Two Novel Modifications to Semi-Markov Smooth Mobility Models

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Abstract—Mobile ad-hoc Network (MANET) plays a crucial role in modern wireless communication. In order to support realistic and accurate protocol simulations, a proper mobility model is desired. In this report we have shown several notable models proposed in the past few years; analysis of the pros and cons of these models are provided. We carefully have analyzed the SMS (Semi-Markov Smooth) mobility model and give out two modifications to this model: (a) Preference to Low Density Areas, and (b) Restricted Weighted Gauss-Markov Mobility Model, which may find a broad set of applications in campus mobile ad-hoc network design.

Index Terms—Mobility Study, SMS model, Markov Chain Process, Restricted Weighted Gauss-Markov Mobility Model

1 Introduction

Mobility models need to meet two goals: (1) they need to be broad enough to accomodate a large variety of examples, and (2) simulation of the models can be practically mastered. A series of Models, based on ideal or practical situations, have been developed by researchers such as Babak Pazand [4] and Jean-Yves Le Boudec [1] in recent years. We first take a brief look at these classical models.

1.1 Classic Models

1.1.1 Random Walk[4]

The random walk mobility model is the simplest mobility model, generating completely random movement patterns. It was designed for simulations in which the movement patterns of mobile nodes are completely unpredictable. In this model a mobile node is initially placed in a random location in the simulation area, and then moved in a randomly chosen direction between $[0, 2\pi]$ at a random speed between $[V_{min}, V_{max}]$. The movement proceeds for a specific amount of time or distance, and the process is repeated a predetermined number of times. Figure 1 shows the result of a single node executing the random walk mobility model with a constant travel time. Two variations of the random walk mobility model were proposed by Nain et al to address the problem experienced when mobile nodes reach the boundary of their simulation area. In the random walk with wrapping approach, when a mobile node reaches an edge, it wraps to the opposite edge and continues its movement with the same direction and speed. Figure 2 demonstrates this process. In a further approach, random walk with reflection, when a mobile node reaches any edge of the simulation area, the node changes its angle of movement to $\alpha + \pi/2$ and its velocity remains constant (Figure 3). The approach employing reflection clearly generates more accurate movement patterns, simply because real life mobile nodes are more likely to reflect their movement when reaching an obstacle.

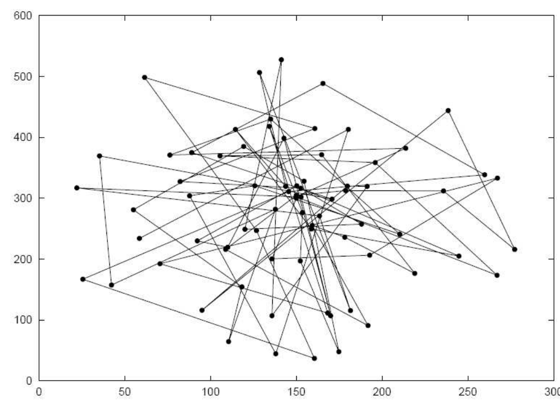

Fig. 1. The random walk mobility model employing constant time

This model simulates the movement unrealistically, and doesn't do so well in sharp and sudden turns, and is also hard to observe the wrapping in reality.

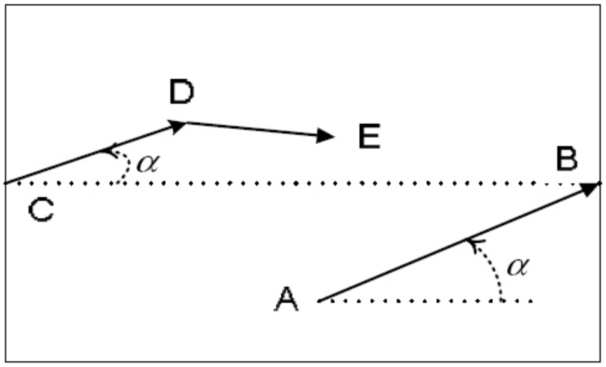

Fig. 2. Wrapping approach in the random walk mobility model

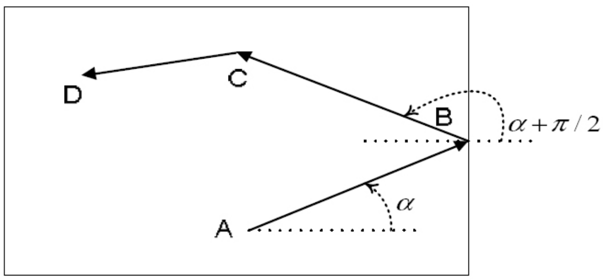

Fig. 3. Reflection approach in Random Walk mobility model

1.1.2 Random Waypoint[4]

The random waypoint mobility model introduces specific pause times between movements, and was first proposed by Broch et al. The random waypoint model is the most popular mobility model employed in contemporary research, and can be considered a foundation for building other mobility models. In this model, each node starts its movement from an initial point in the simulation area by selecting a random destination, the waypoint, and a random speed from a predefined range of $[V_{min}, V_{max}]$. Once the mobile node reaches its waypoint, it pauses for a specific amount of time, after which the above process repeats. The movement pattern of a mobile node employing this mobility model is illustrated in Figure 4. Although there is widespread use of the random waypoint model, some major drawbacks affecting simulation results have been reported. This model lacks of the regular movement models, and introduces sudden stops, and it shows speed decay and density wave problems. Even worse, it is unable to reach a steady state and has memory-less movement behaviors.

