Swarm Group Mobility Model for Ad Hoc Wireless Networks

Dongsoo S. Kim, and Seok K. Hwang

***Abstract*—This paper proposes a new group mobility model for wireless communication. The mobility model considers the psychological and sociological behavior of each node and the perception of other nodes for describing interactions among a set of nodes. The model assumes no permanent membership of a group, capable of capturing natural behaviors as fork and join. It emulates a cooperative movement pattern observed in mobile ad hoc networks of military operation and campus, in which a set of mobile stations accomplish a cooperative motion affected by the individual behavior as well as a group behavior. The model also employs a physic model to avoid a sudden stopping and a sharping turning.**

***Index Terms*—ad hoc networks, mobility model, swarm group mobility, behavioral motion model, perception model, mobility features.**

I. INTRODUCTION

AD hoc wireless networks consist of mobile hosts equipped with wireless communication devices. The transmission of a mobile host is received by all hosts within its transmission range due to the broadcast nature of wireless communication and omni-directional antennae. If two wireless hosts are out of their transmission ranges in the ad hoc networks, other mobile hosts located between them can forward their messages, which effectively builds connected networks among the mobile hosts in the deployed area. Due to the mobility of wireless hosts, each host needs to be equipped with the capability of an autonomous system, or a routing function without any statically established infrastructure or centralized administration. The mobile hosts can move arbitrarily and can be turned on or off without notifying other hosts. The mobility and autonomy introduces a dynamic topology of the networks not only because end-hosts are transient but also because intermediate hosts on a communication path are transient.

A precise and realistic mobility modeling is very critical for analyzing a network performance and designing network architecture in wireless communication networks. In cellular networks, a user's mobility behavior directly affects signal traffic, channel holding time and call blocking/dropping probabilities [4]. Hence, a real network deployment and a network algorithm implementation must be based on a realistic mobility model. An unrealistic mobility model may cause an invalid conclusion so that it leads to inefficient deployment of the network system. Global position data are considered as the primary information in cellular network, but the major concern in the ad hoc networks is the relative distance among mobile hosts to maintain the connectivity without using the excessive routing function of the mobile hosts [8], [18], [29], [30], [32] and to minimize the transmission power while keeping identical connectivity in order to maximize the battery lifetime of the mobile hosts [5], [16].

This paper is organizated as follows: First, we discuss related work in Section II. Then, in Section III, we propose a new mobility model for ad hoc wireless communication called the Swarm Group Mobility (SGM) model. The model simulates the behavior of natural objects in terms of their positions. This research does not intend to simulate the detail motion like the joint movement of a natural object so that the SGM model simplifies many aspects of perception, physics and reasoning into the account of geographical movement of mobile hosts. The model generally reflects the behavior of individual mobile as well as a group of mobiles so that it gives valuable synthetic information for analyzing and designing systems or protocols in both cellular and ad hoc wireless networks. Simulation in Section IV illustrates that the SGM model is able to abstract new features of mobility models suitable to the study of wireless networks. Finally, Section V concludes our research and presents further research areas.

II. RELATED WORK

A random walk (RW) mobility model was derived from the Brownian motion, which is a stochastic process that models random continuous motion [19]. Lei and Rose [20] used the Brownian motion with drift process to model the mobility of the individual mobile user. The RW model has been widely adopted by the cellular communication community to model the behavior of wireless mobile hosts (MHs). An MH of the model moves from its current location toward a random direction and with a random speed, which are arbitrarily chosen from the ranges of $[0, 2\pi)$ and $[v_{\min}, v_{\max}]$, respectively. Researchers have used the model to study the cell residence time of a mobile user, and handover/location management [1], [2], [3], [12], [23], [26], [27], [28], [33]. The model does not retain any information about its past location and velocity (direction and speed) in determining the current velocity. This memoryless decision may create unrealistic motion as in sudden stopping and sharp turning. To overcome this unrealistic rendering, many derivatives were introduced including a Gauss-Markov mobility model [22], in which the velocity at time t is calculated as a weighted sum of the velocity at $t - \Delta t$, a mean velocity, and a Gaussian

This work was supported in part by the National Science Foundation under grant CCF-0514975

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random velocity. Another variation is a random destination model [9], in which a mobile host chooses its velocity and distance in travel from a given distribution and then moves in the direction. When the node completes the travel for the given distance, it calculates a new velocity and a distance in travel.

