes in the network is too sparse, it may be difficult to extract social structures from the social graph, thus raising challenges to assess centrality values. Aiming to avoid the

drawbacks of the former researches, we adopt a new method to calculate the utilities. For intra-community (shown as dash arrow in Figure 5), we use the active degree as the utility to decide the potential message carrier. For inter-community (shown as solid arrow in Figure 5), we define the probability of visiting destination community as the utility to select qualified candidates for message relaying between communities. The calculation of utilities is described in detail in the next section.

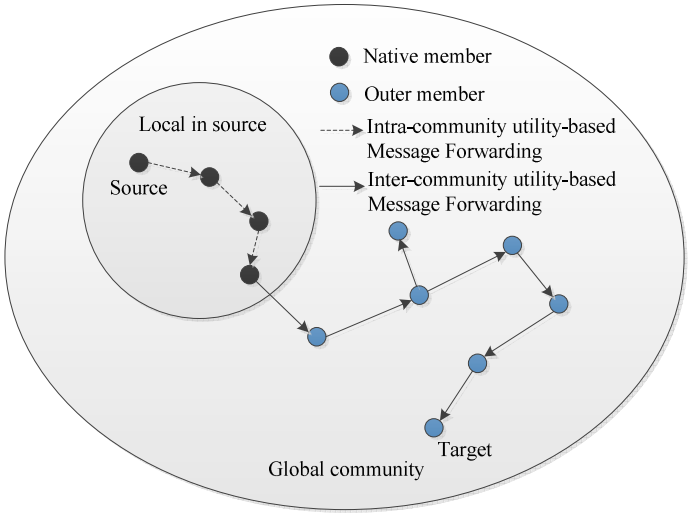


Figure 5: A schema of message flow according to the InterCom routing protocol

4.1 Routing within the same Community

4.1.1 Intra-community Utility

In a community, some nodes stay at a location for a longer time than other nodes. We call them lazy nodes that do not always participate in community's activities and by contacting fewer nodes. On the contrary, some nodes interact with more nodes and are more likely to visit other communities, we call them active nodes. By selecting active nodes as relay allows enhancing the probability of message flowing from a source community to outer communities. Thus, we select the active degree as the intra-community utility in our routing protocol.

Each node in the network will maintain an intra-community utility that is determined by the probability of node leaving its own community for other outer communities. The higher the active degree the node has, the easier the node distributes messages to other communities. The calculation method for *intra-community utility* (*IU*) is performed in a complementary way respect to the willing to leave the native community expressed through the so-called *outer willingness utility* (*OWU*) as follows:

$$OWU(i) = \alpha\, RS + (1-\alpha)\, IS$$

$$where \quad \begin{cases} RS = \dfrac{\sum_{C_y \in \mathbf{C},\ C_y \neq C_{Na}(i)} SA_{C_y}(i)}{\sum_{C_x \in \mathbf{C}} SA_{C_x}(i)} \\ IS = \dfrac{\sum_{C_x \in \mathbf{C},\ C_x \neq C_{Na}(i)} \sum_{A_x \in \mathbf{A}} ST_{C_x,A_x}(i)}{|\mathbf{A}|} \end{cases} \tag{14}$$

where $C_{Na}(i)$ denotes the native community of node i and $\mathbf{C}$ is the community set. α is the weight coefficient mentioned before to adjust the influence of interest and social relationship on human mobility. The term RS is the probability of node i leaving its native community by only considering the impact of social relationships and the term IS represents the probability of node i moving to outer communities driven by social interests. Therefore, $OWU(i)$, representing the willing to leave the native community, is essentially the comprehensive probability of node i selecting the destination outside of its native community by considering the weighted impacts of social relationships and interests; finally, the intra-community utility $IU(i)$ can be calculated as the complement of $OWU(i)$ respect to 1:

