Constructing Realistic Mobility Model: A New Framework

(Research Paper)

Track – Emerging Information Technologies, DSI 2004

Abstract

A good mobility model can help researchers to study the user mobility issues in many areas (wireless LAN context switching). In this paper, we propose a new framework for constructing a realistic mobility model incorporating decision and operation models. We use the revised social force model to simulate the realistic mobile users' movements and artificial neural networks (ANN) models to create a decision model within the proposed mobility framework.

Keywords: wireless and mobile technology, mobility modelling, artificial neural networks, simulation

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Introduction

Wireless and mobile networks are quickly becoming the networks of choice, because of large bandwidth and thanks to the flexibility and freedom they offer. With the increasing use of small portable computers, wireless networks, and satellites, a trend, known as mobile computing, to support computing on the move has emerged. Wireless and mobile networks are being used in diverse areas such as travel, education, stock trading, military, package delivery, disaster recovery, and medical emergency care. Wireless networking is specifically appropriate for situations wherein installation of physical media is not feasible and which require on-the-spot access to information. Since a user may not maintain a fixed position in such environments, the mobile and wireless networking support allowing mobile users to communicate with other users becomes crucial. A possible scenario may involve several different networks that can support or can be modified to support mobile users. When dealing with different wireless networks, a universal mobile device should be able to select the network that best meets user requirements.

Wireless and mobile networks have provided the flexibility required for an increasingly mobile workforce. A recent study (Ahmavaara et al., 2003) suggests that the deployment of wireless LAN techniques has been switching from private stub network (e.g., the home network) to public area networks (e.g., access points of public network). The wireless LAN is rapidly becoming a convenient access solution for all possible wireless devices such as PDA, laptop, and cellular phone. The worldwide number of wireless LAN based wireless subscribers increased from 170 million in 2001 to over 290 million in 2003 and it is expected to grow to 1.2 billion by 2007 (Forrester Research, 2004).

Due to the rapid growth in wireless communication, models of deployment and management of these wireless networks are in great demand. Mobile and wireless systems basically cover two areas – mobility and computing. In this research, we explore the mobility management, more specifically, mobility modeling. Precious studies in mobility management involve creating an assortment of mobility models to pinpoint the movement pattern of wireless and mobile users (i.e., Guerin, 1987; Haas and Pearlman 1998; Bettstetter, 2001; Royer et al. 2001; Camp et al., 2002; Jardosh et al., 2003). However, there is little research in mobility management, to the best of our knowledge, in terms of utilizing the data of wireless and mobile users' movement pattern to detect users' decision making process (i.e. avoiding congestion in the simulated area).

The purpose of this paper is to create a new framework for constructing a realistic mobility model which also incorporates decision making functionalities. Artificial neural networks (ANN) models are employed in creating a decision model within the proposed framework.

Contributions of this research are two-fold. First, we simulate the mobile user movement using a revised social force model of Helbing et al. (2000) and as such broaden the horizon of the mobility management research. Second, we seek to extend the prior research in mobility modelling by proposing a new comprehensive mobility framework incorporating decision and operation models.

The remainder of this paper is organized into five parts: literature review, research framework, user movement simulation, decision model, simulation experiment, and conclusion.

Literature Review

There exist a wide variety of mobility models that have been postulated from both analytical and simulation-based studies on mobile systems. Bettstetter (2001) presented a concise categorization for various mobility models. Camp et al. (2002) compared a variety of mobility models using survey and simulation-based techniques.

