Journal of Mobile Multimedia, Vol. 10, No. 1&2 (2014) 107–127

GEO-SOCIAL MOBILITY MODEL FOR VANET SIMULATION

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Vehicular Ad Hoc Network (VANET) can be viewed as a special case of an ad hoc network formed by moving vehicles communicating through short-to-medium range wireless transmission. This emerging wireless technology allowed for a wide range of applications varying from safety and accident avoidance to leisure and entertainment. The VANET's special features, such as high node mobility, made the design and validation of its protocols a challenging task. A realistic simulation environment is then required. Since the vehicles mobility is driven by the human mobility characteristics and is controlled by the geographical restrictions of the roads, the work presented in this paper is aimed to having a realistic mobility model that incorporates both the social aspects of human mobility together with the geographical restrictions that governs the movement of the mobile nodes. The model is based on using realistic data sets rather than randomly generated data.

Keywords: VANET, Mobility Model, Social Network

1 Introduction

Vehicular Ad-hoc Networks (VANETs) can be considered as a special case of ad hoc networks where nodes are moving vehicles communicating together through short-to-medium range wireless transmission. Vehicles dynamically organize themselves into an opportunistic network where communication are intermittent and packets are routed using "store-carry-forward" approach. In such approach, messages are routed opportunistically from a mobile node to another until reaching the destination. Consequently, users' mobility has high influence on the devices connectivity and the overall network performance.

VANETs have attracted researchers' attention lately because of the need to provide safer roads by extending the drivers' view through wireless data exchange. VANET applications have varied not only to provide safety and reduce the number of accidents, but also to include Convenience (traffic management) by providing efficient driving though dissemination of traffic flow information and available parking. Moreover, applications domain became broader to comprise commercial applications providing leisure and comfort such as coverage extension, localized advertising and shopping, peer to peer gaming and file sharing. The diversity of VANET applications imposes different requirements on the network protocols.

Validation of Vehicular ad hoc network protocols is generally performed through simulation, as the use of a real test bed is still impractical. A VANET simulator should accurately simulate the communication protocols as well as the vehicles mobility. Most of the existing simulators, like ns-2, OPNET...etc, have accurate and well tested models for communication protocols, however realistic representation of vehicles' mobility is still needed.

Network simulators, in general, either rely on mobility traces or synthetic models for modeling vehicles' movements. Mobility traces are based on real measurements, while synthetic models are based on mathematically modeling the vehicles' movements. In general, synthetic models are preferred over mobility traces since the real traces of movement are limited and always tied to specific scenarios thus cannot represent the generic movement activities of the nodes [25].

In this paper, we present a Geo-Social mobility model that incorporates both the social aspects of human mobility together with the geographical restrictions that governs the movement of the mobile nodes. The model is based on using realistic data sets rather than randomly generated data. Within this paper the terms mobile node and vehicle will be used interchangeably, the same for node, anchor and possible destination.

The outline of the paper is as follows: Section 2 presents the related work. Section 3 presents the motivation and the paper contribution. Section 4 describes the simulator on which the work is based and the suggested mobility model in details. Finally the conclusion is given in section 5.

2 Related Work

A VANET simulator is composed mainly of two components: a communication simulator and a traffic simulator. The communication simulator is responsible for simulating network communication protocols, while the traffic simulator is responsible for simulating the nodes mobility at macroscopic as well as microscopic levels. Most of the existing simulators, like ns-2, OPNET...etc, have accurate and well tested models for communication protocols, however realistic representation of vehicles' mobility is still needed.

2.1 Evolution of Mobility Models

During the previous two decades many studies have been conducted to analyze the mobility characteristics of humans. Models sophistication have evolved through the years starting from the simple random moving towards the complex hybrid ones. The earliest mobility models were random; the vehicles destinations and speed were randomly assigned during the simulation like in the random waypoint model [20]. However, if one would take a closer look, one would realize that vehicles are driven by persons, which means that the movement of the cars is dramatically affected by people's behavior and is far from being random. The next generation of mobility models have been produced considering one or more of the human mobility metrics [23], namely temporal dependecies, or spatial dependencies, or both. Based on the temporal dependency both the Gauss-Markov [16] model and the Smooth Random [6] model were produced. Both models assume that at a certain time interval; the direction, speed and location depends on previous time intervals. The latter eliminates sharp turns and sudden stops by defining preferred set of speed with a high probability instead of uniform distribution of speeds.

Considering the spatial dependencies where the nodes move in groups and are influenced by the surrounding nodes, many variations of models were produced [29]. The most important one is the Reference-Point group mobility model [9] which enables the random motion of the group and the individual motion of a node in its group. Every group has a logical center and all mobility characteristics depend on the logical center motion. The nodes are distributed within the geographical scope of the group. For the Structured-Group mobility model [7] the movement of the groups is not random but rather towards a common destination or a goal.

In the Cluster Based mobility models [2], nodes are arranged in groups called clusters. In this model nodes can be of three types either cluster head, or gateway or normal node. These nodes called cluster-heads collect the data sent by each node in that cluster. Cluster head maintain IP addresses of cluster members and members maintain the IP address of the head.

Recently Complex vehicular traffic models were produced. They include complex traffic behavior by considering traffic rules like topological map, vehicle speed, obstacles, and desirable points. An example of this type of models is the Free Way mobility model [3] which includes spatial and temporal dependencies and imposes geographical restriction. The Manhattan mobility model [3] predicts the mobility patterns of mobile nodes on bidirectional streets. The simulation area is composed of horizontal and vertical streets which imposes the geographical restriction of networks. The model also simulates the spatial and the temporal dependencies.