A random waypoint (RWP) mobility model is widely used in the wireless communication community [10], [11], [14], [17]. An MH of the model chooses a random destination in a given space and then moves in a random steady speed toward the destination. Once the host reaches the destination, it takes a pause for a random time before choosing a new destination and moving in a steady speed toward the new destination. The model tends to concentrate on the middle of its deployment region, caused by the so-called *border effect* [24], which indicates the spatial distribution of nodes is not uniform. Many research results of ad hoc mobile networks are based on the assumption of uniform snapshot of networks nodes, the border effect has a limitation in applying the model to the mobile ad hoc networks [6]

The mobility models described above are classified as entity mobility models, where the motion of each MH is independent of other MH motions. The entity models are useful in evaluating the performance of cellular communication networks, because a spatial distribution is its primary interest in this environment to acquire the cell residence time of a host, the frequency of cell boundary crossover, and so on. The relationship between MHs is not the main concern in the cellular networks. In ad hoc wireless networks, however, a MH communicates with its neighbors so that it is imperative to identify the relationship among MHs. There are several situations where the group of hosts accomplish a cooperative motion similar to military mission and civilian tasks. For example, a group of military soldiers in a mission cooperate to maximize the efficiency of the mission and to defend themselves from enemy attack. A vehicle on a highway tries to match its speed with other vehicles to avoid collision so that the distance between two nearby vehicles is maintained consistently even though they travel at the high speed. To find reasonable relationships among the movements of mobile nodes for developing and evaluating many aspects of ad hoc networks, it is important to develop a realistic group mobility model.

The exponential correlated random (ECR) model was known as the first group mobility model used in the wireless communication community [15]. In the model, a new position is computed as the weighted sum of the previous position and a Gaussian random deviation. To determine the weight, which results in determining the behavior of group mobility, the model uses two parameters, an exponential correlation (τ) and a variance (σ). Unfortunately, it is not easy to render a wanted motion pattern by choosing the pair of parameters (τ, σ).

Hong *et al.* proposed the reference point group mobility (RPGM) model [15]. To represent the behavior of a group of MHs, the model defines a logical reference center for each group. All hosts in the group follow the reference center. The physical movements of the group center and its group members are determined by two motion vectors: a group motion vector and a random motion vector. The model gives a path by defining a sequence of check points, on which a group follows. A group moves from one check point to the next check point before the reference center computes a new group motion vector. The RPGM model can generate a group-based motion for simulating ad-hoc networks. However, the model has several drawbacks. First, the model requires each node in a group to have a complete knowledge about the reference center regardless of their physical location and topological relation. In the nature of ad-hoc networks, such a global knowledge may not be available to each MH. Secondly, the model causes a sudden starting/stopping and a sharp turning of each MH. This unrealistic modeling is caused by using only the group motion vector to decide the motion of each MH. Third, the model requires a strong membership of each MH to a group so that a dynamic fork (departure of a node from a group) and join (addition of a node to a group) cannot be produced, which is frequently observed in the real world.

To overcome the problem of the global knowledge, the reference velocity group mobility (RVGM) model has been proposed by Wang et at., in which each mobile group has a characteristic group velocity instead of a group position [31]. A member node in a group determines its velocity by considering a random motion vector and its group velocity so that it can be regarded as the time derivative of the displacement-based group mobility in the RPGM model. The velocity representation of the RVGM model can provide a distinct membership in a velocity coordinate space, which can be utilized to predict a group partition and mobility pattern.