Guerin (1987) proposed a mobility model that laid the foundation for a number of mobility models in the later research. In his model, a user's moving path is partitioned into different segments. For each segment, a user selects its moving direction (in the range $[0...2p]$) and speed. Between two consecutive segments, a random pause time is also selected. Royer et al. (2001) modified the mobility model proposed by Guerin (1987). Instead of moving for some period of time, each node moves until it reaches the boundary of the simulation area. Haas and Pearlman (1998) and Pearlman et al. (2000) bring the reflection direction (q) into the mobility model. When a node reaches the simulation area boundary, it is reflected back into the simulation area in the direction of either ($-q$), if it is on a vertical edge, or ($p-q$), if it is on a horizontal edge. Based on Guerin's mobility model, Hong et al. (1999) proposed a group mobility model. They presented approaches that model the boundaries of the simulation area as a border that cannot be crossed. On the contrary, the boundless simulation area mobility model described by Haas and Pearlman (1997) removes this limitation by allowing nodes to wrap around to the other side of the simulation area when they encounter a border. The effect of this change is to create a simulation area modeled as a torus, rather than a rectangular surface.

Another popular type of mobility models is the random waypoint model (RWM) proposed by Broch et al. (1998) and has been extensively studied in (Royer et al. 2001; Bettstetter et al. 2002; Bettstetter and Wagner 2002; Resta and Santi 2002). In the RWM, each node selects a random point in the simulation area as its destination, and a speed v from an input range $[v_{\min}, v_{\max}]$. The node then moves to its destination at its chosen speed. When the node reaches its destination, it rests for some pause time. At the end of this pause time, it selects a new destination and speed and resumes movement.

The recent work proposed by Jardosh et al. (2003) introduced the obstacle concept in the simulation environment. In their model, a ground plan of building is constructed first, and then pathways interconnecting and leading into and out of buildings using a Voronoi path computation (Dijkstra, 1959) are computed.

Helbing et al. (2000) proposed the social force model to simulate the human beings movement under stress. This model classifies a set of force sources that can affect human being's behaviors. As a result, it is more viable to use this model to mimic the mobile user movement. The force sources for each mobile user can be classified as: the constant force to the destination, the mutual forces among mobile users (to prevent collision), and the mutual forces among human beings and boundaries (to avoid hitting walls).

In this paper, we modify the social force model proposed by Helbing et al. (2000) and use the revised model to simulate the mobile user movement in the real world. The key improvement of the proposed model over precious mobility models is that the mobile users in our model are able to explore paths to the desirable destinations based on the revised social environment (i.e., avoiding congestion in the simulated area).

Drawing upon the data (inputs) from simulation and profile models, decision model (applying artificial neural networks) make suggestions (outputs) to the operation model for a mobile user to take actions in the mobile system. Decision model also gathers the user mobility information from the operation model and updates the user profile database. In this research, artificial neural networks (ANN) models are used to create the decision model.

ANN model is a parallel distribution processor made up of processing units, which have a natural propensity for storing experiential knowledge and making that knowledge available for use (Tam & Kiang, 1992). Major benefits of ANN include nonlinearity and adaptivity which traditional model-fitting techniques (i.e., regression) do not possess. First, ANNs are capable of detecting and extracting nonlinear relationships and interactions among predictor variables. Second, ANN's inferred patterns and associated estimates of precision do not depend on any assumptions relating to a distribution of the variables. The design of an ANN is motivated by an analogy with the brain, which is a living proof that fault tolerant parallel processing is not only physically possible but also fast and powerful.

In essence, the decision model can be viewed as a typical classification problem with discrete outputs (i.e., exits or destinations). Applications of ANN to classification have been extensively studied in the past few years. Various kinds of neural-network architecture including multilayer perceptron (MLP) neural network, radial basis function (RBF) neural network, self-organizing map (SOM) neural network, and probabilistic neural network (PNN) have been proposed. Because of ease of training and a sound statistical foundation in Bayesian estimation theory, PNN has become an effective tool for solving many classification problems in the areas of pattern recognition, nonlinear mapping, and business analysis. Musavi et al. (1994) used the Monte Carlo simulation method to investigate the generalization ability of back propagation (BP), radial basis function (RBF) and probabilistic neural network (PNN) classifiers. Their findings suggest that PNN classifier is most efficient than those of back propagation (BP) and radial basis function (RBF) architectures. Using data from the US oil and gas industry, Yang et al. (1999) compared PNN and BP methods in bankruptcy prediction. The results show that PPN with pattern normalization and Fisher discriminant analysis achieve the better estimations than BP approach. Etheridge et al. (2000) compared the performance of three ANN approaches – BP, categorical learning, and PNN. When the overall error is considered, the PNN is the most reliable in classification, followed by backpropagation and categorical leaning network. Most recently, Lin et al. (2004) presented the fault detection and alarm processing in loop system with fault detection system (FDS). FDS consists of adaptive architecture with probabilistic neural network (PNN). In this research PPN is used as the de facto ANN model to create the decision model.

