RoRo-LT: Social Routing with Next-place Prediction from Self-assessment of Spatiotemporal Routines

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***Abstract*—Current trend in store-carry-forward fashioned opportunistic networks is towards utilizing social ties in communities. However, keeping social knowledge/network information up-to-date is a non-trivial task due to ever-changing dynamics such as mobility and other human behavior. Therefore, social-based message forwarding proposals in which network information are initially provided to mobile nodes are subject to lose actuality within time. Motivated with this shortcoming, this study presents a social unicast routing scheme, called RoRo-LT, which is based on self-assessment of people's daily routines. Without requiring any network information, RoRo-LT provides an up-to-date social awareness with long-term spatiotemporal observations. In RoRo-LT, nodes in contact estimate their own future trajectories and decide on forwarding according to their social similarities. In comparison to well-known forwarding schemes, RoRo-LT's performance results indicate a high socio-spatial awareness as well as a reasonable effectiveness for opportunistic routing.**

***Keywords*—delay-tolerant networks, social networks, opportunistic routing, context-awareness, next-place prediction**

I. Introduction

Recently, significance of social collaboration has gained currency in the domain of wireless communications [1]. Specific tendencies in social space unite people together at specific points of interests. Therefore, with the advances in tiny-sensor technologies and ubiquity of smart phones, public awareness on urgent issues can be raised in more efficient and distributed ways. In this regard, mobile-phone sensor networks (MPSNs) have been emerging in order to provide cheap and dynamic solutions [2]. Nevertheless, human mobility is a key challenge for social routing. In the last decade, effects of mobile entity behaviors on networking have been studied thoroughly with several mobility models and routing approaches [3], [4]. Instead of avoiding undesirable effects of mobility, opportunistic communication schemes have been introduced in order to exploit movements of mobile node carriers. Intermittent connectivity problems are tackled with delay/disruption-tolerant networking (DTN) [5] in which every mobile entity adopts a suitable store-carry-forward mechanism.

In DTN, message forwarding has to be selective for two main reasons. First, bandwidth in the communication environment must be used efficiently. Routing algorithms depending on multi-copy packet forwarding relay excessive message replicas which severely affect channel capacities. Second, randomness in forwarding might not necessarily provide high delivery ratios. Majority of the opportunistic methods rely on packet switching in consideration of past encounters, frequency of inter-contact times. However, reachability to high number of network elements in a vicinity and information dissemination to distant regions in cities is only possible by understanding mobile entity behaviors and predicting the future status of intermittently connected networks [6].

In this paper, we propose an opportunistic message forwarding algorithm, called **RoRo-LT**, which provides an opportunistic **ro**uting by analyzing daily **ro**utines of MPSN nodes. LT stands for location and time data; such that we create long-term observation sets from spatiotemporal history of every mobile-phone carrier in order to predict their future locations. We keep track of fine-grained GPS data of each mobile-phone. During encounters, each mobile node extracts its own history data, creates a set of predicted outputs for future locations and trajectories, and compares its results with others in order to decide on social routing. Forwarding works as follows: When any two node come across, each node estimates its own future-locations and the node holding the message compares trajectory estimations. If there is no similarity, the message is forwarded to the other node. In this regard, RoRo-LT provides an introspective analysis which does not require global network knowledge. Contrary to the popular opinion of obtaining social similarities from physical and/or network context, our aim is to provide a local service that with the behavioral context. To the extent of our knowledge, this study is the first to specifically explore periodicity and regularity of mobile encounters in social networks with the following contributions:

- **Long-term observations:** Unlike existing social-based proposals that are bound to short-run observations, RoRo-LT utilizes a large and concatenated history data for a better understanding of social periodicities. In [7], we have shown that daily-life routines of mobile-phone carriers can play an important role for opportunistic networking. In this study, we extend our experiments for social routing.
- **Self-assessment:** Next-place prediction studies are getting popular in the domains of ubiquitous computing and crowdsourcing. Unlike centralized or off-line methods, we unveil an on-the-fly target location estimation which does not require global knowledge.
- **Other DTN objectives:** RoRo-LT's prediction methods and outputs are not only congruent for selective message forwarding, but also for several DTN objectives such as reliable communication and data dissemination. For reliable communication, the presented algorithm is capable of estimating future locations. In this way, nodes can decide on forming clusters

with respect to their predicted displacements. For data dissemination, nodes can estimate their own future trajectories so that during contact times they can agree on relaying any message to considered necessary directions. In brief, our online prediction approach is a helpful tool to find socio-spatial ties. This study focuses on unicast performance of RoRo-LT, but it can be also adopted for multicast or broadcast scenarios.