Society is something that precedes the individuals and obviously affect their mobility to socialize and to move in groups. Accordingly, vehicles mobility is dramatically affected by the human social behavior, which urges the need to integrate the individuals' social mobility model along with the geographical one to produce a model that is capable of providing a realistic modeling of the human mobility. Behavioral mobility modeling started to gain popularity lately. Social mobility modeling, thus, became a recent trend in modeling nodes' movements in a wireless network in general and VANETs in particular. The Community based mobility model [25] captures the behavior of individuals moving in groups and between the groups. It considers the type of the relation between the members of the group. The Home Cell Community Based mobility model [8] is based on the previous model but adding the feature of the node attraction towards locations and not only towards each other. A major advance in this group of models is the Time Variant Community mobility model [18] that takes into consideration the time factor when forming the communities and managing the attraction towards locations. Socila-based mobility models are further discussed in details in the following subsection.

2.2 Social-Based Mobility Models

Although many mobility models have been produced to model the human mobility and predict the movement of the mobile nodes, most of the work done so far is too simple to completely mimic the human mobility with all of its aspects. Each new paper has been advancement over the previous models, but yet the work is not complete. Below, the most significant mobility models that consider the social aspect of the human mobility, are presented.

2.2.1 Community Based Mobility Model

In this model, the social network is represented as a weighted graph where the nodes are the moving individuals and the weighted edges represent the strength of the social tie amongst them. The model takes care of the fact that the social tie between the different nodes differs according to the time of the day. An example that explains the previous theory is; On Monday morning one is more likely to socialize with one's coworkers but on the weekend one's social network is the family and friends. To reflect the previous facts, an [N*N] symmetric matrix, called the interaction matrix is fed to the simulator as input. Each value is a number between 0 and 1 representing the social tie between the two nodes represented by the row and the column within the matrix.

The interaction matrix is then used to generate another matrix by setting a threshold value. All the entries in the interaction matrix above the threshold are set to 1 and the values below the threshold are set to zero forming a binary matrix called the connectivity matrix. The idea behind this is; two individuals are interacting if they have a relatively strong social tie. The detection of the communities is done by removing the edges with the highest centrality [19] one by one until a certain threshold value is reached. This is done because if two communities are connected with few edges then all the paths through the nodes in one community to the nodes in the other community must traverse one of these edges which will then be characterized by its high centrality.

The simulation area is then subdivided into squares, with each community randomly assigned to one of the squares. To drive the movement of the nodes each one is assigned a destination and the square containing this destination point is now associated with the node. The first goal is assigned randomly, the subsequent ones are chosen by calculating the square with the highest attractiveness to the node in question. The attractiveness is represented as the summation of the social ties of the node with all the other nodes associated with the candidate square divided by the number of nodes associated with that square. The square with the highest attractiveness is the winner to be the next destination for that node.

To simulate the fact that the movement patterns and communities differ according to the time of the day; each interval of time the social network is changed. The interval of time as well as the social network is input to the system. Thus the communities are to be reconstructed and then randomly associated with squares each interval of time [25].

By analyzing the previous work, it can be noticed that many important features of human mobility are ignored. One of the most significant features is the attractiveness towards places. In this model the destination is chosen based on the attractiveness toward acquaintances residing in the location ignoring the location itself which contradicts what happens in real life. A simple counter example is; after work one wants to go back home to have some rest even if none of the family members is at home at that time.

Another ignored human mobility feature is the presence of hierarchy in the periods of the repetition of actions. In other words, some actions are repeated daily like going to work and others monthly like going to the bank. Having fixed periods totally neglects the previous fact.

A major disadvantage that cannot be disregarded is the overhead caused by reloading a different social network each time interval and rebuilding the clusters and associating each with a random square which will increase the effect of the randomization on the simulation results.

2.2.2 Social Network Theory-based Mobility Models

This model is very similar to the one presented in [25]. The main difference lies in the way the next goal is chosen. This model gives two different mechanisms for choosing the destination of the node. The first mechanism is similar to the one presented in [25] which chooses the new goal to be in the grid that exerts the maximum attractiveness on the node in question. The second mechanism involves a randomization factor that is a property of the grid squares and represents the probability of the selection of each square to be the next goal [24].

Although this model has included many traces of human mobility, including the temporal regularity; it has not tackled any aspect of the micro mobility of the nodes. Moreover, the geographical boundaries that control the human movement and may in fact also affect the social aspect were almost totally ignored. Furthermore, the spatial regularity was not simulated and the attractiveness towards a place was based on the nodes residing at that place ignoring the attractiveness towards the location itself.

2.2.3 N-Body: Social Based Mobility Model for Wireless Ad Hoc Network Research

Based on the same concept that was presented in [25]; another mobility model, The N-Body Mobility model [32] is produced. The model also takes as input an [N*N] social matrix and reflects the strength of the social tie in terms of groups formation and attraction towards a certain destination through the implementation of mutual forces between the nodes of the model. It uses the inter-nodal forces to manage the mobility of the nodes within the groups in order to mimic the flock movements [28].

The N-Body model differs from earlier work since the correlated movements are completely and quantitatively controlled by inter-nodal forces. The dynamics of the model are based on the Gay-Berne potential [5] which mimics the speed matching, group entering and collision avoidance behavior of group movements.

During the simulation, nodes are placed randomly on the simulation area and goals are randomly selected for each node. When the nodes start moving, they are attracted by two types of forces; the destination and the neighboring nodes, which will cause the nodes to deviate from their trajectory towards the goal. When the nodes reach the goal, they pause before moving to the next goal.

Nodes with very high inter-nodal attraction forces tend to stick together forming a group. The attraction to the destination of a node is inversely proportional to the distance between the node and that destination. Thus, nodes with different goals that form one group move together visiting all the goals of the different nodes starting with the goal with the highest attraction [32].

Although this model managed the micro mobility of nodes within the group, it ignored the spatial and temporal regularity that characterizes the human mobility. Moreover, the fact that all the nodes forming a group stick together to visit the goals of the group members one by one cannot be applied to real VANET, since the car chooses the destination and moves towards that destination regardless of the acquaintances that it might encounter on the way.