III. Swarm Group Mobility Model

The motion of swarming individual identities is a natural behavior. Group mobility such as herds of land animals, infantry soldiers on a battlefield, and vehicular transportation on a highway consists of individual units but exhibits some characteristics of team collaboration in the population. There seems to be a centralized control over all members of the group, but it is an aggregated behavioral tendency of independent units, each of which is acting on the basis of its own local perception [25]. We call such a group motion a Swarm Group Mobility model (SGM). To describe group mobility using the SGM, we simulate the psychological and sociological behavior of an individual node and some level of perception and physics.

A. Physics Model

In the model, a node is initially located randomly on xy-euclidean space and assigned initial random velocity whose speed and direction are in the range of $[v_{\min}, v_{\max}]$ and $[0, 2\pi)$, respectively. $v_{\min}$ and $v_{\max}$ are the minimum and maximum speed at which a node travels. The maximum speed can be considered as a speed limit in a vehicular transportation simulation, or as an equilibrium speed balance of propelled force and aerodynamic resistance. In addition to the maximum speed, each node also has a constant parameter of a maximum acceleration. In real world, the acceleration of a node is depending on its mass and propelled force. Assuming that a node has a maximum propelled force, it is reasonable to have the corresponding maximum acceleration for the given mass. Using the maximum acceleration overcomes a sudden starting and stopping in other mobility models such as the random walk and the random way point models [24], [33]. As a result of the given maximum acceleration, it can also model a slow curve at a high speed due to a physics law.

B. Perception Model

Each node in the model emulates its visual or audio senses. However, a precise perception modeling itself is out of the scope of this paper. The perception model in this paper is simplified to extract a direct effect on its movement. The motion of a node is heavily dependent on the sensing and cognitive process of the node and its environment. For example, if an node is assumed to be a human being moving during daytime, it highly relies on directional visual sense, but an omnidirectional audio sense is the main cognitive input process during nighttime. For a high-speed vehicular simulation, the visual attention angle is highly dependent on the speed of the vehicle. This paper does not intend to discover the cognitive processes themselves, but wants to find how much neighbors of a node affect its movement.

The nodal behavior in the SGM depends only on nearby neighbors. The neighborhood of a node is defined as a cyclic region centered at the node. To model the sensitivity, the communication theory of attenuation ratio is borrowed. The attenuation of a signal is defined as the reduction or loss in signal power as it propagates through a system such as $P_{\text{send}}/P_{\text{recv}}$ [21], where P_{send} is the signal power sent by a signal source and P_{recv} is the signal power received by a signal receptor after traveling through a media. For free space, attenuation is proportional to αd^n, where d is the distance from the signal source, n is a path loss exponent (mostly $n = 2$ and for environment with obstacles, $n > 2$), and α is a constant coefficient. Henceforth, $P_{\text{recv}} = P_{\text{send}}/\alpha d^n$, in that the received signal power is inversely proportional to the attenuation. An node movement is sensitive to the received signal power, but the relationship between the motion sensitivity and the received signal power is still being researched. There are many unknown factors in the relationship, and it might depend on the kind of signals. For example, it is reasonable to assume that the sensitivity of an audio signal is proportional to decibel, or $n \log d$. For some environments, attenuation might have an exponential dependence on distance, that is, $P_{\text{send}}/P_{\text{recv}} = \alpha e^d$.