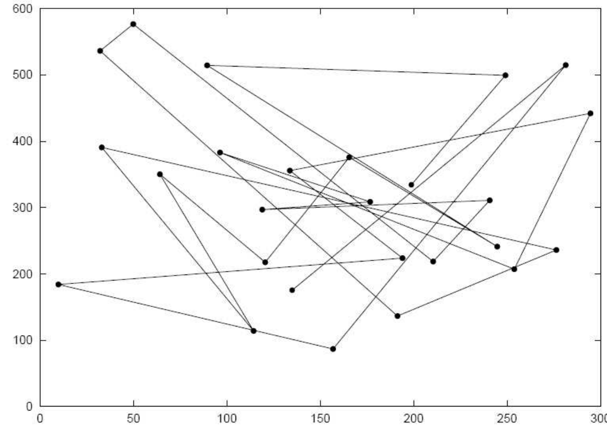

Fig. 4. Movement pattern by using the random waypoint mobility model

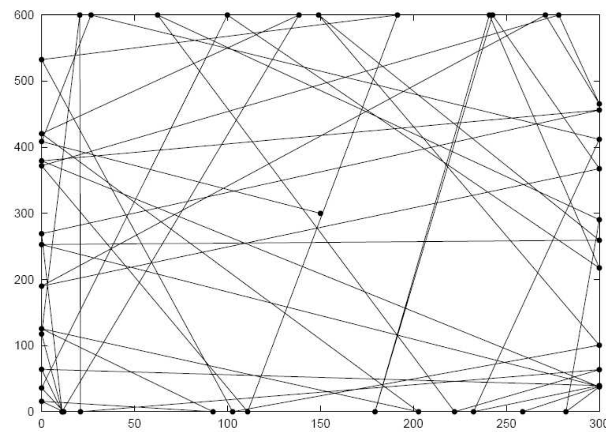

Fig. 5. Movement pattern by using the random direction mobility model

1.1.3 Random Direction[4]

In order to eliminate the density wave phenomenon the random direction mobility model has been developed by Royer et al. In the random direction model, each mobile node chooses a random direction between $[0, 2\pi]$ and starts its movement in that direction from the center, towards the boundary of the simulation area. When the node reaches the boundary, it pauses for a constant time and selects another movement direction between $[0, \pi]$. This procedure is repeated a predetermined number of times. Figure 5 shows the movement pattern of a mobile node employing the random direction model. The same as Random Walk, there is no realistic movement pattern in this model. Moreover, errors may be introduced into the routing protocols evaluation, because its average distances between

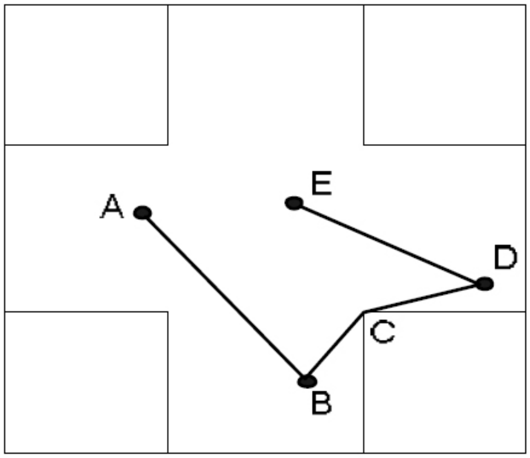

Fig. 6. The Swiss Flag mobility model

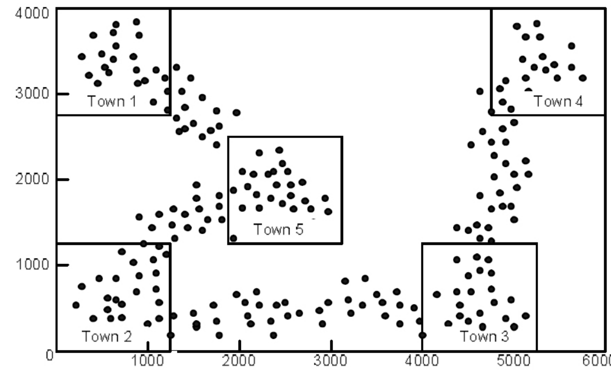

Fig. 7. Movement pattern the restricted random waypoint mobility model

mobile nodes are much higher than other models.

1.1.4 Swiss Flag[4]

Le Boudec has defined a novel modification to the basic random waypoint model, in order to obtain a uniform distribution of average speeds throughout a simulation and to overcome the drawback of speed decay inherent in the standard random waypoint model. In this model, the simulation area is considered as a combination of connected areas forming the shape of the Swiss flag. Each mobile node starts its movement from a random location and travels to a random destination through the shortest path between two points. Sometimes these routes consist of a breakpoint, resulting in an actual path with two segments. The node shown in Figure 6 commences its movement from A, travels to B, and pauses for a specific time. Location D is then chosen randomly, which results in the shortest path to it including two segments with one breakpoint. As the Random Waypoint, it also lacks the regular movement model. And the nodes are always concentrating in the center and corners.

1.1.5 Restricted Random Waypoint[4]

In a very large area network, it is unlikely that a mobile node moves between random points located far from each other. In reality, a mobile node more likely travels within small part of a network and, after some movements in a specific area, may choose a distant location. To model this movement behaviour, the restricted random waypoint mobility model was proposed by Blazevic et al. The main characteristic of this model is its coverage of a large geographic area. The model may be considered as representing a small number of towns directly connected by highways. Two types of mobile node are considered, ordinary nodes and commuter nodes. An ordinary node commences its movement by randomly selecting a town, and then moving within the town according to the random waypoint model. After a number of movements specified by a stay-in-town parameter, the node chooses a random destination in another town and travels there through a specific highway connecting the two towns. Commuter nodes perform the above process with their stay-in-town parameter equal to 1. Figure 7 shows an example of this model with 5 towns and 4 highways connecting towns 1 and 5, towns 5 and 2, towns 2 and 3, and towns 3 and 4. Long journey are need to all mobile nodes. And it is both lack of scalability and consideration of the constraints of the real movement.