Research Framework

A mobility simulation system not only consists of the mobility simulation itself, but also includes modules that compute strategies to improve the system's performance, survivability, etc. In order to simulate the realistic user (human being) movement, we need to construct the user movement profile instead of using random model to determine users' behaviors. The realistic user movement is simulated by using the social force model (Helbing et al. 2000). A centralized decision model collects the simulation results. The decision model along with the operation model is the interface between the real mobile system (Wireless LAN access points, authentication servers, etc.) and the simulation model.

Figure 1 shows the proposed system framework. There are four major models in the mobility framework including profile model, simulation model, decision model, and operation model.

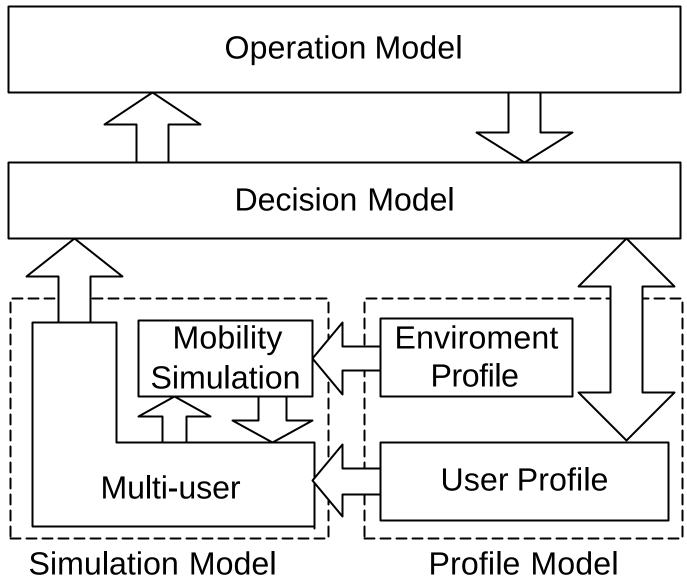

Figure: Mobility Framework

Profile Model

The profile model contains user profile and environment profile. The user profile is a database that contains a set of user-movement profiles. For each user, a profile specifies his desired moving speed, interests (stops at which interesting point), and final destination (leaves the system or stays in the system). A user profile also defines the short-term destinations (interesting points) and the long-term destinations (the exit points). The environment profile is a database that contains a set of environmental settings. A graphical map on a two-dimensional Cartesian coordinates constructs each environment profile. The map is a ground plan of a building that is composed of walls, a set of entrances/exits, a set of interesting points, and a set of obstacles.

Simulation Model

The simulation model contains mobility simulation and multi-user sub-models. It takes the inputs from the profile model and generates the simulation reports for the decision model. The multi-user sub-model maintains the states of a set of mobile users that reside in the simulation system. It takes the inputs from the user profile periodically and updates each user's states from the mobility simulation sub-model. It also provides state reports of multiple users to the decision model. The updating time interval is (Δt). The mobility simulation takes inputs from multi-user sub-model and simulates the movements for each user based on the environment profile. The whole mobile system is simulated on a sequence discrete time interval (such as Δt). For each mobile user *i*, at the beginning of k^{th} time interval ($k\Delta t$), the movement link is drawn between the positions (x_i^k, y_i^k) and (x_i^{k-1}, y_i^{k-1}), where the link distance is

$d_i^k = \sqrt{(x_i^k - x_i^{k-1})^2 + (y_i^k - y_i^{k-1})^2}$ and the instant direction is $q = \tan^{-1}\left(\dfrac{y_i^k - y_i^{k-1}}{x_i^k - x_i^{k-1}}\right)$. The consecutive links simulated for each time interval Δt construct a path between a pair of consecutive interesting points specified in the user profile. At the end of each time interval Δt the users' states are updated in the multi-user sub-model and the mobility simulation model checks if there are new mobile users enter the system or existing mobile users leave the system.