2.2.4 A General Social Mobility Model for Delay Tolerant Network

The model takes as input a social network that should be reflected in the movement of the nodes without inducing any social relation based on the structure of the model. The social network is represented as a symmetric N*N matrix of random numbers, where each value is a number in [0,1] that represents the strength of the social tie between the two nodes and thus the frequency of their meetings. Each value is associated with a set of active ticks to represent the periods of time where the probability of meeting of the two nodes is higher. This idea is to simulate the concept of active relationship. An example is; on Monday morning the probability that an individual meets their coworkers is higher than meeting their friends. Each node is also associated with a social sphere representing the frequently visited locations to simulate the concept of spatial regularity; where the nodes visit few places regularly.

Anchors are randomly distributed on the simulation area. Nodes interactions occur only at the anchors, which represent the locations visited by the nodes. The nodes pause at the anchor for a certain time "Dwell time" which is a property of the place itself and differs according to the type of the place. An example; if the location represents work then the dwelling time is eight hours but for a restaurant is it two hours only. After the dwelling time expires, the node selects the next location to move to. The goal is a point within the boundaries of the anchor.

The selection of the next target is based on the node attraction towards the location itself and towards the nodes related to that location. The strength of the attraction is not constant but heterogeneous and periodic.

Although this model has been a great step in the domain of social mobility model; many points still need further investigation and improvements. The model used random data in various parts of the simulation. There is a crucial need to use real input data for the model representing the social network instead of random data in the following parts:

- The weight of the social tie between the nodes of the input social network
- The length of the period where the relationship is active and the interval between active periods should be extracted from real traces.
- Location information should be integrated to get the actual social sphere of the nodes and the real shape of the anchors
- The anchor function that relates the node to the different anchors should be based on GPS traces which makes it possible to approximate the collocation probability (i.e. the ratio between number of times a node was located at an anchor and the total number of simulation periods)
- The dwelling time at different anchors should be related to the nature of that anchor (work, caf, shopping mall...etc)
- The speed distribution among nodes should be based on real traces, rather than random.

The temporal regularity was realized by having periods of fixed length, however in real life, periods of different periodicity exists. Some actions are done daily like going to work, others are weekly and others are monthly. Hierarchical periods should be implemented to simulate this fact.

In this model, the concept of active relations was integrated to simulate the fact of the variation of the one's social sphere according to the time of the day. However, a mobility profile was not included; the set of locations that are important at a specific time should be defined [12].

Although this model was a big step in the simulation of the social mobility it totally ignored the geographical restrictions that govern the vehicles movement on the road. A graphical model should be integrated with the social model taking into consideration the following:

- Including obstacles on the road.
- Vehicles should have variable speed that changes according to many factors.
- The micro mobility represented in the interaction between the vehicles that move in groups to avoid collision and manage the speed etc.
- Having macro anchors with micro anchors within their boundaries to represent the exact goal of the vehicle.
- Defining the mobility of the node within the anchor boundaries.
- Placing the anchors on the simulation area tailored to a certain scenario rather than randomly.
- Considering stationary infrastructures in addition to moving nodes.

Furthermore, a geographical tool is needed to customize the parameters, including a visualization of the simulation area and the placement of the anchors, setting the anchors functions, setting the dwelling time and assigning the home anchors of the nodes.

2.2.5 A New Group Mobility Model for Mobile Adhoc Network based on Unified Relationship Matrix

Most of the social based mobility models represent the social tie between the mobile nodes through a connectivity matrix that is fed to the simulator as input. The values within the matrix are numbers in [0...1] representing the strength of the social relationship between the nodes. The work in this paper is based on reinforcing the existing techniques of defining social relations between mobile nodes by forming an additional matrix, the unified relationship matrix (URM). It has the role of representing not only the social relation between the nodes falling under the same group type (friends, family, colleagues...etc.) but also the inter-type relations between nodes belonging to different groups. An example of this case is a party having attendees tied by the friendship relations and represented by the matrix $L_{friends}$, and others tied by the family relation that is represented by the matrix L_{family}. Some of the nodes falling under the friends group have acquaintances that are members of the family group this relation is represented by the matrix L_{mix}. In this case the unified relationship matrix that includes both the inter-type and intra-type relations will look as follows:

$$L_{URM} = \begin{vmatrix} L_{friends} & L_{mix} \\ L_{mix}^T & L_{family} \end{vmatrix}.$$

Within the model, four rules govern the movement of the groups along with the individual nodes that are either forming groups or moving independently on the simulation area. The first rule is concerned with the movement of the individual nodes that is based on the attraction velocity towards other nodes. The second rule is dedicated to avoiding collisions between neighboring nodes by maintaining a small distance among the adjacent vehicles. The third rule is concerned with groups formation and the calculation of the group velocity in terms of the velocity of its members using the URM. The fourth rule is based on the third rule and outputs the new position of the group considering its attraction towards the different existing groups that is obtained from the URM. The speed of the group movement is a function of the speed of the nodes that are members of that group.

As for the individual nodes, the decision to join a certain group happens upon reaching their goal. Three options are then available; either to remain within the same group, or to join another group or to escape outside all groups areas. The choice between both the first and second options together and the third option is based on the sociability factor of the node. A threshold is generated using a random distribution. If the sociability factor is greater than the threshold then the new goal of the node is chosen outside all groups areas. If not, the attraction of the node towards the different existing groups is then calculated. The node joins the group that exerts the highest attraction upon it [14].

The work in this paper has reinforced the existing social mobility models by introducing the unified relationship matrix to manage the groups' movement dynamics. Albeit the undeniable contribution of the study, it has completely ignored the physical aspects that characterize the human mobility and thus cannot be sufficient to produce a satisfactory and realistic mobility model.

