Smooth is Better than Sharp: A Random Mobility Model for Simulation of Wireless Networks

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ABSTRACT

This paper presents an enhanced random mobility model for simulation–based studies of wireless networks. Our approach makes the movement trace of individual mobile stations more realistic than common approaches for random movement.

After giving a survey of mobility models found in the literature, we give a detailed mathematical formulation of our model and outline its advantages. The movement concept is based on random processes for speed and direction control in which the new values are correlated to previous ones. Upon a speed change event, a new target speed is chosen, and an acceleration is set to achieve this target speed. The principles for a direction change are similar. Moreover, we propose two extensions for modeling typical movement patterns of vehicles. Finally, we consider strategies for the nodes' border behavior (i.e., what happens when nodes move out of the simulation area) and point out a pitfall that occurs when using a bounded simulation area.

Keywords

Wireless and mobile communication networks, modeling and simulation, mobility modeling, user movement, random direction model, random waypoint model, border effects.

1. INTRODUCTION AND MOTIVATION

The movement pattern of users plays an important role in performance analysis of mobile and wireless networks. In cellular networks, for example, a user's mobility behavior directly affects the signaling traffic needed for handover and location management (location updates and paging) [9].

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The extra signaling messages over the air interface consume radio resources and increase the associated database query load. In addition, mobility has major effect on the channel holding time in circuit–switched services (see e.g. [19, 14, 35, 11]). The latter has in turn huge influence on the call blocking and dropping probability (see e.g. [30, 23]).

The modeling of a user's movement is thus an essential building block in analytical and simulation–based studies of these systems. Mobility models are needed in the design of strategies for location updating and paging, radio resource management (e.g., dynamic channel allocation schemes), and technical network planing and design (e.g., cell and location area layout, network dimensioning). The choice of the mobility model has a significant effect on the obtained results. If the model is unrealistic, invalid conclusions may be drawn.

With the increasing number of subscribers and the decreasing cell size in future cellular systems, the mobility pattern of users will even more influence the performance of the network. Smaller cells result in an increased mobility–related signaling load and more database queries. Models that proved to be a good choice in simulation of macro–cellular environments show some drawbacks when being applied in micro– and pico–cellular environments [23, 39].

Mobility modeling also plays an important role in analysis of algorithms and protocols in wireless local area networks (WLANs) and self–organizing wireless ad hoc networks. Whereas in cellular networks there exists a number of approaches that model the macroscopic movement behavior of users (e.g., random walk from cell to cell, description of the cell residence time), in these cases we need a "microscopic" model.

This paper presents such a model. It can be used in simulations of mobile and wireless networks in which the individual movement behavior of users should be reflected. We employ a combination of principles for direction and speed control that make the movement of users (e.g., pedestrians and cars) more smooth and realistic than in previously known random models. Nevertheless, the model description and implementation are still very simple. We denote this model by *Smooth Random Mobility Model.*

The remainder of this paper is organized as follows: In Section 2 we make an approach to classify mobility models used by researchers in the wireless networking and mobile computing community. We describe some commonly used models and their application and derive a "concept map" for mobility models. In the following, we present our en-