Decision Model

The decision model receives the reports from simulation model. The artificial neural networks are applied in creating this model. It provides the suggestions for the operation model to take actions in the system. It also gathers the user mobility information from the operation model and updates the user profile database.

Operation Model

The operation model serves as the interface to the real mobile system. It gathers the information from the real mobile system and takes actions based on the suggestions from decision model.

User Movement Simulation

In this section, we describe components/sub-models of the user profile and simulation models in details.

Environment Profile

The environment profile is a database that contains a set of environmental settings. A graphical map on a two-dimensional Cartesian coordinates constructs each environment profile. The map is a ground plan of a building that is composed of walls, obstacles, a set of entrances/exits, and a set of interesting points.

Walls

Basically, the wall model pulls the mobile user back on the path when he moves away from the center of the path. We simulate the walls as a sequence of obstacles, shown in Figure 2.

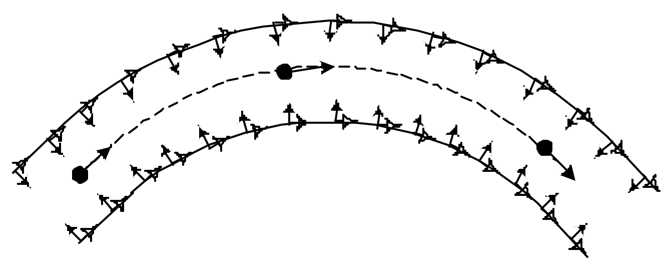

Figure 2: Wall Model

At a given time t, the direction of the force from the wall is orthogonal to the wall. If the corner of the wall is the end point of the distance between the mobile user and the wall, the force from the wall is orthogonal to the user movement direction. The closer to the wall, the stronger the force is. When the distance between a mobile user and the wall is less than a threshold d, additional force is given that is vertical to the wall force, shown in the hollow arrows. This force prevents the mobile user stick on the wall.

Obstacles

The force from an obstacle can be considered a segment of wall model. The distance is calculated by the distance between the center of mobile user and the nearest point of the obstacle. Similar to the wall model, when the distance between the mobile user and the obstacle is less than *d*, additional force (with hollow arrow) is added to prevent the mobile user stick on the obstacle. Note that only the line-of-sight obstacles will put force on mobile users. For example, mobile user *i* gets the force from object *A*, while mobile user *j* get the forces from both the object *A* and *B* (shown in figure 3).

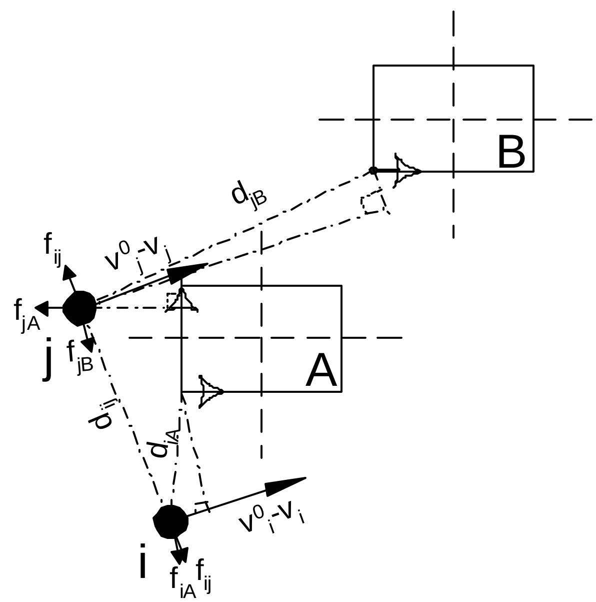

Figure 3: Obstacle Model

Entrances/exits

The entrances/exists can be the starting and ending point of the simulation of a mobile user.

