V-MBMM: Vehicular Mask-based Mobility Model

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Abstract—**Simulation is the most commonly used approach to analyze and evaluate the performance of solutions proposed for VANET. The validity of results depends heavily on the used models, in particular the mobility model, which plays an important role. This paper presents a new mobility model, V-MBMM, which is an adaptation of the human mobility model MBMM to simulate vehicle displacement in an urban area. The novelty with V-MBMM is that attraction weights, determined based on survey data and information on terrain characteristic and urban infrastructure are assigned to all roads. The weights reflect the degree of interest of areas for moving vehicles. Vehicles displacements are simulated by Markov chains that take into account road topology and roads attraction weights. To validate our model, several simulation tests were conducted on a real map. The obtained results show a good degree of realism for vehicles motion.**

Keywords — mobility model; VANET; MBMM; attraction powers.

I. INTRODUCTION

Vehicular Ad hoc Networks (VANET) are a particular class of Mobile Ad hoc Network (MANET) formed by the set of moving vehicles capable of communicating and self-organizing in order to build the network. They are distinguished from other classes of MANET by the high nodes density, the high nodes mobility and the low degree of freedom in nodes movements. Several mobility models have been proposed for MANETs [1]; the most commonly used being the Random Waypoint Model (RWP). In this model, the mobile chooses a random destination and moves toward it with a randomly chosen velocity. Once the destination reached the mobile pauses, chooses a new destination and then repeats the process again.

All models presented in [1], including RWP, do not capture the main characteristics of vehicles mobility and are therefore unusable for VANET. In particular, they consider an open area without obstacles and ignore the influence of the external environment on vehicles movements.

The first mobility models proposed for VANET are Manhattan and Freeway [2]. These models integrate geographic constraints into the mobility pattern by restricting nodes movement to the roads of a specified map. The Freeway model simulates the vehicles motion in a freeway. A map has several freeways with multiple lanes in both directions. The movement of each vehicle is restricted to its lane and its velocity is temporally dependent on its previous velocities. Manhattan mobility model was proposed for the movement in urban area. A map corresponds to a grid composed of a number of horizontal and vertical streets each one with two lanes for each direction. Vehicles move in the same way as in Freeway model. Whenever a vehicle reaches an intersection, it determines with some fixed probability whether it should turn left or right or keep straight on. Manhattan and Freeway are very simple models; they do not capture important aspects of vehicular traffic. There is no dependency between neighboring vehicles and Manhattan model defines no control mechanisms at intersections (there is no stop or pause at intersections, and no queuing at roads intersections).

In [3], the authors were interested in modeling vehicles behavior at intersections and proposed the Traffic Light Model (TLM). In TLM, intersections are ruled by traffic lights. Vehicle accelerates from rest up to the maximum possible speed and decelerates gradually to stop when approaching intersection with red signal. When the signal turns green, vehicles leave the intersection each towards a randomly chosen direction. The lack of this model is that it ignores interactions between moving vehicles. Several models aiming to reflect as closely as possible the real behavior of vehicular traffic have been proposed in recent years.

A detailed overview of these models can be found in [4]. All models are graph-based and use the same general principle. The graph represents the road topology. The commonly used graph types are: a simple grid as that considered in Manhattan model and a graph representing real road topologies extracted from the maps of the US Census Bureau TIGER (Topologically Integrated Geographic Encoding and Referencing) database [5]. Each vehicle selects its initial and final position either randomly or based on a set of attraction points defined on the graph. The vehicle moves towards the selected destination through the shortest path calculated based on some criteria such as roads length and traffic congestion. However, the level of details considered in various models of the literature is different. The more realistic models, such as SUMO [6] and VanetMobiSim [7], consider vehicles motion taking into account more detailed characteristics such as road speed limit and multilane roads with lane changing.