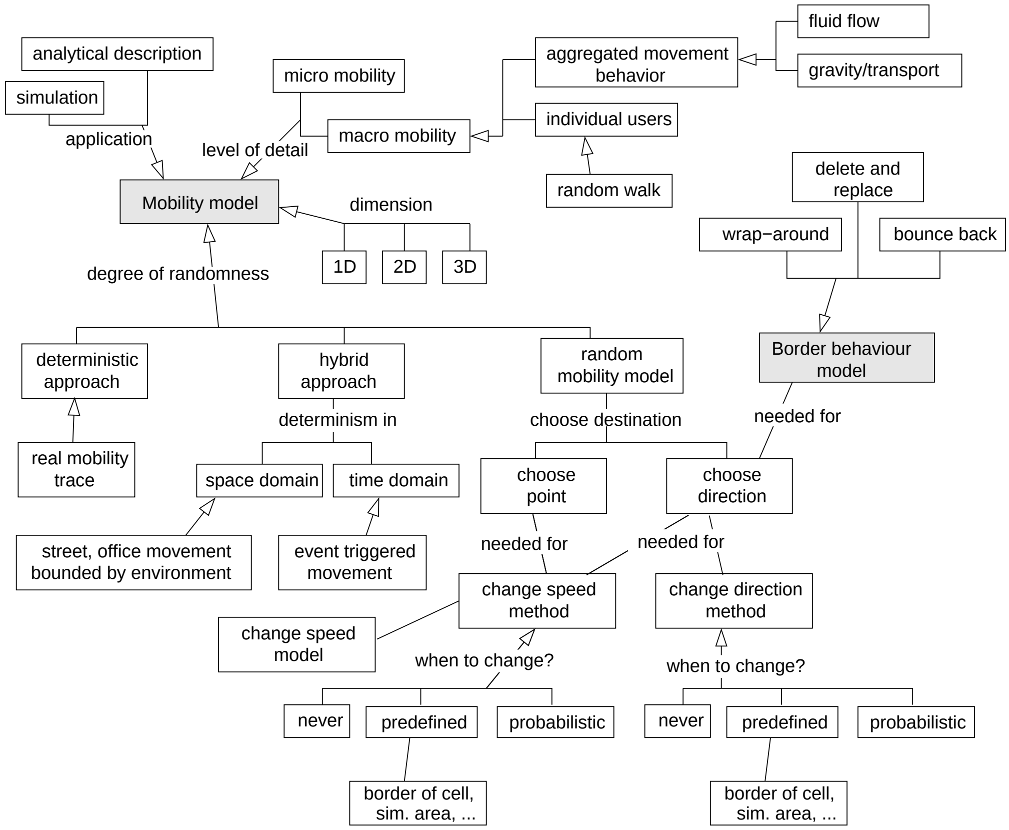

Figure 1: Concept map of mobility models used in simulation and analysis of wireless communication systems

hanced model and outline its advantages. Section 3 gives a mathematical formulation of the movement principles. We describe in detail how to model the speed and direction behavior of mobile stations. Furthermore, we propose two extensions, which model typical movement patterns of vehicles. Section 4 describes different approaches for border behavior, i.e., what to do if nodes move out of the system plane. In particular, we consider the impact of the border behavior on the spatial user distribution in a limited simulation plane. Here, we point out a pitfall: Using the wrong border behavior can lead to incorrect simulation results. Finally, Section 5 sums up the main features of our model and concludes this paper.

2. MOBILITY MODELS

There exists a variety of mobility models that find application in different kinds of simulations and analytical studies of wireless systems. Fig. 1 shows a concept map illustrating some criteria which can be used for categorization.

Analytical mobility models are in general based on rather simple assumptions regarding the movement behavior of users, but they allow to calculate mathematical expressions with respect to system performance. Several authors derive the distribution of a user's cell residence time [19, 45, 44, 33]. For example, Zonoozi and Dassanayake [44] show that the cell residence time with their model can be described by a generalized gamma distribution. Combining these "mobility metrics" with traffic models allows to estimate important system performance parameters, such as channel holding time and handover and location update events [19, 14, 34, 44].

Let us briefly describe the mobility assumptions used by these authors. Hong and Rappaport [19] assume that mobile users are uniformly distributed over a cell. Each user chooses a direction φ (taken from a uniform distribution $[0 \dots 2\pi[$) and a speed v (uniformly distributed on the interval $[0 \dots v_{max}]$). Once these values are chosen, they remain constant until the user crosses the boundary of the cell. Guérin [14] uses a more general model, in which direction changes are also possible within a cell. The model in [44] allows direction changes only to a certain extent ($\pm\Delta\varphi_{max}$).

Lin, Fang, and Chlamtac [31, 12] assume a generally distributed location area residence time as given. From this, they derive the probability distribution of the number of location area crossings for a given distribution of the interservice time (i.e., the time between the beginning of two served (unblocked) calls).

Another analytical model is the Brownian mobility model. It models the movement of users based on Brownian motion, such that we can calculate the probability distribution of the physical location of a user at a given time t, provided that we know his or her location at a previous time $t_0 < t$. Lei and Rose use such a model in one dimension [29] and in two dimensions [28].

Models used for simulation–based studies describe the movement of users in a more detailed manner. On the other hand, in general, they do not allow to derive analytical expressions.

For example, the European Telecommunications Standards Institute (ETSI) defined a set of test scenarios for system simulation of UMTS (Universal Mobile Telecommunication System). The document [10] describes mobility models for three environments: an indoor office, an outdoor pedestrian, and a vehicular environment. The model for the outdoor pedestrian environment uses a Manhattan–like street structure (rectangular grid). Pedestrians walk along streets in a straight line and can change their direction at intersections with a given probability. Also speed changes are possible after given intervals. The model for the vehicular environment is a random mobility model without a street structure. Cars move with constant speed ($v = 120$ km/h) and can change their direction every 20 m (with a probability of 20%). Only direction changes of up to $\pm 45°$ are possible.

Jugl and Boche [4] extend ETSI's model to get more realistic results. They analyze mobility–related parameters of their model, such as the cell residence time and the cell boundary crossing rate, in comparison to ETSI's model. Furthermore, in [23], Jugl investigates the influence of the users' mobility behavior on the characteristics of handover traffic, blocking probability, signaling traffic, and the capacity in CDMA systems.

Let us now consider the different levels of detail in mobility modeling. Researchers in vehicular traffic theory distinguish between three levels of description: microscopic, mesoscopic (kinetic), and macroscopic. A microscopic model describes the movement of a single vehicle by its space and speed coordinates at a given time t. Such approaches include very detailed "car following" models [13]. At the mesoscopic level, the homogenized movement behavior of several vehicles is reflected. For example, a distribution function is derived that describes the number of vehicles with a certain location (x, y) or speed v at time t. When modeling on a macroscopic scale, one is interested e.g. in the density, mean speed and speed variance, and traffic flow of vehicles.

