A Simple Mobility Model Realizing Designated Node Distributions and Natural Node Movement

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***Abstract*—In mobile wireless networks such as WSNs, WMNs and MANETs, movement of sensor nodes, clients and relay nodes has a great impact on the performance. Nevertheless, geography is too simplified in random-based mobility models such as RWP, while it is unrealistic to prepare trace-based mobility patterns for potential combinations of geography and mobility. To fulfill the gap, this paper provides a new method to automatically generate natural mobility patterns realizing designated node distributions. The goal of this work is to synthesize the movement patterns that can capture real (or intentional) node distributions. The method determines the probabilities of choosing waypoints from the subregions, satisfying the given node distributions. For this purpose, the relationship between the probabilities and node distributions is analyzed. Based on the analysis, the problem is formulated as an optimization problem of minimizing the error from the designated node distribution. Since the problem has non-linear constraints, a heuristic algorithm is designed to derive the near-optimal solutions. Several experiments have been conducted to show that a variety of node distributions could be realized in the proposed mobility model where the maximum error from the given node distributions was around 0.5%. Additionally, a case study has been conducted to show the applicability of the method.**

***Keywords*-Waypoint Mobility Model ; Node Density Distribution ; Mobile Wireless Networks**

I. Introduction

In mobile wireless networks and applications such as wireless sensor networks (WSNs), wireless mesh networks (WMNs) and mobile ad-hoc networks (MANETs), node mobility has a great impact on their performance [1]–[3]. For instance, an end-to-end route on MANET is likely to be established over a high-density region in the AODV protocol, or the route lifetime may be longer than those established over highly-dynamic subregions. The other examples include data dissemination over delay tolerant networks, V2V communications [4]–[6], balanced client-association control on WMNs or WiFi spots [7], [8].

The random waypoint (RWP) mobility model [9] has been widely used in performance evaluation of mobile wireless networks. In the RWP model, each node randomly chooses destinations as well as speed and pause time from the designated ranges. Since such a random-based mobility model has several well-known characteristics and can be implemented simply, it is available in most network simulation systems. Meanwhile, it has not been considered to *capture real or intentional node distributions* in those models, since they focus on generalizing the random movement behavior. For example, in the RWP model, it has been analyzed that the node density is higher near the center of the region than that near the border, which is not usually seen in the real world. In our real life, deployment of people, vehicles or some other potential members of mobile networks may vary depending on time (morning, afternoon, evening or night), region (indoor, outdoor, city sections or shopping malls), or some other factors. On the contrary, to simulate the real-world's movement of nodes, the real traces are often reproduced from the observation of movements of pedestrians, vehicles and so on. Although it is helpful to observe the unique performance in specific time and space, it cannot be used for general-purpose performance evaluation.

This paper provides a new method to automatically generate natural mobility patterns realizing designated node distributions. The goal of this work is to synthesize the mobility patterns that can capture real (or intentional) node distributions. The method determines the probabilities of choosing waypoints from the subregions, satisfying the given node distributions. For this purpose, the relationship between the probabilities and node distributions is analyzed. Based on the analysis, the problem is formulated as an optimization problem of minimizing the error from the designated node distribution. Since the problem has non-linear constraints, a heuristic algorithm is designed to derive the near-optimal solutions.

Several experiments have been conducted to validate the methodology. It has been shown that the proposed method could yield a variety of node density distributions. Node distributions such as a "checkerboard" distribution where subregions with or without nodes coexist randomly are usually difficult to reproduce in waypoint mobility models. Despite this fact, such distributions may be useful to represent the snapshot of vehicles and people location outside in city sections, since subregions with and without nodes can represent streets and buildings, respectively. It is also worth noting that the maximum error from the designated node distributions was only 0.5%, which indicates sufficient accuracy achievement.

Through a study of performance evaluation of the AODV protocol that is a well-known routing protocol on MANETs, the proposed method is effective to elaborate the evaluation plans of real performance, which cannot be seen using the random-based mobility.

II. Related Work and Contribution

1) Work on Random Mobility Analysis: It has been recognized that node mobility affects the performance of mobile wireless networks [3], [10]–[12] and many mobility models have been proposed so far [1].

Random-based mobility models such as the Random Waypoint (RWP) model [9] and the Random Direction (RD) model [13] are often used due to their availability in many network simulators, and some analytical researches have revealed their properties [14]–[16]. The results have shown that the node density distribution is not uniform; *e.g.* there is a high-density peak at the central point of the simulation area. Some approaches make the random-based mobility models configurable. For example, Gloss et al. have proposed a variant of the RD model with variable directions and speeds for different destinations [17].

The random-based mobility models have further been analyzed with respect to node velocity/density distributions at the initial and steady states. Since the performance tests should be done in the steady states, the non-steady states should be minimized for efficient simulations. For this purpose, several analytical techniques have been proposed [18]–[23]. In Ref. [18], Yoon et al. have focused on the node velocity distribution in the RWP model and shown the presence of the harmful effects before the convergence. They have also presented the sound mobility model based on the RWP model [24] that maintains the average velocities of nodes through simulations to avoid the harmful effects. In Ref. [20], McGuire has derived the node density distribution for a general class of mobility models. Nain et al. have analyzed the node density distribution in the random direction model, and described its usefulness compared with the RWP model [21]. In Ref. [22], a generic random mobility model called “random trip model” has been proposed that can immediately reach steady states.