We compare and contrast RoRo-LT with well-accepted DTN approaches over different scenarios: By using the Opportunistic Network Simulator (ONE) [8], an intermittently connected network environment is designated in a campus map with several mobile nodes which communicate over the WiFi protocol. In terms of network efficiency and knowledge utilization, our performance results are promising when compared to well-known DTN-based approaches.

The rest of the paper is organized as follows. Section II discusses the related work. Section III describes the procedures behind our next-place prediction algorithm. Section IV introduces RoRo-LT. Section V presents the experimental setup. Section VI discourses on the performance analysis and experimental results. Finally, Section VII concludes with the discussion and future work.

II. Related Work

Several analogical surveys for DTN-based routing can be found in [9], [10], [11]. The most-known taxonomic distinction in opportunistic networking is between studies which adopt stochastic and deterministic approaches. In general, stochastic methods such as Epidemic [12], Spray&Wait [13], and Spray&Focus [14] are based on (semi-)epidemic packet relays which face with flooding issues in population-dense areas and cannot perform well for sparse network architectures. As Jain et al proposed in [15], routing decisions can be taken more rigorously with knowledge utilization during nodal contacts. By this means, network oracles such as contacts summary, queuing information, and instantaneous buffer occupancies help for deterministic decisions so that routing performance and QoS are increased. MaxProp [16], PRoPHET [17], and RAPID [18], EBR [19] provide selectiveness by utilizing physical context such as encounter history tables, delivery probabilities, similarities, and dependencies.

Recent studies show that investigating node-to-node relations in terms of delivery/encounter likelihood estimations provides transmission effectiveness only up to a certain degree [11]. Pioneer examples of broader context utilization such as FRESH [20], HiBOp [21], and CAR [22] prove that relationships can be understood smoothly for selection of most appropriate nodes in routing. Considering scalability, any router has to provide a scheme which compares local context not only with context from encounters, but with other context types as well. In addition, determination level must be increased with either decentralized or distributed decision making algorithms for context-awareness (CA). In this regard, the impact of social relationships are getting popular in DTN-based scenarios. Early archetypes such as Label [23], SimBET [24], and PeopleRank [25] exploit social dependencies among network entities. Similarities (or sometimes dissimilarities) are investigated with either contact-based data acquisition or information related with current network architecture. For instance, graph theory measures such as centrality and cohesion may dramatically increase networking performance as the experimental analyses in BubbleRAP [26] and dLife [27] already demonstrate. However, relationships and network status are ever-changing; so that updating the network status information concurrently for all partakers is one of the main challenges in social routing. Besides, the number of intermittently connected networks and the density of each may vary from time to time. Yet, most of the social opportunistic schemes rely on scenarios in which these information are obtained beforehand or provided regularly. It is obvious that self-taught network information is necessary to predict near-future status and characteristics of the network participated. We strongly believe that user context in terms of behaviors and activities rather than social dependencies plays much more important role for understanding long-term relationships.

Depending on information types exploited, we categorize DTN-based routing approaches with regard to 3 fundamental context groups: behavioral context, physical context, and environmental context. As shown in Figure 1, behavioral context, physical context, and environmental context consist of user information, contact information, and network information, respectively. We also distinguish the approaches according to their determinism levels. Determinism together with information exploited forms up CA. Intrinsically, network entities in all DTN-based approaches utilize physical context from contacts. CA can be broadened with either behavioral context, or environmental context, or both. To our knowledge, majority of the stochastic and encounter-based proposals solely depend on physical context. Besides, approaches which make use of several network context engender the scope of social-routing. Current social-based routers mostly focus on graph theory and similarity metrics since it is practically hard to obtain overall network status information. If network context is wanted to be comprehended thoroughly, there is always need for information retrieval from info-centers and/or by distributed sensing.

Comprehension of the overall network status can be also possible with behavioral CA. Distributed collaboration of ubiquitously dispersed behavior-aware nodes can envision the network status for a specific time. Besides, several user information such as activities, points-of-interest (POIs), mobility traces which may repeat periodically can give insights for social (dis)similarities. However, there are very few studies for behavioral CA in the domain of DTN. MobySpace [28]