An example for a macroscopic movement model used in analysis of wireless systems is the fluid flow model [43]. This family of analytical models describes the mobility in terms of "the mean number of users crossing the boundary of a given area."

A second approach used for modeling the macroscopic movement behavior is the family of gravity models [27]. They are also derived from transportation theory. Such models give an aggregated description of the movement of several users (as the fluid model); they range from city scale to international scale. The authors in [32] describe such a model. They use the concept of trips, area and time zones, population groups, and so on. The paper [41] also falls into this category. It models the daily movement of users using an activity–based travel demand model.

Another frequently used approach in cellular networks is the family of random walk models, also denoted as Markovian mobility models. They describe the movement of individual users from cell to cell. Not the exact location of a user is of interest but just the cell in which he/she resides. The model is basically defined by a state–transition diagram in which a cell is represented by a state and the movements by transition probabilities between the states. A user either stays within his/her cell or moves to one of its neighboring cells with a certain probability. A typical random walk model in one dimension is described in [3]. Two dimensional random walk models are used e.g. in [1, 6, 40]. Recent enhancements include a random walk model presented by Akyildiz and Lin *et al.* [2]. From these models we can also derive analytical measures for the crossing rates of cell and location area boundaries and alike [42].

In the remainder of this paper we focus on micro–mobility models. There exists a variety of generalizations of the model by Guérin [14] that are used in simulation–based studies of wireless systems. Basically this class can be described as follows: Users can move freely anywhere in the system area. The values for the user's direction φ are taken from a uniform distribution on the interval $[0 \ldots 2\pi[$, i.e. users do not have any preferred direction. The speed values v follow, for example, a uniform distribution or a normal distribution [16]. After a randomly chosen time, taken from an exponential distribution, the user chooses a new direction. The same procedure is performed for speed changes. The stochastic processes for direction and speed change are in general not correlated to each other [16]. A node is therefore completely described by its current space vector $(x(t), y(t))$, its current speed $v(t)$, and its current direction $\varphi(t)$; where $0 \le x \le x_{max}$ and $0 \le y \le y_{max}$, $0 \le v(t) \le v_{max}$, and $0 \le \varphi < 2\pi$. We denote this model as random direction model.

In [15, 36], Haas and Perlman use a simplified version of the random direction model. All users have always constant speed v_0 and move with an initial direction φ_0 chosen from a uniform distribution. Only when a user reaches the border of the simulation plane it changes its direction. In fact, it "bounces" back with $-\varphi_0$ or $(\pi - \varphi_0)$, respectively. This model has also been used by other authors, e.g., in [17]. In [20], Hong and Gerla present an interesting group mobility model that is based on the random direction model.

Another random mobility model is the so–called random waypoint model. It is used by several authors in the ad hoc networking community (e.g., in [5, 37, 38, 7, 8, 21, 18]). It models the movement of a user as follows: A user randomly chooses a destination point in the system area, moves with constant speed v (chosen between $]v_{min}, v_{max}]$, uniformly distributed) on a straight line to this point, and then pauses for a certain time before it again chooses a new destination. This model is very similar to a generalized random direction model. The difference is that not the direction φ is chosen but the destination point. A node is described by its current space vector $(x(t), y(t))$, its current speed $v(t)$, and its current destination point $(x_d(t), y_d(t))$.

Let us now consider the degree of randomness of different approaches. Basically we can distinguish between three cases: (1) models that allow users to move anywhere in the system plane following a pseudo–random process for speed and direction; (2) models that bound the movement of users by streets, buildings, and so on, but use a pseudo–random process for speed and direction choice at crossings; and (3) models that bound the movement of users to a predefined path.

We already gave many examples for first case, e.g., the random waypoint and the random direction model. ETSI's inhouse and pedestrian outdoor models with a simple Manhattan–like street structure is an example for the second type. Such models are also described in detail in [32].

A deterministic approach for simulations would be to allow users to move only on a predefined mobility path (type 3). Such a path can describe typical movement patterns of pedestrians and vehicles. We can distinguish two cases. In the first case, the direction and speed are both given, and no random process is incorporated at all. In the second case, the direction trace is given but the speed is chosen randomly. Note that such traces can exist in different levels of detail (cells, areas, etc.). Lam, Cox, and Widom [27] describe a family of macroscopic mobility models based on traces. Nevertheless, since tracing the actual mobility behavior of users is a very complicated task and usually such information is hard to obtain from network providers, researchers often use random models.

Last but not least, wireless researchers also invented models for three–dimensional movement. The authors of [24, 25, 26] model user movements in buildings, including vertical movements in staircases and elevators.