Interesting points

In the simulation environment, multiple interesting points attract the mobile users to stay for a random period of time. Take an airport lounge for example; the interesting points in the lounge can be the coffee bar, the smoking room, waiting areas, and security check points. The interesting points can be viewed as various depots between starting point and the destination for a mobile user. A mobile user's profile specifies which interesting points are attracted to the user and the environment profile specifies the stop time period on each interesting point.

User Movement Profile

The user movement profile defines the following attributes for a mobile user:

- Starting points: can be any of entrances/exits or any internal point of the simulation area.
- Destination: can be any of interesting points or entrances/exits.
- Interesting points: specify how many stops during the movement simulation.
- Desired movement speed $\boldsymbol{v^0}$.

Mobile User Movement Model

In our situation, it is important that agents can move in arbitrary directions without artifacts caused by the modeling technique. The social force model (HELBING et al., 2000) is a generic coupled differential equation model for pedestrian movement. We propose the modified model as following:

$$m_i \frac{dv_i}{dt} = m_i \frac{v_i^0 - v_i}{t_i} + \sum_{j \neq i} f_{ij} + \sum_{W} f_{iW} + \sum_{O} f_{iO} \tag{1}$$

where m_i is the mass of the pedestrian and $\boldsymbol{v_i}$ its velocity. v_i^0 is its desired velocity.

In consequence, the first term on the models is the exponential approach to the desired velocity, with a time constant t_i. The second term on the model is the interaction between mobile users; and the third item on the model is the interaction of the mobile user with the environment. The specific mathematical form of the interaction term does not seem to be critical for our applications as long as it decays fast enough. Fast decay is crucial in order for the users to cut off the interaction at relatively short distances. This is important not only for efficient computing, but plausible with respect to the real world. For instance, mobile users at a distance of several hundred meters will not affect a mobile user, even if they are at a very high density level. Exponential force decay is given as following:

$$f_{ij} = A_{ij} \exp\left(\frac{r_{ij} - d_{ij}}{B_{ij}}\right)\frac{r_i - r_j}{d_{ij}} \tag{2}$$

where f_{ij} is the force contribution of mobile user j to mobile user i; r_i and r_j is the position of mobile users i and j, $d_{ij} = |r_i - r_j|$, $r_{ij} = r_i + r_j$ is the sum of their radii, A_{ij} ,B_{ij} are constants. For the environmental forces, f_{iW} is given as following:

$$f_{iW} = A_{iW} \exp\left(\frac{r_{iW} - d_{iW}}{B_{iW}}\right)\frac{r_i - r_W}{d_{iW}} \tag{3}$$

By the same token, the obstacle forces f_{iO} is given as following:

$$f_{iO} = A_{iO} \exp\left(\frac{r_{iO} - d_{iO}}{B_{iO}}\right)\frac{r_i - r_O}{d_{iO}} \tag{4}$$

<u>Mobility Simulation</u>

A mobile user starts with a plan (a corresponding user profile). The plan specifies the user's expectations during the movement. The expectations are a set of interesting points located within the simulating area. For example, in the airport lounge, a mobile user has several locations that the user must visit such as the security check point and a particular waiting area. At the meantime, several interesting points are optional to visit, such as the coffee bar, smoking room, and bathroom. The movement of a mobile user can be considered as a sequence of movements among interesting points and entrances/exits.