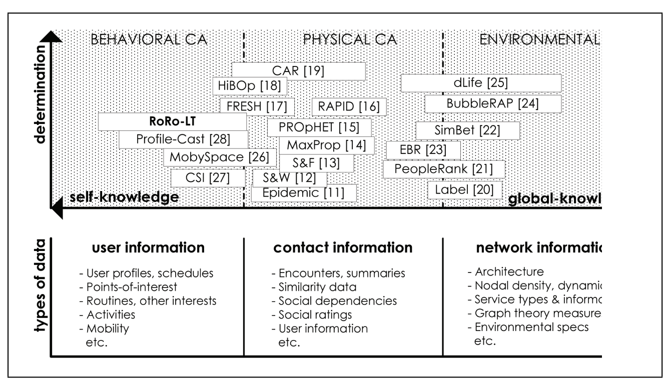


Fig. 1: DTN-based proposals with respect to CA

employs forwarding between nodes with similar destinations. CSI [29] provides routing with a behavior-oriented service. As the most similar study to ours, Profile-Cast [30] analyzes contact similarities with respect to mobility traces and profile information. We position our study in the middle of the behavioral CA as we provide a deterministic social routing with long-term spatiotemporal self-observation sets.

For behavior-awareness, various off-line algorithms exist in the research field of ubiquitous computing. In order to utilize such proposals in opportunistic networking schemes, algorithms must be adapted for on-the-fly scenarios. For instance, specifically to our study, studies such as analysis of mobility traces [31], [32], estimation on human activities and behaviors [33], periodicity forecasting [34], next-place prediction [35], [36], [37] can be adopted as online learning schemes for DTN-based routing. We strongly believe that, in the near future, technological advances will bridge such online learning algorithms together with opportunistic networking scenarios.

III. Next-place Prediction Model

In this section, we clearly define the next-place prediction problem and our methodology by providing related definitions and procedures.

A. Problem Definition

Definitions regarding to the model are given below:

Definition 1: A daily trajectory set L_d is composed of a sequence of ordered pairs (l_i, t_i) where l_i and t_i stand for a spatial coordinate and its corresponding time-stamp, respectively. Cardinality of L_d is denoted by k which equals to the number of GPS records with fixed time intervals.

Definition 2: A weekly observation set W is denoted by $W = \bigcup_{d=1}^{7} L_d$ where d represents a unique day of a week. Equipollently, W_1 stands for the set which holds observations of the preceding week, W_2 stands for the ones of the preceding of W_1, and so forth.

Definition 3: For $\forall L_d$, number of measurements up to the current time is $c \in \mathbb{N}^+$. Thusly, t_c stands for current time. t_g stands for target time where $g \in \mathbb{N}^+$. t_g relative to t_c is equal to $t_c + t_g$ and denoted by t_{c+g}. Similarly, l_c denotes the current coordinate measurement whereas l_{c+g} is the coordinate when t_{c+g}. $\forall L_D$, the location which corresponds to t_c is denoted with ϵ_c.

Definition 4: A transitory history H of current day d is composed of h previous measurements back from current location and time pairs and denoted as $H = \bigcup_{i=c-h}^{c} (l_i, t_i)$.

Definition 5: An estimated spatial element is denoted by θ. An estimated trajectory between t_c and t_g is shown as $\Theta = \{\theta_c, \ldots, \theta_{c+g}\}$. Each sequential element of Θ is a result of next-place prediction.

Problem: Given the definitions, our motivation is to create Θ sets at any t_c in a specific day ($\exists! D$) by utilizing $L_D \subset W_1$. The depth of history for weekly observations may be increased for a better Θ estimation; so that W_2, W_3, or more can be utilized as well. Increasing the number of weekly observation sets can provide more efficiency in periodic pattern recognition. Procedures of the model are discussed in the next sub-section.

B. Methodology

The next-place prediction model has 3 main procedures: self-periodicity measurement, inter-periodicity estimation, and next-place prediction. These procedures are based on local evaluation, so that network entities are able to use the overall model on their own for a routing decision which is explained in the next section. The procedures are explained below:

1) Measuring self-periodicity: We define self-periodicity level of a node as the similarity between its 2 different equally-sized spatiotemporal sets. Local calculation of periodicity with regard to spatiotemporal measurements is shown in Algorithm III.1. H is compared with the corresponding spatiotemporal records $\{\epsilon_{c-h}, \ldots\ \epsilon_c\} \in \exists! L_d, L_d \subset \exists W$. According to the similarity ratio value between them, a high periodicity label or a low periodicity label is returned. There is tolerance interval for comparison, meaning that if the distance between each location from H and L_d is under a threshold (τ), they are taken as similar records.

2) Estimating inter-periodicity: We define inter-periodicity level of a node pair as the similarity between their equally-sized and contemporaneous spatiotemporal Θ sets. Similar to the self-periodicity measurement, node pairs estimate inter-periodicity level as presented in Algorithm III.2.

