Opportunistic Routing Based on Daily Routines

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Abstract—Opportunistic routing is being investigated to enable the proliferation of low-cost wireless applications. A recent trend is looking at social structures, inferred from the social nature of human mobility, to bring messages close to a destination. To have a better picture of social structures, social-based opportunistic routing solutions should consider the dynamism of users' behavior resulting from their daily routines. We address this challenge by presenting *dLife*, a routing algorithm able to capture the dynamics of the network represented by time-evolving social ties between pair of nodes. Experimental results based on synthetic mobility models and real human traces show that *dLife* has better delivery probability, latency, and cost than proposals based on social structures.

Index Terms—social structures; network dynamics; daily routines; opportunistic routing

I. INTRODUCTION

The pervasive deployment of wireless personal devices is creating the opportunity for the development of novel applications. The exploitation of such applications with a good performance-cost tradeoff is possible by allowing devices to use free spectrum to exchange data whenever they are within wireless range. Since every contact is an opportunity to forward data, there is the need to develop routing algorithms able to bring messages close to a destination, with high probability, low delay and costs. Most of the proposed routing solutions focus on inter-contact times alone [1], while there is still significant investigation to understand the nature of such statistics (e.g., power-law, behavior dependent on node context). Moreover, the major drawback of such approaches is the instability of the created proximity graphs [2], which changes with users' mobility.

A recent trend is investigating the impact that more stable social structures (inferred from the social nature of human mobility) have on opportunistic routing [2], [3]. Such social structures are created based on social similarity metrics that allow the identification of the centrality that nodes have in a cluster/community. This allows forwarders to use the identified hub nodes to increase the probability of delivering messages inside (local centrality) or outside (global centrality) a community, based on the assumption that the probability of nodes to meet each other is proportional to the strength of their social connection.

A major limitation of approaches that identify social structures, such as communities, is the lack of consideration about the dynamics of networks, which refers to the evolving structure of the network itself, the making and braking of network ties: over a day a user meets different people at every moment. Thus, the user's personal network changes, and so does the global structure of the social network to which he/she belongs.

When considering dynamic social similarity, it is imperative to accurately represent the actual daily interaction among users: it has been shown [4] that social interactions extracted from proximity graphs must be mapped into a cleaner social connectivity representation (i.e., comprising only stable social contacts) to improve forwarding. This motivates us to investigate a routing solution able to capture network dynamics, represented by users' daily life routine. We focus on the representation of daily routines, since routines can be used to identify future interaction among users sharing similar movement patterns, interests, and communities [5]. Existing proposals [6], [2], [3] succeed in identifying similarities (e.g., interests) among users, but their performance is affected as dynamism derived from users' daily routines is not considered.

To address this challenge, we propose *dLife* that uses timeevolving social structures to reflect the different behavior that users have in different daily periods of time: *dLife* represents the dynamics of social structures as a weighted contact graph, where the weights (i.e., social strengths) express how long a pair of nodes is in contact over different period of times. It considers two complementary utility functions: *Time-Evolving Contact Duration* (TECD) that captures the evolution of social interaction among pairs of users in the same daily period of time, over consecutive days; and *TECD Importance* (TECDi) that captures the evolution of user's importance, based on its node degree and the social strength towards its neighbors, in different periods of time.

In this paper, we show the performance gain of *dLife* against proposals that are only aware of social structures and node centrality metrics, e.g., *Bubble Rap* [2]. We also analyze the impact that centrality metrics have on routing, since by determining the relative importance of a node within the community such metrics create potential bottleneck points. For that, we created a community-based version of *dLife*, called *dLifeComm*, for a fair comparison with *Bubble Rap*. Results show that both versions of *dLife* manage to capture the dynamism of social daily behavior along with social interaction strength, resulting in improved delivery probability, cost, and latency. Our findings also highlight the impact that centrality has on routing performance when comparing the performance of two community-based approaches (*dLifeComm* and *Bubble Rap*).

This paper is structured as follows. Section 2 briefly analyses the related work. Section 3 presents *TECD* and *TECDi* utility functions along with the algorithms for both versions of *dLife*. Section 4 presents the evaluation methodology, setup, and results. In Section 5 the paper is concluded and future work is presented.

