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Capturing Social Bonds for a Realistic Human Mobility Model

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Abstract

Studies on mobile applications for ad-hoc networks predominantly rely on simulations to evaluate various distributed algorithms. This has given rise to the need for realistic mobility models that incorporate social characteristics of human mobility. Based on basic properties of user movements captured via GPS traces and user interviews, we propose FRIW (Free Radicle Inspired Walk). FRIW leverages the free radicle concept from chemistry and social network theory to model social ties and group mobility in a campus setting. We find that FRIW is successful in generating realistic mobility patterns that can be used for modelling user movements in ad hoc network simulations.

1. Introduction

Mobile devices that can communicate directly with each other and also act as routers to connect two or more devices that are out of range have given rise to the idea of mobile ad-hoc networks. These networks have been studied in a variety of contexts including communication in hostile territory and disaster relief operations. In recent years, mobile ad-hoc networks are being explored as alternative means of connectivity and content-sharing among specific communities [1] [2], for example participants at a conference or inhabitants of a campus.

Distributed algorithms that enable content sharing and communication in such networks are often designed to exploit structural properties of these networks. Examples include identifying stable routes for opportunistic forwarding or using the history of contact between nodes to predict future contact [3] [4] [5] [6] [7]. Simulation studies of ad-hoc networks fuelled by mobility patterns of nodes are typically used to evaluate the efficacy of such algorithms. However, the strength of these algorithms can only be tested if the mobility patterns used in the simulation are realistic. Mobility patterns on a typical university campus for example, are highly dependent on the movement of users carrying the devices. The movement of users in turn is not random but significantly influenced by their social bonds and commitments [8], [9]. However, to date there is very limited information on mobility patterns of human walks in a campus setting and the social relations that engineer this movement. The few available traces include varied scenarios like tourists in a theme park or attendees of a conference, and provide limited insights for a campus setting [10]. In addition, almost all traces provide only partial insights in terms of either temporal [11] or spatial [12] metrics, whereas capturing the inherent social dynamics of a campus community would require both temporal and spatial dimensions.

Given the above mentioned gaps in literature of campus-based human walks, our paper has two primary goals: first, to understand mobility patterns and social dynamics in a typical campus setting and second, use this understanding to design a realistic mobility model for campus users. To comprehend mobility patterns of users we capture detailed GPS traces over four days of fifteen mobile users in an academic campus. The insights in user mobility gleaned from these traces is augmented with interviews of twenty-five randomly chosen people on the campus, with a bid to understand their schedules, mobility patterns and social interactions. To our knowledge, this is the first study that attempts to capture not only mobility patterns on a campus but also the social and group dynamics that lead to these mobility patterns. Analysis of the data collected reveals key patterns and structures in user mobility. Some interesting insights from our study point to specific group behaviour. We find that social ties that motivate users to come together as a group goes beyond a particular location to the same group traveling to multiple locations. We also find that these groups change according to the time of day and also notice distinct daily temporal patterns in social ties and group formations.

While social ties are identified as a key parameter in the first part of our study on human mobility, most existing mobility models do not consider social relationships and often are limited to location-based preferences instead [13]. To this end, we propose a probabilistic mobility model that captures key properties of social ties along with temporal and spatial properties of user movement on an academic campus. Our model is inspired by the free radicle mechanism (borrowed from chemistry) to model social bonds, group formations and their transition and is thus called FRIW : Free Radicle Inspired Walk. FRIW use simulations via which depending on specific rules, nodes probabilistically decide where to move at every time-stamp. The simulations use as input an evolving social network model (SNM), which defines the social obligations of every pair of nodes which also change as the simulation progresses. The mobility model mechanism is decoupled from the social network model so that mobility patterns for a range of scenarios can easily be generated. The mobility traces generated by FRIW are evaluated by comparing their statistical features to other human mobility traces. We find that the inter-contact time and flight distributions of FRIW exhibit truncated power-law characteristics, much like what has been found in other human mobility traces [11] [14] [15]. Additionally, cluster analyses on the overall social network model that emerges after the simulations reveal well-formed groups among the nodes, indicating that FRIW produces realistic social mobility patterns.

The rest of the paper is organized as follows: Section 2 details the process of capturing real-life mobility patterns and Section 3 covers related work in the area of human mobility traces. Section 4 contains the details of FRIW and Section 5 elaborates on the evaluation of our proposed mobility model. We conclude in Section 6.