Mathematically, this model can be express as follow. It was define that domain Λ is connected, but not necessarily convex. And there are L subdomains $\Lambda_l \subset \Lambda, l = 1, 2, \ldots, L$. (In the original model)[**?**][12], $\Lambda_l$is a square. This model executes a number of trips with endpoint in some other subdomain l_n and goes there along the shortest path. l_n is chosen by the transition matrix $Q(l, l_{n-1})$. And there is a pause between the trips.

More precisely, phase is determined by $I_n = (l, l_{n-1}, r, \Phi)$, with which $l, l_{n-1} \in 1, 2, \ldots, L$ (Where l is the destination subdomain, andl_{n-1} is the origin one). $r \in N$(remaining number of trips in the same subdomain, including this one.) and $\Phi \in pause, move$(identify the state of mobile node). If $l \neq l_{n-1}$ then $r = 0$ else $r \geq 1$. If $\Phi = move$, then Φ is set to pause, a pause is executed at the current location, for a duration obtained by the current location's distribution, which is depend on the subdomain, and l, l_{n-1}, r are unchanged. Else Φ is set to $move$, and nd l, l_{n-1}, r are updated as follows. If$r \geq 1$, r is decremented by 1. If $r \geq 2$, l_{n-1} and l are unchanged. If $r = 1$ (means the previous trip was the last with endpoints in the current subdomain), l is set to a new destination subdomain chosen according to the transition matrix $Q(l, l_{n-1})$. Then if $r = 0$, l_{n-1} change to l and a new values of r is obtained by a probability distribution than relies on l. Then a new endpoint is selected uniformly in $\Lambda_{l'}$ and the trip is a shortest pathway from the current point to this endpoint.

1.1.6 Gauss-Markov [4]

Liang and Haas first proposed the Gauss-Markov mobility model and an implementation of this model has been presented by Camp et al. The main disadvantage of random mobility models is their sudden and sharp turns, which are unrepresentative of real user movements. To address this problem, a nodes speed and direction at time n should be a function of speed and direction at time n-1, which is:

$$V_n = f(V_{n-1})$$

and

$$D_n = f(D_{n-1})$$

This assumption is the fundamental basis of the Gauss-Markov model, which provides more realistic movement behaviors.

Here, α is a parameter and $0 \leq \alpha \leq 1$, used for changing the degree of randomness of the model. When α is closer to 0, the randomness will increase, resulting in sharper turns; when α is closer to 1, the model tends to a linear movement pattern. $V_{x_{n-1}}$ and $D_{x_{n-1}}$ are random variables chosen from a Gaussian distribution, with S and D the mean speed and direction of the movement, respectively. At each time interval, the next coordinate of the mobile node is calculated using the equations:

$$X_n = X_{n-1} + V_{n-1}\cos(D_{n-1})$$

$$Y_n = Y_{n-1} + V_{n-1}\sin(D_{n-1})$$

The movement pattern of a mobile node employing the Gauss-Markov mobility model with parameters α =0.75, $\overline{V} = 10$, $\overline{D}$ = 90, n=1 with 1000 movements, is illustrated in Figure 8.

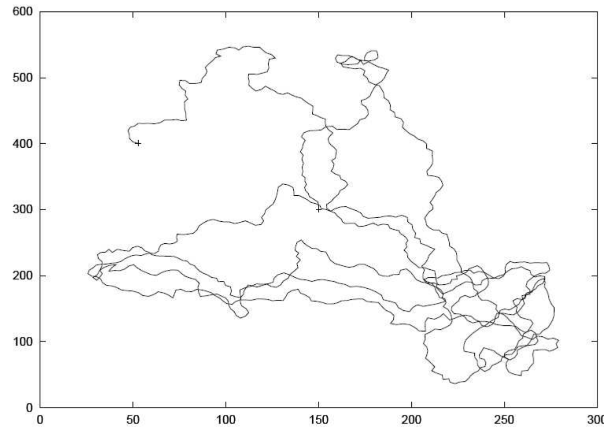

Fig. 8. Movement pattern of the Gauss-Markov mobility model

Though it avoids many problems that other models may incur, it still does not have enough consideration on obstacles and users' travel decisions.

1.1.7 Smooth Random[4]

Another mobility model, that addresses unrealistic movement patterns, is the smooth random mobility model, described by Bettstetter. As its name indicates, changes to the current direction and speed are smoothed, eliminating both sharp and sudden turns, as well as sudden stops. In this model, instead of employing a uniform distribution of speeds between $[0, V_{max}]$, a preferred set of speeds is defined and a high probability is assigned to each of them.