3) Predicting next-places: The steps in next-place prediction are given in Algorithm III.3. Each $\theta_i \in \Theta$ is calculated as follows. l_c is directly assigned to θ_c. The coordinate shift between l_c and $\epsilon_c \in \exists! L_d, L_d \subset \exists W$ is added to $\epsilon_{c+1}, \ldots, \epsilon_{c+g}$ and assigned as $\theta_{c+1}, \ldots, \theta_{c+g}$, respectively.

Algorithm III.1 Self-periodicity Measurement

Input: H, $\exists! L_d \subset \exists W$
Output: Self-Periodicity Level: $Low \vee High$
$SimCount \leftarrow 0$;
for $i = c - h \mid h = n(H)$ **to** $i = c$ **do**
  if Distance between $l_i \in H$ and $\epsilon_i \in L_d \leq \tau$ **then**
    $SimCount \leftarrow SimCount + 1$
  end if
end for
if $SimCount/h \geq 0.5$ **then**
  return $High$
end if
return Low

Algorithm III.2 Inter-periodicity Estimation

Input: Θ from each node pair
Output: Inter-periodicity Estimation Level: $Low \vee High$
$SimCount \leftarrow 0$;
for $i = c$ **to** $i = c + g$ **do**
  if Distance between $\theta_i \in \Theta$ from first node and $\theta_i \in \Theta$ from second node $\leq \tau$ **then**
    $SimCount \leftarrow SimCount + 1$
  end if
end for
if $SimCount/h \geq 0.5$ **then**
  return $High$
end if
return Low

Algorithm III.3 Next-place prediction

Input: $\exists! L_d \subset \exists W$
Output: Θ
$\theta_c \leftarrow l_c, \theta_c \in \Theta$
$xDiff \leftarrow$ x-coordinate difference between l_c and $\epsilon_c \in L_d$
$yDiff \leftarrow$ y-coordinate difference between l_c and $\epsilon_c \in L_d$
$shift = (xDiff, yDiff)$
for $i = c + 1$ **to** $i = c + g$ **do**
  $\theta_i \leftarrow \epsilon_i + shift, \theta_i \in \Theta$
end for
return Θ

IV. RoRo-LT: A Social Routing Service with respect to Spatiotemporal Routines

In this section, we describe our opportunistic routing scheme RoRo-LT which aims to exploit daily routines of mobile-phone users in the interest of message forwarding. With the next-place prediction model presented in Section III, mobile-phones are individually able to recognize their carriers' periodic situations in terms of socio-spatial orientations.

A. Impact of Socio-Spatial Dissociations

In the daily life, people gather at several locations such as business centers, schools, shopping malls, houses and form several socio-spatial groups for particular time periods. However, cohesiveness in such temporary groups are subject to be broken swiftly because of people's further relations, private reasons, or other factors. Considering such dynamics, as already discussed in Section II, social-based DTN routing schemes which adapt conjectural network/group information may suffer from actuality. To our knowledge, current information about network status can be obtained in a distributed way by individual observations. Individuals may still be unaware of the overall network characteristics, but ubiquity of information from each individual unwittingly forms up an overview about the network. In other words, social and spatial differences among people may provide social pervasiveness of information. The sole goal of RoRo-LT is to determine whether node pairs in communication will be in the same region or not after a specified target time. As a unicast protocol, message on hand is relayed to the contacts encountered at t_c if only they are predicted to be distant from the node itself at t_{c+g}. By this means, RoRo-LT enables self-seeking of socio-spatial dissociations in order to reach different places.

B. Focusing on the User

Majority of the people in the world live with routines. Certain locations as gathering-places create several intermittent social relationships based upon temporal and spatial routines. At the same time, however, high diversity in people's routines immediately breaks off those relationships. RoRo-LT focuses on estimation of possible future locations of each mobile entity in order to exploit from breakaways in urban life.

C. Forwarding Mechanism

The flowchart of RoRo-LT's forwarding mechanism is depicted in Figure 2. When a node establishes a connection with another node, the self-periodicity measurement procedure is called as the first step. For the current day d, the node compares its own H with its own history in $L_d \subset W_1$. Comparing the spatiotemporal records between ϵ_{c-h} and ϵ_c with H, the next-place prediction function is called if a high similarity is found. Otherwise, the self-periodicity is measured for the same corresponding time periods in each older $L_d \in W_i$ sets until a high similarity is detected. If a high similarity score cannot be assured after all of the history records are traced, then L_d with the highest similarity score is selected as the input for next-place prediction procedure.

With the next-place prediction algorithm, contact pairs estimate their own future trajectory for a given target time (t_g). In each individual node, next-coordinates between the times t_c and t_g are written in Θ. In the final step, the node with the message requests Θ of its contact and estimates inter-periodicity level. The node with the message forwards it to its contact only if the forecasted next-locations of contact pairs are non-similar.