2. Capturing Human Mobility Patterns

We use two methods to understand how users move about on a campus and interact with each other: GPS traces from mobile phones of volunteers and personal interviews. Using a mobile app for Android phones (GPS logger), GPS traces of 15 student volunteers were captured. The latitude and longitude positions of the students were captured at an interval of every 2 seconds, starting from 8:30 am till 6:30 pm in the evening, over a span of four days. It should be noted here that all users in the study were only walking around campus and did not use any motorized/non-motorized modes of transport. We selected days in the middle of a regular term for the logging, so as to capture regular mobility patterns of students. These mobility trace files were then analysed using Google Earth and basic data-mining tools.

We also conducted interviews with 25 people on campus , selecting a cross-section of candidates to interview – ranging from students across years to research associates and staff. We asked them questions on their daily routine/schedule on campus: locations they typically went to and with whom, how much time they spent at each location, and who else they typically interacted with during these times. The following mobility patterns clearly emerged from our study of user movements and social interaction, which are discussed below under the heads of spatial , temporal, mobile and social properties :

Spatial Properties*:* Analysis of the traces shows that users typically move on well-defined paths. Most users follow these paths and very rarely deviate away from them. Figure 1 depicts the path captured for one user as rendered by Google Earth.

Figure 1: Mobility trace of one particular user on one day (depicted in green).

We also find that the busiest paths lead to locations where many users tend to congregate – places like the library, classrooms, dining hall, food joints, gymnasium, dorm etc. We call these locations 'sinks', as users tend to move to these locations and spend a relatively large amount of time in these places. By superimposing the paths of multiple users over multiple days, the most popular paths and sinks are calculated, which are depicted in Figure 2. Our findings are similar to the GPS mobility traces discussed by Rhee et. al. [12], which show users walking on a few well-defined paths. Our findings also reinforce previous studies [16] that have highlighted that the popular random-way point model is an unrealistic mobility model for many scenarios of mobile- ad-hoc networks.

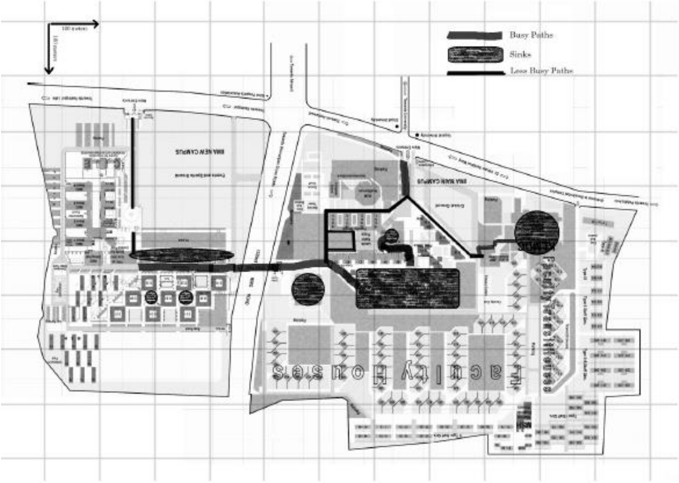


Figure 2: The most popular paths and sinks on campus.

Temporal Properties: Through the GPS traces, we observe students moving along the same paths and repeatedly visiting a limited number of locations. Additionally, the data from the interviews clearly reveal that the users have fairly predictable schedules. A typical daily schedule of a student is from the dorm to the mess, and then classrooms, the mess again, then the library, the sports complex, the mess and back to the dorm. These patterns repeat daily, thus lending weight to the argument of repeated temporal patterns in the mobility.

Mobile Properties: The GPS traces were also used to calculate the speed at which users were moving to get a sense of when they were static or dynamic. The patterns indicated that there were long periods (a few minutes to a couple of hours) when users were static at popular sinks (mess, library, dorm, classrooms, eating joints) interspersed with moderate bursts of mobility (upto 15 minutes at a time) from one sink to another.

Social Properties: Distinct social ties emerge when people were asked about their interactions with others on campus. We find that participants tend to spend time within fixed groups, and often engage in different activities with the same set of friends. However, the group composition and size varies according to the activities in question. What is clear is that users tend to not only meet their groups at sinks but also move around the campus in groups. For example, a large group of students who live in the same dorm may make their way to a common class and later break up into smaller study groups that go to different locations on campus. The interviews reinforce the perception of the strong influence social ties have on individual user movement. These social ties not only go beyond a particular location, but also change according to the time of day. We noticed distinct daily temporal patterns in social ties and group formation.