Employing a preferred set of speeds, each with high probabilities, corresponds to real world mobile nodes tending to travel at preferred speeds. Another feature of this model is the acceleration or deceleration parameter, resulting in changes from current to targeted speeds, occurring incrementally. If the current speed is less than the targeted speed, a random value is chosen from $[0, a_{max}]$, a to accelerate the node; otherwise, a random value is selected from$[a_{min}, 0]$. During the acceleration or deceleration, at each time interval the speed is calculated using

$$V(t) = V(t - \Delta t) + a(t)\Delta t$$

In order to have smooth and incremental turns, each mobile node changes its direction by $\Delta\phi(t)$ degrees at each time slot. $\Delta\phi(t)$ is the maximum allowable direction change. During a loop repeated for $\frac{\Delta\varphi(t^*)}{\Delta\phi(t)}$ time intervals, the mobile node changes

Simulation area	1000m*100m
Preferred set of speed	$\{0, 13.9m/s\}$
Acceleration, Deceleration	$[0,2.5]$, $[-4,0]$
Probabilities	$p(v=0)=0.3 \quad p(v=v_{\max})=0.3$

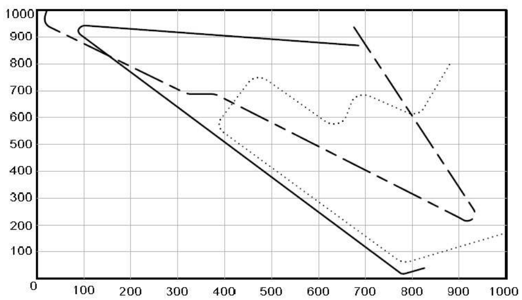

Fig. 9. The movement pattern of three nodes with Smooth Random

its current direction by $\Delta\phi(t)$ degrees until it reaches the targeted new direction.

Figure 9 illustrates the movement pattern of three mobile nodes based on the following values:

The changes to the current direction and speed are smoothed, eliminate the sharp and sudden turns and stops. It is somewhat similar to Gauss-Markov, and also lacks of consideration on obstacles, and does not focus on the regular elements of users' movement.

1.2 Limitation of Random Waypoint and other Random models

The Random Waypoint model and its variants are designed to mimic the movement of mobile nodes in a simplified way. Because of its simplicity of implementation and analysis, they are widely accepted. However, they may not adequately capture certain mobility characteristics of some realistic scenarios, including temporal dependency, spatial dependency and geographic restriction[5]:

1) **Temporal Dependency of Velocity:** In Random Waypoint and other random models, the velocity of mobile node is a memoryless random process, i.e., the velocity at current epoch is independent of the previous epoch. Thus, some extreme mobility behavior, such as sudden stop, sudden acceleration and sharp turn, may frequently occur in the trace generated by the Random Waypoint model. However, in many real life scenarios, the speed of vehicles and pedestrians will accelerate incrementally. In addition, the direction change is also smooth.
2) **Spatial Dependency of Velocity:** In Random Waypoint and other random models, the mobile node is considered as an entity that moves independently of other nodes. This kind of mobility model is classified as entity mobility model in Ref.[3]. However, in some scenarios including battlefield communication and museum touring, the movement pattern of a mobile node may be influenced by certain specific 'leader' node in its neighborhood. Hence, the mobility of various nodes is indeed correlated.
3) **Geographic Restrictions of Movement:** In Random Waypoint and other random models, the mobile nodes can move freely within simulation field without any restrictions. However, in many realistic cases, especially for the applications used in urban areas, the movement of a mobile node may be bounded by obstacles, buildings, streets or freeways.

Random Waypoint model and its variants fail to represent some mobility characteristics likely to exist in Mobile Ad Hoc networks. More importantly, mobility models need to mimic the movement that follow the physical law for more accurate analysis and simulations of realistic mobile networks. In the following sections, we shall discuss some of those models.

1.3 Semi-Markov Smooth Mobility Model

This idea of (SMS) Semi-Markov Smooth Mobility Model is proposed by Ming Zhao [2]. Given the fact that existing random mobility models have limitations such as speed decay and sharps turns, it is desirable to have a model that can more closely mimic the movements that abide by the physical law for accurate analysis and simulations.

In each SMS movement there are three consecutive phases: **Speed Up** phase, **Middle Smooth** phase and **Slow Down** phase. It is proved both theoretically and by simulations that the SMS model has no average speed decay problem and always maintain a uniform spatial distribution. Here below is a brief description of the three phases.

1.3.1 Speed Up Phase(α-Phase)

For every movement, an object needs to accelerate its speed before reaching a stable speed. During time interval $[t_0, t_\alpha] = [t_0, t_0 + \alpha\Delta t]$, an SMS node travels with α time steps. At initial time t_0, the node randomly selects a target speed $v \in [v_{min}, v_{max}]$, a

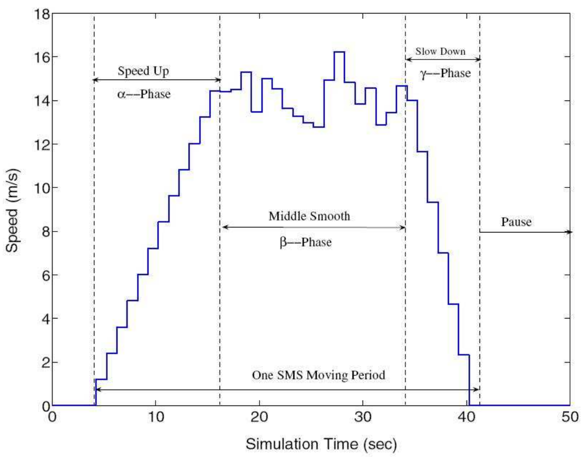

Fig. 10. An example of speed vs. time in one SMS movement[2]

target direction $\phi_\alpha \in [0, 2\pi]$, and the total number of time steps $\alpha \in [\alpha_{min}, \alpha_{max}]$. These three random variables are independently uniformly distributed. In reality, an object typically accelerates the speed along a straight line. Thus, the direction ϕ_α does not change during this phase. To avoid sudden speed change, the node will evenly accelerate its speed along direction ϕ_α from starting speed $v(t_0) = 0$, to the target speed v_α, which is the ending speed of α-phase, i.e., $v(t_\alpha) = v_\alpha$. An example of speed change in α-phase is shown in Fig. 14, where the node speed increases evenly step by step and reaches the stable speed v_α of the movement by the end of this speed up (α-phase).