In this paper, we present V-MBMM (V-MBMM: Vehicular Mask-based Mobility Model), which is an adaptation of the individual mobility model MBMM [8] to VANET. The considered graph in V-MBMM is extracted from a real map. The originality of this new model is that as in real life, the path taken by a vehicle to reach some destination is not necessarily the shortest path. In V-MBMM vehicles displacement are determined based on survey data and information on terrain characteristic and urban infrastructure describing zones attractivity. This information varies continuously during the day and is added to road topology by assigning dynamic attraction powers to all roads. This makes the spatial and temporal vehicles distribution more realistic. Vehicles displacements from one intersection to another are modeled by a Markov chain whose probabilities depend on roads attraction power. Other parameters are also taken into consideration in order to make vehicular traffic behavior more realistic.

The reminder of this paper is organized as follows: Section 2 presents the MBMM. The detailed description of our model is given in Section 3. Simulation environment and performance evaluation of the proposed model are given in Section 4. Finally, Section 5 presents the conclusion and some perspectives.

II. MASK-BASED MOBILITY MODEL (MBMM)

MBMM [8][9][10] is a time variant model with spatial and geographical constraints. It simulates human displacement in an area divided into square cells of equal size. The area may be a map of any given city. Each cell is assigned an attraction weight which depends on the terrain characteristics representing areas of interest for individual motion in a given zone. Weight values are dynamic and change periodically during the day. At each step, the individual moves from the center of the current cell to the center of one neighboring cell as shown in Figure 1. The direction to be taken at each step is chosen according to a Markov chain of nine steps. The transition probability of each cell is calculated by dividing cell weight by the sum of all the nine cells.

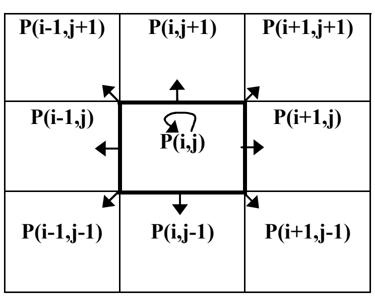


Figure 1. Grid based displacement. The bold lines square is the current position from which the individual moves to any of its eight neighboring cells or stays in place according to the values of the transition probability.

To eliminate unrealistic behavior, such as return to the back cell after a motion, a correction mask is applied to the displacement Markov chain. This mask is composed of the same cells which regroup the nine states of the Markov chain. The mask is dynamic; it is based on the direction taken on the previous step. According to the current state of the individual, two situations may arise:

Individual in motion: the mask is initially filled with the values of each Markov chain step. In order to prevent any return, the cells in the mask presenting the back, back right and back left directions are assigned to zero. The new mask has then a maximum of six cells that are not null. To make the motion more realistic, this mask also reduces the probability of staying in place and that of moving left or right. This reflects the fact that human displacements tend more to go forward (and forward right and left) than to turn straight left or straight right.

Individual at rest: This means that the individual stayed in the same cell in the previous step. It is the only case where the individual is allowed to return back in the trajectory. Correction mask is not applied to the Markov chain and the individual can moves to any of the nine cells.

In MBMM, each twenty four hours day is divided into five periods; work-day (in the morning), lunch break (at noon), work-afternoon, evening (dinner and party) and finally the rest period. At each period, several attraction poles are defined in the area (e.g., university in work-day, restaurant in lunch break, etc.). Information concerning the existence of these poles is added to the environment by increasing the weight of cells around each pole. This permits the smooth convergence of the individual in motion towards attraction poles. A full model description is available in [8][9].

III. V-MBMM : VEHICULAR MASK-BASED MOBILITY MODEL

The MBMM model checked in real environment showed very good results in terms of motion simulation. Then we do some enhancements of this model for VANET case.