In summary, we find that nodes mostly travel on fixed paths and move to popular locations, where they are static for relatively long durations. Moreover, some nodes move in groups and congregate at popular locations and might disband after a while or move out as a group. Once a group has disbanded, nodes usually reorganize to form new groups at new locations. In the next section, we discuss past work on human mobility traces and models, and their relevance to the scenario in question: users in a campus community.

3. Review of Human Mobility Traces and Models

A significant amount of literature exists for human mobility models, which can broadly be categorised as trace-based versus synthetic models [13]. Trace-based models are based on actual traces of user mobility that have been collected at a particular event or in a particular environment. However, data-sets consisting of actual traces are very limited owing to the difficulty in such an exercise. On the other hand, a wide range of synthetic models have been proposed, ranging from the simple yet popular random model (ref) to more sophisticated models based on temporal, spatial and social properties of human mobility. This paper is interested in capturing the properties that arise in mobility patterns as a result of group dynamics and social ties, and this is the lenses we use to examine related work in human mobility models.

SWIM [17], a mobility model based primarily on location preferences for nodes, uses the concept of a home location for each node. Different locations have varying popularity, which along with the distance from the home of a node, determines how the next destination for a node is selected. The traces generated by SWIM exhibit a limited amount of group behaviour at fixed locations, but SWIM does-not use a social model as input for the traces and neither does it model group mobility behaviour (nodes travelling together as a group). Musolesi & Mascolo [18] propose a mobility model (CMM) where nodes are initially placed in particular locations in groups identified according to the social network model. Nodes then individually calculate their next destination, depending on which destination seems most attractive in terms of the ties in the social network model. However, the drawback to this model is that, if a caveman model [19] is assumed for the social network, which in many cases may not be inaccurate, and the initial groups are formed according to this model, later calculations for destinations will not lead to any differentiation – since nodes are already with others with whom they have social ties. All destinations will appear equally attractive/unattractive, leading this model to effectively select destinations randomly. HCMM [20] builds on the CMM model to incorporate user preferences to choose shorter distances to longer ones. While this assumption might work well when a user has to choose a grocery store for example, it doesn't hold in a campus setting where distances are relatively small to begin with. In a typical campus, users choose their next location based on additional external constrains, for example: which block their next class is in or whether they need to go to the library for a study group session. Choosing shorter distances as an integral part of the mobility model is non-intuitive for our scenario. SLAW : self-similar least action walk [21], introduces a mobility model that creates synthetic traces of human walks for a small community like a company or campus. However, an integral assumption of SLAW is that people plan their movement in a gap-preserving manner, by visiting nearby places first and further ones later. However, as discussed above, this assumption will not hold for a student community in a campus, where predetermined class schedules and other group events will dictate the order in which students visit locations. Yang et.al. propose a mobility model called HWW [22], that considers heterogeneous human popularity as noticed in realistic social networks. They attempt to capture overlapping community structures at different parts of a day and hence come closest to our model of groups forming and disbanding over time. However, unlike FRIW, these groups form only at specific locations and group movement is not captured or modelled. GeSoMo [23], proposed by Fischer et. al, is a social mobility model that uses a social network model to guide the mobility patterns of humans. Though the paper claims that they model group mobility, nodes are primarily attracted to particular locations (called anchors) based on who else is there at that location, and the pull exerted by the anchor itself. Group mobility in this scenario seems more incidental than planned. Moreover, the simulation parameters used in the study, a small area (500m x 500m) and limited transmission radius (15 meters for Bluetooth), do not seem to capture a realistic campus setting or the technology our application is based on (wi-fi with longer range of around 100 meters).

None of the models described above incorporate the notion of popular paths that are followed by users and most do not use social ties to guide group movement, whereas FRIW incorporates both these features. Additionally FRIW captures the notion of evolving social ties which feed into groups forming and disbanding organically as in real-world situations. Table 1 summarizes the above discussion and classifies the various human mobility models along seven key dimensions. Some of the dimensions used in the table below are adapted from Karamshuk et. al. [13] while others emerged from our study discussed in the previous section. The first dimension captures the scale of the mobility model, as we are not interested in geographical regions larger than a typical campus. The next two dimensions represent spatial properties of paths taken and key destinations. Dimensions 3-5 represent social properties of group meeting, group mobility, and whether an SNM is used as input for the mobility model. The last dimension looks at whether a specific map can be used as part of the mobility model.