1.3.2 Middle Smooth Phase(β-Phase)

In reality, after the speed acceleration, a moving object should have a smooth motion according to its stable velocity. Correspondingly, once the node transits into β-phase at time t_α, it randomly selects β time steps to determine the middle smooth (β-phase) duration interval: $(t_{\alpha,\beta}] = (t_\alpha, t_\alpha + \beta\Delta t]$. Where β is uniformly distributed over $[\beta_{min}, \beta_{max}]$. Within β-phase, the mobility pattern at each time step is similar to what is defined in Gauss Markov (GM) model [3]. In detail, the initial value of speed v_0 and direction ϕ_0 in β-phase are v_α and ϕ_α, respectively. Then, the following speed and direction of an SMS node at each time step fluctuate with respect to v_α and ϕ_α. Hence, we respectively substitute v_α for V and ϕ_α for ϕ, where V and ϕ denote the asymptotic mean value of speed and direction, represented in equation (4) in [8]. We assume that the memory level parameter $\zeta \in [0, 1]$, used for adjusting the temporal correlation of node velocity, is constant for both speed and direction at each time step. Hence, by adjusting the parameter ζ, we can easily control the degree of temporal correlation of velocity between two consecutive steps. The standard deviation σ_v and σ_ϕ are set as 1. This implies that the speed or direction difference between two consecutive time steps are less than 1 m/s or 1 rad within β-phase. Specifically, the speed and direction at the jth time step for an SMS node in β-phase are:

$$
\begin{aligned}
v_j &= \zeta v_{j-1} + (1-\zeta)v_\alpha + \sqrt{1-\zeta^2}\tilde{V}_{j-1} \\
&= \zeta^j v_0 + (1-\zeta^j)v_\alpha + \sqrt{1-\zeta^2}\sum_{m=0}^{j-1}\zeta^{j-m-1}\tilde{V}_m \\
&= v_\alpha + \sqrt{1-\zeta^2}\sum_{m=0}^{j-1}\zeta^{j-m-1}\tilde{V}_m
\end{aligned}
$$

and

$$
\begin{aligned}
\phi_j &= \zeta\phi_{j-1} + (1-\zeta)\phi_\alpha + \sqrt{1-\zeta^2}\tilde{\phi}_{j-1} \\
&= \phi_\alpha + \sqrt{1-\zeta^2}\sum_{m=0}^{j-1}\zeta^{j-m-1}\tilde{\phi}_m
\end{aligned}
$$

where $\tilde{V}_j$ and $\tilde{\phi}_j$ are two Gaussian random variables with zero mean and unit variance. As shown in Fig. 14, the node speed gently fluctuates around the target speed v_α within β-phase.

1.3.3 Slow Down Phase (γ-Phase)

In real-life, every moving object needs to reduce its speed to zero before a full stop. In order to avoid the sudden stop event happening in the SMS model, we consider that the SMS node experiences a slow down phase to end one movement. In detail, once the node transits into slow down (γ-phase), at time t_β, it randomly selects γ time steps and a direction $\phi_\gamma \in [0, 2\pi]$. Where γ is uniformly distributed over $[\gamma_{min}, \gamma_{max}]$. In γ-phase, the node evenly decelerates its speed from v_β, the ending speed of β-phase, to $v_\gamma = 0$ during γ time steps. Fig. 14 shows the exact case of speed change in γ-phase. Also in reality, a moving object typically decelerates the speed along a straight line before a full stop. Thus, the direction ϕ_γ does not change during the α-phase. Furthermore, in order to avoid the sharp turn event happening during the phase transition, ϕ_γ and ϕ_β are correlated. Specifically, ϕ_γ is obtained from the above formula, by substituting β for $j-1$.

At the phase ending time $t_\gamma = t_\beta + \gamma\Delta t$, the node fully stops and finishes the current movement which lasts over time interval $[t_0, t_\gamma]$.

1.3.4 Semi-Markov Process of SMS Model

We consider pause as another phase, then the stochastic process of SMS model is described as an iterative four-state transition process. Let I denote the set of phases in an SMS movement, then $I(t)$ denotes the phase of SMS process at time t, where $I = \{I_\alpha, I_\beta, I_\gamma, I_p\}$. Accordingly, $\{Z(t); t \geq 0\}$ denotes the process which makes transitions among phases in the stochastic modeling of SMS movements. Since the transition time between consecutive moving phases (states), i.e., phase duration time, has discrete uniform distribution, instead of an exponential distribution, $\{Z(t)\}$ is a semi-Markov process [9]. This is the very reason that this mobility model is called Semi-Markov Smooth model because it has an Semi-Markov process and it complies with the physical law with smooth movement. Let $\pi = (\pi_\alpha, \pi_\beta, \pi_\gamma, \pi_p)$ denote the time stationary distribution of SMS process. Then, the time stationary distribution for each phase of SMS model is:

$$\pi_m = \lim_{t\to\infty} Prob\{I(t) = I_m \in I\} = \frac{E\{T_m\}}{E\{T\} + E\{T_p\}}$$

where $E\{T_m\}$ is the expected duration time of m-phase in an SMS movement. $E\{T\}$ and $E\{T_p\}$ are the expected SMS movement period and pause period, respectively. Specifically, $E\{T\} = E\{\alpha\Delta t\} + E\{\beta\Delta t\} + E\{\gamma\Delta t\}$. Since Δt is a constant unit time, for the sake of simplicity, Δt is normalized to 1 second in most scenarios.