2) Work on Mobility Generation: Besides a large number of efforts on design and analysis of conventional random-based mobility models and their variants, several approaches have been presented to generate mobility patterns from observations, statistical parameters, or geography. In [25], mobility patterns are generated considering obstacles such as buildings. Since environmental context such as obstacles, pathways and their details should be considered for more realistic mobility, the recent approach in [26] has proposed a method to create realistic node movement patterns in terrains where any shapes of obstacles with doorways and pathways can be incorporated. Some methods focus on modeling the behavior of people moving around several spots. In [27], a macroscopic mobility model for wireless metropolitan area networks has been presented where different types of zones such as workplace, commercial and recreation zones and people such as residents, workers, and consumers. Then an existing urban transportation planning technique is used to estimate the user density in each zone. Hsu et al. have presented the Weighted Way Point (WWP) model [28] to yield the movement behavior of people walking among spots such as cafeterias, libraries and classrooms at university campus. Given residence time distributions in those spots and a set of transition probabilities of node movements between the spots, it uses a Markov model to determine the node behavior. However, residence time information may not be obtained without long-term monitoring. Also since the WWP model only considers transition probabilities between spots, the pathways between spots are not modeled, which result in limited applicability to general areas. Ref. [29] can create a statistical mobility model from access logs to base stations. In our previous work, the UPF (urban pedestrians flow) model has been presented and provided as a part of the MobiREAL tool [30]. Many types of excellent efforts like [31]–[35] have been dedicated to model and analyze people movement using real traces or to synthesize mobility models based on statistical features.

3) Our Contribution: Our work falls into the latter category where mobility patterns are generated from observations of peoples, statistical parameters, or geographical information. However, it is quite different from those approaches since we provide a unique approach to generating mobility patterns in a simulation field for arbitrary node distributions, and the mobility is realized as a fully stateless waypoint model. In addition, our method does not need detailed log such like access logs containing unique ids of nodes used in Ref. [28], [29]. This is, as long as we know, the first approach and has a great advantage for many network simulators since a variety of geography and node distribution patterns can be abstracted in the mobility model that can easily be implemented. We may also take an advantage that the proposed method can be applied to systematic generation of mobility as well as observation-based generation. This feature allows performance testers to asses the feasibility of protocols and applications based on a variety of node residence patterns, while they can use a common waypoint model.

III. Proposed Waypoint Mobility Model

In this section, we propose a new waypoint mobility model in which nodes move on the simulation area based on destination probabilities, which are the probabilities of choosing destinations at each waypoint. At first, we explain that for any set of destination probabilities, a corresponding steady state of node density distribution exists. Based on this property, we represent a node density distribution by destination probabilities. Using the representation, we provide an algorithm to determine the destination probabilities. We also derive a sufficient condition to maintain the derived node density distribution from the beginning of the node movement. This allows starting simulations with steady states, which may save simulation time and improve efficiency.

A. Basic Mobility Model

We consider a waypoint model where each node continues the process of (i) choosing a destination point from a simulation area, (ii) moving straightly toward the destination point with a constant velocity, and (iii) staying at the point for a certain time period. The simulation area is divided into $m \times n$ square cells and these cells are numbered sequentially from top left (0) to bottom right ($mn-1$) as shown in Fig.1. The choice of destination points is done in the following steps; (i) each node in cell i selects a destination cell (say j) according to a pre-defined probability $p_{i,j}$ (this probability is called *destination probability*), and (ii) the node randomly selects a destination point in cell j. These probabilities satisfy the following equation due to the definition.

$$\sum_{j=0}^{mn-1} p_{i,j} = 1 \ (0 \leq i \leq mn-1) \tag{1}$$

Next, we show that the mobility model introduced above with *an arbitrary set of destination probabilities* can reach a steady state of node density distribution. We let f_i^t denote the number of nodes which depart from an origin cell i at time t, $T_{i,j}^{pass}$ the transit time between cell i and cell j, and T^{pause} the pause time at the destination point.

For each cell j, f_j^t satisfies the following equation because the number of nodes that depart from cell j equals the number of nodes that have already arrived at cell j and have stayed for T^{pause} at cell j.

$$f_j^t = \sum_{i=0}^{mn-1} f_i^{t-T_{i,j}^{pass}-T^{pause}} \cdot p_{i,j} \ (0 \leq j \leq mn-1) \tag{2}$$

We assume that in a steady state the number of nodes per moving from an origin cell to a destination cell per unit time is constant and denote it as f_j. This is called *flow rate*. The flow rate must satisfy the following equation.

$$f_j = \sum_{i=0}^{mn-1} f_i \cdot p_{i,j} \ (0 \leq j \leq mn-1) \tag{3}$$

Eq.(3) can be represented as a matrix (4).

$$\underbrace{\begin{pmatrix} p_{0,0}-1 & p_{0,1} & \cdots & p_{mn-1,0} \\ p_{0,1} & p_{1,1}-1 & \cdots & p_{mn-1,1} \\ \vdots & \vdots & \ddots & \vdots \\ p_{0,mn-1} & p_{1,mn-1} & \cdots & p_{mn-1,mn-1}-1 \end{pmatrix}}_{(\mathbf{P}-\mathbf{E})} \underbrace{\begin{pmatrix} f_0 \\ f_1 \\ \vdots \\ f_{mn-1} \end{pmatrix}}_{\mathbf{F}} = \underbrace{\begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}}_{\mathbf{0}} \tag{4}$$

This matrix indicates that at least one of the following conditions must be satisfied; (i) $\mathbf{F} = \mathbf{0}$, (ii) $\mathbf{P} - \mathbf{E} = \mathbf{0}$, and (iii) $(\mathbf{P} - \mathbf{E})$ is not invertible. However, (i) $\mathbf{F} = \mathbf{0}$ is not acceptable because $\mathbf{F}$ represents the set of flow rates between cells and therefore $\mathbf{F} = \mathbf{0}$ means no mobility at all. (ii) $\mathbf{P} - \mathbf{E} = \mathbf{0}$ is not meaningful for our purpose because it means that all nodes stay their initial cells. Therefore, in order to make Eq.(3) satisfiable, (iii) $(\mathbf{P} - \mathbf{E})$ must be non-invertible. Since the summation of all elements in any column in the matrix are zero due to Eq.(1), the rank of the matrix must be less than $m \times n$. Thus, (iii) $(\mathbf{P}-\mathbf{E})$ is always non-invertible, and it is proved that the proposed mobility model reaches steady states for any sets of destination probabilities.