2.2.6 A Fuzzy Realistic Mobility Model for VANET

A new type of mobility models has been proposed. It is based on the fact that both the mobility of the nodes and the environment are not precise. The locations for instance can't be described by sharp coordinates and may be distributed over a large area. To solve this imprecision, a fuzzy mobility model has been introduced.

The input of the fuzzy system is the current location and time, the output is the next destination. The moving nodes in the system have been grouped according to their type (personal, public...etc.). The mobility behavior of the vehicles depends on their group. For each group, and for each location, all possible destinations have been prioritized according to the probability of visiting them at that time of the day. This prioritization is a property of the node group.

The fuzzy system is composed of several parts; the fuzifier, the rules system, the inference engine and the defuzzifier[31]. The input of the fuzzifier is the time and the location expressed precisely in terms of hour and x,y coordinates respectively. The fuzzifier changes the input to be fuzzy, for example, by mapping the time to morning, afternoon or evening. The fuzzy states are fed to the inference engine whose output is sent to the defuzzifier to output a precise decision for the next destination of the node [1].

Although the model handles one of the most important problems of the mobility simulation which is the imprecision of the input, it totally ignored the geographical aspects such as the obstacles and used the Dijkstra's shortest path algorithm to select the path from the source to the destination. Another limitation is in the grouping of the vehicles and choosing the destination based on the group type. The groups are too generic and members of one group

Table 1. Mobility Models Comparison

model	Temporal reg.	Spatial reg.	Geog. re-strict.	Social model.	Realistic time re-press.	Micro mobil-ity
Comunity based mobility model 2.2.1	yes	no	no	yes	no	no
Model based on social net-work theory 2.2.2	yes	no	no	yes	no	no
N-Body 2.2.3	no	no	no	yes	no	yes
A general social mobility model 2.2.4	yes	yes	no	yes	Not fully	no
Mobility Model based on URM 2.2.5	yes	yes	no	yes	Not fully	no
A fuzzy realistic mobility model 2.2.6	yes	yes	no	yes	yes	no
Proposed Geo-social model 4	yes	yes	yes	yes	yes	yes

could have different preferences. So the generalization is a huge limitation for the performance of the model.

3 Motivating Remarks and Contribution

After analyzing the previous models, we can notice that none of the existing models is yet complete in the way it models the vehicles mobility. The word complete signifies how close it is to simulating the actual human mobility. The more the model considers characteristics of human mobility the more it is close to be realistic. Although efforts have been deployed in this area of research, the models produced so far lack one or more of the significant human mobility traces as shown in table 1.

As obvious from the above analysis, some ignored the temporal regularity others the spatial regularity others the geographical restriction...etc [23].

Examining the related work suggests the need for a socio-geographical mobility model that simulates the human mobility characteristics and is to be integrated with any VANET simulator. The suggested model should consider the social context; in which there is a direct reflection of the input social network on the mobility of the nodes. the active social relation concept; when there is a high probability to meet at that time period. the spatial regularity; which reflect the human behavior to visit certain location regularly. The social sphere is that set of places frequently visited. Finally, the temporal regularity since human visits to places are periodic.

The contribution of the work presented in this paper is summarized in the following points:

1. Integrating the social mobility aspects with the geographical model to have a more complex and sophisticated model that mimics the human mobility with most of its characteristics.

2. Predicting the mobility traces of the nodes given the social network that relates the

nodes together.

3. Minimizing the reliance on random data as input to the mobility model and using real traces.
4. Putting the social relation in a mathematical framework by predicting the social tie between the nodes given some characteristics and information about the nodes.
5. Enhancing the map representation in the simulator with additional data allowing intelligent routing and enabling the loading of any selected area from Open Street Map to the simulator.

4 The Geo-Social Mobility Model

The first goal of this work is to incorporate the social mobility aspects in the simulator and blend them together with the geographical mobility restrictions so that both work in harmony to control the vehicles movements in a way that mimics the real life scenarios with all its variations. A brief discussion of the simulator used in our work, followed by a detailed discussion of our proposed approach are given below.

4.1 The VANET Simulator

The purpose of the VANET Simulator is to have realistic mobility traces that mimic the behavior of the vehicles with its variant scenarios. It takes also into consideration the roads networks and the variant speed and acceleration, the different traffic light and rules...etc.

Despite the fact that the proposed mobility model can be integrated with any simulator, one had to be chosen for deployment and testing purposes. SUMO was found to be the most suitable simulator to serve the purpose of this work since it allows the loading of digital maps from free sources like the OpenStreetMap. It has a fine handling of the vehicles micro mobility aspects and their traces are ns-2 compatible. It has documentations and online available examples and is still under development and improvement.

The SUMO is a microscopic and discrete time mobility generator. The roads network can be manually generated through an interface or imported into the simulator from a digital map like the Open street Map. The mobility generator is purely microscopic where each vehicle has its own identifier and is characterized by its departure time and route in the network. Vehicles can be generated in many ways; for large scale networks, they are generated through the origin to destination matrix, where the source node and the destination node of each vehicle is identified. The other possibility is to identify the entire route of each vehicle, which is more applicable in the public transport simulation scenarios. The vehicles routing is done through a traffic assignment employing a routing procedure such as shortest path calculations under different cost functions and allows dynamic link weight assignment during the simulation . The SUMO has very advanced microscopic features, including the traffic lights implementation, the lane changing simulation and the management of the vehicles speed[21].

4.2 Geo-Social Model

The proposed Geo-social model will mainly affect the choice of the source and the destination of the vehicles, in the VANET simulator, to be driven by both their attraction towards their acquaintances and towards locations of interest according to the time of the day rather than being chosen randomly. An example is that one is more likely to meet work colleagues in the morning and personal friends in the evening. As well as one is more likely to go to work place in the morning and to social clubs in the evening.