1.4 Weighted Waypoint Model

The major difference between Weighted Waypoint (WWP)[6] Model and other classical Random Models are (a)Mobile Node no longer randomly chooses its destination. Such model can be identified popular locations due to the survey of students. And we assume different weights to them. (b)*The weights of the destination location depends on not only the current location but also the current time.* Since students at dormitory are more likely to go to classroom at 8:00 a.m, however, they are likely to go to cafeteria at lunch time. (c)*The pause time distribution at each location is different.* You can easily understand that students stay in library for longer time than in cafeteria.

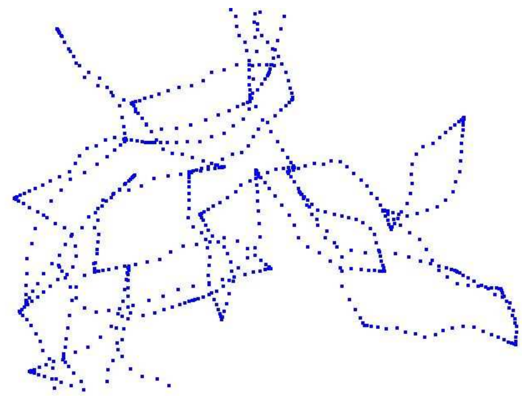

Fig. 11. An illustration of one node's moving trace in an SMS randow walk

1.5 Our Contributions

Ming Zhao [2] developed the corresponding NS2 code for simulation to his SMS mobility model. To test the result of his research we used the C++ programming language to develop a visual simulation of the SMS model. Also, the existing SMS model assumes that all mobile nodes move independently, i.e. their moving behaviors are irrelevant from other mobile nodes. We have proposed two strategies to modify the existing SMS model: (a) Preference to Low Density Areas and (b) Restricted Weighted Gauss-Markov Mobility Model. We believe that the two modifications to the SMS model can mimic real-life moving behaviors more precisely.

2 A C++ Program Simulating the SMS Model

In our C++ program Simulating the SMS model, we assume all the nodes walk in an area of size 1000×1000. For simplicity, we assume all the nodes initially start from α-phase, and when a node reaches the bound of the area, it "dies" (vanishes from the graph) and immediately "respawns" at a random point within the bound of the graph. This assumption will cause a relatively lower node density in near-boundary areas, which can be intuitively understood (because a node moving near the bound is very likely to "die" and "respawn"). Fig. 11 shows the moving trace of one node in the SMS model. As shown in Fig. 11. We can clearly see the process of acceleration and deceleration. We also notice that during the α and γ phase the node is moving along a straight line with constant acceleration or deceleration rate, while during the β phase the node slightly changes it moving angle and speed, which fits the established SMS model.

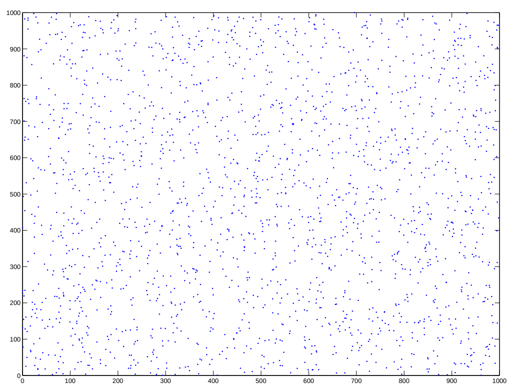

Fig. 12. SMS model of 2000 nodes, at time = 0

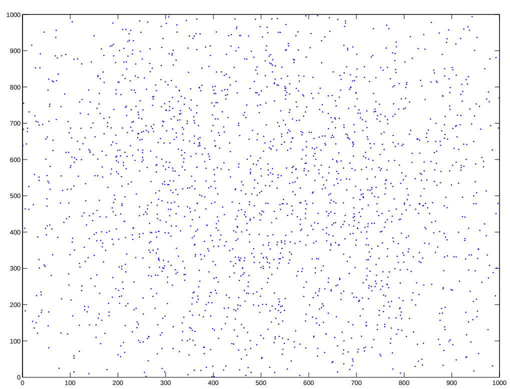

Fig. 13. SMS model of 2000 nodes, at time = 2000

Fig. 12 and 13 shows the location distribution of 2000 nodes in an SMS model, representing $t = 0$ and $t = 2000$ scenarios respectively. Note that nodes in Fig. 12 is more evenly distributed than nodes in Fig. 13. As we have pointed out earlier, the "die" and "respawn" mechanism leads to a little bit convergence of the node locations, yet the effect is minor.

Fig. 14 shows the average speed of the 2000 nodes in the process of simulation. We note that after a period of significant fluctuation, the average speed converges to a relatively steady value between 7 and 8, which fits the no-speed-decay characteristic of SMS mobility model. The reason behind the average speed fluctuation right after the simulation starts may be influenced by the fact that all the nodes start at α phase.