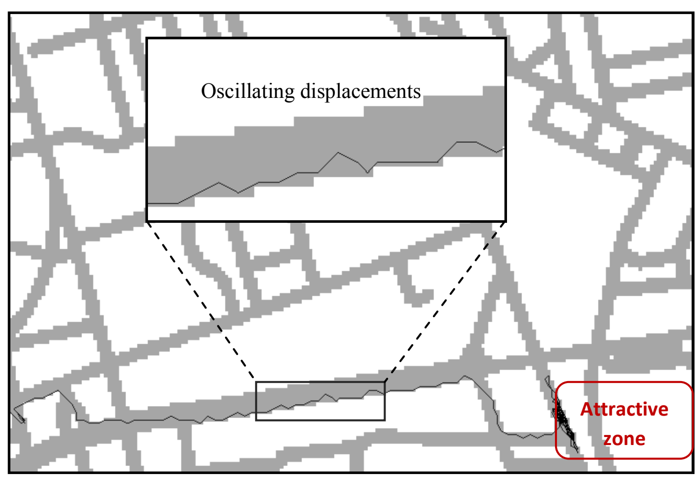


Figure 2. Vehicle trajectory obtained with MBMM. The trajectory presents some oscillating displacements and the vehicle blocks when approaching the attractive zone.

Unlike individuals who can move in several types of terrain such as buildings, roads, fields, etc., vehicles movements are restricted to roads. This restriction and mainly the difference of behavior between individual in motion and driver make the direct application of MBMM not suitable for VANET. To analyze the behavior of MBMM when directly used to simulate vehicles motion, we at first made some simulation tests. The considered simulation environment is the map of the city of Belfort, France, divided into cells of equal size. To have a precise terrain characterization, we used a small cell size of 5m*5m. Each cell is characterized by its terrain type (road, building) and its attraction weight. To limit the displacement to roads, the value of zero is assigned to the attraction weight of all cells which are not roads.

Figure 2 shows the trajectory of one vehicle obtained with MBMM. The first abnormal behavior that can be observed is the presence of some oscillating displacement in the trajectory. This is due to the fact that MBMM is a grid-based model and thus may give up to nine possible directions after each displacement. In our case study, a vehicle chooses a new direction whenever it moves 5m (horizontal or vertical displacement) or $5\sqrt{2}$m (diagonal displacement). This does not reflect the real situation where vehicles change direction only at intersections or when they encounter an obstacle. The second problem observed is the blocking of a vehicle when approaching an attraction zone. When a vehicle comes close to such a zone, it tends to go straight, in a Euclidian sense, to the zone center. The reason is that the cells surrounding each attraction zone are assigned a high weight values. In the case where there is no direct road leading to a zone the vehicle may block without ever reaching its objective.

In order to correct abnormal scenarios listed above and adapt MBMM to vehicular traffic we define V-MBMM, a new graph-based mobility model that simulates vehicles movements and behavior for urban environment. The road topology considered in V-MBMM is extracted from a real map. All roads are modeled as bidirectional roads with single lane in each direction. Roads are weighted with dynamics values representing their attraction degree during all day periods. Traffic at intersections is regulated by means of traffic lights.

Initially, vehicles are distributed on roads according to attraction weights values. A road with high weight and low density has more probability to receive a new vehicle than that with low weight and high density. Whenever a vehicle reaches an intersection, it chooses the next direction to take based on roads attraction weight, traffic density, and information on already visited roads. This is done by mean of three parameters assigned to each road: *attraction weight*, *freedom coefficient* and *progress coefficient*.

A. Attraction weight (w)

Vehicles move from one intersection to another following a Markov displacement process. A new Markov chain is defined at each intersection. The number of states of the chain is equal to the number of road segments that come together at the intersection (three for T-shaped intersection, four for 4-way intersection, etc.). The transition probability from state *i* to state *j* is function of roads attraction weights, it is defined by:

$$P_{ji} = w_j / \sum_{k=1}^{n} w_k \quad (1)$$

where, w_j is the attraction weight of road *j* and *n* the number of roads segments at the current intersection.

A transition matrix *T* is given by:

$$T = [p_{ji}]_{nxn} \quad (2)$$

To eliminate unrealistic scenarios like those mentioned for MBMM in Section 2, two coefficients, discussed below, are applied at each step to the displacement Markov chain.

B. Freedom coefficient (Fc)

This coefficient is defined in order to control the traffic density on roads. Applying this coefficient to Markov chain increases the probability that a vehicle selects, among all possible roads, the least congested one.