Table 1: Comparison of human mobility models across key dimensions.

Model	Scale : Campus View	Spatial : Fixed Paths	Spatial : Popular Locations	Social : Group Meetings	Social : Group Trips	Social: Uses SNM	Preferred Location Map
CMM	✓		✓	✓		✓	
HCMM	✓		✓	✓		✓	✓
SWIM	✓		✓	✓			✓
SLAW	✓		✓				
HHW			✓	✓		✓	
GeSoMo	✓		✓	✓	✓	✓	
FRIW	✓	✓	✓	✓	✓	✓	✓

In the next section, we provide details of the internals of FRIW and how it is designed to generate realistic human walk patterns.

4. FRIW: Free Radicle Inspired Walk

The primary objective of FRIW is to model real life social ties, group dynamics and the movement of users on a campus setting as dictated by these social ties.

To simulate this behaviour, FRIW uses two concepts – one borrowed from social network theory, in terms of the social network model (SNM), and the other borrowed from chemistry – the free radicle concept. Both these concepts and how they are used by FRIW are explained shortly.

The network area is divided into a grid, with each cell in the grid of size 50 meters * 50 meters. Each cell in the grid is classified as a *path*, a *sink* (popular location) or a null cell. Figure 3 shows an example of a campus grid, with paths and sinks. Nodes can only move on paths and can enter sinks.

A node in the network is positioned inside a particular cell and at each time period, the node needs to decide which adjoining cell to move to, if it needs to move. This decision is based on a few different parameters including the status of the node, the social bond exerted by nodes in neighbouring cells and the type of neighbouring cells, as explained below.

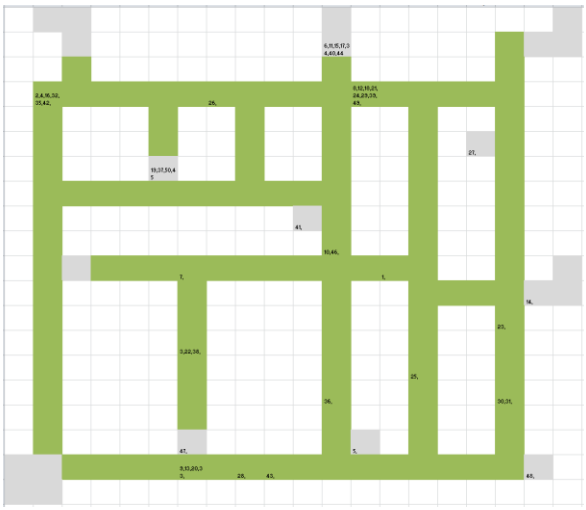


Figure 3: A snapshot of FRIWs visualization tool (campus layout). Green cells denote paths, grey denote sinks, and numbers denote node ids.

Node State *:* A node could be in one of three different social states : group member, individual or free-radicle. When a node is a *group member*, its current group commitments have not finished and hence it does not attract additional nodes. When a node is in *individual state*, its group commitments have finished and it is free to roam but is not looking to attract nodes or form a new group. When a node has *free-radicle* status, it is actively looking to attract new nodes around it to form a new group.

In addition a node could be in one of two mobility states : *walking* or *static*. If a node is on a path, its state is *walking*, if its in a sink then it could be *static*, provided it has not yet spent the prescribed time in the sink yet.

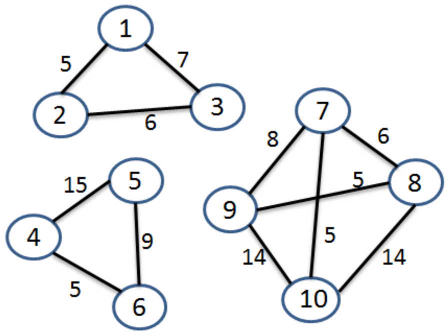
Social ties of nodes: The model assumes that nodes spend time with each other as described by a social network model (SNM) which is described by using *an Interaction Matrix (IM)*. If there are n nodes in the network, then the Interaction Matrix is a matrix of size n x n (the lower triangular matrix is used), and each entry in the matrix describes the amount of interaction between 2 nodes, as known from the row and column number of that entry. For example, the interaction time between node n1 and node n2 can be obtained by the formula shown below:

Interaction time $_{n1,n2}$ = IM(max(n1,n2), min(n1,n2)) …….. equation 1

Figure * shows an example of an Interaction Matrix of 10 nodes, and the corresponding social network graph. Note that in this case, the social network graph is very close to a small-world network also called the caveman model [19] since the graph consists of seperate clusters.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1										
2	5									
3	7	6								
4	0	0	0							
5	0	0	0	15						
6	0	0	0	5	9					
7	0	0	0	0	0	0				
8	0	0	0	0	0	0	6			
9	0	0	0	0	0	0	8	5		
10	0	0	0	0	0	0	5	14	7	

Interaction Matrix



Social Network Graph

Figure 4: Social network model of 10 nodes as described by the corresponding Interaction Matrix and Graph.