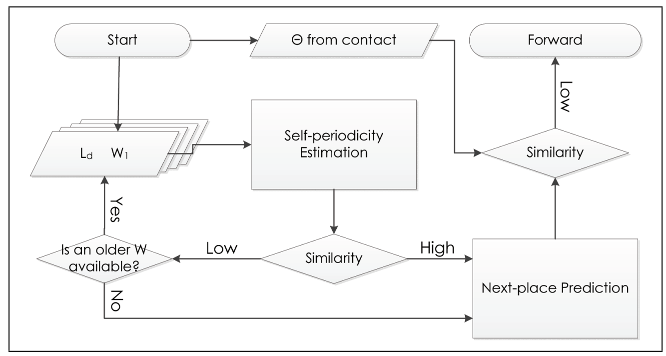


Fig. 2: Forwarding mechanism

D. Discussion

RoRo-LT's forwarding mechanism is symmetric; without loss of generality, nodes which discover others in the same radio range call the same periodicity-awareness functions. During communication, nodes request estimation sets (Θ) with the same format, structure, and size from their contacts.

V. Experimental Design

For a subtle evaluation of RoRo-LT, the Opportunistic Networking Environment (ONE) simulator [8] is designated to create intermittently-connected mobile network scenarios with various parameters. In the simulations, several groups of mobile-phone carriers are formed with different daily routines in the campus map of University of Twente. The parameters of the network setup and models are introduced in this section. Table I shows the experimental design parameters.

A. Network Setup

The campus map of University of Twente is used as our simulation testbed. Dispersed over an area of approximately 2000m by 2000m, the campus contains several POIs: 6 research and faculty buildings, 5 residential centers, 1 library, 1 shopping venue, 1 sport center, and 3 recreational areas are assigned as POIs. As the MPSN of our scenario, a total of 12 worker and student groups are generated with varying

TABLE I: MPSN Scenario Parameters

Simulation run-time	*24hours*
MPSN simulation map	*UT campus* $(2000m \times 2000m)$
POIs	*17 fixed locations*
Network population	*100-1000 nodes under 12 workgroups*
Movement model	*Shortest Path Map Based Movement*
Node wait time	*10mins-4hours*
Node speed	*0.5m/sec-1.5m/sec*
GPS granularity	*5mins-30mins (30mins*)*
Transitory history depth	*10*
Target time (t_g)	*30mins-5hours (1hour*)*
Location Tolerance (τ)	*10m,50m,100m*,500m,1000m*
Bandwidth	*1.375MBps*
Radio Transmit Range	*30m*
Message size	*500kB-1MB*
Buffer Size	*25MB*
Time-to-live	*30mins-5hours (1hour*)*

Except as provided elsewhere, "*" demonstrates the default parameters.

populations including a total of 100 to 1000 individuals. The network architecture does not contain any fixed or mobile infrastructures. Identical mobile-phones (carried by pedestrians) with WiFi interfaces which have 30m radio range compose the overall network.

B. Mobility Model

Shortest path map-based movement model is used to simulate people's mobility. Depending on their daily activities, mobile nodes under different worker and student groups move with a purpose. In the simulations, a worker can drop over places such as his/her house, office, and restaurant whereas a student can shuttle between places such as his/her house, faculty, and library. Their POI probabilities may differ from time to time, from day to day, and from week to week. In addition, their wait times in specific localities may vary as well. For each worker and student group, each simulation test runs for 24 hours where different POI probabilities and wait times are assigned to the nodes.

C. Next-place Prediction Model Parameters

GPS granularity, target time (t_g), location tolerance (τ), and transitory set length (h) are the next-place prediction model parameters. In the simulations, each mobile node keeps track of spatiotemporal activities in fixed time intervals, called granularity. The importance of a message (event) is defined with t_g; meaning that that event information is wanted to be delivered within t_g. During similarity detection in periodicity measurement procedures, τ defines the tolerance interval in terms of distance for spatial comparisons. In self-periodicity measurement, h defines the depth of comparisons. All of these parameters are tested with different values in the simulations.

D. RoRo-LT Parameters

Unicast messages are generated in every 25-35 seconds by random pedestrians. Considering that messages may contain critical event information, their sizes are decided to vary between 500 KBytes to 1 MBytes. Providing a store-carry-forward mechanism, nodes are able to store messages in their internal memory. Allocated buffers works in circular fashion where oldest messages are dropped whenever no space left for an upcoming message. On the other hand, equal time-to-live (TTL) durations are assigned for all messages; so that all nodes store events for the same period of time. TTL is equal to t_g.