$$IU(i) = 1 - OWU(i) \tag{15}$$

4.1.2 Message Forwarding in intra-community

In general, the entire process of message forwarding in opportunistic networks mainly includes two phases: 1) distribution phase; 2) relaying phase. For distribution phase, the source node is required to distribute a certain number of message copies into the network. The goal of doing this is to guarantee the success rate of message delivering and accelerate the spreading speed of message copies. Since in community-based opportunistic networks, the nodes within the same community have higher probability to encounter with each other, the spreading of message copies within the source community (i.e., the community where the source node locates) guarantees the presence of a suitable number of copies in the network. Especially in the sparse network, the advancement of message distribution in source community is far more significant. Therefore, the aim of intra-community forwarding strategy is to help the message spreading, from low-utility to high-utility, as well as to keep sufficient amount of messages copies existing in the network. Therefore, we consider three scenarios in our protocol. Note that the message delivering we discuss here is only constrained between two nodes whose host community is the same.

When message-carrying node p encounters its peer q, they will exchange their intra-community utility value firstly. According to the consequences after the exchange, we can get the utility value of the message-carrying node $IU(p)$ and the utility value of the encountering node $IU(q)$.

If $|IU(p) - IU(q)| \leq \delta$ where δ is the relaying threshold value, we can consider the utility value of message-carrying node similar to the encountering node. Message-carrying node will duplicate its own message copy to the encountering node and retain its own message copy.

If $IU(q) - IU(p) > \delta$, we can consider the utility value of message-carrying node much smaller than encountering node. The message-carrying node will duplicate the message copy to the encountering node and delete its own message copy.

If $IU(p) - IU(q) > \delta$, we can consider the utility value of the message-carrying node much larger than encountering node. If it has a message copy, the encountering node will delete its own message copy.

The idea behind the intra-community strategy is easy to be understood. Through the copying process between two nodes with similar utility, we can guarantee enough message copies circulating in the intra-community. The message delivering from low-utility to high-utility can ensure the message having higher probability to reach destination after each encountering. Although the messages are capable of following the most effective way to contact members belonging to the outer communities through the two above schemes, the total amount of message copies can increase monotonically which will cause excessive consumption of energy and cache. Due to this reason, when two message carriers encounter with each other, the one having lower utility deletes its message to relieve its cache space.

4.2 Routing between Communities

4.2.1 Inter-community Utility

As mentioned above, the utility function of the distribution phase occurring in an intra-community aims at guaranteeing that a sufficient number of message copies can flow among the network. When this goal is achieved, the next step consists in an effective strategy to select qualified relay nodes towards the target node. As the ultimate goal is to send the message or its copies to the target node, delivering such messages to the peers of the target node (i.e. those that share the same target node community), can be considered as an equivalent successful delivery because of the encountering high probability in an intra-community. Therefore, our selection of qualified relay in an outer-community is based on either the probability of contacting the target or the probability of entering into the target node community. Since in our mobility model, the movement of a node is determined by its interests and social relationships, the node that share similar interests or have intimate social relationships with the target node or with the target node community, has higher success rate to deliver the message. Based on this consideration, the calculation method for inter-community utility $OU(i)$ is shown as follows.

$$OU(i) = \frac{\sum_{A_m \in \mathbf{A}} P_{C_d, A_m}(i)}{|\mathbf{A}|} + \alpha PR(i,d) + (1-\alpha) ID(i,d) \tag{16}$$

where C_d represents the target community (i.e., the community where the target node d locates). Hence, $P_{C_d, A_m}(i)$ denotes the probability of node i to enter into the target community when following the interest A_m. Considering the node usually has multiple interests, which are defined by the general set $\mathbf{A}$, the term $\frac{\sum_{A_m \in A} P_{C_d, A_m}(i)}{|\mathbf{A}|}$ is the probability of node i to visit the target community taking into account all possible interests. $\mathrm{RS}(i,d)$ is the social relationship strength between node i and target d, which also denotes the probability of node i to encounter d. $ID(i,d)$ is the interests comparison function between node i and target node d, which reflects the interest

difference between i and d. As one can note, the more evident the interest difference the nodes demonstrate, the smaller the value of $ID(i,d)$ is:

$$ID(i,d) = 1 - \frac{\sum_{A_m \in \mathbf{A}} \sum_{C_n \in \mathbf{C}} |ST_{C_n,A_m}(i) - ST_{C_n,A_m}(d)|}{|\mathbf{A}|} \quad (17)$$