3. AN ENHANCED RANDOM MOBILITY MODEL

In the last section we have seen a variety of existing approaches that are used to model the mobility of users in wireless networks. This section presents our enhanced mobility model, which we denote as *Smooth Random Mobility model*. With respect to Fig. 1, it can be classified as follows: It is a random mobility model for movement in two dimensions on a microscopic scale. A new destination is chosen by direction φ. The speed and direction change are both probabilistic. The movement of nodes is not bounded by physical structures (such as streets, buildings, etc.) but nodes are allowed to move anywhere in the simulation plane. Furthermore, there is no correlation between different nodes, i.e., effects like "node following" or "group movement" are not modeled.

We use two stochastic processes: one process determines at what time a mobile station changes its speed, and the other process determines when the direction will be changed.

Basically speaking, we enhance the random direction model with some new features, which make the simulated movement of nodes (cars and pedestrians) more realistic.

It has already been criticized by Hong and Gerla in [20] that many researchers use a mobility model where the new choice for speed v and direction φ is not correlated to previous values (such as in the random waypoint model). This may cause unrealistic movement behavior with sudden speed changes ($\frac{\partial}{\partial t}v(t) \to \infty$) and sharp turnings (large $\frac{\partial}{\partial t}\varphi(t)$ while v is high). Our model includes both autocorrelation features. The speed is changed incrementally by the current acceleration of the mobile user, and also the direction change is smooth: Once a station is intended to turn, the direction is (in general) changed in several time steps until the new target direction is achieved. This creates a smooth curve rather than a sharp turning. Sections 3.1 and 3.2 give a mathematical formulation of these principles.

Last but not least, we model two typical movement patterns of vehicles when they are turning (Section 3.3).

Our model can be used in both discrete–time and continuous–time simulations. In both cases, we denote the simulation time by t (in s), where $t \geq 0$. In a discrete–time simulation, we quantize the simulation time into equidistant time steps. The time between two time steps is denoted as Δt, and usually set to be 1 s. The term $t/\Delta t$ then represents the time step number.

In the following description, we use the general term "node" to denote any kind of network–enabled device. This can be e.g. a pedestrian with his or her mobile terminal or a user or device inside a vehicle. Furthermore, we use the term "node class" to denote a particular type of node (in a particular scenario) with its resulting characteristic movement parameters (e.g., pedestrian, car in downtown, and bicycle).

3.1 Speed control

Our concept for modeling the speed behavior of nodes is based on the use of target speeds (the speed a node intends to achieve) and linear acceleration. A node goes with constant speed v until a new target speed is decided by a random process. The node then accelerates (or decelerates) until this desired speed is achieved (or again a new target speed is chosen in the meantime).

The speed behavior of a node at time t can therefore be described by three parameters:

- its current speed $v(t)$ in m/s,
- its current acceleration $a(t)$ in m/s^2, and
- its current target speed $v^*(t)$.

In addition, we define three static speed parameters that characterize a certain node class: Each node class has

- a maximum speed v_{max},
- a set of preferred speeds $\{v_{pref0}, v_{pref1}, \ldots\}$, and
- maximum values for acceleration/deceleration.

The maximum speed v_{max} reflects the maximum possible speed of a node class or the maximum allowed speed in the given scenario, e.g. $v_{max} = 50$ km/h for cars in downtown. We must have $0 \leq v(t) \leq v_{max}$ at any time t. The set of preferred velocities $\{v_{pref0}, v_{pref1}, \ldots\}$ models the fact that the speed distribution of vehicles and pedestrians over time is not uniformly distributed on $[0, v_{max}]$, but both user classes tend to move with certain "travel speeds" most of the time. For example, a car in downtown intends to move with the maximum allowed speed v_{max} and also frequently stops at crossings and traffic lights or due to jams ($v = 0$). The maximum values for acceleration and deceleration reflect the physical speed–up and slow–down capabilities of a node class. For example, a sports car can change its speed much faster than a truck.

In a simulation, we proceed as follows: At the beginning, all nodes are created with an initial speed $v(t=0)$, which is chosen from a certain speed distribution $p(v)$. We use a distribution in which the preferred speed values have a high probability, and a uniform distribution is assumed on the entire interval $[0, v_{max}]$. For example, if we have three preferred velocities $v_{pref0} = 0$, $v_{pref1} = \frac{3}{5}v_{max}$, and $v_{pref2} = v_{max}$, we use a distribution

$$p(v) = \begin{cases} p(v=0)\,\delta(v) & v = 0 \\ p(v = \frac{3v_{max}}{5})\,\delta(v - \frac{3v_{max}}{5}) & v = \frac{3v_{max}}{5} \\ p(v = v_{max})\,\delta(v - v_{max}) & v = v_{max} \\ \frac{1-p(v_{pref})}{v_{max}} & 0 < v < v_{max} \\ 0 & \text{else} \end{cases} \quad (1)$$

with $p\,(v_{pref}) = p(v_{pref0}) + p(v_{pref1}) + p(v_{pref2}) < 1$.