The interaction matrix in FRIW is not static, but changes over time leading to what we call an evolving social-obligation matrix. This ensures that nodes form groups according to the current weight of their interactions in the interaction matrix and as these weights change over time, groups dynamically split up, and new groups are formed.

In the beginning of the simulation run, an initial interaction matrix is used as input to start off nodes on their walks. If two nodes are in the same cell for that time unit, they are assumed to be neighbors and to have spent one time unit together. At each time unit of the simulation, the interaction matrix is updated, decrementing the corresponding weights by one. For example, if nodes p and q were neighbors for one time unit, the weight in the pth row and qth column is decreased by one. Thus at any point in time, the interaction matrix reflects how much interaction time is currently pending for each pair of nodes, or in other words how much social obligation is remaining between each pair of nodes.

Note that each node individually decides its next move, by calculating cumulative social pulls (calculated by using the pending interaction time) from each of the four of its neighbouring cells and moves to the cell with the strongest pull. Ties are broken randomly. Social pull (SP) for a node n to a cell c is defined as:

$$SP(n:c) = \sum\nolimits_{i\,\in Population(c)} IM(\max(n,c)\,,\min(n,c)) \qquad \text{……equation 2}$$

Where Population(c) is the set of all nodes in cell c and IM(a,b) is the Interaction time for nodes a and b.

If two nodes exceeded the time denoted in IM, then their entry in IM becomes negative. Thus it is possible that nodes are attracted to some nodes and are repelled from other nodes. This helps in situations when two groups happen to converge onto the same path. The negative values that get accumulated in the interaction matrix assures that both groups diverge at the first possible opportunity. Similarly, when the group obligation time for a set of nodes has finished (and the corresponding values in the interaction matrix become negative), the nodes look for opportunities to break away from each other, and the group effectively disbands.

Change of State

Once a node has finished all its group obligations (all values for its interaction matrix with other nodes are zero or negative) , its state changes from *group member* to *individual*. The node then moves around on the paths on the campus quite randomly and could reach a sink. After a pre-determined time its state changes from *individual* to *free-radicle*. By this time, it has managed to distance itself from many or most of its original group members. If a node is in the free-radicle state and is additionally at a sink, it starts attracting neighbouring nodes (nodes in its own cell and neighbouring cells), to form a new group in its own cell. This implies that the interaction matrix entries for all pair-wise combinations of these nodes be updated with a positive value say p (p denotes that amount of time the new group will stay together). The nodes status now changes from *free-radicle* to *group member*. After the prescribed time of staying in the sink, the new group moves out together and starts traveling on a path.

Choosing the path

As mentioned above, at each time period, a node calculates its next move. If it is on a *Path* (recall that cells are classified as paths, sinks or null cells), then it is dynamic, and cannot go back to the previous cell it came from or stay in the current cell. It has to choose its next location from the remaining neighbouring cells that are non null cells. For this set of permissible moves, the node calculates the social pull from each of the cells in the set. It then moves to the cell with the strongest social pull.

Figure 5 provides an example scenario of node movement and cell choice. As shown, four nodes: N2, N3, N4 and N5 are at cell B2 at time **t**, and their Interaction Matrix at the end of time t is also shown in the figure. N3, N4 and N5 belong to the same group as suggested by the Interaction Matrix entries of ‘10’ and N2 is an individual node who happens to be on the same path for the last three time periods, as reflected by the ‘-3’ entries in the Interaction Matrix. Note that except for the four corner cells which are null cells, all the others are path cells in this scenario.

At time t+1, the nodes (sequentially) start calculating where to move next, from the three choices of B1, B3 and C2 (A2 is not considered as the nodes were there at time t-1 , and B2 is not a choice as it is the current location of the nodes). N2 first decides and then N3, N4 and N5, in that order. The social pull (SP) for each choice is calculated according to equation 2.