Contact pairs generate their own Θ just after connection established. Node with the message requests Θ of the other node. The size of Θ in contact pairs is dependant on granularity since number of future locations are estimated by extracting contemporaneous spatial records from the predetermined history set. High frequency in spatiotemporal records requires more processing time for future-trajectory estimation. Since connections are intermittent most of the time, estimation process must be handled within communication window of contact pairs. Therefore, the effect of granularity on both next-place estimation and routing is discussed in Section VI.

VI. Performance Analysis

Extensive number of tests are held in order to assess the performance of RoRo-LT. The effect of next-place prediction procedures and parameters are analyzed within routing tests. In addition, effectiveness of RoRo-LT is compared with the following well-accepted DTN-based routing schemes: Epidemic [12], Spray&Wait [13], MaxProp [16], PRoPHET [17], and BubbleRAP [26]. This section explains the evaluation steps and presents the results in detail.

A. Evaluation Metrics

The results are assessed with the following measures:

1) Delivery success ratio: The total number of successfully delivered unique messages divided by the total number of created unique messages. Each unique message is created at certain time, and has an unique identification number to be distinguished from others in the network.

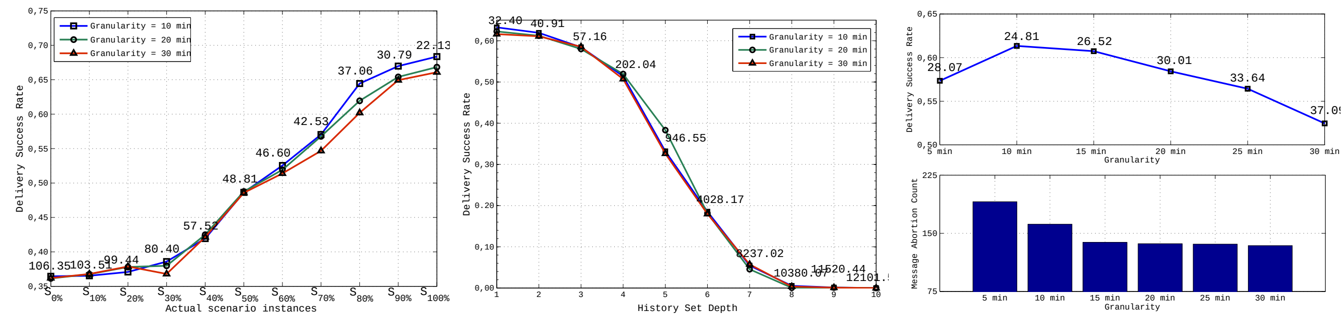
2) Average latency: Average delay of messages from creation to delivery.

3) Message abortion count: Number of aborted transmissions between nodes.

B. Evaluation Methodology

For the performance assessment of RoRo-LT, different scenarios are generated with different periodicity levels for all nodes. In order to have weekly observation sets to be utilized as history in actual routing simulations, a varying set of POI probabilities are assigned to the MPSN groups. In ONE, POI probability refers to the probability of being present at a specific location. In the simulations, nodes which have zero POI probability for several POIs have a random movement whereas a 100% POI probability means presence at the specified POIs is a certain event. Thus, nodes with high POI probabilities have higher periodicities, and vice versa. On the other hand, same settings are run for 10 times with different number of nodes varying from 100 up to 1000. The results given in this section represent average values for all node numbers and run counts.

A set of controlled experiments are held to depict a trade-off between routing and the next-place prediction model parameters. As the first evaluation, the effect of people's routines on RoRo-LT performance is investigated. For the actual scenario S, equivalent scenarios in which only POI probabilities



(a) Performance of the next-place prediction model in RoRo-LT is investigated by testing history sets with different periodicity similarities to the actual scenario. History sets are created on the same scenario, but with varying POI probabilities for mobile-phones in each run.

(b) The effect of history depth on routing is investigated by gradually increasing the search depth for each run. In each subsequent simulation run, the self-similarity procedure finds best history matchings in an older sets at every turn, which causes extra execution delay for each time.

(c) Decrease in GPS sensing frequency does not cause a big trouble for routing performance. Decrease in delivery success ratio is remarkable, but the variance in loss is low. The number of aborted messages is almost same for all granularities, except for 5 and 10 minutes.

Fig. 3: Performance Evaluation of RoRo-LT parameters

differ are run beforehand. In a gradual manner, these history scenarios are named from $S_{0\%}$ to $S_{100\%}$ to have similar instances of the actual scenario with varying periodicities from 0% to 100%, respectively. As the second evaluation, the effect of history depth on RoRo-LT is investigated. As the forwarding traces history until a best-matching history is found, searching process may substantially a problem for routing. To investigate this issue, actual scenario utilizes different history depths. The impacts of granularity and location tolerance interval (τ) are examined as well. The results are given in Section VI-C.