B. Node Density Distribution

Using the above equations, node density at each cell can be represented by destination probabilities. In order to analyze the relationship between node density and destination probabilities, we calculate *cell transit time* of nodes traveling from cell i to cell j and the number of nodes moving through a cell.

At first, we explain how to calculate the cell transit time. As shown in Fig.2, we denote an origin point in cell i and a destination point in cell j as (x_i, y_i) and (x_j, y_j), respectively. The transit distance between these points is represented as $\sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$. Considering the fact that destination points (and origin points) are chosen randomly in these cells, the average transit distance (denoted by $L_{i,j}$) between cell i and cell j can be calculated as the average of the transit distances for all combinations of origin points in cell i and destination points in cell j. Similarly, the transit distance on cell k for nodes that travel from cell i to cell j is shown in Fig. 2. (x_{k1}, y_{k1}) and (x_{k2}, y_{k2}) are the intersection points of the line segment between (x_i, y_i) and (x_j, y_j) on the two sides of cell k. Therefore, the average distance (denoted $L_{i,j,k}^{pass}$ hereafter) can be calculated as the average of the line segments for all combinations of origin points in cell i and destination points in cell j. For simplicity, we assume that all the nodes move at the same speed (denoted as V), but this can be relaxed [1]. We also assume that the nodes stop for the same pause time T^{pause} after arriving at their destination points. Hereafter, $T_{i,j,k}^{pass}$ denotes the average cell transit time on cell k for nodes moving from cell i to cell j. $T_{i,j,k}^{pass}$ is represented by the following equation. It is noted that the value of $T_{i,j,k}^{pass}$ is zero if cell k has no intersection with the line segment

[1] If we would like to use a velocity distribution instead of a constant velocity for more realistic cases, we may use the same formulation except that V must be determined by observation of the average velocity with the velocity distribution. It is well-known that this observed average value might be different from the average of the given velocity distribution [36]

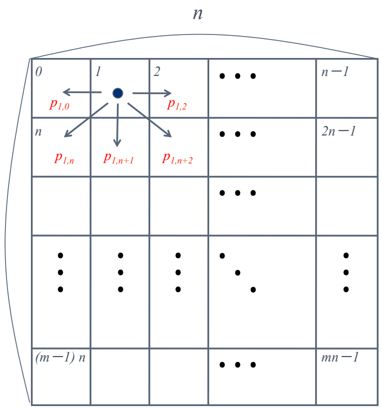

Figure 1. Simulation Area

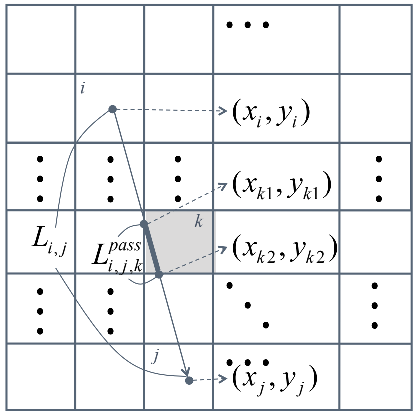

Figure 2. Transit Distance on Cell k

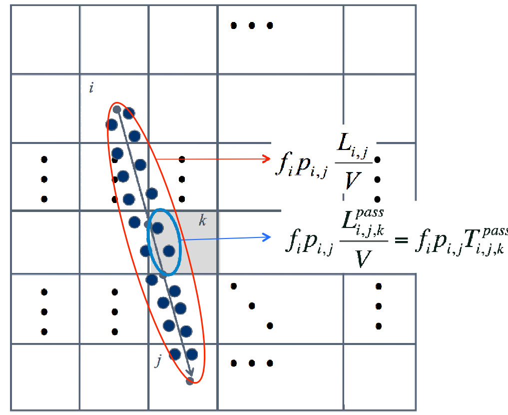

Figure 3. The Number of Nodes at Cell k

$(i.e. L^{pass}_{i,j.k} = 0)$.

$$T^{pass}_{i,j,k} = \begin{cases} \frac{L^{pass}_{i,j,k}}{V} & (j \neq k) \\ \frac{L^{pass}_{i,j,k}}{V} + T^{pause} & (j = k) \end{cases} \quad (5)$$

Next, we show how to represent the number of nodes in each cell (*node density*) by destination probabilities. The number of nodes moving from cell i to cell j per unit time can be represented as $f_i p_{i,j}$. The transit time for these nodes can be represented as $T^{pass}_{i,j,k}$. Thus the number of nodes at cell k among these nodes is introduced by $f_i p_{i,j} T^{pass}_{i,j,k}$ (Fig. 3). Since nodes might pass through cell k for different combinations of origin-destination cells, the total number of nodes at cell k can be represented as the following equation in a steady state.

$$d_k = \sum_{i=0}^{mn-1} \sum_{j=0}^{mn-1} f_i p_{i,j} T^{pass}_{i,j,k} \quad (6)$$