In the following, we describe the speed change over time. As mentioned above, a node goes with constant speed v until a speed change event occurs. Upon this event, a new target speed v^* is chosen from (1). We model the frequency of speed change events according to a Poisson process: In a discrete–time simulation with normalized time $t/\Delta t$, a speed change event occurs with a certain probability p_{v^*} each time step, where $p_{v^*} \ll 1$. Using continuous time t, we can choose the time between two speed change events from an exponential distribution [22] with $\lambda = p_{v^*}/\Delta t$:

$$p(t) = \frac{p_{v^*}}{\Delta t} \cdot e^{-p_{v^*} t/\Delta t}. \tag{2}$$

The value for p_{v^*} determines the time between two speed change events. The mean time between two events is $\mu_{v^*} = \frac{\Delta t}{p_{v^*}} = \frac{1}{p_{v^*}}$ s. For example, we set $p_{v^*} = 0.04$ to obtain $\mu_{v^*} = 25\,\text{s}$.

Let t^* denote the time at which a speed change event occurs and a new target speed $v^* = v^*(t^*)$ is chosen. Now, an acceleration $a(t^*) \neq 0$ must be set. It is taken from

$$p(a) = \begin{cases} \frac{1}{a_{max}} & \text{for } 0 < a \le a_{max} \\ 0 & \text{else} \end{cases} \tag{3}$$

if $v^*(t^*) > v(t^*)$, or from

$$p(a) = \begin{cases} \frac{1}{a_{min}} & \text{for } a_{min} \le a < 0 \\ 0 & \text{else} \end{cases} \tag{4}$$

if $v^*(t^*) < v(t^*)$. Clearly, a is set to 0 if $v^*(t^*) = v(t^*)$. The term a_{max} is the maximum possible acceleration, and a_{min} is the maximum possible deceleration of this node class. For cars we may use $a_{max} = 2.5$ m/s^2 and $a_{min} = -4$ m/s^2 (see Table 1). These values could depend on v_{max} of the node class, in a way that nodes with high v_{max} can speed up and slow down in a shorter time than slow nodes.

	Car downtown
v_{max}	13.9 m/s
v_{pref}	0, 13.9 m/s
a	$-4 \ldots 2.5$ m/s^2
μ_{v^*}	25 s
$p_{v_{pref}}$	$p(v = 0) = 0.3$
	$p(v = v_{max}) = 0.3$

Table 1: Example parameters for speed control

In the following time steps, the speed continuously increases or decreases. Each step, a new speed $v(t)$ is calculated according to

$$v(t) = v(t - \Delta t) + a(t)\Delta t \tag{5}$$

until $v(t)$ achieves $v^*(t)$. The time it takes a node to achieve the new target direction is $\Delta t_{speed/slow} = \frac{v^*(t^*) - v(t^*)}{a(t^*)}$ if no new speed change event occurs between $t = \left[t^*, t^* + \Delta t_{speed/slow}\right]$. After this procedure, we set $a = 0$ and the node moves again with constant speed $v(t) = v^*(t^*)$ until the next speed change event occurs.

Fig. 2 shows a simulation trace of a node's speed behavior. It was generated with the parameters listed in Table 1. The figure illustrates that the current speed value $v(t)$ is correlated to the previous speed value $v(t - \Delta t)$, which makes the speed change smooth.

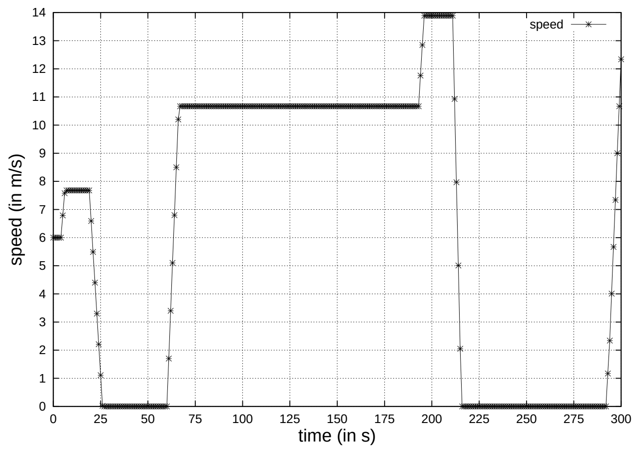

Figure 2: Speed behavior $v(t)$ of car in downtown

3.2 Direction control

The principle for direction control is similar to the speed control principle. Each node has an initial direction $\varphi(t = 0)$ which is chosen from a uniform distribution

$$p(\varphi) = \frac{1}{2\pi}; \quad 0 \le \varphi < 2\pi. \tag{6}$$

A stochastic process decides when to change direction. A node moves in a straight line until a direction change event occurs. This happens with a probability $p_{\varphi^*} \ll 1$ each time step. With continuous time, the time between two direction changes follows an exponential distribution with a mean time between two direction changes of $\mu_{\varphi^*} = \frac{\Delta t}{p_{\varphi^*}} = \frac{1}{p_{\varphi^*}}$ s.