Hence SP(N2,B1) = SP(N2,B3) = SP(N2,C2) = 0. Since ties are broken randomly, N2, decides to move to C2.

For N3, SP(N3, B1) = SP(N3, B3) = 0, SP(N3,C2) = -3 . Hence N3 randomly chooses between B1 and B3 and moves to B1.

Next, for N4 : SP(N4, B1) = 10, SP(N4, B3) = 0, SP(N4,C2) = -3. Hence N4 moves to B1.

Similarly (not shown in Figure 5) , SP(N5,B1) = 20, SP(N5, B3) = 0, SP(N5, C2) = -3. Hence N5 also moves to B1.

This scenario illustrates how FRIW enables nodes that are in a group to stay and move together, and ensures that individual nodes quickly break away from the group.

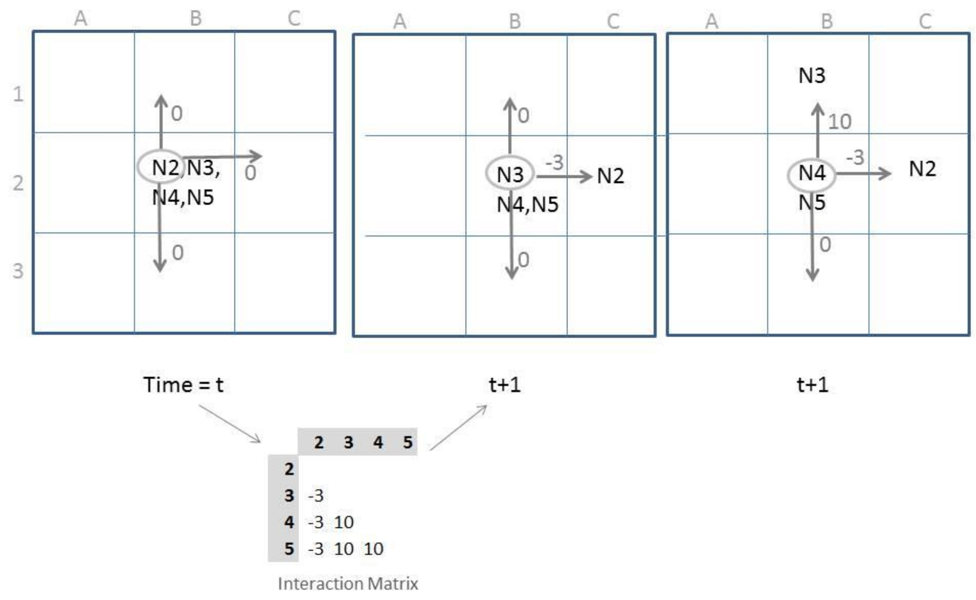


Figure 5: Scenario describing node movement as a group and corresponding interaction matrix

Mimicking Realistic User Mobility

The state changes, interaction matrix manipulations and path decisions described above help in mimicking realistic user movement on campus. Nodes start out in groups of various sizes and move to different locations as groups. After spending time in their group, nodes set out by themselves to other locations (or move out as a group and the group disintegrates on the path). Individual nodes or sub-groups then converge at new locations to form new groups. These new groups may then move out as a group or individually to other new locations and so on.

Without any central intervention, nodes individually mimic user movements and social behaviour in a community setting. This behaviour is also clearly evident when the node movements are observed using the visualization tool associated with the FRIW simulator, the details of which are provided in the next section.

5. Evaluation of FRIW

5.1 Simulation Model

We have developed a simulation tool to model and evaluate FRIW, along with an accompanying visualization tool that accepts inputs and helps monitor node movement in real time. Many parameters required for the simulation are not hard-coded but considered as inputs and can be changed according to different scenarios. The ability to customize the simulations enables the modelling of a vast range of campus scenarios. This decoupling of scenario details from node behaviour ensures that the FRIW simulator can be used to generate mobility traces for different kinds of locations.

In our prototypical scenario, the network area is divided into cells of size 60 meters * 60 meters. The simulation runs for 300 time units and at each time unit nodes move from one cell to another neighboring cell. Each time unit in the simulation is assumed to be 1 minute long. Hence nodes move an average distance of 60 meters in 1 minute (1m/sec) which is considered a reasonable walking speed for humans.