II. RELATED WORK

Most of the existing opportunistic routing solutions are based on some level of replication [7]. Among these proposals, emerge solutions based on different representations of social similarity: i) labeling users according to their social groups (e.g., *Label* [8]); ii) looking at the importance (i.e., popularity) of nodes (e.g., *PeopleRank* [9]); iii) combining the notion of community and centrality (e.g., *SimBet* [3] and *Bubble Rap* [2]); iv) considering interests that users have in common (e.g., *SocialCast* [6]).

Such prior-art shows that social-based solutions are more stable than those which only consider node mobility. However, they do not consider the dynamism of users' behavior (i.e., social daily routines) and use centrality metrics, which may create bottlenecks in the network. Moreover, such approaches assume that communities remain static after creation, which is not a realistic assumption.

On the other hand, prior-art also shows that users have routines that can be used to derive future behavior [5]. It has been proven that mapping real social interactions to a clean (i.e., more stable) connectivity representation is rather useful to improve delivery [4]. With *dLife*, users' daily routines are considered to quantify the time-evolving strength of social interactions and so to foresee more accurately future social contacts than with proximity graphs inferred directly from inter-contact times.

III. THE *dLife* ALGORITHM

The major motivation to devise social-based opportunistic routing has to do with the higher stability that social similarity has in comparison to inter-contact times. However, the dynamism of users' social behavior (extracted from daily routines) should be considered in order to guarantee a more realistic representation. This major aspect is missing from existing social-based routing solutions, such as *Bubble Rap*.

Thus, we propose *dLife* that uses two novel utility functions: *TECD* to forward messages to nodes that have a stronger social relationship with the destination than the current carrier; with *TECD* each node computes the average of its contact duration with other nodes during the same set of daily time periods over consecutive days. Our assumption is that contact duration can provide more reliable information than contact history, or frequency when it comes to identifying the strength of social relationships. The reason for considering different daily time periods relates to the fact that users present different behavior during their daily routines [5]. If the carrier and encountered node have no social information towards the destination, forwarding takes place based on a second utility

function, *TECDi*, where the encountered node gets a message if it has greater importance than the carrier.

A second version of *dLife*, *dLifeComm*, is designed to allow an easier comparison of solutions that are focused on the dynamics of the network (i.e., *dLife*, based on users' daily routine) and solutions that are focused on the structure of network (i.e., *Bubble Rap*, based on node centrality). *dLifeComm* uses *TECD* and *TECDi* to exploit communities that arise from social interaction. Communities are detected based on the K-Clique algorithm [10], as occurs with *Bubble Rap*: *TECD* is used to forward within a community based on the social strength that the carrier and encountered nodes have towards the destination, and not their centrality; *TECDi* is used to forward data based on users' importance outside a community.

We start this section by explaining how K-Clique is used to detect social structures (i.e., communities) by *Bubble Rap* and *dLifeComm*. Then, we explain how to capture the dynamics of the network by computing *TECD/TECDi*. Finally, we show how to use *TECD* and *TECDi* to create the *dLife* and *dLifeComm* algorithms.

A. Usage of Social Structures

A social structure defined as a K-Clique community [10] is a union of all cliques (complete subgraphs of size k) that can be reached from each other through a series of adjacent cliques, where cliques are adjacent if they share k - 1 nodes.

Both Bubble Rap and dLifeComm use the K-Clique algorithm to detect the social structure in a proximity graph. The main difference between them is that the former uses the detected structure to compute the centrality of nodes within and outside communities, lacking a representation of the different levels of social interaction that users have over different daily periods of time. On the other hand, dLifeComm considers continuously updated social information, computed based on TECD and TECDi, for forwarding over the detected social structure. That is, the fixed communities detected are the same as in Bubble Rap, but the links considered for forwarding within and between communities change over time as they represent different levels of social strength in different time periods. This means that while Bubble Rap considers a fixed social structure, dLifeComm is aware of its dynamics: the network is still a fixed collection of linked individuals, but now users' daily routines influence the way links are used.

Contrary to *Bubble Rap* and *dLifeComm*, *dLife* does not use any social network analysis algorithm, such as K-Clique, to detect a fixed global social structure: *dLife* relies on *TECD* and *TECDi* utility functions to capture the dynamics of the network by identifying time-evolving social structures that reflect the different interactions that users have over different daily periods of time. With *dLife* the static structure of traditional network analysis can be thought of as different snapshots taken during specific periods of time.

B. Time-Evolving Contact Duration (TECD)

TECD aims to capture the evolution of social interactions in the same daily period of time (hereafter called daily sample)



Figure 1. Contacts a user A has with a set of users $x(CD_{(a,x)})$ in different daily samples ΔT_i

over consecutive days, by computing social strength based on the average duration of contacts.