Once a node is intended to change its direction, a new target direction φ^* is chosen from (6). The direction difference between the new target direction chosen at time t^*, $\varphi^*(t^*)$, and the old direction $\varphi(t^*)$ is $|\Delta\varphi(t^*)| = |\varphi^*(t^*) - \varphi(t^*)|$. We set

$$\Delta\varphi(t^*) = \begin{cases} \varphi^*(t^*) - \varphi(t^*) + 2\pi \\ \quad \text{for } -2\pi < \varphi^*(t^*) - \varphi(t^*) \le -\pi \\ \varphi^*(t^*) - \varphi(t^*) \\ \quad \text{for } -\pi < \varphi^*(t^*) - \varphi(t^*) \le \pi \\ \varphi^*(t^*) - \varphi(t^*) - 2\pi \\ \quad \text{for } \pi < \varphi^*(t^*) - \varphi(t^*) \le 2\pi \end{cases}$$

and get the correct sign for the direction change (left or right turn). Note that $\Delta\varphi(t^*)$ is uniformly distributed between $-\pi$ and π. Next, $\Delta\varphi(t^*)$ is divided into several incremental direction changes $\Delta\varphi(t)$. In each time step during a curve, a node should turn an angle of $\Delta\varphi(t)$. To do so, we set a "curve time" Δt_c, which can be taken, e.g., from a uniform distribution on the interval [2 s, 10 s]. We set the incremental direction change to

$$\frac{\Delta\varphi(t)}{\Delta t} = \frac{\Delta\varphi(t^*)}{\Delta t_c}.$$

During the curve, we have

$$\varphi(t) = \varphi(t - \Delta t) + \Delta\varphi(t) \tag{7}$$

until $\varphi(t)$ reaches the new target direction $\varphi^*(t^*)$ or until a

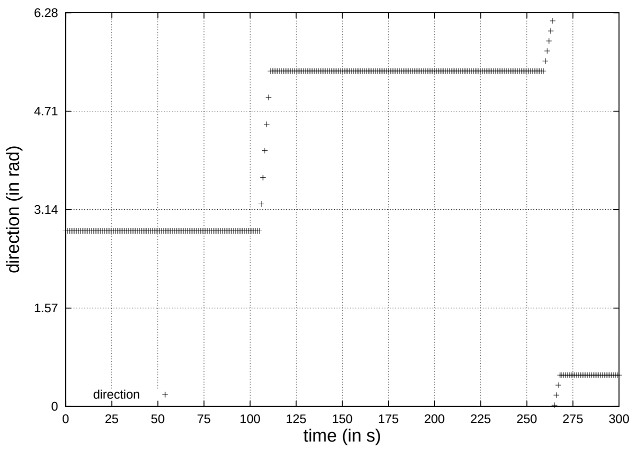

Figure 3: Direction behavior $\varphi(t)$ of a car in downtown

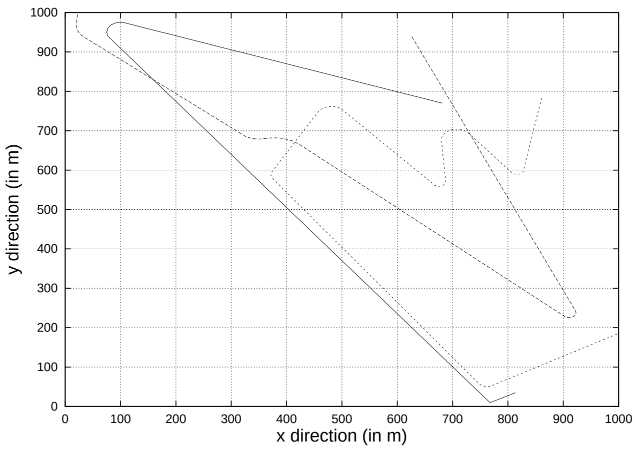

Figure 4: Three mobility traces

new direction change event occurs in the meanwhile. After the curve, $\Delta\varphi(t)$ is again set to zero.

Note that the value for Δt_c and the node's speed during the curve $v(t)$, $t^* < t < t^* + \Delta t_c$, determine the curve radius. If a node goes with constant speed $v(t^*)$ through the curve (i.e., $v(t) = v(t^*)$ for $t^* < t < t^* + \Delta t_c$), the curve has a radius of $r_c = \frac{v(t^*)\Delta t_c}{|\Delta\varphi(t^*)|}$. With our principle, nodes with low speed go curves with a smaller radius, and nodes with higher speed have a larger r_c.

To summarize, we can say that the direction behavior of a node at time t is described by three values:

- its current direction $\varphi(t)$,
- its current direction change $\Delta\varphi(t)/\Delta t$ in s^{-1}, and
- its current target direction $\varphi^*(t)$.