The mobility simulation sub-model takes inputs from multi-user sub-model and based on the environment profile simulates the movements for each user. The whole mobile system is simulated on a sequence discrete time interval (such as Δt). For each mobile user *i*, at the beginning of k^{th} time interval ($k\Delta t$), the movement link is drawn between the positions (x_i^k, y_i^k) and (x_i^{k-1}, y_i^{k-1}), where the link distance is $d_i^k = \sqrt{(x_i^k - x_i^{k-1})^2 + (y_i^k - y_i^{k-1})^2}$ and the instant direction is $q = \tan^{-1}\left(\frac{y_i^k - y_i^{k-1}}{x_i^k - x_i^{k-1}}\right)$. We use the mobility model presented in a precious section to calculate the movement direction and distance during each time interval Δt. The consecutive links simulated for each time interval Δt construct a path between a pair of consecutive interesting points specified in the user profile. At the end of each time interval Δt the user's states are updated in the multi-user sub-model and the mobility simulation model checks if there are new mobile users entering the system or existing mobile users leaving the system.

Decision Model

Based on the moving pattern received from the simulation model of the mobility framework, the decision model determines the destinations for the mobile-service users. As discussed in the literature review section, (PNNs) are utilized to create the decision model in this research.

<u>Probabilistic neural networks Basics</u>

PNN was first proposed by Specht (1990). The architecture of a typical PNN is as shown in Figure 4.

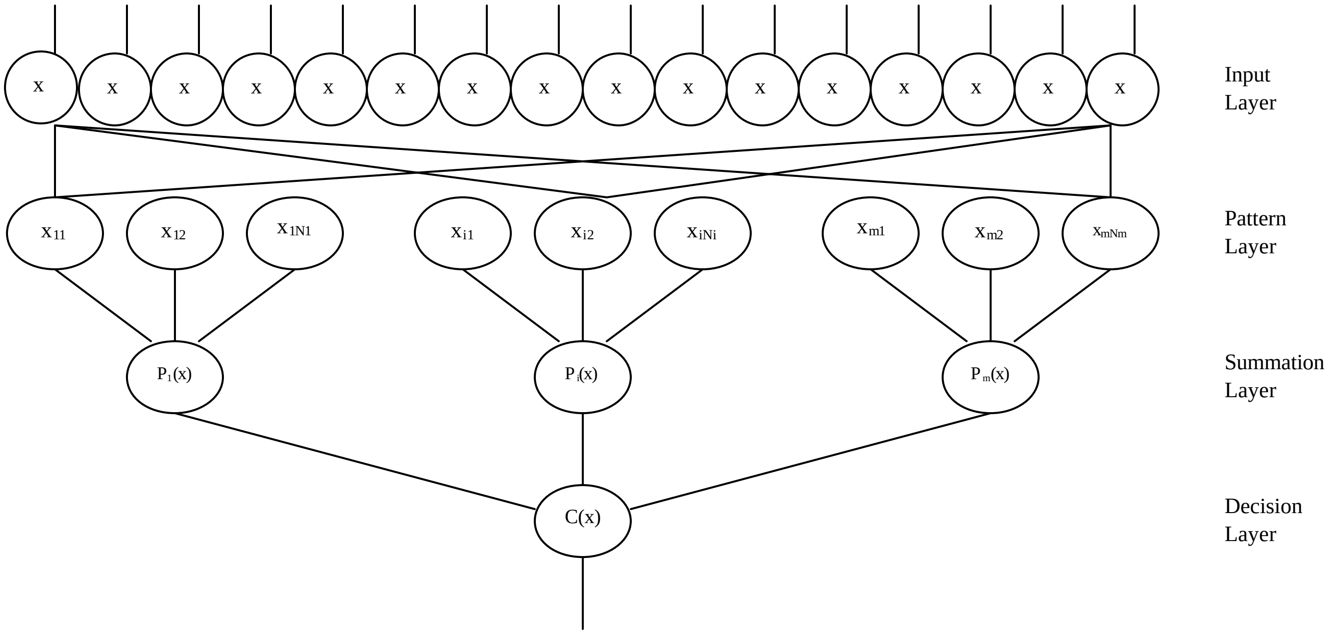

Figure 4: Probabilistic Neural Networks

The PNN architecture is composed of many interconnected processing units or neurons organized in successive layers. The input layer unit (vector x) does not perform any computation and simply distributes the input to the neurons in the pattern layer. On receiving a pattern x from the input layer, the neuron x_{ij} of the pattern layer computes its output