Fig. 1 shows how social interactions (from the point of view of user A) varies during a day. For instance, it illustrates a daily sample (8 pm - 12 am) over which the social strength of user A to users D, E, and F is much stronger (less intermittent line) than the strength to users B and C. Fig. 1 aims to show the dynamics of a social network over a one-day period, where users' behavior in different daily samples lead to different social structures.

As illustrated in Fig. 1, users' social strength in a given daily sample depends on the average contact duration that they have in such time period: if user x has n contacts with user y in a daily sample ΔT_i , having each contact k a certain duration (*Contact Duration* - $CD(x, y)_k$), at the end of ΔT_i the *Total Contact Time* ($TCT(x, y)_i$) between them is given by Eq. 1.

$$TCT(x,y)_i = \sum_{k=1}^{n} CD(x,y)_k$$
 (1)

The Total Contact Time between users in the same daily sample over consecutive days can be used to estimate the average duration of their contacts for that specific daily sample [5]: the average duration of contacts between users xand y during a daily sample ΔT_i in a day j ($AD(x, y)_{ji}$) is given by a cumulative moving average of their TCT in that daily sample ($TCT(x, y)_{ji}$) and the average duration of their contacts during the same daily sample ΔT_i in the previous day ($AD(x, y)_{(j-1)i}$) as illustrated in Eq. 2.

$$AD(x,y)_{ji} = \frac{TCT(x,y)_{ji} + (j-1)AD(x,y)_{(j-1)i}}{j} \quad (2)$$

The social strength between users in a specific daily sample may also provide some insight about their social strength in consecutive k samples in the same day, ΔT_{i+k} . This is what we call *Time Transitive Property*. This property increases the probability of nodes being capable of transmitting large data chunks, since transmission can be resumed in the next daily sample with high probability.

TECD (cf. Eq. 3) is able to capture the social strength $(w(x, y)_i)$ between any pair of users x and y in a daily sample ΔT_i based on the Average Duration $(AD(x, y)_i)$ of contacts between them in such daily sample and in consecutive t - 1 samples, where t represents the total number of daily samples. When k > t, the corresponding AD(x, y) value refers to the daily sample k-t. In Eq. 3 the time transitive property is given

by the weight $\frac{t}{t+k-i}$, where the highest weight is associated to the average contact duration in the current daily sample, being it reduced in consecutive samples.

$$TECD = w(x,y)_i = \sum_{k=i}^{i+t-1} \frac{t}{t+k-i} AD(x,y)_k \quad (3)$$

C. TECD Importance (TECDi)

TECDi aims to capture the *Importance* $(I(x)_i)$ of any user x in a daily sample ΔT_i , based on its social strength (*TECD*) towards each user that belongs to its neighbor set (N(x)) in that time interval, in addition to the importance of such neighbors.

TECDi is based on the *PeopleRank* function [9]. However, *TECDi* considers the social strength between a user and its neighbors encountered within a specific ΔT_i , while *PeopleRank* computes the importance considering all neighbors of x at any time. It is worth mentioning that the dumping factor (d) in *TECDi* has a similar meaning as in *PeopleRank:* to introduce some randomness while taking forwarding decisions.

$$TECDi = I(x)_i = (1 - d) + d \sum_{y \in N(x)} w(x, y)_i \frac{I(y)_i}{N(x)}$$
(4)

D. Distributed Algorithm

dLife decides to replicate messages based on *TECD/TECDi*. If the encountered node has better relationship with the destination in the current daily sample, it receives messages' copies. By having higher weight (i.e., high social relationship), there is a much greater chance that the encountered node will meet the destination in the future. If relationship to destination is unknown, replication happens only if the encountered node has higher importance than the carrier.

dLife's operation happens as follows (cf. Alg. 1): when the CurrentNode meets a Node_i in a daily sample ΔT_k , it gets a list of all neighbors of Node_i in that daily sample and its weights towards them (Node_i.WeightsToAllneighbors computed based on Eq. 3). Then, every Message_j in CurrentNode's buffer is replicated to Node_i if the latter's weight towards the destination (getWeightTo(Destination_j)) is greater than CurrentNode's weight towards the same destination. Otherwise, CurrentNode receives Node_i's importance, and messages are replicated if Node_i is more important than the CurrentNode in the current ΔT_k .