We assume a network size of 1200 meters * 1200 meters with 50 nodes participating in the data sharing application of the mobile ad-hoc network. Nodes spend a fixed amount of time units at each sink called the *sleep time* which is set to 15 time units in our experiments. Recall that once a node has finished all of its group obligations, it remains as an individual before actively forming a new group as a free-radicle. This amount of time is called the *free time* and is set to 20 time units. When a new group is formed, the IM entries for all pair-wise members is updated to a value called the *group bond time*. Thus the group bond time is the amount of time the new group stays together and is set to 15 time units. The simulation parameters used in this study are shown in Table 2 and correspond to the campus properties and mobility behaviour observed in our study. However network properties and mobility behaviour can differ significantly from scenario to scenario. An undergraduate campus setting, an office park setting or a conference venue setting could all significantly differ in average group size, sleep times at sinks, location and number of sinks, layout of paths, free time versus group bond time etc. FRIW comes with default values for these parameters but allows users to fine-tune these parameters for individual scenarios as well. Also instead of constant values, FRIW allows parameters like sleep time and group bond time to be values from a particular distribution if the scenario calls for it.

Table 2: Parameters used in the simulations

Simulation Parameters	Default Values
Network Size	1200 m * 1200 m
Number of nodes	50
Speed of Nodes	1 m/sec
Total Simulation Time	300 minutes
Sleep Time	15 minutes
Free Time	20 minutes
Group Bond Time	15 minutes
Initial Group Size	5

In addition to the parameters described above the FRIW simulator requires the following inputs from the user:

1) A map of the campus, with sinks, paths and original node locations. These can be specified using the graphical user interface of FRIW's visualization tool (see Figure 3 for a sample map used in the simulations).

2) The initial Interaction Matrix : This matrix denotes the original groups in which nodes are in when the simulation starts off. Typically, the social network graph for the initial Interaction Matrix would be close to a small-world network (tight clusters of nodes), as denoted earlier in Figure 4. Subsequent updates to the IM will be taken care of by the simulator. The initial IM used in the simulations has groups of size 5 and group bond time of 15 time units.

The output of the FRIW simulator is a time based trace of individual node movements. These traces can be obtained in a variety of formats that are compatible with popular network simulators like NS2, and GlomoSim. Hence this mobility trace file can be directly used as an input to a MANET simulator.

5.2 Properties of Human Walks

Studies on human mobility have reported distinct statistical features that captured traces have exhibited. These traces include GPS recordings of human walks in different locations [12], interaction between mobile devices [11] and individual cell-phone tracking [15]. As reported by Lee et. al [21], the following metrics (and their specific properties) can be used to characterize human walks :

Inter-contact time (ICT) is defined as the time that elapses between two consecutive meetings of a pair of nodes. ICTs are of particular importance in communication and information sharing networks as they influence the speed of information sharing [23] . Past studies have shown that the distribution followed by ICTs in human walks is similar to a truncated power-law distribution [11].

Flight length is defined as the distance a node moves between two consecutive pause times. Human flights have been shown to follow a truncated power-law distribution [12] , [14].

In addition, pause times and contact times of nodes also play an important role as described below.

Contact Time is the time two nodes spend with each other before they part. Again, contact times are of particular interest to data-sharing networks as they impact the stability of a link and hence the reliability of a route.

Pause Time, defined as the amount of time a node is static in-between dynamic phases, also has a role to play in how stable network links are, especially if they pause together in the same location.

Since the FRIW model has pause times (sleep time at sinks) and contact times (the Interaction Matrix) as inputs to the model, this study measures and reports the ICTs and flight lengths of the mobility traces generated by FRIW (see Figure 6).

As seen in Figure 6(a), the inter-contact time (ICT) distribution for FRIW is characterized by a power law/exponential decay characteristic (also called truncated power-law characteristic), a feature that has also been noticed in other human mobility traces, as we noted earlier. Figure 6(b) plots the flight time distributions and as nodes move around at constant speed in our simulations, the plot represents flight length distributions as well. As can be seen, the flight length distributions exhibit truncated power-law features as well, a characteristic shown by many human mobility traces [12].