The idea behind the definition of $ID(i,d)$ is that through the calculation of interest similarity of node i and target d, we can derive the encountering probability of them by only considering the impact of social interests. As mentioned before, the impact of social relationships and interests are different, hence we use the weighted coefficient α proposed in section 3.2.2 to adjust their mutual influence on inter-communities message delivery. Actually $OU(i)$ is the sum of the probability of node i visiting target community C_d and the probability of node i encountering target d, from two different perspectives (social relationships and interests).

4.2.2 Message Forwarding in Outer-community

As mentioned above, the purpose of message transmission in intra-community is to deliver messages to highly active carriers as well as to guarantee a sufficient number of message copies. However, for sparse community whose members are few, even though each member in the community has successfully received message copies, the total amount of copies may not be sufficient to ensure an adequate dissemination. Hence, the mechanism of message routing in inter-community is similar to that of intra-community, which also includes three behaviors: duplication, delivering and deletion. However, with respect to inter-community, the nodes cannot be treated at the same way because they come from different host communities. In our routing strategy, the nodes in inter-community can be classified into two categories: native member and outer member. A native member is the node from the source community, while an outer member is the node that does not belong to the source community. Since the encountering between native members is the focus of the message forwarding strategy for intra-community, the scenarios for inter-community mainly include two cases: native members encountering outer members and outer members encountering outer members. The forwarding strategy for inter-community is discussed in detail as follows.

When message-carrying native member p encounters an outer member q, they will first exchange their inter-community utility value. After this exchange, we can compute the utility value of the message-carrying node $OU(p)$ and the utility value of the encountering node $OU(q)$.

If $|OU(p) - OU(q)| \leq \varphi$, where φ is the relaying threshold value, we can consider the utility value of message-carrying node similar to the encountering node. Message-carrying node will duplicate its own message copy to the encountering node and retain its own message copy.

If $OU(p) - OU(q) > \varphi$, we can consider the utility value of the message-carrying node much larger than that of the encountering node. If it has a message copy, the encountering node will delete its own message copy.

If $OU(q) - OU(p) > \varphi$, we can consider the utility value of the message-carrying node much smaller than that of the encountering node. The message-carrying node will transfer a message copy to the encountering node and delete its own message copy.

When message-carrying outer member p encounters an outer member q, they will exchange their inter-utility value firstly. After the exchange, we can compute the utility value of the message-carrying node $OU(p)$ and the utility value of the encountering node $OU(q)$.

If $OU(p) > OU(q)$, the utility value of the message-carrying node is larger than that of encountering node, the encountering node will delete its own message copy (if any).

If $OU(p) < OU(q)$, the utility value of message-carrying node is smaller than that of the encountering node, the message-carrying node will transfer a message copy to the encountering node and delete its own message copy.

The most evident difference between the two cases (i.e., native members vs. outer members and outer members vs. outer members) is that forwarding behavior between native members and outer members includes message duplication which is not performed when outer members encounters outer members. The goal of exploiting the message duplication process is to spread messages to the outer community space in order to enhance the success rate of message delivery and to reduce transmission delay especially in sparse networks. Since in most cases, the outer members are the overwhelming majority of the network, the message duplication carried out by the members will result in a sharp rise of message copies amount turning into an expensive occupation of network resources. Due to this reason, the operation of message copying is only constrained between native members and outer members. For message forwarding between outer members, the only purpose is to find the most cost-effective relaying path to destination. Notice that, since in our mobility model the nodes coming from the same community have highest probability to encounter each other, it is reasonable that the target node or its peers, which are from the same community, will set the utility value to the maximum value.