As discussed before, Eq.(4) is not sufficient to uniquely determine f_j from $p_{i,j}$ because the rank of the matrix is smaller than $m \times n$ and it only represents the relation between $p_{i,j}$ and f_j. In order to calculate the node density distribution for a given set of destination probabilities, we have to add some other equations to the matrix to raise its rank to $m \times n$. We assume that the number of all nodes is 1 as represented by Eq.(7). Then Eq.(8) is derived from Eq.(6) and Eq.(7). Using Eq.(8) as well as Eq.(4), we can represent f_i by destination probabilities since the rank of the matrix becomes $m \times n$. By applying f_i to Eq.(6), we can get the node density distribution obtained by $p_{i,j}$.

$$\sum_{k=0}^{mn-1} d_k = 1 \quad (7)$$

$$\sum_{j=0}^{mn-1} \sum_{k=0}^{mn-1} p_{0,j} T^{pass}_{0,j,k} \cdot f_0 + \sum_{j=0}^{mn-1} \sum_{k=0}^{mn-1} p_{1,j} T^{pass}_{1,j,k} \cdot f_1 + \cdots + \sum_{j=0}^{mn-1} \sum_{k=0}^{mn-1} p_{mn-1,j} T^{pass}_{mn-1,j,k} \cdot f_{mn-1} = 1.0 \quad (8)$$

C. Realizing Steady Node Density Distribution

In steady states, the number of nodes in each node flow never changes. In order to avoid a transitional state toward a steady state, such node flows should be realized at the beginning of the simulation. We apply an appropriate destination cell to each node to create the node flows. The number of nodes departing from cell k for cell j on cell i in the steady state is $f_k p_{k,j} T^{pass}_{k,j,i}$. Thus, the percentage of the nodes, whose destination cells are cell j, at cell i can be represented as Eq.(9). Using this variable, we set the initial destination cell to each node to maintain the node density distribution during the simulation.

$$p'_{i,j} = \sum_{k=0}^{mn-1} \frac{f_k p_{k,j} T^{pass}_{k,j,i}}{d_i} \quad (9)$$

IV. Deriving the Set of Destination Probabilities for a Given Node Distribution

In this section, we explain how to derive a set of destination probabilities to realize a given node density distribution in the proposed waypoint mobility model. Of course, there is a naive approach that creates arbitrary node distributions by letting nodes stay in only their initial cells. Also, adjusting pause times at destination cells is another approach to producing a certain node density distribution. However, the former method is not acceptable at all, and in the latter case some mobility characteristics such as contact time are greatly affected because nodes tend to stay longer at high-density regions. Thus, we propose a method that adjusts only the set of destination probabilities to create the designated node density distributions. In order to produce arbitrary node density distributions, we formulate the problem to derive a

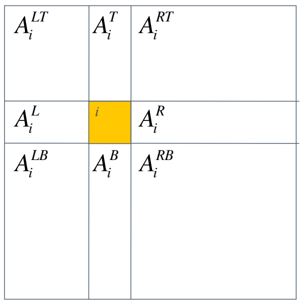

Figure 4. A set of cells located on θ direction

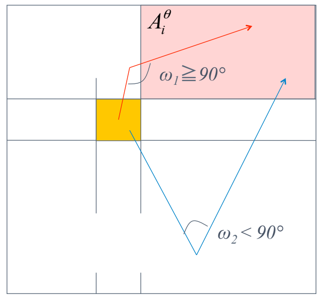

Figure 5. Natural and Unnatural Node Movement for Region A_i^θ

set of destination probabilities as the optimization problem of minimizing the error from the designated node density distribution. Since the problem has non-linear constraints, we also give a heuristic algorithm to derive solutions. In addition, we model some node movement characteristics by using the destination probabilities. This model can be used to characterize the behavior of nodes in the derived mobility model to assure not only node density distribution but also node movement characteristics.

A. Node Movement Characteristics

In the real world, we hardly see that a node moves toward a certain direction but turns to the opposite way suddenly. To get rid of the node movement, we define the U-turn movement in the proposed mobility model. In order to count such nodes at cell i in each direction, we divide all cells except cell i into the eight regions as shown in Fig.4. The u-turn movement is defined as the node movement that a node arrives at cell i from a region and goes to the same region again. We represent this movement by a set of destination probabilities.

We denote each region as A_i^θ where θ is one of the directions from cell i. For this region, we define f_θ as the number of nodes moving from A_i^θ to cell i per unit time and $p_{i\theta}$ as the sum of destination probabilities whose destination cells are in A_i^θ. These variables is represented by existing variables in Eq.(10) and Eq.(11), respectively. Therefore, the number of nodes at cell i that come from A_i^θ and go to A_i^θ again can be $f_{\theta i} p_{i\theta}$. By calculating the number of such nodes for each region, the percentage of nodes at cell i that go back to the incoming regions can be represented by Eq.(12).

$$f_{\theta i} = \sum_{k \in A_i^\theta} f_k p_{ki} \tag{10}$$

$$p_{i\theta} = \sum_{k \in A_i^\theta} p_{ik} \tag{11}$$

$$b_i = \frac{\sum_{\forall \theta} f_{\theta i} p_{i\theta}}{f_i} \tag{12}$$

In order to make a given node density distribution, nodes might move on only several specified cells to keep the given densities of the cells. The nodes never move around the simulation area in that case. Thus, we want to guarantee some "randomness" of node movement to avoid such a situation. It is impossible to realize arbitrary node distributions in the situations where nodes move on all cells equally in the simulation area. Therefore, when nodes visit on cells according to the cells' density, we think that the randomness of node movement is assured. In order to make nodes move in such a way, we represent the randomness of node movement by a set of destination probabilities as well.