To find out the connection quality, we define a circle of diameter 200 to be a "communication circle". A mobile node located at the center point of a circle can communicate with all the mobile nodes

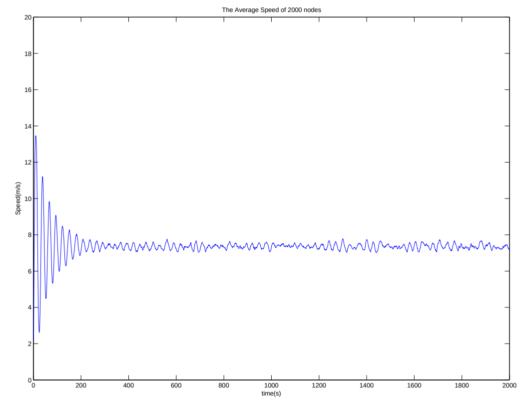

Fig. 14. SMS model: Y axis - the average speed of 2000 nodes, X axis - time

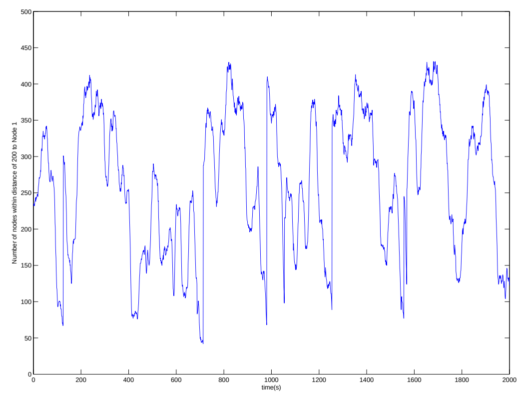

Fig. 15. SMS model: Y axis - the number of nodes that is within the distance of 200 to Node 1, X axis - time

within this circle. Suppose we observe one of the 2000 nodes and record the number of nodes that can communicate within this node. Fig. 15 illustrates the number of nodes that can communicate with this node. We note that there are sharp fluctuations over time. At the peak there are almost 450 nodes that can be communicated with, while at the lowest point the number falls to 50.

3 Two modifications to the SMS model

3.1 Preference to Low Density Areas

Since in real life the nodes are not likely to move independently: their moving behaviors are largely influenced by other mobile nodes. We can enhance the SMS model by letting nodes choose their moving directions according to some preset rule, which

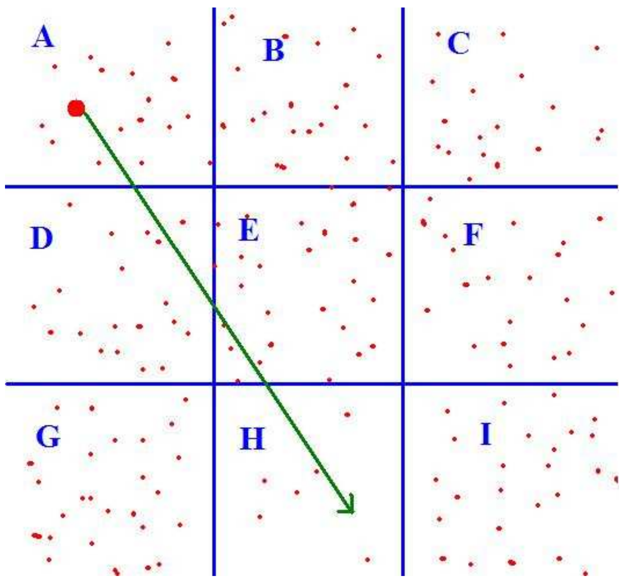

Fig. 16. Preference to Low Density Areas. Big red dot: the subject node, Small red dot: other nodes.

is relevant to other nodes' current state. Of course this will destroy the Semi-Markov property for the node's next state is no longer only determined by its current state. For consistency we still call it an SMS model, but with modifications.

The rule we set is as follows: first we cut the 1000×1000 square into 9 equal-sized subsquares with names A, B, ... and I. When a node finishes the pause state it examines all the 9 subsquares and finds out the square with the lowest node density, and we name this subsquare the "target square". Then the node will choose a point randomly in the "target square" and set it as its moving direction in the upcoming α-phase. The remaining process is the same with the previous SMS model. Note that although a point in the "target square" is selected as its moving direction, the node does not necessarily need to reach that point. In other words, the node will look for a new "target square" the instant it finishes a set of α, β, γ and pause phases.

An example of Preference to Low Density Areas is illustrated in 16. The big red dot represents the subject dot and the small red dots represents all other nodes. At the end of its pause phase, the subject node is in subsquare A and finds out that the subsquare with the lowest node density is H. Hence it selects a point in H randomly as its moving direction and starts a new round of α-phase.

3.2 Restricted Weighted Gauss-Markov Mobility Model

In the campus scenario, we observed moving bicycle riders, who speed up, keep at an almost constant speed, then slow down and pause for a certain period of time. Since the speed of riders is not so high, we assume that they could slow down suddenly at the time they got their destinations. Which means there are only 3 phase rather than 4 in the moving process for a bicycle rider on campus.

3.2.1 *Overall description*

In our model, we denote the moving of a mobile node as

$$I_n = (l_{n-1}, l_n, d, t_n, P_{n-1,n}, v_n, \alpha, \tau_n)$$

where,l_{n-1}, l_n represents the original and destination location in the subarea $\mathcal{A}_{l_{n-1}}$ and $\mathcal{A}_{l_n}$; d is the distance between l_{n-1} and l_n; t_n is the time slot in the day; $P_{n-1,n}$ means the probability that at the time t_n, l_{n-1} move to l_n; α is the acceleration chosen by the node; and τ_n is the pause time after reaching the destination.

3.2.2 *Choosing a destination*

In the school scenarios, we take 6 location areas[6], Dormitory (D), Classroom (Cl), Library (L), Cafeteria (Ca), Other place on campus (OP), and Off-campus (OC) into consideration. And we also assume that the destination can not be the same as the current location, which means $l_{n-1} \neq l_n$.