$$\phi_{ij}(x) = \frac{1}{(2\pi)^{d/2}\sigma^d} \exp\left[-\frac{(x - x_{ij})^T (x - x_{ij})}{2\sigma^2}\right] \qquad (5)$$

where d denotes the dimension of the pattern vector x, s is the smoothing parameter and x_{ij} is the neuron vector. The summation layer neurons compute the maximum likelihood of pattern x being classified into C_i by summarizing and averaging the output of all neurons that belong to the same class

$$p_i(x) = \frac{1}{(2p)^{d/2} s^d} \frac{1}{N_i} \sum_{j=1}^{N_i} \exp\left[-\frac{(x - x_{ij})^T (x - x_{ij})}{2s^2}\right] \qquad (6)$$

where N_i denotes the total number of samples in class C_i. If the *a priori* probabilities for each class are the same, and the losses associated with making an incorrect decision for each class are the same, the decision layer unit classifies the pattern in accordance with the Bayes's decision rule based on the output of all the summation layer neurons

$$\hat{C}(x) = \arg\max\{ p_i(x)\}, \qquad \text{i = 1, 2, …, m} \qquad (7)$$

where $\hat{C}(x)$ denotes the estimated class of the pattern x and m is the total number of classes in the training samples. One issue associated with the PNN is the determination of the network structure. This includes determining the network size, the pattern layer neurons and an appropriate smoothing parameter.

<u>PPN Training</u>

The original PNN structure (Specht, 1990) is a direct neural-network implementation of the Parzen nonparametric probability density function (PDF) estimation and Bayes classification rule. Although the training scheme of the original PPN is very simple and fast, one major drawback is that potentially a very large network will be formed since every training pattern needs to be stored. This leads to increased storage and computational time requirements during the testing phase. One natural idea to simplify the PNN is to reduce the number of neurons, i.e., use fewer kernels but place them at optimal places. Streit *et al.* (1994) improved the PNN by using finite Gaussian mixture models and maximum likelihood (ML) training scheme. However, the ML-based training does not necessarily lead to a minimum error performance for the classifier. This may be due to the fact that the Gaussian mixture model may not be an accurate assumption for some of the feature space distribution and the training data set is often inadequate. Juang & Katagiri (1992) proposed a new learning scheme based upon the minimum classification error (MCE) criterion. Gish (1992) pointed out that minimization of the number of errors is not the only benefit of the MCE. The MCE criterion is also inherently robust. The robustness stems from its counting misclassifications and ignoring the magnitude of the error, i.e., ignoring how far the misclassified events are from the decision boundary. Because of its robustness, MCE has been widely used in pattern classification applications. In this study, MCE is used to train the PNN based decision model.

<u>Inputs and Outputs</u>

The decision model takes input data from multi-user model. The input data include the historical data for all mobile users in the system: positions and corresponding moving speed, moving directions, interesting points, and final destination.

Outputs of the decision model to operation model are the operation patterns that used in the real system, for example the context switch operations based on a current user's position and moving speed.

The decision model also takes inputs from the operation model. The input data is the historical data of user movements in the real system. By comparing with the data stored in user profile model, a new user movement profile can be added in the user movement database. The new user profile can be used by next round user profile selection in the simulation model. This process refines the simulation process and helps the simulation model to generate the simulated scenarios that are more close to the real mobile environments.

Simulation Experiment

Figure 5 shows a simulation experiment of a user movement in a building. In this experiment, a user might choose any of three possible user profiles. For each simulation, a user visits the interesting points nearby. When the building is really crowded on the main path (the crowd situation is not shown), the user might take an alternative route to the interesting point, shown as a solid route. Note that the alternative path may not be the shortest path, since social forces select the alternative route. As such, this specific property of our model simulates the real world very well, because in the real world, a mobile user may not know the shortest path to the destination before the user enters the building. And a natural way to avoid congestion in the building is to go with the opposite direction of the congestion point.