Algorithm 1 Forwarding with dLife

begin
foreach $Node_i$ encountered by $CurrentNode$ do
receive($Node_i$.WeightsToAllneighbors)
foreach $Message_i \in buffer.(CurrentNode) \& \notin buffer(Node_i)$ do
if $(Node_i.getWeightTo(Destination_i) >$
$CurrentNode.getWeightTo(Destination_i))$
then $CurrentNode.replicateTo(Node_i, Message_i)$
else
receive($Node_i$.Importance)
if $(Node_i.importance > CurrentNode.importance)$
then $CurrentNode.replicateTo(Node_i, Message_i)$
end

As mentioned before, *dLifeComm* combines the notion of community, as *Bubble Rap*, and social strength for forwarding: when a user has a message to another user in a different community, it forwards the message towards the destination's community using *TECDi*. The assumption is that users with higher importance have higher probability to reach the destination's community faster. When the destination's community is reached, forwarding is done towards the destination, by replicating the message to users with higher social strength (*TECD*) towards the destination, and not higher centrality, as in *Bubble Rap*. The main goal is to avoid congestion points.

dLifeComm's operation is rather simple (cf. Alg. 2): when the CurrentNode meets a $Node_i$, it gets a list of all neighbors of $Node_i$ and its weights towards them ($Node_i$.WeightsToAllneighbors computed based on Eq. 3) in the current daily sample ΔT_k . If $Node_i$ belongs to the same community as the destination of $Message_j$, the message is replicated if the weight of $Node_i$ towards the destination is greater than CurrentNode's weight towards this destination. If $Node_i$ belongs to a different community, CurrentNodereceives $Node_i$'s importance, and messages are replicated if $Node_i$'s importance is greater than that of the CurrentNode.

As *Bubble Rap*, *dLifeComm* allows users - not in the destination community - to delete messages already delivered to such community, to avoid useless replications. It is worth noting that *dLifeComm*'s algorithm is different from that of *Bubble Rap* as it uses *TECD/TECDi* instead of local/global centralities for forwarding within/between communities.

Algorithm 2 Forwarding with <i>dLifeComm</i>
begin
foreach $Node_i$ encountered by $CurrentNode$ do
receive($Node_i$.WeightsToAllneighbors)
foreach $Message_j \in buffer.(CurrentNode) \& \notin buffer(Node_i)$ do if $(Node_i.isInCommunityOf(Destination_i))$
if $(Node_i.getWeightTo(Destination_i)) >$
$CurrentNode.getWeightTo(Destination_i))$
then $CurrentNode.replicateTo(Node_i, Message_i)$
else
receive($Node_i$.Importance)
if $(Node_i.importance > CurrentNode.importance)$
then $CurrentNode.replicateTo(Node_i, Message_i)$
end

IV. *dLife* EVALUATION

This section starts by describing the evaluation methodology and experimental settings. Then, our considerations about the results obtained when comparing *dLife* with *dLifeComm* and *Bubble Rap* are presented considering two scenarios: one based on simulations built with different mobility patterns, and another based on real human traces.

A. Evaluation Methodology

Performance analysis of *dLife*, *dLifeComm*, and *Bubble Rap* is done on the Opportunistic Network Environment (ONE).

Each simulation, in both scenarios, is run ten times (with different random number generator seeds) to provide results with a 95% confidence interval. All results are analyzed in terms of average delivery probability (i.e., ratio between the number of delivered messages and total number of created messages), average cost (i.e., number of replicas per delivered message), and average latency (i.e., time elapsed between message creation and delivery).

B. Experimental Settings

The heterogeneous simulation scenario is part of the Helsinki city and has 150 nodes distributed in 8 groups of people and 9 groups of vehicles. Nodes are equipped with a WiFi interface (11 Mbps/100 m). One vehicle group represents police patrols and follows the *Shortest Path Map Based Movement* where nodes randomly choose a destination point and take the shortest path to it. Their waiting times are between 100 and 300 seconds. The remaining groups represent buses, each composed of 2 vehicles following the *Bus Movement* and with waiting times between 10 and 30 seconds. Vehicles speeds range from 7 to 10 m/s.

People follow the *Working Day Movement* with walking speeds ranging from 0.8 to 1.4 m/s, but can also use buses. Each group has different meeting spots, offices, and home locations. People spend 8 hours at work and present 50% probability of having an evening activity after leaving work. In the office, nodes move around and have pause times ranging from 1 minute to 4 hours. Evening activities can be done alone or in a group, and can last between 1 and 2 hours.