The main factors that affect the human mobility are both the temporal regularity and the spatial regularity. The temporal regularity is simulated by defining the social sphere **S** for each vehicle that is taking part in the simulation. The social sphere contains the frequently visited locations by that vehicle along with the purpose of the visit. Thus, for each vehicle V_i:

$$S_i = A_1, A_2, A_3...A_n \tag{1}$$

Were A_j is an anchor or in other words a possible destination on the map and n<number of all anchors of the map. When the next destination is to be chosen for the vehicle V_i, the attraction towards each anchor in its social sphere S_i is calculated, and the anchor with maximum attraction value is chosen.

For an Anchor A_j in the social sphere of vehicle V_i, the attraction function T_{ij} at a time t is as follows.

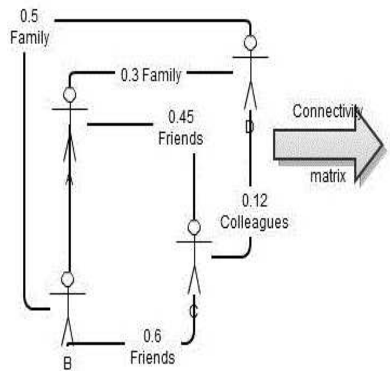
$$T_{ij}(t) = (1 - x)St_{ij}(t) + xSl_{ij}(t). \tag{2}$$

Where $St_{ij}(t)$ denotes the attraction of V_i towards its social acquaintances that have the Anchor A_j as their next destination and has the possibility to meet them at that destination. The meeting possibility is calculated by taking into account the cars speed which indirectly reveals the traffic condition, the distance to the destination and the pause time at the destination. Sl_{ij} denotes the attraction of the vehicle V_i towards the anchor A_j because of the properties and the characteristics of the anchor itself. The constant x is to specify which component is more influential in the overall visiting likelihood and is proportional to the visiting regularity measures of V_i such as visiting periodicity for that anchor.

To calculate the attraction towards acquaintances, the simulator will be given as input a data-set representing a social network, from which a social graph is to be inferred. The nodes of the social graph will represent the vehicles drivers and the edges will represent the social tie between the different vehicles drivers in terms of type (friendship, family...etc) and strength (a decimal number between 0 and 1). The next step is to translate the social graph to an [N*N] connectivity matrices, where N is the number of available vehicles. Each type of social relation will be represented by a different matrix. Which means there will be a matrix representing the friendship tie, another representing the family tie and a third representing the work colleagues tie...etc. Within each matrix a '0' is added if no relation of that type exists between the two nodes otherwise a numerical value is added signifying the strength of the relation, as shown in Figure 1. Let **F** be the matrix representing the family relation, **R** the matrix representing the friends relation and **W** representing the coworker relation. Since by intuition two people may be tied by one or more different social relation, like being friends and coworker at the same time, the social relation between two vehicle b and c is calculated as follows:

$$A_{bc}(t) = F[b, c] + R[b, c] + W[b, c]. \tag{3}$$

However, the equation 3 is not yet complete. It does not simulate the fact that different social relations are not equally important at all day times. Since for example, people are more



Friends	A	B	C	D
A	1	0	0.45	0.3
B	0	1	0.6	0
C	0.45	0.6	1	0
D	0.3	0	0	1

Family	A	B	C	D
A	1	0	0	0.3
B	0	1	0	0.5
C	0	0	1	0
D	0.3	0.5	0	1

colleague	A	B	C	D
A	1	0	0	0
B	0	1	0	0
C	0	0	1	0.12
D	0	0	0.12	1

Fig. 1. Social network transformed into connectivity matrix

likely to meet their colleagues in the mornings during the working days and their friends in the evenings. To reproduce this scenario the equation 3 is to be modified in such a way that each matrix is multiplied by a certain factor that either increments or decrements the values of the social tie, according to the time of the day, which means that this constant for each matrix will vary with the time. The equation will then be as follows:

$$A_{bc}(t) = (Cf_t * F[b,c]) + (Cr_t * R[b,c]) + (Cw_t * W[b,c]) \tag{4}$$

Where **Cf**, **Cr** and **Cw** are constants whose values vary with time and are tuned using real data sets collected in 4.4.

The social attraction of a vehicle V_i towards a location A_j in its social sphere S_i is calculated to be the summation of the social attraction between the vehicle V_i and all its acquaintances having A_j as their next destination:

$$St_{ij}(t) = A_{i1}(t) + A_{i2}(t) + A_{i3}(t)...A_{in}(t) \tag{5}$$

where the numbers from 1 to n denote the vehicle V_i acquaintances having A_j as their next destination and A_{in} denotes the social attraction between two vehicles V_i and V_n and is calculated as shown in equation 4.

To calculate the second part of equation 2 which is the attraction of the vehicles towards locations **Sl**, the concept of the social sphere is re-used. The social sphere S_i of a mobile node Vi contains the frequently visited locations of that node. It also contains information about the purpose of the visit to the locations and/or the type of the location. The attraction towards each location in the social sphere is calculated according to the time of the day and the properties of the location itself. For this to happen, the map representation is extended to contain more information about the possible vehicles destinations. To simplify the task, the locations on the map were classified into one or more of the predefined six classes; Residential Area,Institution, Daily Necessities,Socializing and Entertainment, Cultural, Physical Area. For each class, the locations properties have been specified such as the pause time, the periods were the visit probability is higher...etc. The classification procedure and the classes description will be discussed in details in section 4.6.