RoRo-LT's performance is also compared with other well-known DTN strategies. The evaluation steps and results are discussed in Section VI-D.

C. Evaluation of RoRo-LT Parameters

Evaluation results for RoRo-LT are given in Figure 3. Figure 3(a) shows how message delivery is affected when the self-similarity in the history set W_1 changes. In each comparison, the actual scenario utilizes only W_1; so that history depth is 1. If the past trajectory records of the mobile-nodes get similar to the ones in the actual scenario, self-similarity procedure of the next-prediction prediction model provides more accurate estimations for inter-periodicity estimation. The performance of the model is also remarkable in terms of latency results (in minutes) which are shown above of each mark on the graph. More similarity to the actual scenario helps messages to be delivered more quickly. On the other hand, as Table II presents, abortion count out of 2891 messages is almost same for all scenarios with different periodicity similarities.

As shown in Figure 3(b), the effect of history depth is also examined in terms of delivery success ratio and latency. It is evident that RoRo-LT cannot perform well when the self-similarity procedure increases the depth of search. As Table III shows, number of aborted messages gradually increases for the tests where nodes trace more history records.

The effect of granularity is shown in Figure 3(c). Interestingly, high frequency in history sets does not improve routing performance. However, as expected, the number of aborted

TABLE II: Message abortion count w.r.t. history scenarios

Scenarios utilized	$S_{0\%}$	$S_{20\%}$	$S_{40\%}$	$S_{60\%}$	$S_{80\%}$	$S_{100\%}$
Abortion count	97	89	85	91	88	86

TABLE III: Message abortion count w.r.t. history depth

History Depth	1	3	5	7	9
Abortion count	81	102	155	262	596

messages are almost same for all granularities, except for very frequent ones. Abortion dramatically increases for the cases where records are taken in every 5 or 10 minutes since inter-periodicity estimation has to deal with more frequent records.

When too much precision is requested for self-similarity, RoRo-LT cannot perform well as Figure 4 demonstrates. When the actual scenario is tested with different history sets obtained from the scenarios $S_{20\%}, \ldots, S_{80\%}$, RoRo-LT has a reasonable performance for $\tau = 50m$ and $\tau = 100m$. Increasing τ gradually decreases the self-similarity comparison performance and RoRo-LT delivery success rates.

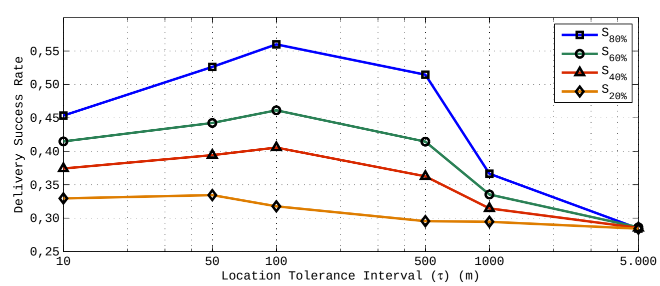


Fig. 4: Forwarding mechanism

In this sub-section, several trade-offs between RoRo-LT's service parameters are presented. The rest of the evaluation is done and discussed with the best trade-off values which are shown as default parameters in Table I.