To simplify this problem, we divide time into 2 kinds of time slots, one is more likely to move, the other one is more likely to state at the current location, which means pause. Students tend to move during the break of classes, it is assumed that there are no other school activities at noon, which may increase the moving. The moving time can be represented by $t_m \in$$\{(7:30, 8:00)$,$(9:40, 10:00)$, $(11:40, 12:00)$,$(13:40, 14:00)$,$(15:40, 16:00)$, $(17:40, 18:00)$,$(18:15, 18:60)$,$(22:00, 22:30)\}$. And the pause time $t_p \in$$\{(8:00, 9:40)$,$(10:00, 11:40)$, $(12:00, 12:15)$,$(12:15, 13:40)$,$(14:00, 15:40)$, $(16:00, 17:40)$,$(18:00, 18:15)$,$(18:30, 22:00)$,$(22:30, 7:30)\}$.

The probability of mobile node choosing its targeted area $\mathcal{A}_{l_n}$ from its current area $\mathcal{A}_{l_{n-1}}$ varies from different time slots. At the first step, we assume that the probability from current area to targeted areas are the same, which is $\frac{1}{5}$. We use the Finite State Machine (FSM) model17 to identify this.

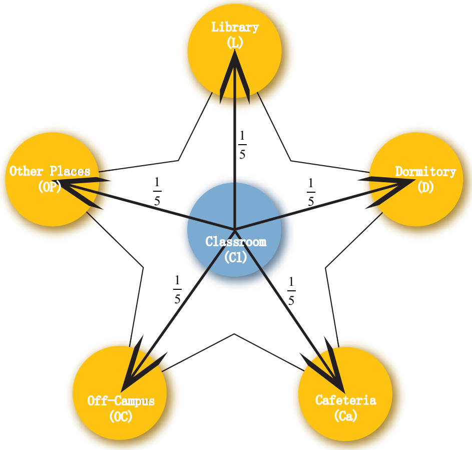

Fig. 17. FSM model of choosing a targeted area at given time

After choosing the targeted area, the destined location is chosen randomly in the targeted area. Therefore, the distance d that mobile node need to travel has been figured out by l_{n-1} and l_n.

3.2.3 Choosing an expected speed

After the destination has been determined, we make an assumption that the mobile node travel to its destination directly via the shortest way, the straight line to its destination.

Then, an expected speed is chosen before moving forward. At this case, the node speeds up to the expected speed v from 0 with the acceleration α.

It is possible that the mobile node does not reach its chosen speed v when it get to its destination. So, we assume that the distance between the source and destination is long enough, and the acceleration is low enough to guarantee the reachable of the chosen speed. v is uniformly selected in (v_{min}, v_{max}), in which, the v_{min} and v_{max} need to be further investigated in our later work.

3.2.4 Choosing an acceleration

How to make sure the mobile node can reach its expected speed before getting its destination? From the uniform linear motion in physics,

$$\begin{cases} d = \frac{1}{2}\alpha t^2 \\ v = \alpha t \end{cases}$$

we get

$$\alpha = \frac{v^2}{2d}$$

In order to guarantee reaching the expected speed before reaching the destination, the maximum acceleration $\alpha_{max} = \frac{v^2}{2d}$. So, the acceleration is chosen uniformly from 0 to $v^2/2d$.

3.2.5 Smooth phase

In reality, after speed up for a certain period of time, a moving node is likely to travel in a stable velocity, which is related to the expected speed. This phase is similar to Gauss-Markov model, and the SMS model mentioned above, but not the same.

In our work, we place restrictions in the direction of the moving node during the smooth phase. It moves without direction change. The current speed relies on previous speed v_{n-1}; constant mean value of speed $\overline{v}$, which is the expected speed here; and the $\widetilde{v}_{n-1}$, is random variable from a Gaussian distribution.[3][2]

$$v_n = \xi v_{n-1} + (1-\xi)\overline{v} + \sqrt{1-\xi^2}\widetilde{v}_{n-1}$$

ξ is the memory level parameter, used for adjusting the temporal correlation of node speed, where $\xi \in [0,1]$. By modifying the parameter ξ, we can easily control the degree of temporal correlation of speed between two consecutive time slots.

3.2.6 Choosing a pause time

Under the assumption we raised in advance, the mobile node stop at the time it reaches its destination, and pause for a chosen time τ_n.

In reality, the pause time τ_n is relative to the current area and the targeted area, and also relies on what time is it now. We first assume that the pause time is randomly chosen from $[0, \tau_{max}]$. In our future work, we'll find out how to choose the pause time better.

4 Future Work

A simulation and in-depth analysis for the Preference to Low Density Areas modification remains a task for our future work. On work of the weighted random waypoint modification, we'll gather some data from SJTU, and specify the probability of students' movement in the specified time slots, the minimum and maximum expected velocity, and the maximum pause time in the given time and location. Then, we can fully establish our SJTU mobility model.

We also want to simulate the Restricted Weighted Gauss-Markov Mobility Model to see the how to guarantee the communication quality under a limited transmission power, which maybe helpful in modifying the protocol.

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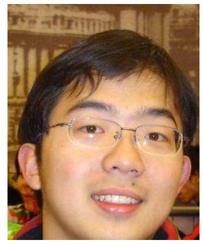
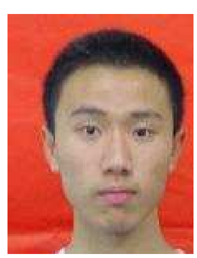


CUI Jianwei is a very kind guy.

LIN Shudong is a very funny guy.

XU Juefei is a very smart guy.



DU Chongwei is a very handsome guy.