Fig. 3 shows a simulation trace of a node's direction behavior, generated with the parameters in Table 2. Fig. 4 shows the top view on the simulation plane with the x–y–movement trace of three nodes. It is an exercise for the reader to find our which curve represents the movement described by the speed behavior of Fig. 2 and the direction behavior of Fig. 3.

	Car downtown
$\mu_{\varphi_{new}}$	50 s
Δt_c	$1 \ldots 10$ s^2

Table 2: Example parameters for direction control

3.3 Correlation between direction change and speed change

The random processes for speed change and direction change, as described above, are running completely independent from each other. This fact makes the implementation simple but is in general not true in reality. In this section, we propose two additional (optional) principles that model typical movement patterns of cars and bicycles in downtown. Both movement patterns correlate the direction change with the speed change.

3.3.1 "Stop–turn–and–go" behavior

Using the concept of preferred speeds, we can easily model "stop–and–go" behavior. We set $v_{pref0} = 0$ and assign a rather high probability $p_{v_{pref0}}$ to this value. A speed change event will therefore frequently result in a target speed $v^* = 0$ (stop event).

In reality, a stop of a car or bicycle is often followed by a direction change (e.g., at crossings with traffic lights). We include this behavior in our mobility model: Whenever a node comes to a stop ($v(t) = 0$), we choose a target direction φ^*. Here, we do not use a uniformly distributed direction change as in Section 3.2, but choose $\Delta\varphi$ from

$$p(\Delta\varphi) = \begin{cases} \frac{p_{\varphi^*}}{2} & \text{for } \Delta\varphi = \pm\frac{\pi}{2} \\ 1 - p_{\varphi^*} & \text{for } \Delta\varphi = 0 \\ 0 & \text{else} \end{cases} .$$

The term p_{φ^*} is the probability that the node will turn. Its value must be higher than that in the usual direction control with $v \neq 0$ (Section 3.2). Moreover, the curve radius r_c should be smaller, since curves at crossings are usually sharper. When the node chooses a new target speed $v^* \neq 0$ it will move around this curve.

3.3.2 Slowdown of turning nodes

We also propose to model the slowdown of vehicles before they are turning. This is reasonable for modeling cars and bicycles because of physical laws (vehicles can drive only up to a certain maximum speed around a curve with given radius) and because of human driving behavior. It is not our intension here to model a correct quantitative behavior, but we would like to enhance our model with the principle that nodes typically slow down when a curve is ahead.

In a simulation, we proceed as follows (see Fig. 5): At time t^* a node decides that it will change its direction. A new target direction φ^* and a curve time Δt_c are chosen as described in Section 3.2.

From the curve radius r_c we derive a maximum value for the curve speed $v_{c,max}$, which should be a fraction of the theoretically maximum possible speed, given by $v_c = \sqrt{\mu_s g r_c}$, where $g = 9.81$ m/s^2 and μ_s is the coefficient of static friction (e.g. $\mu_s = 0.4 \ldots 0.7$ for cars). If $v(t^*) > v_{c,max}$, we force the acceleration of the node to a negative value, i.e., $a(t^*)$ is taken from (4). The direction change is rescheduled to $t^{**} = t^* + \Delta t_{slow}$, with $\Delta t_{slow} = \frac{v(t^*) - v_{c,max}}{a(t^*)}$. If no other direction change or speed change event occurs in the slow down period $]t^*, t^{**}]$ it is guaranteed that the node will have a speed $v(t^{**}) = v_{c,max}$ when it enters the curve. We set $a(t^{**}) = 0$ such that the node will drive with constant speed $v(t) = v_c$ and constant direction change $\Delta\varphi(t)$ around the curve if no other direction change or speed change event occurs.

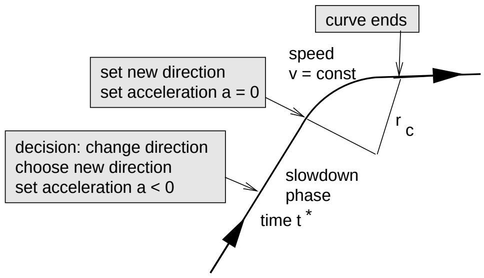

Figure 5: Modeling the slowdown of vehicles before turning

4. USER DISTRIBUTION AND BORDER BEHAVIOR

In simulations with a random direction model, nodes are allowed to leave the simulation area (see Fig. 4). Whenever a node is subject to leave, we need a "border rule" that defines what to do with this node. Such a rule is also required for our model. The following basic principles can be found in the literature: The node subject to leave can be (a) bounced back to the system area according to a certain rule, (b) "deleted" and a new node is initialized according to the node initialization distribution, or (c) wrapped around to the other side of the simulation plane.