The social sphere of each vehicle is described in a tabular form as shown in table 2.The first row represents the different nodes ID, which is unique for each destination. The second

Table 2. Vehicle Social Sphere

Loc ID	4	7	22	31
Attraction	0.22	0.44	0.14	0.2
Purpose	work	home	sport	leisure

row describes the frequency **F** of the vehicle to visit each location as compared to all its visits. It is calculated as follows:

$$F_{ij}(t) = \frac{Nbofvisitsof V_i tolocation A_j in S_i}{Totalnbofvisitstoalllocationsin S_i} \tag{6}$$

Thus, the location attraction $Sl_{ij}(t)$, which signify the probability of a vehicle i to visit the place j, will be:

$$Sl_{ij}(t) = F_{ij}(t). \tag{7}$$

As previously mentioned, the map locations are classified according to the possible purposes of visits to these locations, some locations can then fall under more than one class at the same time. An example is hospitals; they are work places for the doctors but service institutions for the patients. The third row in the table signifies which of the classes are to be taken into consideration and thus identify the correct characteristics of the place for each vehicle.

As well as social relations, also locations attraction, varies with time. One goes to work in the mornings but back home in the evenings. To simulate this fact, a constant is multiplied with the function $F_{ij}(t)$ in equation 7 to increment the probability of the visits to some places rather than the others according to the time of the day and the location classes. The constants will be attribute of the classes the location belongs to. If a location falls under more than one class then the purpose of the visit will identify the correct class and thus the correct attributes. Thus the location attraction $Sl_{ij}(t)$ will be:

$$Sl_{ij}(t) = C_{xt} * F_{ij}(t) \tag{8}$$

Where x represent the class of the location and C_x is a constant that varies according to the time of the day **t**.

Finally by combining the equations 8, 5 and 2, the attraction value T_i to each location in the social sphere S_i of the vehicle V_i is calculated at time **t**. To choose the next destination of the vehicle the maximum value of all the calculated attraction values is taken and the equivalent location is chosen to be the next destination.

4.3 Predicting the Mobility given the Social Network

By intuition, one can infer that the human mobility is influenced by many tangible and non tangible factors that affect the choice of the next destination. The question that arises is; which factors will be taken into consideration?, and which of them will be dominating? In other words, how to combine all of the factors and quantify them so that the simulator decision reflects the input data? This step is realized through the definition of an attraction function that measures the attraction of the vehicle towards all the possible destinations and favors the destination that exerts the highest attraction value on the moving vehicle. As explained in details in the previous section, the function contains variables representing time, location attraction, acquaintances attraction and some other factors, along with constants that should be tuned to have an accurate significance of parameters affecting the human mobility aspects. The attraction function needs as input the social network and the corresponding social sphere of each node of the social network to reproduce the mobility traces of the nodes. Thus the second goal is fulfilled and the mobility traces are produced through this function and relying on the input social data.

4.4 Reliance on Real Data as Input

To meet the third goal of this work; the social network, the corresponding social sphere and the mobility traces are to be based on real data. In more details, the simulator will be given as input a social network, through which it will be able to build a labeled social graph with the edges defining the type of the social relation between the vehicles. This stage is dramatically affected by the availability of data sets from which social network information is to be extracted. The lack of large data sets has driven previous models to use random data, which resulted in models that do not fully represent the human behavior. To avoid the previous problem, this work insists on building the social network based on real data, taking advantage of the emerging usage of smart phones. The purpose of the experiment is to build a social network amongst the participant and map it to their mobility traces in order to find the relation between the social ties of the individuals and their mobility activities.

The social data collection experiment took place in the city of Ulm, Germany. Android phones were given to the participants on which a tracking application was running. The participants were chosen with great care to incorporate the different types of social relations. The experiment was launched in May 2013 and lasted for one month. The timing was chosen to be a regular month away from the summer vacations or the special occasions to reflect the normal repetitive behavior of the human mobility. The number of registered participants was 89, of these, 64 have registered a level of participation that is greater than 90%. The level of participation was measured according to the time the tracking application was on during the whole period and the quality of answering the questionnaires that were sent during the experiment period.

The application for collecting the mobility traces is called "Tracker" and was programmed in java. At the client side the location information is recorded in a local database at time intervals that were fixed a priori. The location data is in the form of longitude, latitude, accuracy and timestamp. When the phone was online via WIFI, the location information was sent to the server on which the data processing took place. For each participant, the frequently visited locations were marked. By the end of the experiment marked locations were sent to the user to label them, in terms of the purpose of visiting the place and probably the name of the location if not recognized by the server. The users were requested to define their acquaintances from the participants of the experiment and the type of the relation through his friends list. The meetings with these acquaintances were detected and recorded by the server. The scenario of people meeting frequently without having actual social bound was also considered by comparing the traces of all the participants and when several participants are at the same place at the same time a meeting is recorded. Shown in Figure 2 one graphical interface of the tracking application.

As previously mentioned the social network graph is a labeled graph, with the nodes rep-

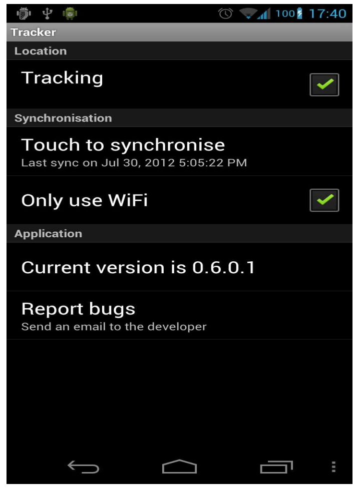


Fig. 2. The Graphical Interface of the Tracking Software

resenting the participants in the experiment and the edges representing the relation between them, if any. The label on the edges represent both the strength and the type of the relation between the nodes. The type of the relation is extracted from the gathered friends list of the users, since in this list the type of relation is requested. The strength of the relation that a node A has with another node B is calculated from the gathered data to be the number of the meetings between the Nodes A and B divided by the total number of meetings reordered for node A with all other nodes.

4.5 Putting the Social Relation in a Mathematical Framework

The strength of the relation between the mobile nodes is represented by the numbers in the connectivity matrices. In the previous step these numbers were calculated from the mobility traces to be affected by the number meetings. As a matter of fact, there exist many alternatives to calculate these values, according to the available set of data. In the absence of the mobility traces, it is possible to rely on questionnaires to rate friends closeness. But this is not always significant, since close friends can have less number of meetings due to distance factors. Another way to do it is by having information and statistics about the participants forming the input social network; one can infer the probability of them to meet. The idea presented in this section is inspired by the work done in the SUPSI lab in Switzerland.