For the randomness of node movement, we model the node density of each region and the number of nodes moving for each region. The node density of A_i^θ can be represented by Eq.(13). Next, we count how many nodes move from cell i to region A_i^θ. We count not only the nodes moving from cell i to A_i^θ directly but also the nodes pass through at most one waypoint since nodes might have to stop at their waypoints and go to A_i^θ to avoid obstacles. In addition, for such nodes, we count only the node whose trajectories have an angle which is larger than 90 degrees as shown in Fig.5, so that we can omit the nodes moving to the different direction of A_i^θ first from cell i. The number of such nodes for A_i^θ can be represented by Eq.(14). $N_{i,k}$ is a set of cells through which nodes can reach to cell k from cell i with the trajectories which have an angle greater than 90 degrees. By calculating the correlation between d_i^θ and $p'_{i\theta}$ for each region, we can know how many nodes move according to node density. If the correlation is high, it means that many nodes go to crowded region and few nodes go to uncrowded region from cell i.

$$d_i^\theta = \sum_{k \in A_i^\theta} d_k \tag{13}$$

$$p'_{i\theta} = \sum_{j \in A_i^\theta} p_{i,j} + \sum_{j \in N_{i,k} \setminus A_i^\theta} \sum_{k \in A_i^\theta} p_{i,j} p_{j,k} \tag{14}$$

B. Problem Formulation

Next, we summarize the problem to derive the set of destination probabilities for a given node density distribution. The node density of cell k (denoted as D_k) is given as an input. Node velocity V and pause time T^{pause} are also given to calculate $T_{i,j,k}$. As shown in Section III-B, we can calculate $T_{i,j,k}$ from these values. We can also calculate destination probabilities $p_{i,j}$, node density d_k and the number of nodes departing from a cell per unit time f_j for each cell from these input variables. Then, we will see the problem in detail. The inputs and outputs to the problem are listed as follows.

- **Input Parameters**
  - Target density of nodes for all cells: D_k D_k must satisfy $\sum_{k=0}^{mn-1} D_k = 1$.
  - Node velocity: V
  - Pause time: T^{pause}
- **Output Parameters**

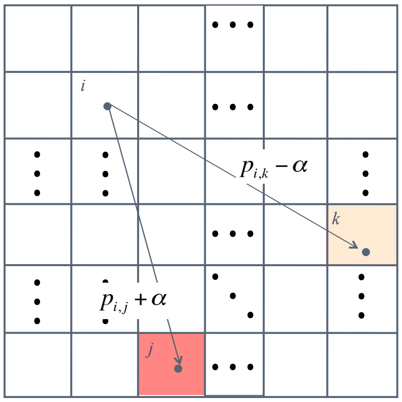

Figure 6. Cell Selection to Change the Node Density Distribution

- Destination probability for all pairs of cells: $p_{i,j}$
- Derived density of nodes for all cells: d_k
- The number of nodes departing from a cell per unit time for all cells: f_j

In order to derive the set of destination probabilities for a given node density distribution, we use the following objective function that minimizes the sum of the differences between the obtained density and the given density of all cells.

$$\min \sum_{k=0}^{mn-1} |d_k - D_k| \tag{15}$$

The above objective function is subject to the following constraints as shown in III-B.

$$\sum_{k=0}^{mn-1} d_k = 1 \tag{16}$$

$$\forall i \sum_{j=0}^{mn-1} p_{i,j} = 1 \tag{17}$$

$$\forall i, j \ 0 \leq p_{ij} \leq 1 \tag{18}$$

C. Heuristic Algorithm

Since the optimization problem has non-linear constraints, it is probably hard to solve. Therefore, we propose a heuristic algorithm that improves the value of the objective function step by step, by modifying the set of destination probabilities. We adopt a simple, SA-like strategy which repeats to choose two destination probabilities, modify them to generate another set of destination probabilities and accept it only if it improves the value of the objective function. The key technique to reach a good solution is to choose two "appropriate" destination probabilities and modify them.

At first, the heuristic algorithm sets the uniform probabilities $p_{i,j} = 1/mn(\forall i, j)$ as a candidate set of destination probabilities. In the iteration process, two destination probabilities whose origin cells are same are modified in such a way that one probability $p_{i,j}$ is increased by α and the other probability $p_{i,k}$ is decreased by α (Fig.6). The α can be determined randomly, but it must satisfy $p_{i,k} \leq \alpha \leq 1 - p_{i,j}$ so that $p_{i,j}$ and $p_{i,k}$ are in [0,1]. The selection of cells i, j and k affects the derived node density distributions. It is hard to find an appropriate selection of cells that is expected to improve the value of the objective function because the change of two destination probabilities affects all node flow rates. For instance, by increasing p_i, we can expect that the densities of cells between cell i and cell j increase. In fact, those densities may not be increased in some cases because f_i might be decreased by this operation. Similarly, by decreasing $p_{i,k}$, the density of cells between cell i and cell k may not be decreased. From the above discussion, we select cells i,j and k randomly among all cells. After the cell selection, the algorithm increases $p_{i,j}$ by α and decreases $p_{i,k}$ by α. If the value of the objective function decreases after this operation, the algorithm accepts the set of destination probabilities and continues to perform this operation. Otherwise, the algorithm discards the set of destination probabilities and uses the previous set of destination probabilities for the next operation. By applying this operation iteratively, we can get the set of destination probabilities that can realize the given node density distribution nearly.

For some purposes of performance evaluation, we have to add some requirement for node movement to make the mobility more realistic. In the proposed method, by calculating measurement factors shown in Section IV-A and modifying destination probabilities so that the probabilities can meet the requirement during the cell selection process, we can get the set of destination probabilities not only realizing a given node density distribution but also satisfying the requirement of node movement.