All methods guarantee that the number of nodes in the system area remains constant, which is often required in simulations. In the first case, a new angle (and possibly a new speed) must be chosen, e.g. as explained in Section 2 (Haas and Perlman). In the second case, we delete the leaving node and place a new node on a randomly chosen point in the system area. In the last case, a leaving node enters the system area on the opposite side, while keeping its current speed and direction parameters. This approach models the system area as a torus. In the cases (a) and (c) we may optionally assign a different identifier, address, etc. to the node. This might be of interest if the algorithm subject to evaluation is based on the these values (e.g., in leader election algorithms).

These models seem to be quite easy to use. However, we must be careful about the effect of the border behavior on the resulting spatial node distribution. Let us give an example: At the beginning of a simulation, we place a given number of nodes on the system area using a uniform distribution in both dimensions (Most studies that use a random mobility model do so.). We use border behavior (b), i.e., we "delete" each node that leaves the system area and generate a new node. Where should we place the new node on the system area? What is the resulting user distribution in the steady state of the simulation? Using again a uniform distribution for random placement of leaving nodes, results in a higher node density in the middle of the area and a lower density at the area edges. Fig. 6 shows a histogram obtained through simulation on a 1000×1000 m^2 area using a basic random direction model. We divided the entire area into 20×20 subareas and counted the number of nodes in this subarea every time step. The sum of all subareas is 100%. In the middle of the area more than 0.4% of the nodes reside, whereas there are less than 0.1 at the borders.

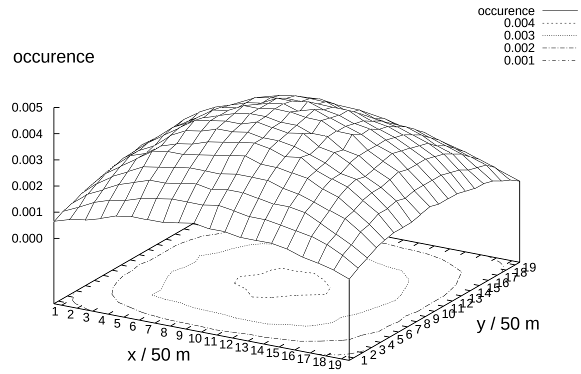

Figure 6: Histogram: Spatial node distribution

A similar effect occurs is we use the random waypoint model (Section 2) on a limited two–dimensional area. This is done in many evaluations of ad hoc networking protocols (see e.g. [38, 7, 18]). The described effect also occurs here because the random waypoint model does not use an angle φ for direction control but chooses a destination point in the system area. Nodes in the middle of the area have a uniformly distributed angle, but nodes at the border are more likely to move back to the middle. The resulting spatial node distribution is not uniformly distributed but looks like in Fig. 6.

When evaluating algorithms or protocols is such a scenario, this effect may lead to invalid results and wrong conclusions. For example, if we analyze dynamic channel allocation algorithms in a cellular environment, we will (in the mean) always need more channels in the middle of the simulation plane, since here the user density is the highest. Furthermore, the inhomogeneous user distribution makes the generation of "hot spots" at the beginning of the simulation useless. We can overcome these problems by using a torus–like system area (wrap–around border behavior).

5. CONCLUSIONS

Based on a classification of mobility models used in wireless network research, we presented an enhanced random mobility model, which belongs to the class of random direction models.

We use two stochastic principles for direction and speed control in which the new values for speed and direction are correlated to previous values. This feature makes the movement of nodes more smooth than simple approaches to random movement, and this is the reason why we denote our model as Smooth Random Mobility model. While the movement behavior of nodes becomes more realistic, the implementation and computation effort is still low.

Our concept for speed control is based on so–called target speeds. A speed change event occurs according to a Poisson process. Upon this event, a new target speed is chosen from a general speed distribution. By defining a set of preferred speeds, we are able to model typical speed patterns such as long stop or long travel periods as well as "stop and go behavior." The time between two direction changes is modeled in a similar way.

Furthermore, we proposed two extensions that model typical mobility patterns of vehicles in which speed and direction change are not independent from each other. Whereas in the first extension a speed change event (a stop event) triggers a direction change event, in the second extension, a direction change event triggers a speed change (slowdown) event.

We see a particular application area of our model in simulations of ad hoc networks and micro–cellular environments, in which the movement of individual mobile stations is of interest and is not bounded by the scenario. In wireless ad hoc research, the enhanced model can be applied to investigate the performance of routing protocols, power management, clustering algorithms, and alike.

Our principles can easily be employed in existing simulation tools, and they can also be applied to other advanced mobility models, e.g., to the group mobility model presented in [20]. In fact, our model represents a compromise between simple models, such a basic random waypoint model, and very realistic mobility models, such as models from transportation research or movement traces. The latter are usually very complicated to implement and/or need a huge database (in particular for long simulations).

Last but not least, we discussed the impact of the border behavior on the spacial node distribution and pointed out a pitfall: Applying a random direction model or a random waypoint model on a limited simulation plane can create a non–uniform node distribution. This might lead to unwanted effects in studies of networking algorithms (e.g. in evaluation of radio resource allocation algorithms).

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