The idea is based on the fact that people with common interests or common characteristics tend to have higher probability to meet and socialize. Thus, the more two people have in common, the higher is the probability of them to be in contact. An example is; two people working in the same department and speak the same language tend to have more contact then two who doesn't share any common language. However, different characteristics have also variant impact on the contact probability, which means that not all the properties are of the same significance.

Since the idea is to map social information into a numerical value signifying the meeting probability of the two nodes, then each property is to have a mathematical equation that maps it into a numerical meeting probability . An example is the language property, its equivalent mathematical equation is as follows [13]:

$$D = 1 - \Sigma \frac{sharedlanguages}{allspokenlanguages} \tag{9}$$

The D designates the social distance of two people and indirectly implicates the meeting probability. The greater the distance the weaker the social tie and thus the less the probability of the meeting. The weight of a property represents how significant is the property in affecting the meeting probability of the participants. Let D_{iab} be the mathematical equation that maps the property **i** that is shared between the individuals **a** and **b** into a numerical value. Let W_i be the weight or the significance of the property **i** on the meeting probability. Let **n** be the number of common properties between two individuals **a** and **b**. The meeting probability M_{ab} will be calculated as follows:

$$M_{ab} = \frac{w_1 * D_{1ab} + w_2 * D_{2ab} + w_3 * D_{3ab} ... + w_n * D_{nab}}{n} \tag{10}$$

However, the experiment by SUPSI was run only in the campus, which restricts the participants to be belonging to one social group and omit the variation in the data set. Moreover, they restricted the weight of each property to either 1 for the significant characteristics or to 0.2 for the less significant ones which leads to non accurate results. Standing on that ground we decided to use the experiment run in Ulm, that is intended to collecting social information and its related mobility traces, to evaluate and to investigate more characteristics and produce the equivalent mathematical equations in order to have an alternative way for building the connectivity matrices. A questionnaire is given to the participants about the languages they speak, sports they practice, job position...etc. The effect of sharing each common property will be compared against the recorded contacts between the participants that share it and a mathematical equation will be developed to map each property to a meeting probability. The results will be then compared with those who were previously detected at the SUPSI labs and a conclusion is to be drawn.

4.6 Generic Location and Map Representation

The main components of a VANET simulator are the mobile nodes or the vehicles, the mobility model that governs the movements of the vehicles to mimic the real life behavior of cars and finally the simulation area on which the vehicles move. Since the purpose is to have a realistic VANET simulator, then as much as it is important that the vehicles and the mobility model mimic reality, it is as well needed that the simulation area produces a real geographical environment for the simulation. The map representation within the simulator is then of vital importance to produce realistic mobility traces of a certain location. Since we are not only concerned with having a geographical based mobility model but rather socio-geographical, then mapping between the available social data and the location where it was produced is needed. The already existing VANET simulators rely on having a representation of a certain country or location where all the traces are forced to be produced [27, 17, 11]. Many of them used the GDF map where the road topology is imported from a Geographical Data File (GDF) [10]. Unfortunately, most GDF file libraries are not freely accessible. Others used the TIGER map in which the road topology is extracted from the TIGER database [30]. The level of detail of the maps in the TIGER database is not as high as that provided by the GDF standard, but this database is open and contains digital descriptions of wide urban and rural areas of all districts of the United States only.

Other simulators like the MATsim [4] and SUMO have the feature of importing the map from digital sources like the OpenStreetMap. However, for an advanced social based mobility model, simple location description is not enough. The geographical map should support the social model by providing more location information assisting the mobile nodes in selecting the destination in such a way that mimic the human brain when taking the decision to visit a place. Extending the representation of the map locations with information and statistics is thus crucial to achieve a realistic social based mobility model. The representation of the places include the type of the location (work location, leisure...etc) and the pausing time at the place which differs according to the type of the place. An example of the pausing time is; people tend to stay at work 8 hours but at a restaurant around 2 hours. As previously mentioned the attraction of the vehicle towards a certain location is reflected by the type of each possible destination and according to the time of the day one place is favored than the other, which is reflected in the attraction value.

The technique presented in this work is based on the Open Street Map. The OSM uses a tagging system to represent the place name and properties along with the co-ordinates of the place to stand for its exact location. The maps are updated through ground surveys, aerial photography or government resources [26]. The Open Street Map offers the feature of exporting a selected area as an XML file, in which the locations are described by tags. This feature have been used to produce a software that integrates any Open Street Map extracted XML file with the VANET simulator, classifies the locations according to their type and adds more information about the places based on the classes they belong to, such as the pause time that the vehicles need to spend at each location and the parking areas around the place classifies according to their distance from the desired destination.

The main challenge of this technique was the identification and classification of the locations, since the different points on the Open Street Map are represented using user-defined tags. There is no fixed metadata, as these tags are defined by different users. However, a large set of predefined tags is available and can be reused for describing a new point on the map. The paper mentioned in [15] provides an insight on the tagging techniques used by the users. The difficulty was then to handle the semi controlled vocabulary and use it to identify and classify the points on the map.

Another challenge arises from the intention to extend the different locations with additional data, like the type and the pausing time. In this matter we relied on surveys to identify the locations of interests that can be possible destinations for the vehicles, the time where the probability to visit these locations is high, as well as the pause time at the place itself.

As the system is vehicular based, the place itself is not the destination but rather the parking lot attached or near to that place. The parking places for a certain destination are then to be identified and classified according to their distance from the destination and sent to the simulator decision engine to decide which will be the next destination for the vehicle.