For the experiments based on real human traces, we use the Cambridge traces [11] between 36 nodes. Data was collected in different locations for two months while Cambridge University students moved performing their daily activities.

Traffic load comes from a file previously generated with established source/destination pairs, where a total of 6000 messages are generated in each scenario.

Message TTL values are set at 1, 2 and 4 days, as well as 1 and 3 weeks. Since we want a fair comparison against *Bubble Rap*, we choose the TTL values in which *Bubble Rap* has the best performance behavior in terms of delivery probability and cost [2], as well as TTL values that can represent the different applications that cope with opportunistic networks. Message size ranges from 1 to 100 kB. The buffer space is of 2 MB to create a realistic scenario, as users may not be willing to share all of the storage capacity of their devices. Message and buffer size comply with the universal evaluation framework that we have proposed [7] based on the evidence that prior-art on opportunistic routing follows completely different evaluation settings, making the assessment a challenging task.

To assess the performance of *dLifeComm* and *Bubble Rap*, we consider K-Clique and cumulative window algorithms for community formation and node centrality computation as proposed by Hui et al. [2]. The parameter k (= 5) is chosen

based on simulations in which *Bubble Rap* has the best overall performance in terms of the considered evaluation metrics.

As *dLife* considers daily samples (cf. Section III), our findings (omitted due to limited space) show that 24 daily samples (i.e., each of one hour) brings *dLife* to its best. The reason is that the shorter the samples, the more refined the information on social strength and users' importance is, since the social weight is updated more frequently.

C. Experimental Results

We start by providing some considerations about our findings: the average number of contacts per hour is of approximately 920 in the heterogeneous scenario and of approximately 29 in the human traces. Moreover, contacts are more sporadic in the trace scenario than in the heterogeneous one, in which contact frequency is more homogeneous. We also notice that the average number of unique communities is higher in the heterogeneous scenario (~69) than in the trace scenario (~6.7). Furthermore, most of the created communities encompasses all the existing nodes (150 for the heterogeneous simulations, and 36 for trace). This means that independently of the level of contact homogeneity, nodes are still well connected.



Figs. 2(a) and 2(b) show the average delivery probability: for the simulated heterogeneous scenario (cf. Fig. 2(a)), dLife and dLifeComm have a performance 39.5 and 31.2 percentage points better than Bubble Rap, respectively. The main reason for that is that Bubble Rap has to go through the process of forming communities to perform suitable forwarding. Since communities are not immediately available, Bubble Rap relies on node global centrality to increase the probability of reaching destinations. However, in this scenario, the centrality of nodes is very heterogeneous where a few nodes (~17%) have very high centrality and the remaining nodes have mid/low centrality. Since most of the messages are originated in nodes with mid/low centrality, this results in a increase in message replication as Bubble Rap replicates when meeting a node with higher centrality. Such behavior quickly exhausts buffer space, which worsens as TTL increases since messages are allowed to live longer in the system, having higher probability to be replicated. Both versions of *dLife* also experience buffer exhaustion as TTL increases, and *dLifeComm* is affected by the community formation. However, since replication occurs wisely due to *dLife*'s capability of capturing the dynamism of nodes' behavior, these effects are mitigated.

With real traces (cf. Fig. 2(b)), *dLife* and *dLifeComm* still have better performance (reaching up to 31.5 and 31.3

percentage points, respectively) than *Bubble Rap*, which shows a similar behavior as reported by Hui et al. [2], where delivery probability increases with TTL, since K-Clique creates an average of 6.7 communities encompassing almost all nodes in each one. Thus, a 2-day TTL is enough to reach a node in the destination community increasing the probability of delivery. However, since *Bubble Rap* relies on a central local node to deliver inside a community, and since there is still a probability that such node may not be well connected with the destination, the probability of delivery does not benefit from a higher TTL.

The good performance of both versions of *dLife* is due to network dynamics (from users' daily routines). This allied to the network structure (i.e., communities), made dLifeComm outperform *Bubble Rap*, but still suffering with the community formation overhead; while by only considering such dynamics, *dLife* turns out to be the best proposal. We believe that the similar performance behavior of both proposals in the human trace scenario is due to the fact that very little communities are formed and most of the nodes belong to such communities, thus reducing the effect of the overhead seen in the heterogeneous scenario. Additionally, results suggest that the usage of centrality has a higher impact (i.e., negative) than the usage of community formation, as centrality creates bottlenecks: this can be easily seen when comparing *dLifeComm* (combining the notion of community and TECD/TECDi) and Bubble Rap (combining the notion of community and centrality).