4.3 Buffer Management

In opportunistic networks, the storage space consumes fast due to their intrinsic delay-tolerant characteristics, leading to a more urgent demand for efficient cache management respect to common networks. Thus, how to manage the cache efficiently is one of the most important and challenging issues to improve the performance of the routing algorithm. In order to control the number of the message copies circulating in the network and thus reducing the resource consumption of the network, a cache management strategy is proposed as follows:

a) Every message will include a TTL (Time to Live) value upon creation. The TTL will decrease over time. The node will examine whether the TTL is expired (e.g. decrease to zero) or not. If TTL decreases to zero, the message will be deleted from the cache.

b) When a new message is inserted into the buffer, it will be en-queued at the end of the buffer. When the message carrier encounters appropriate message-relaying opportunity, the message at the head of the buffer will be transmitted first. The buffer message processing is FIFO-based.

c) When a message reaches its destination, other copies of this message should be discarded as their existence would waste precious resources in terms of buffer and energy. Therefore, the destination node will adopt an epidemic strategy with a given TTL to send a small ACK message to other nodes nearby to inform them

of discarding the redundant copies.

5 Routing Evaluation

In this section, we conduct extensive simulations using a Matlab based simulation framework to evaluate the proposed InterCom routing protocol and compare it with existing community-based routing schemes. All the simulations are based on our InterCom model.

5.1 Reference Algorithms

By looking at the literature of the last few years, it is possible to find a lot of research works on forwarding strategies for opportunistic networks; however, since our goal is to provide a cost-effective social-based routing protocol, we have chosen the following well-known and widely-diffused routing protocols (Bubble Rap, Simbet and PRoPHET) as benchmarks. To run Bubble Rap, we are required to configure three main parameters: C-Window duration, C-Window windows and K-Clique; thus, according to [Hui, 11] we set those parameters to 1000s, 5 and 5 respectively. In Simbet, we only need to configure the tuning parameter α which is set to 0.5 in our simulation according to the recommendation suggested by [Daly, 07]. In [Lindgren, 03], it has been proven that PRoPHET is able to have a promising routing performance when initialized probability P_{init} , coefficient of indirect visits β and aging constant γ are set to 0.75, 0.25 and 0.98 respectively. Thus, in our evaluation we use the same simulation settings.

5.2 Metrics

We define the following metrics to evaluate the different routing protocols in opportunistic networks:

- *Delivery Ratio*: the percentage of messages delivered successfully out of the number of total messages generated. It is always considered as the most fundamental criterion to analyze the performance of a routing protocol.
- *Delivery Delay*: the duration between the message generation time and the message delivery time. Delivery delay is an important concern in routing design.
- *Overhead*: the total number of messages transmitted during the simulation across all nodes. This value could be used to estimate the energy efficiency of a routing protocol.
- *Caching time*: the average time of cache being occupied during the simulation across all nodes. Long caching time means messages last in the buffer for longer, and consequently a low caching time is desirable.

5.3 Simulation Setup

For convenience, we still use the simulation scenario proposed in section 3.2 to evaluate the performance of InterCom routing protocol. The default settings of the network and our routing protocol are listed in Table 1.

Parameter	Value
Simulation time	2000s
Queue model	FIFO
Wireless protocol	IEEE 802.11g
Message size	128KB
Buffer size	8MB
Message generation rate	1 msg/5s
Utility threshold value δ	0.1
Utility threshold value φ	0.1

Table 1: Simulation parameters for network model

5.4 Simulation Results

In this section, we present and discuss the results obtained after performing the simulations. In particular, we first evaluate the performance of the selected forwarding protocols with different numbers of nodes and, then, analyze the performances by varying the TTL.