The approach to overcome the previously mentioned challenges is based on building the system's own dictionary out of the most commonly used tags. The Open Street Map tags are in the form of <key: value>. An example of the possible tags describing buildings on the map is: <building: apartment>, <building: hotel>, <building: hospital>, <building:

school>...etc. The dictionary is divided into six classes of tags, through which the locations classification and properties attachment takes place. Each possible location tag that is to be detected by the software is listed under one or more of the dictionary classes[22]. The six classes are:

1. Residential: Representing the homes and living areas.
2. Institutions: Formal locations providing indirect service like universities, offices...etc.
3. Daily necessities: Locations that provide direct service like markets, shopping malls, post office...etc.
4. Socializing and Entertainment: Are locations that evolve social interaction like clubs, pubs, cinemas...etc.
5. Cultural: involving museums, libraries, churches...etc.
6. Physical Areas: Examples of this category are swimming pools, sports ground, sports center...etc.

By examining the previous categories, one will notice that there is no obvious borders separating them. In other words, one place may fall under many categories and thus have different properties. The choice of the right properties to be applied, like the pausing time, is based on the purpose of the visit to the place. An example is the bank, it may be a daily necessity when one visits it to withdraw money, and may also be an institution if one works at the bank. The pausing time of the vehicle will be chosen to be eight hours or ten minutes based on the purpose of the visit that will be specified from the gathered social data. The dictionary is then be filled with the most commonly used tags that are extracted and placed in the dictionary under one or more of six categories, based on intuition.

The Open Street Map selected area will be integrated with the VANET simulator by giving the extracted XML file as input to the software. The software will parse the file, analyze the different tags and compare their values with the dictionary. If there is a hit, the location is registered and the corresponding categories are added. This operation is repeated until the XML file ends. The software then outputs the data registered into files with the format required by the simulator to draw the map.

Several tests were run to rate the performance of our maps parser and locations classifier. Several areas in different countries were randomly selected and given to the software to extract the possible destinations and classify them. By analyzing the output, as shown in the samples below, our technique has proven great success in all of the test cases. The minimum performance was 95% of locations detection out of all possible vehicles destination. Below are two examples of test cases run in two different cities; Munich and London.

An area from the city of Munich in Germany was randomly selected from the Open Street Map with the following bounds: minimum latitude = 48.1498300, minimum longitude= 11.5509300, maximum latitude= 48.1533500, maximum longitude= 11.5563400. The area is approximately 0.18 km^2. The output XML file was then given to the software as input, after being manually analyzed to compare the results of the software against the manually extracted data. The area contains a large number of tagged locations. Some of these tags are descriptive, in other words, they explain the functionality of the place. Others are non-descriptive and one can never guess the functionality or the type of the place by simply reading the tag. An example of such tags is <building=yes name=Gebude D>. Total of 259 tags were manually extracted from this area, of which 128 were non-descriptive tags. In this example out of the 128 non-descriptive tags a total of 124 locations contain tag <building= yes>. The total number of descriptive tags in the selected area was 131. These tags include the possible vehicular destination tags along with traffic signs, traffic lights, highway tags...etc. Only 25 of them were found to be possible vehicles destination. All 25 locations were correctly detected and classified by the software. So the accuracy of the classifier remains 100% in this example.

To deal with the non descriptive tags, the assumption that the tag <building= yes> always signifies a residential area was made. The reason on which the assumption was based is that the residential areas or the residential buildings are, in most of the cases, poorly tagged since they are of interest to a fewer number of people when compared to the commercial and service buildings. By manually checking these 124 locations through Google earth and other maps, 61% of them were actually found to be residential buildings and thus our assumption is proven to be valid.

Another area from London, UK was randomly selected with the following bounds: minimum latitude= 51.5160940, minimum longitude= -0.0770950", maximum latitude= 51.5171450, maximum longitude= -0.0750510. The area is approximately 0.03km^2. In this area a total of 58 locations with non-descriptive tags were found. Example of the non-descriptive tags in the selected London area: <tag k="area" v="yes"> <tag k="level" v="0"> <tag k="name" v="Rumours"> <tag k="source" v="photograph">.

Out of the 58 locations a total of 34 locations contain the tag <building= yes> and were considered to be residential areas. The total number of locations with descriptive tags in the selected area was 73, 41 of them were possible vehicles destinations. The number of the locations the software was able to detect is 40. The non detected tag was <Shop=tattoo>. So the overall accuracy of the classifier is 97% in this example.

5 Conclusion

After analyzing the previous models, the problem became very obvious. None of the existing models is yet complete in the way it models the vehicles mobility. The word complete signifies how close it is to simulating the actual human mobility. The more the model considers characteristics of human mobility, the more it is close to be realistic. Although efforts have been deployed in this area of research, the models produced so far lack one or more of the significant human mobility traces as obvious from the above analysis. Some ignored the temporal regularity, others the spatial regularity and others the geographical restriction...etc [23]. Examining the related work suggests the need for a socio-geographical mobility model that simulates the human mobility characteristics and is to be integrated with any VANET simulator. The purpose of this work is to blend together the social aspects of the human mobility with the geographical aspects that restrict the movement of the vehicles. This is done by enhancing the SUMO simulator that only reflects the geographical aspects of the vehicles mobility, with the social aspects that will direct the cars movement. Thus, making it eligible for testing the unicast social based routing protocols and many other applications and protocols aiming at building an intelligent and efficient VANET network. Moreover, the geographical model is extended and enhanced to support the integration of the social aspects. Hence, the simulator has the possibility to produce mobility traces for any geographical area by giving it the map data files as input and post process the locations information to extend the specification and the properties of the locations with data that supports the social profile. This work focuses on avoiding the usage of random data and builds the theory based on gathered information of a social network and its equivalent mobility traces. The work presented contributes in putting the social relations into a mathematical framework and bases the theory for predicting the mobility of the vehicles on the available data.

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