(a)	Random Waypoint(RWP)
(b)	Flat
(c)	Gradation
(d)	Checkerboard
(e)	Manhattan1
(f)	Manhattan2

Table I
INTENDED NODE DENSITY DISTRIBUTIONS

Region	100(m)×100(m)
Number of Nodes	200
Node Velocity	1.5(m/s)
Pause Time	15(s)
Radio Range	10(m)

Table II
SIMULATION ENVIRONMENT

V. ASSESSMENT

In this section, we validate that the proposed method can produce appropriate destination probabilities from given node density distributions. We have conducted the experiments for the six node distributions shown in Table I through simulations. (b) Flat is a flat node density distribution and nodes are distributed uniformly in the simulation area. In

(c) Gradation, the left cells have higher node densities, and the right cells do not. In (d) Checkerboard, cells with sparse density and cells with dense density are mixed side by side, and four peaks are seen in the simulation area. In addition, we adopted two manhattan mobilities [2] as the cases (e) and (f). These mobilities can be produced by only specifying very low node density (or zero density) to "building" cells. Then, the produced mobility makes nodes move on pathways. The difference between (e) and (f) is the number of building cells.

We gave the above node density distributions as inputs to our proposed method and calculated the sets of the destination probabilities for them. After that, we have executed simulations with the sets of the probabilities and measured the node density at each cell in the simulations. The experiment is performed with a square field with $100(m) \times 100(m)$ for 1800 seconds of simulation time. Table II summarizes of our simulation parameters. We have shown given node densities and the corresponding measured node densities in Table III. The derived node density distributions are shown in Fig.7. Gray cells mean that the error from the given node density is more than 0.5%. On the other hand, cells with bold numbers mean that the error is below 0.01%. Measured node traces of 10 nodes in each node distribution are shown in Fig.8. Each trace is emphasized by a red line in the figures.

From the tables and the figures, we can see that the proposed method can make a variety of node density distributions with sufficient achievement of node density requirement. In fact, the differences between input densities and measured densities are at most 0.1% as shown in Tables III (b), (c) and (d). On the other hand, as shown in Tables III (e) and (f), it is difficult to realize exact manhattan mobilities by the proposed mobility model. However, the error of obstacle cells is below 1.0% and the derived mobility model can keep sufficient accuracy. In Fig. 8, we can see that the waypoints are selected depending on the node density since there are many waypoints in the cells whose node densities are high. In addition, in Fig. 8 (b), we can see that there are fewer traces crossing the central area. By doing that, the proposed method prevented to create a peak in that area so as to create the flat node distribution. In the case of (c), the many waypoints were selected in left cells to realize gradation node density patterns. As shown in Fig. 8 (e) and (f), there are many traces on the pathways.

VI. Case Study

In this section, we show how the proposed mobility model is used in simulations through a realistic case study. In this case study, we have conducted performance evaluation of AODV under several node density distributions. Each node sends packets at 60s intervals to a node selected randomly. We have executed simulations in the cases of (a) RWP, (b) Flat, (e) Manhattan1 and (f) Manhattan2 with the simulation parameters shown in Table II. Fig.9 shows how many packets were transmitted through each cell in the four cases. We can easily expect that network traffic is congested around the center of the area in case (a) as shown in Fig.9 (a). On the other hand, there is a lot of traffic on borders in case (b). This is because nodes stop at circumference cells frequently and packet routes on those cells become stable. Since packets must go through "intersection cells" in cases (e) and (f), these cells seem to have more traffic compared with other cells. In addition, comparing cases (e) and (f), we can see more traffic on the center road in case (e) because there are a few intersections connected to the pathways.

VII. Conclusion

In this paper, we have proposed a new method to automatically generate a set of destination probabilities realizing designated node distributions. We have formulated the problem to derive the set of destination probabilities as the optimization problem of minimizing the error from the designated node density distribution. For the problem, we have also given the heuristic algorithm to derive solutions. Through several experiments, we have shown that the proposed mobility model can produce various node density distributions and is useful for performance evaluations of mobile network applications.

As future work, we are planning to implement a toolset that generates many mobility patterns with various node distributions for common network simulators. Moreover, in order to evaluate network performance under more realistic situations, we will extend the proposed mobility model so that it can change a node density distribution to another with a certain time and handle to add or delete several nodes through an experiment.

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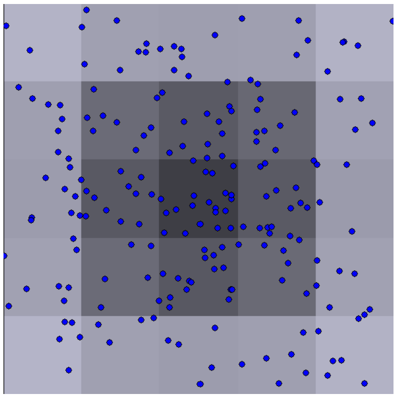
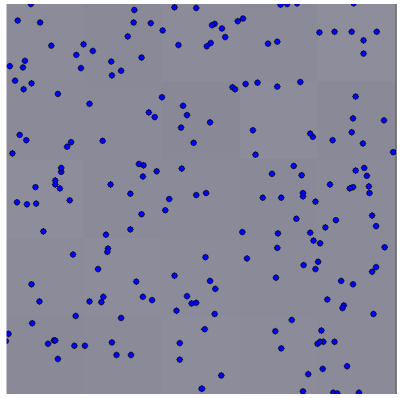
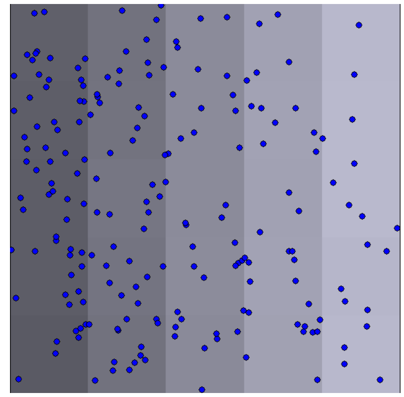