As long as a road has not reached its maximum capacity, depending on the number of vehicles on that road and road length, the freedom coefficient is set to 1. In case of congestion, the freedom coefficient is calculated by the following equation:

$$Fc_i = (nbVeh_i+1)/maxCap_i \quad (3)$$

$nbVeh_i$ is the number of vehicle on road *i* and $maxCap_i$ its maximum capacity.

C. Progress coefficient (Pf)

Progress coefficient has the same role as the correction mask used in MBMM. It can correct trajectories by inhibiting abnormal displacements. However, as MBMM is a grid based model and V-MBMM a graph based model, the displacement rules applied in V-MBMM are slightly different.

The objective of progress coefficients is to define repulsion points in the trajectory in order to force vehicles to move forward on roads. This prevents incorrect movements such as: return to the previous road after motion, traversing a roundabout repeatedly, etc.

Unlike attraction weights and freedom coefficients which are common to all vehicles, progress coefficients are specific to each vehicle. At each intersection, the progress coefficient values of the current and the *N* last visited roads are determined. To prohibit return to a previous position, the value of zero is assigned to the last traversed road. The values assigned to the rest of roads (*N*-1 last visited) are determined so as to reduce the probability of return back into the trajectory. This is achieved by decreasing the attraction weight of these roads.

D. Speed regulation

In V-MBMM, the vehicle velocity is calculated according to those of the nearby vehicles and traffic control mechanisms used at intersections. A vehicle decelerates when approaching the vehicle in front or a red light at intersections. In the last case, the vehicle decelerates until it stops. In other situations, the vehicle accelerates up to the possible maximum speed. To model this behavior the *Intelligent Driver Model* (IDM) [11] is employed. IDM falls into the car following models category and thus characterizes

(a) The real map

(b) The extracted road topology

Figure 3. Subarea of the simulation area representing Belfort downtown.

the behavior of each driver according to its preceding vehicles. The acceleration of a given driver is described by the following equation:

$$dv/dt = a[1- (v/v_0)^4 - (s^*/s)^2] \quad (4)$$

$$s^* = s_0 + vT + v\Delta v/(2\sqrt{ab}) \quad (5)$$

where, v denotes the vehicle velocity, v_0 the desired velocity, s the distance from preceding vehicle, and $s*$ the so called "desired dynamical distance". This parameter is calculated according to equation (5). It depends on the minimum bumper-to-bumper distance s_0, the desired safety time headway T, the velocity difference to the preceding vehicle Δv and the maximum acceleration and deceleration values a and b.

Finally, V-MBMM is based on the combination of some features issued from MBMM, a grid based model for individual, and others from IDM, an intelligent driver model.

IV. V-MBMM VALIDATION

This section presents the simulation environment and simulation results. Several tests were performed in order to illustrate the realism of V-MBMM to model the vehicular traffic in urban case.

A. *Simulation environment*

V-MBMM was tested under the application called *Territoire Mobile*. This application, written in C++, represents the city of Belfort in the north-eastern France. The area is 40km*20km. Several data have been used to reproduce the real environment including GIS shapefiles representing the map of the city, survey data and socio-economical information collected by professionals for regional planning needs. The area is divided into square cells of equal size. Each cell is characterized by two major information: *(i) Terrain type*: static information representing the dominant structure presents in the cell (roads, buildings, houses, company locations, etc.), *(ii) Attraction weight*: dynamic information that varies every quarter hour of the day. Attraction weights are computed according to cells terrain type and all other survey data.

To test the proposed mobility model, we at first extracted the road topology from the map and computed the attraction weight of all roads. The weight value of each road is calculated by averaging those of its cells. Figure 3 shows a subarea of the map corresponding to Belfort downtown.

B. *Results*

The first tests were performed by considering the whole territory. The used IDM parameter values are represented in Table 1. All simulations run for a period of 3600 seconds and measurements are recorded after the first 900 seconds to exclude the initiation phase. In each scenario we vary the number of vehicles from 250 to 4000 and calculate the average speed and vehicles distribution versus attraction weight.