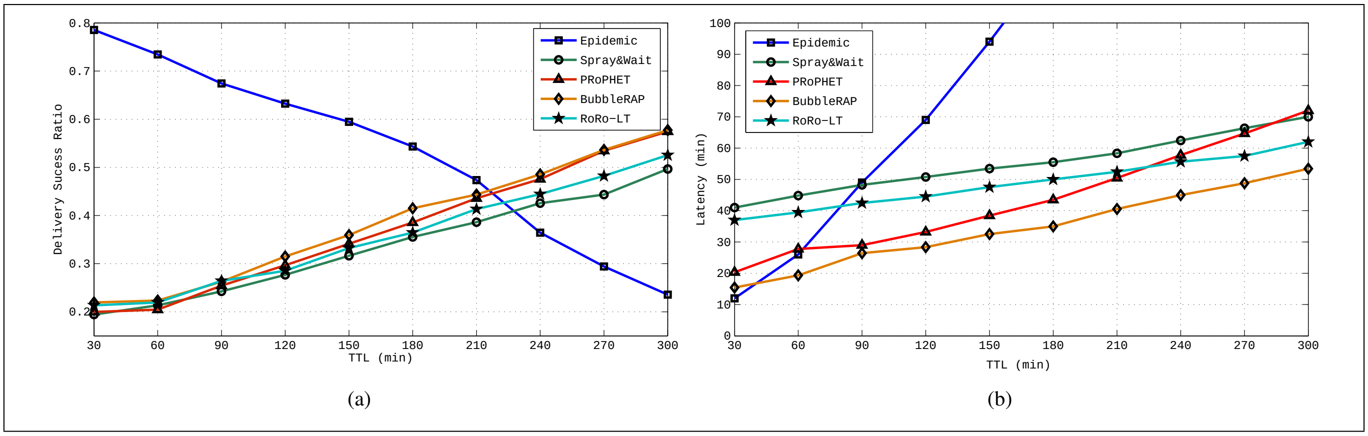


Fig. 5: Performance results for RoRo-LT and several DTN-based routers

D. Comparison between RoRo-LT and Other DTN Routers

Figure 5 contains the performance evaluations of Epidemic, Spray&Wait, PRoPHET, BubbleRAP, and RoRo-LT.

Figure 5(a) shows the delivery success rates of the routers with respect to varying TTL durations. As expected and familiarly known, Epidemic performs very well for lower TTL durations. However, long TTL values causes numerous overflows because of Epidemic's uncontrolled nature. As a controlled mechanism, Spray&Wait utilizes a tradeoff between multi-copy and single-copy in order to make the messages with long TTL values survive in the environment. However, its delivery probability is still low than PRoPHET and BubbleRAP. RoRo-LT provides a reasonable delivery success which is similar to the performance of PRoPHET and BubbleRAP. According to the experiments, RoRo-LT performs better than Spray&Wait and its performance is quite similar to PRoPHET and BubbleRAP in terms of delivery success ratios.

In Figure 5(b), same routers are compared according to their latency values. RoRo-LT's performance in message delivery durations is reasonable, but still not effective as PRoPHET and BubbleRAP. However, as Table IV presents, average hop count value for RoRo-LT is the lowest among all of the routers; meaning that messages are delivered over less hops to the destinations.

TABLE IV: Average Hop Count when TTL=150 mins

Router	Epidemic	Spray&Wait	PRoPHET	BubbleRAP	RoRo-LT
Avg Hop	42.48	24.97	20.01	15.03	9.66

E. Discussion

Provided with history sets which hold self-routines of mobile-phone carriers, RoRo-LT employs a cross examination on contact pairs in order to utilize current social dissimilarities and therefore avoids outdated network information. When its results are analyzed and compared with other DTN-based proposals, RoRo-LT provides a promising online self-evaluation and on-the-fly routing service. Even with the less number of self-measurements, the next-place prediction model featured in the routing service can guarantee a reasonable level of determinism for opportunistic message forwarding.

VII. Conclusion & Future Work

In this study, we have presented RoRo-LT—a self-assessed mobile-phone sensor network (MPSN) routing service which analyzes daily routines of mobile-phone users with long-term observations for the sake of an opportunistic message forwarding scheme. Providing a high level of self-determinism, RoRo-LT keeps track of spatiotemporal activities and employs a set of next-place prediction methods in order to exploit from social dissociations. For a selective message forwarding, MPSN nodes firstly trace their spatiotemporal history tables with intent to find similar routines from their past; secondly utilize these routines in order to generate an estimation for future trajectories; and finally compare their forecasted locations with others during encounters. Contact pairs forward their messages if a dissimilarity is expected for the next-places of each other. By this means, RoRo-LT seeks for socio-spatial separations in order to disseminate data over large regions. Without requiring a global network information, locality-based dynamics inside a MPSN are exploited as an on-the-fly evaluation.

We have assessed several performances of RoRo-LT with extensive numbers of tests in a campus map simulation scenario. With this scenario, we have drawn a parallel between the real world and the simulation setup for daily city activities. In pursuit of finding a trade-off between internal parameters of our next-place prediction model, we have analyzed the routing performance with controlled experiments. In addition, we have presented a brief but novel disquisition on existing proposals, current trends, and open research problems for the field of delay tolerant networking by comparing well-known approaches according to their context utilization. We have compared RoRo-LT with a group of well-accepted opportunistic schemes. We have shown that RoRo-LT provides a reasonable performance in comparison to the other approaches.

As future work, we aim to extend our research on opportunistic routing by utilizing several behavioral context types such as activity recognition data sets, user profile information, and multimedia data. We strongly believe that, beside physical and environmental context awareness, understanding user behaviors can play an important role to build up effective social networking services. Our long-term motivation is to implement an adaptive opportunistic communication framework.

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