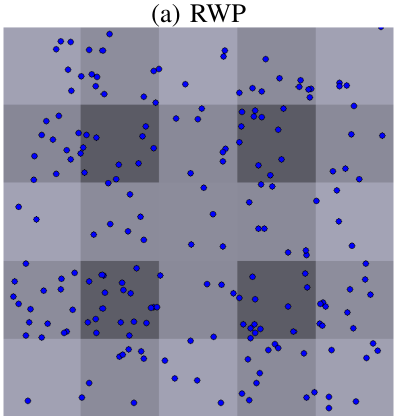
(a) RWP



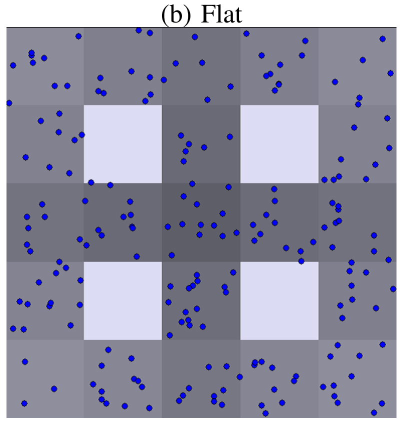
(b) Flat



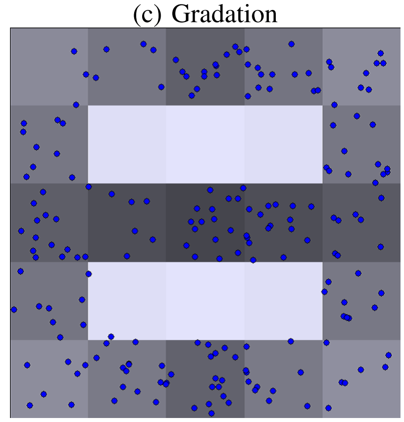
(c) Gradation



(d) Checkerboard



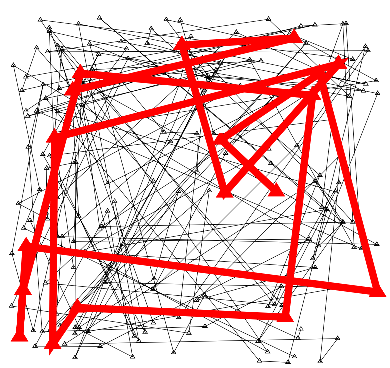
(e) Manhattan1



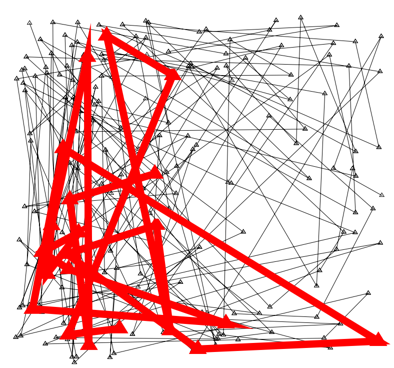
(f) Manhattan2

Figure 7. Snapshots of Six Node Density Distributions

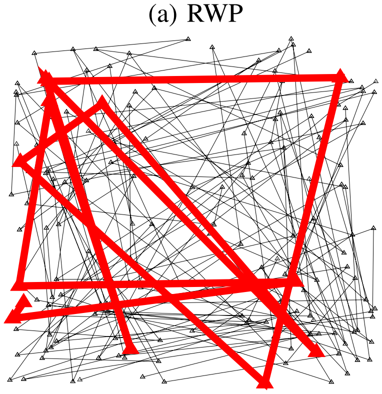
(a) RWP



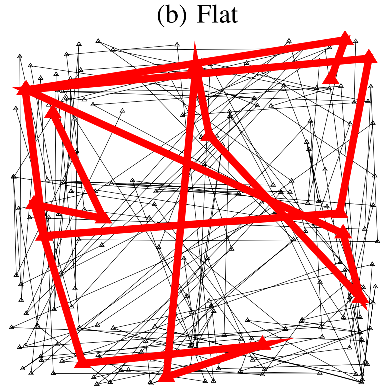
(b) Flat



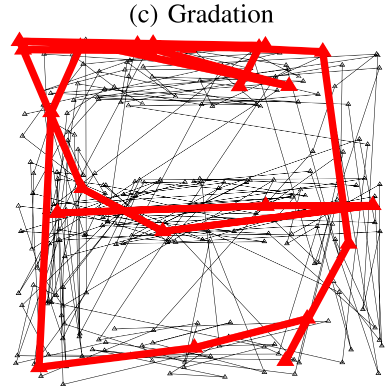
(c) Gradation



(d) Checkerboard



(e) Manhattan1



(f) Manhattan2

Figure 8. Traces of Six Node Density Distributions

2.25	3.09	3.16	3.11	2.29
3.10	5.36	6.11	5.52	3.00
3.25	6.12	7.31	6.08	3.26
3.04	5.36	6.17	5.45	3.04
2.19	3.07	3.25	3.13	2.28

(a) RWP(Measured)

4.00	4.00	4.00	4.00	4.00
4.00	4.00	4.00	4.00	4.00
4.00	4.00	4.00	4.00	4.00
4.00	4.00	4.00	4.00	4.00
4.00	4.00	4.00	4.00	4.00

3.99	4.05	**4.00**	**4.01**	3.90
4.01	4.02	4.10	3.96	4.04
3.92	4.03	4.02	4.04	**4.01**
3.97	3.96	**3.99**	**4.01**	**4.01**
4.07	**4.01**	3.93	3.97	**4.01**