TABLE I. IDM PARAMETER VALUES

Desired velocity v_0	15m/s
Maximum acceleration a	0.6m/s^2
Maximum deceleration b	0.9m/s^2
Bumper-to-bumper distance s_0	1m
Safety time headway T	1s
Vehicle length	4m

Results presented in Figure 4 show that the average speed remains almost constant until a density of 1000 vehicles. The reason is that the considered area is very large and thus no congestion situation occurs. The deceleration mainly happens when vehicles approach red lights at intersections. Above 1000 vehicles, congestion appears gradually causing average speed reduction.

Vehicles distribution according to attraction weights is obtained by calculating the number of vehicles crossing each road during the whole simulation. The purpose being to demonstrate that vehicles density is more important in attractive zones. Figure 5 shows the percentage of vehicles versus attraction weight values. We can observe that for all considered traffic densities, from 100 up to 4000 vehicles, more than 60% of vehicles pass by roads having attraction rate value greater than 0.6 against 3% for less attractive roads (attraction rate smaller than 0.2).

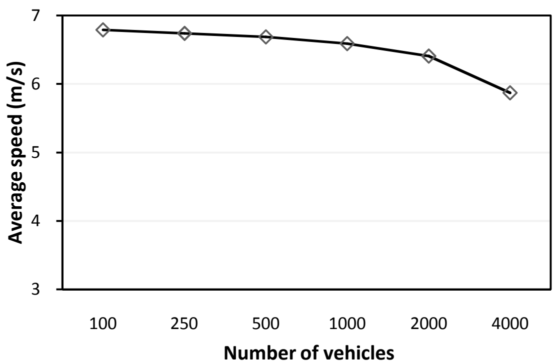


Figure 4. Average speed vs. Number of vehicles.

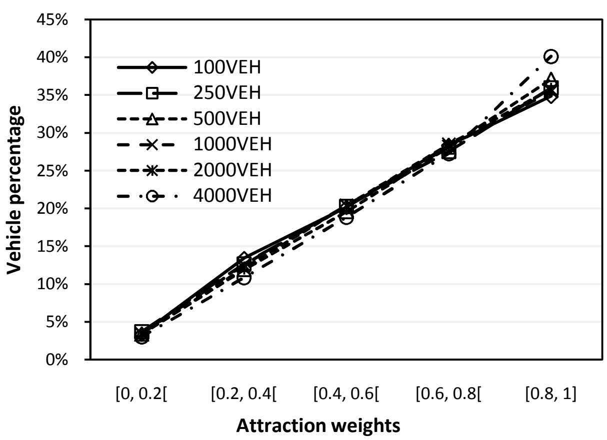


Figure 5. Vehicle density vs. Attraction weights.

To study the impact of the density on the average speed, we achieved some tests scenario in two subareas of 2500m*2500m from the global map. We vary the number of vehicles from 100 to 4000. The first one (SubA1) is Belfort downtown presented in Figure 3 and the second subarea (SubA2) is chosen so that there are fewer intersections in the area. Both curves depicted in Figure 6 show the reduction of the average speed when vehicular density grows as in Figure 4. The results also show that at small densities, the average speed obtained in subarea 1 is smaller than in subarea 2. This is due to the number of intersections, so the possibility that a vehicle stops at a red light, in subarea 1 is higher. And logically, when the density of vehicles grows, the results of the two subareas become close. The reason is that with a high number of vehicles, the probability that a driver encounters a slower vehicle increases. Even if the vehicle does not pass through a red light, it is likely to meet a slower vehicle forcing it to reduce its own speed.