5.4.1 Evaluation by varying the number of nodes

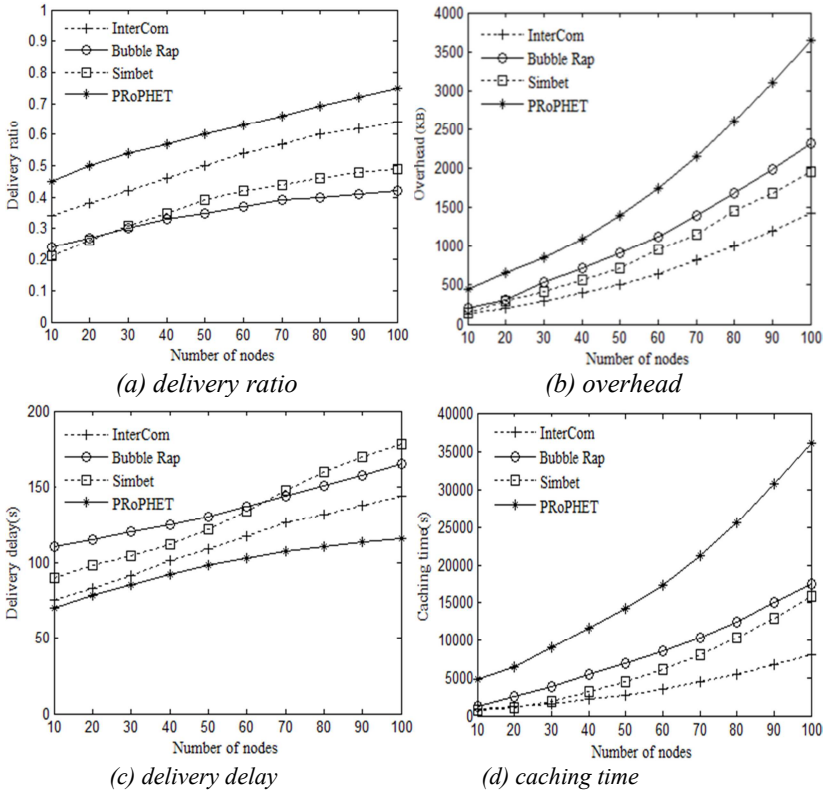
Regarding the *Delivery Ratio*, in Figure 6(a), the performance of all four routing protocols are improved significantly by increasing the number of nodes and the delivery ratio of PRoPHET achieves more than 75% when the number of nodes exceeds 100. The performance of InterCom is only less than 10% with respect to PRoPHET, whilst Bubble Rap and Simbet performances are hardly satisfactory, i.e., lower than 50%. The highest performance of PRoPHET is due to its flooding routing scheme that injects a large amount of message copies into the network. As a consequence, we observe that the overhead and caching time of PRoPHET are much higher than the other routing protocols. Compared with the Bubble Rap and Simbet, the selection of relay nodes in InterCom is based on both the social intimacy and interests similarity with the target node. Since the movements of the nodes in the mobility model are also driven by social interests and social attraction, a higher delivery ratio of InterCom can be obtained.

Figure 6(b) shows the overhead of all the protocols; in particular, the overhead of InterCom is the lowest, equals to only one third of that of PRoPHET. In fact, in InterCom, when both nodes carrying messages encounter each other, the node with lower utility will delete its own copy after exchanging the message so being able to reduce excessive overhead caused by message copying. On the other side, we would like to remark that the very good performance of PRoPHET on the delivery ratio is actually obtained at the expense of a significant overhead.

Regarding the delivery delay shown in Figure 6(c), the performance trend of the routing protocols is quite similar to that of Figure 6(a). In particular, PRoPHET still exhibits the lowest delivery delay, which is less than InterCom, Bubble Rap and Simbet by 24%, 40% and 45% respectively. The reason is that PRoPHET duplicates more messages than the other algorithms, thus speeding up the message delivery with

respect to the other protocols. Although Simbet and Bubble Rap transmit more messages than InterCom, their latency is considerably higher than InterCom.