As for the average cost (cf. Figs. 3(a) and 3(b)). We observe in the simulated heterogeneous scenario (cf. Fig. 3(a)) that *dLife* and *dLifeComm* are cost effective. They produce up to 78% and 68% less replicas than *Bubble Rap*, respectively. This good behavior reflects the wise forwarding decisions that both proposals are able to perform (based on *TECD* and *TECDi*). It is indeed an indication that *dLife* is able to derive a clearer social graph, based on edges with high social strength and vertices with higher importance. Regarding *Bubble Rap*, its cost is expected to increase with TTL: despite getting rid of a message when it reaches the destination's community, to avoid further replication, other replicas continue to be made by other carriers, which explains *Bubble Rap*'s higher cost.

The real trace scenario (cf. Fig. 3(b)) still shows the lower cost of *dLife* and *dLifeComm* in relation to *Bubble Rap* (reaching up to 55% and 50.5% less, respectively). The cost reduction for *Bubble Rap* with a 4-day TTL is due to the sporadic nature of contacts in this scenario. This results in a lower average number of replicas created as there are only few nodes to receive such copies at the time of exchange.

Regarding the average latency (cf. Figs. 4(a) and 4(b)), in the heterogeneous scenario (cf. Fig. 4(a)), dLife and dLifeComm deliver messages with lower latency (48.3% and 46.1% less, respectively) than Bubble Rap. It is easily observed the advantage of taking wiser decisions by using *dLife*: messages are only forwarded in the presence of strong social links or highly important nodes in the current daily sample. Thus, by considering stronger social links with the destination or more important encountered nodes in specific daily samples, messages are delivered faster, since the probability of them coming in contact with the destination in the near future is higher. Bubble Rap does not capture such dynamism which leads it to create replicas that take more time to reach the destination due to the weaker social ties of the carrier with the destination. These results suggest that considering the dynamism of daily routines allows nodes to select the best forwarder in different daily samples, while centrality leads to the identification of a node that may be well connected in average for the complete duration of the experiment, but not in all daily samples.



In the real trace scenario (cf. Fig. 4(b)), dLife and dLifeComm deliver messages faster (83.7% and 84.7% less, respectively) than Bubble Rap in comparison with the heterogeneous scenario. Despite the sporadic contacts of the real trace scenario, some nodes are still well connected and, since both versions of *dLife* are able to identify the best social connections (i.e., independently of the notion of community), messages are replicated to nodes which have the highest probability to meet destinations in the near future, decreasing the distance (i.e., hops) to reach the destination, which in turn reduces the delivery time. Bubble Rap also experiences a reduction in the distance to reach destinations, but its latency behavior remains almost the same in both scenarios. We believe this is due to the fact that most of the existing nodes in the studied scenarios belong to the formed communities, as earlier noted. Since these communities are almost the same for the duration of the experiments, Bubble Rap relies solely on node centrality, which does not capture the dynamism of users' behavior, and thus messages need more time to reach destinations. Despite of considering community formation, dLifeComm is less affected since it also considers the node importance to propagate messages.

V. CONCLUSIONS AND FUTURE WORK

Since social information is quite useful to aid data forwarding in opportunistic networks, we introduce *dLife*, which combines the *TECD* and *TECDi* utility functions to derive, from users' social daily routines, the social strength among users and their importance. Our findings show that by incorporating the dynamism of users' social daily behavior in opportunistic routing wiser forwarding decisions are performed, leading to better delivery probability, cost and latency than proposals based only on social structures, i.e., *Bubble Rap*. Moreover, by comparing *Bubble Rap* with *dLifeComm*, a solution that combines network structure (i.e., communities) with network dynamics (i.e., daily routines), we show that the usage of centrality has a higher impact (i.e., negative) in the system performance than the usage of detected communities.

As future work, we plan to improve dLife's performance with the introduction of randomness: it has been shown that even with complete knowledge on the social relationship among users, delivery probability does not reach its maximum [9]. Additionally, we will extend dLife to have a point-tomultipoint behavior and test it with real traces encompassing large number of nodes (e.g., MIT Reality mining project). And finally to further investigate other variables besides contact duration, coming from proximity, conversational and online social networks, when assessing the impact that a better inference of social behavior may have on opportunistic routing.

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