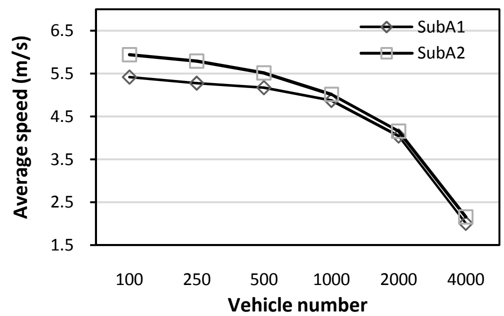
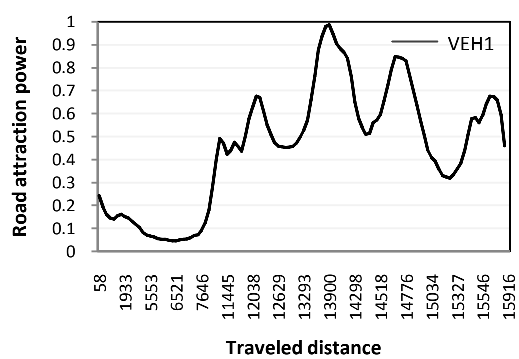


Figure 6. Average speed vs. Number of vehicles.

We performed a latter series of tests in order to analyze the individual behavior of each vehicle and verify if it corresponds to scenarios encountered in real life. Indeed, in real life drivers displacements are not completely random but tend to move from one attractive area to another crossing less attractive regions. To confirm this, we kept track of the attraction powers of the roads traversed by three vehicles: one vehicle starting from low attractive area, one vehicle starting from high attractive area and one vehicle starting from median attractive area. We plot the results in Figure 7. As we can see, the curves have an oscillatory shape indicating that vehicles move from one attractive pole to another (peaks on the curves) across less attractive areas. We can also observe, as in Figure 5, that vehicles are more attracted by high attractive areas; almost 60% of the roads followed by each vehicle have an attraction power above 0.5.



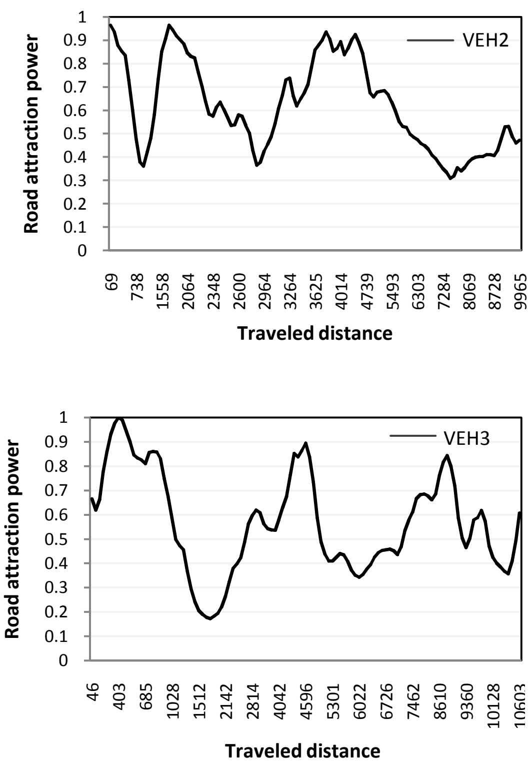


Figure 7. Attraction powers of the roads followed by three vehicles.

The results obtained from the three series of tests show an expected behavior of our model and suggest that it may be used for urban vehicles simulation.

V. CONCLUSION

In this paper we have presented a new mobility model for VANET which is an adaptation of MBMM to vehicles case. Each road in the topology is characterized by an attraction power which represents its degree of interest for drivers. In combination, IDM is used to model vehicles movement on roads. At intersections, the selection of the displacement direction is done according to a Markov chain which takes into account attraction powers. To eliminate incorrect movements, two corrective coefficients determined according to traffic density and the previous movements are applied to the Markov chain. The simulation results concerning the average speed and vehicles distribution according to attraction powers showed that the model reflects with a good degree of realism the vehicular traffic behavior in urban environment.

Some detailed features such as multilane roads are not considered in V-MBMM. Our main goal is to define a non-complex model that reflects vehicles movement with a sufficient degree of realism by taking into account terrain characteristics. Considering the environmental information is the major advantage of the proposed model. This opens several perspectives for future works, particularly the study of radio propagation in VANET. Thus, our next objective is to use V-MBMM and study the radio connectivity between vehicles moving in an urban environment taking into consideration the impact of obstacles such as buildings and trees and the impact of wave guides such as roads on radio signal propagation.

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