Finally, InterCom performs best in terms of caching time (see Figure 6(d)) while the caching time of Simbet and Bubble Rap are almost the same. Due to the excessive message copies that give rise to long occupation of buffer space, the caching time of PRoPHET is much higher than the other protocols.



(a) delivery ratio *(b) overhead*

(c) delivery delay *(d) caching time*

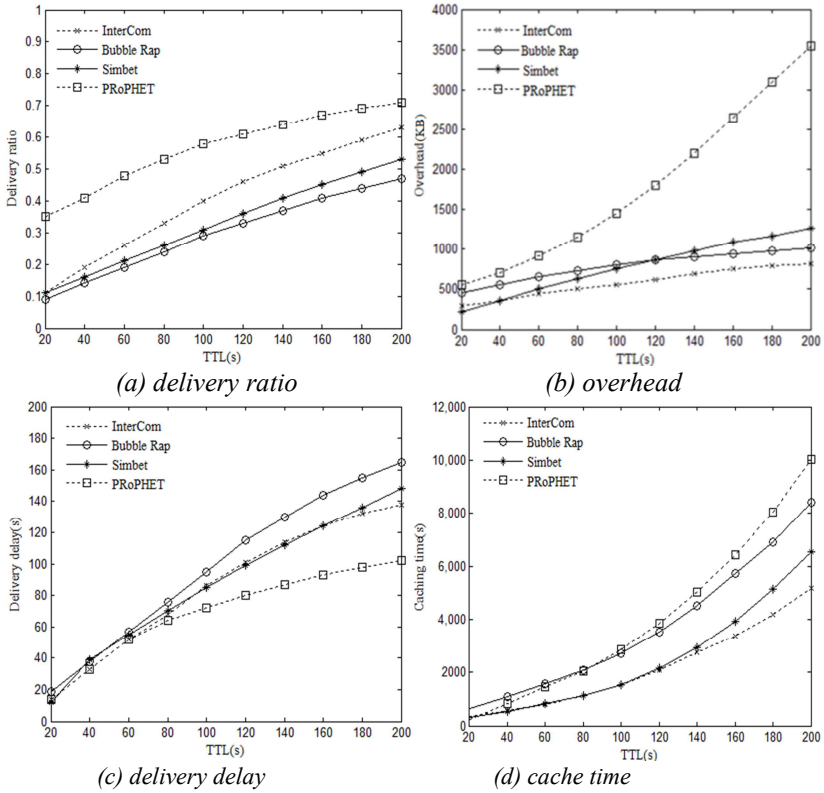
Figure 6: Routing performance with varying number of nodes

5.4.2 Evaluation by varying the TTL

Delivery ratio, overhead, delivery delay and caching time by varying TTL are shown in Figure 7 by keeping constant the number of nodes to 50. By analyzing the delivery ratio (see Figure 7(a)), we can observe that all algorithms deliver more messages to the target node when the TTL increases. However, as the TTL becomes high the increment in the delivery ratio is reduced because the capacity of the network to forward messages becomes the performance bottleneck. PRoPHET outperforms all the other protocols with the highest delivery ratio by achieving 69% of message delivery. With respect to InterCom, although the performance difference with PRoPHET is evident for low TTLs, the performance gap tends to be small by increasing the TTL. When the TTL is set to 200, the delivery ratio of InterCom is only

8% lower than that of PRoPHET.

In terms of overhead (see Figure 7(b)), PRoPHET costs much more than the other protocols. On the contrary, InterCom shows the lowest overhead. As far as Bubble Rap and Simbet are concerned, the Simbet outperforms Bubble Rap both in terms of delivery ratio and overhead. By considering the delivery delay (see Figure 7(c)), for low TTLs (i.e., lower than 50 seconds), all protocols show similar performances. As TTL is increased, PRoPHET is able to deliver messages faster than the other protocols as it duplicates more messages than the other algorithms. As one can note from caching time shown in Figure 7(d), among all protocols Simbet performs the best as well as InterCom by choosing TTL values lower than 120seconds. By increasing the TTL values over 120 seconds, the performances of InterCom are significantly better than those of Simbet. It is worth noting that the caching time of PRoPHET is usually much higher than that of the other three routing protocols. When TTL is set to 200, the caching time of PRoPHET is almost the sum of those of the three reference algorithms.