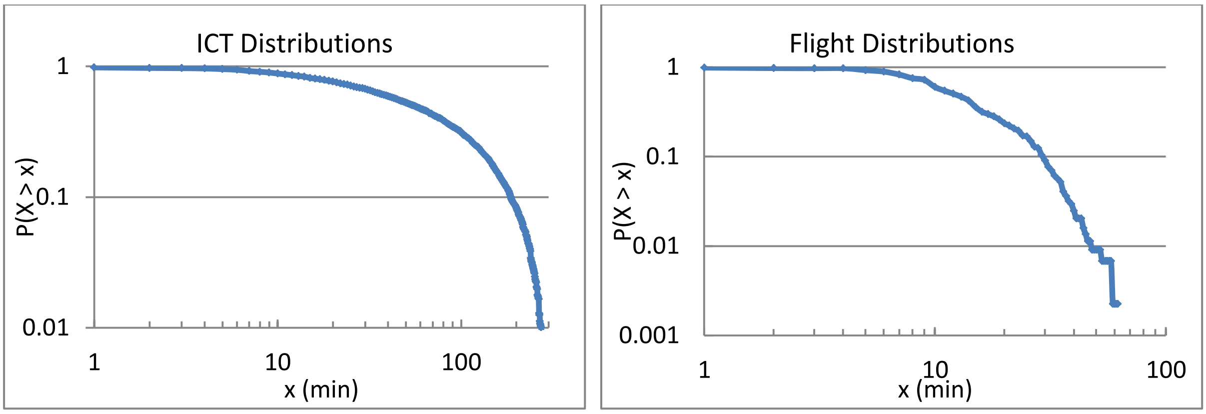


Figure 6:(a) Inter-contact time distributions and (b) Flight distributions for mobility model generated by FRIW exhibit truncated power-law characteristics

5.3 Social Network Model

In addition to the above evaluation, we also undertake a cluster analysis of the final social network model (snm) generated by FRIW, to find out how well our mobility model works in terms of modelling group behaviour and group formation. The snm is captured by recording how many minutes each pair of nodes have spent in each other's vicinity (two nodes are assumed to be in vicinity of each other if they are in the same grid). The final snm is a 50 by 50 matrix with each entry denoting the number of minutes a pair of nodes have been in contact with each other. The rationale behind examining the final snm is that if the snm exhibits a moderate degree of modularity and clusters can be detected, then it goes to show that FRIW is successful in generating group behaviour and social ties.

Note that the snm captures the sum total of all contact times between nodes and not individual interactions, hence the contact times can be expected to be bigger than the actual contact times (especially if nodes come in contact multiple times). The same effect can be expected for group sizes but for a different reason. Nodes may be in the vicinity of other nodes for two major reasons, the first being their social tie which brings them together for some group activity and the second being the location, where they happen to be interacting among a smaller group, but are within range of many more people who also happen to be at that location. Hence, any community detection analysis on the final snm should bear these two facts in mind.

We have used the 'edge betweeness' algorithm provided as part of the igraph module in R to detect communities in the final snm. The input is a graph with nodes as vertices and edges as the total contact time between two notes. Note that all edges with weight less than 20 were removed from the graph as these would denote incidental contacts between nodes (as in our simulations 20 minutes is the minimum time any two nodes spend together in a group).

On an average across simulation runs 10 communities ranging from size 1 to 16 were detected. The average network modularity was calculated as 0.20. At the very least, these results indicate that nodes directed by FRIW were not moving around randomly on their own, but spent time in well-defined groups that could be detected using the clustering algorithm.

6. Conclusions and Future Work

Realistic mobility models are critical for the evaluation of distributed content sharing and communication algorithms in mobile ad-hoc networks. However, social dynamics and group mobility – critical elements to evaluate many of these algorithms – are missing from most mobility models, leading to the significance of our work.

Our study has two phases: in the first part, we attempt to understand mobility walk patterns in a campus setting by using GPS enabled devices to track users across multiple days. We also conduct individual interviews with campus participants to understand group behaviour and social dynamics in this setting. The insights gained from these studies are used in the second part to develop a new social mobility model called FRIW (Free-Radicle Inspired Walk). FRIW uses concepts from social network theory and chemistry (free-radicle concept) to mimic realistic user movement and group formations/movements . The simulator for FRIW enables modelling a wide variety of geographical scenarios and social network models, as these can be provided as inputs through a simple yet intuitive interface. We have also created an inbuilt visualization tool for FRIW which allows us to track dynamic group formations, movements and disbands.

Our evaluation shows that the mobility traces generated by FRIW are realistic in terms of important characteristics like inter-contact time and flight duration distributions. We also find that common clustering algorithms are successful in detecting well-formed groups in the final social network model generated by FRIW, pointing to the presence of distinct group behaviour.

As future work, we plan to use the mobility traces generated by FRIW as a basis for evaluating the performance of node-associativity based route selection and resource discovery algorithms.

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