(b) Flat

6.00	5.00	4.00	3.00	2.00
6.00	5.00	4.00	3.00	2.00
6.00	5.00	4.00	3.00	2.00
6.00	5.00	4.00	3.00	2.00
6.00	5.00	4.00	3.00	2.00

5.85	5.08	**4.00**	**2.99**	2.03
5.96	5.02	**4.00**	2.98	1.97
6.00	4.90	3.97	**3.01**	**2.00**
6.00	4.95	3.95	2.97	2.10
6.09	5.07	4.03	3.05	2.02

(c) Gradation

3.00	4.00	3.00	4.00	3.00
4.00	6.00	4.00	6.00	4.00
3.00	4.00	3.00	4.00	3.00
4.00	6.00	4.00	6.00	4.00
3.00	4.00	3.00	4.00	3.00

3.01	3.92	2.94	**4.00**	**3.00**
4.14	6.04	4.07	6.07	4.03
2.98	**3.99**	3.94	**4.01**	2.92
3.94	**5.99**	4.02	**6.01**	3.91
3.01	**3.99**	**3.01**	**4.00**	**3.00**

(d) Checkerboard

4.00	4.50	5.00	4.50	4.00
4.50	0.00	5.50	0.00	4.50
5.00	5.50	6.00	5.50	5.00
4.50	0.00	5.50	0.00	4.50
4.00	4.50	5.00	4.50	4.00

3.95	4.41	4.96	4.41	3.95
4.39	0.41	5.34	0.41	4.39
5.00	5.43	5.92	5.43	**5.00**
4.39	0.41	5.34	0.41	4.39
3.95	4.41	4.96	4.41	3.95

(e) Manhattan1

4.00	5.00	6.00	5.00	4.00
5.00	0.00	0.00	0.00	5.00
6.00	6.50	7.00	6.50	6.00
5.00	0.00	0.00	0.00	5.00
4.00	5.00	6.00	5.00	4.00

3.96	4.92	5.89	4.92	3.96
4.86	0.35	0.14	0.35	4.86
5.92	6.45	6.85	6.45	5.92
4.86	0.35	0.14	0.35	4.86
3.96	4.92	5.89	4.92	3.96

(f) Manhattan2

Table III
INPUT(LEFT) AND MEASURED(RIGHT) DENSITY(%)

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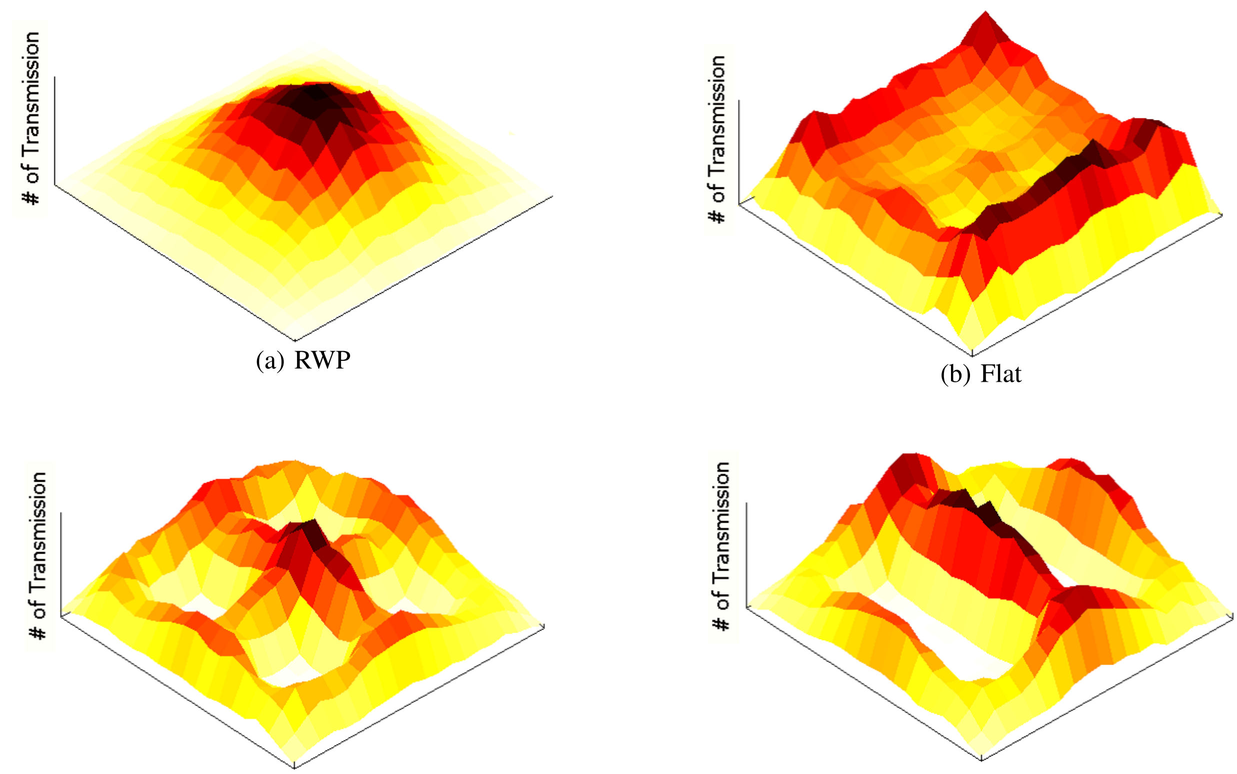

(e) Manhattan1

(f) Manhattan2

Figure 9. Number of Packet Transmission on Ad-hoc Networks

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