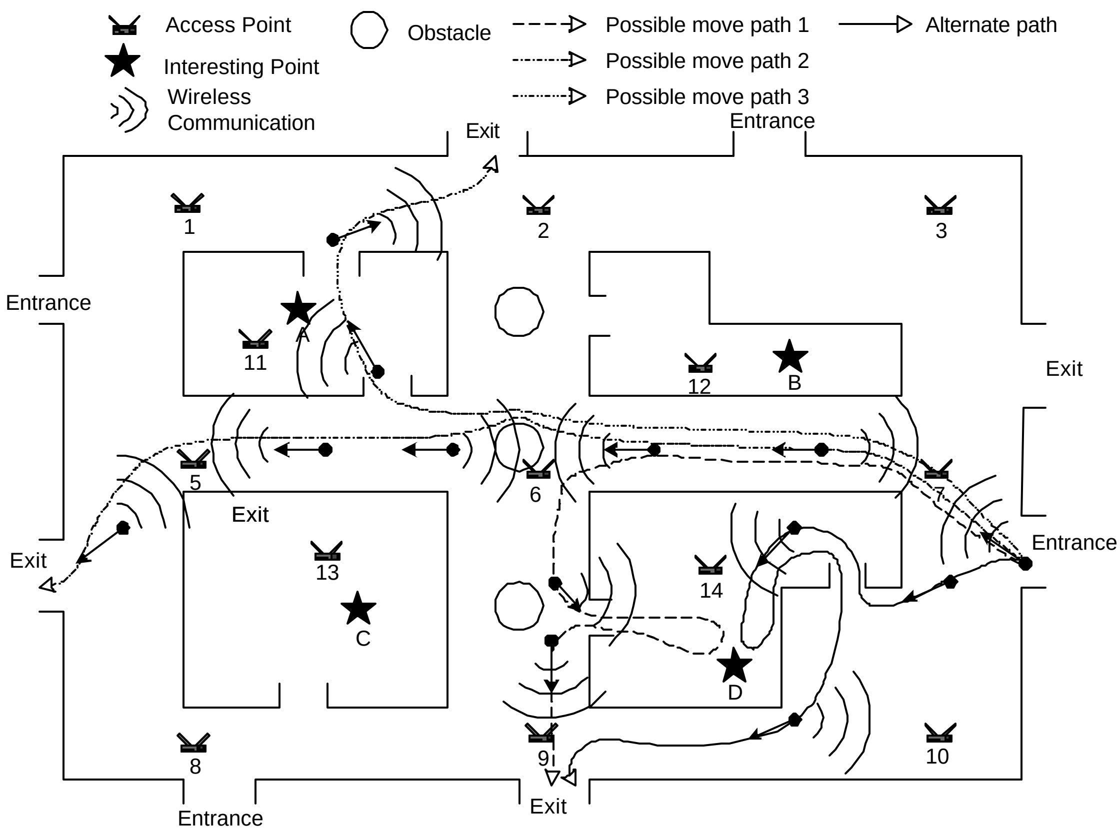

Figure 5: Simulation Experiment of User Movement

Conclusion

In this paper, we propose a new framework for constructing a realistic mobility model incorporating decision and operation models. Our proposed simulation framework can be used as a training system for a wireless LAN or Ad Hoc mobile system. Using the pre-setup user profile, the simulation model can simulate the user movement within the system. At the mean time, the simulation framework takes the feedbacks of the user movement from the real world to update the user profile database. The multi-user sub-model will take the most recent user profile to simulate the user movement.

The decision model provides the operational parameters to the operation model. Based on the historical status of a mobile user in the real world, the operation model takes corresponding operations. In our mobile system the operational parameters might include:

- The population of simulated system.
- The prediction of congestion path.
- The next wireless LAN access point a user might connect to.

Our simulation framework can also help network designers to select the proper Ad Hoc routing protocol and to study the performance of applied Ad Hoc routing protocols.

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