(a) delivery ratio *(b) overhead*

(c) delivery delay *(d) cache time*

Figure 7: Routing performance by varying TTL

According to these results we can argue that InterCom performs the best from the perspective of comprehensive routing performance. Although PRoPHET has relatively better results than InterCom in terms of delivery ratio and latency, the

advantage is obtained at the expense of overhead and caching time. In contrast, InterCom is able to forward messages with a good delivery ratio and latency while maintaining the lowest overhead and caching time. The performances of Bubble Rap and Simbet are almost always worse than those of InterCom.

6 Discussion and Future Works

The main contributions of this paper consist into the design of an interest-driven social-based community mobility model coupled with a two-layer routing protocol well-suited for opportunistic networks. To the best of our knowledge, we are the first to introduce the concept of "interests" within the context of the opportunistic networks. Through comparison with existing mobility models, the proposed model is more in line with the characteristics of real human traces.

Some of the issues to address in the near future are outlined as follows:

a) Although we have introduced the concept of "interests" into the InterCom model, the description of "interests" is still too simple. In our model, for simplicity, the interest is selected randomly from the general interest set at the beginning of a global event. But in real life, there might exist correlation between two consecutive interests. For example, people are more likely to return home to have a rest rather than go to workplace after visiting hospital. Based on this consideration, it would be necessary to define a correlation function among interests.

b) Like most of the current research on opportunistic networks, the main objective of our study consists into the proposal of a mobility model to be applied in a neighborhood scenario by using an opportunistic routing to achieve efficient message exchange between various members and communities. Hence, in our mobility model, the community division is based on geographical information (i.e., belonging to the same community means home locations in the same grid). However, in few particular contexts (e.g. urban searching and rescuing [Aldunate, 06], [Ochoa, 13]), communities are divided according to the tasks assignment or intimacy of social relationship; therefore, our model seems to be not suitable for such scenarios and how to make it more flexible is still an interesting and challenging open issue.

c) One interesting research line that has not been discussed herein consists into the analysis of human features (e.g. gender, age, culture, religion, etc.) impact on community behavior. In this work, we only assume that the personal interests are driven by daily needs (e.g. eating, sleeping, working, entertaining, etc.). However, besides daily needs, the community behavior of human beings is strongly affected by their personal features. For example, considering the entertainments related to the gender, females are more likely to visit the community where a big mall is located while males prefer communities where there are bars. Hence, it would be interesting to take into account, as future works, the human features that could affect the community behavioral.

7 Conclusions

In this paper, we proposed the InterCom model that better takes into account the social features of human behavior pattern (i.e. interests-motivated, geographical priority and time-variance) with respect to pure community-based models. Furthermore, based on this model, we presented a two-layer routing algorithm, named InterCom routing protocol, whose intra-community and inter-community utilities are respectively determined by the activity level of the node and by the probability of contacting the target node. A performance comparison between the InterCom routing protocol and other well-known routing approaches for opportunistic networks (i.e. PRoPHET, Simbet and Bubble Rap) has been carried out in terms of delivery ratio, transmission delay, overhead and caching time. The simulation results show that, by considering interests and social information, messages can be delivered with high probability while keeping overhead and transmission delay low, so providing the best trade-off performances among the analyzed routing protocols.

Acknowledgements

This work has been financially supported by National Science & Technology R&D Program (2012BAJ05B07), International Cooperation Project funded by Hubei Province (2011BFA012) and Fundamental Research Funds for the Central Universities. Moreover, it has been partially supported in the joint bilateral Italy/China project "Smart Personal Mobility Systems for Human Disabilities in Future Smart Cities" (N. CN13MO7).

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