Our goal in this paper is to characterize the metrics of the weight of attraction or repulsion between two nearby particles but not to compute an exact received power. As a result, we propose three perception sensitivity weight models and define a maximum sensing distance to make the simulation model simple. The first sensitivity weight model of a quadratic model is based on the assumption that the motion sensitivity is directly proportional to the received signal power in a free space. If a neighbor of a node is out of its sensing maximum range ($d_{\max}$), we assume that the node is not affected by the neighbor. So, the motion sensitivity function s depending on the distance from a signal source to a signal receptor is described as $s_1(d) = c_1/d^n$. The next model is a logarithmic model in which the motion sensitivity is related to the logarithm of the received signal power as $s_2(d) = c_2/\log d$. The weight of the logarithmic model can be maintained over a much longer distance than other models. From these models, the weight increases infinitely as the distance decreases. To avoid this infinity weight, the constant of the minimum distance $d_{\min}$ can be introduced to make the weight constant within a short distance as $s_i(d_{\min})$. The last model is an exponential model. The exponential model can be used to avoid the case of the infinity weight as $s_3(d) = c_3 \exp(-2\pi d/d_{\max})$. The exponential model shows a slow curve of the weight functions among close neighbors.

C. Behavioral Model

In the SGM simulation, each node emulates its behavior on 2D space. Note that a simulation on 3D space including gravity and buoyancy modeling is out of scope of this paper. The simulation is based on several behavioral models such as centering, target-seeking, collision avoidance, velocity matching, and random navigating. Each behavior or tendency is expressed as a force, and prioritized by being assigned a weight from the sensitivity models discussed in the previous section. The resulting acceleration is denoted as a weighted sum of the forces.

A node has a tendency to move itself toward the center of its neighbors. Why do natural nodes tend to come close to each other? The primary argument might be the consequence of several psychological or sociological considerations such as protecting from attack, taking advantage of search for food or target. The centroid tendency of node j is expressed as $v_j^c = \sum p_i/n - p_j$, where p_i is the position vector of neighbors within the sensing range of node j and n is the number of the neighbors. If a node is in the middle of a cluster, the center of the neighbors $\sum p_i/n$ is near the current position of the node p_j and the effect of the centering tendency is balanced and canceled. For a node on the side of the cluster, however, the majority of neighbors are on one side of the node and the tendency toward the center becomes greater than nodes in the middle of the cluster.

A node makes pursuit of targets within its sensing range. A closer target has a higher priority than other targets, which is modeled using one of the sensitivity models described previously. The target-seek tendency of node j is given by $v_j^t = \sum s(|p_i - p_j|)(p_i - p_j)/\sum s(|p_i - p_j|)$, where the function $s()$ denotes one of the sensitivity weights described in the previous section, and p_i is the position vector of target i within the sensing range of node j.

While the tendencies of centroid and target-pursuit can make nodes come too close each other, the collision avoidance model stimulates nodes to keep away from an impact. This opposite force between two nearby nodes can simulate not only a direct crush avoidance, but also an effect for spreading nodes in a small region by adjusting constants $d_{\min}$ and $d_{\max}$ of the sensitivity weight models. The reasons why nodes tend to spread are the result of efficiency or safety concerns. For examples, an animal seems to look for its own territory for food, a soldier moves forward while maintaining its own coverage, and a driver needs to keep a safe distance from its neighbors to avoid a possible collision. The collision avoidance tendency of node j can be denoted by $v_j^a = \sum s(|p_i - p_j|)(p_j - p_i) / \sum s(|p_i - p_j|)$, where p_i is the position vector of neighbor i within a collision distance from node j.

A node has a tendency of moving in the same direction and speed as its neighbors. The reason for this behavior is that a node esteems that it may be disjoined from a group in a near future unless it follows its neighbors' behavior. The tendency is also prioritized on the distance to the neighbors and denoted by $v_j^m = \sum s(|p_i - p_j|) v_i / \sum s(|p_i - p_j|)$, where v_i is the velocity of neighbor i within a sensing distance of node j.

An intelligent node decides its behavior based on the dynamic models described above: centroid, target-pursuit, collision-avoidance, and velocity-matching. Each model is assigned a precedence to model the attention to the circumstance. In a real group motion, however, a node (e.g. an animal in a herd of land animals) may show an unexpected sudden behavior such as deviating from the group or falling behind the group. A random velocity vector is added to model this unexpected behavior. Combining all the behavior and physics models, the new velocity (v_j) and the new position (p_j) of node j, are computed from the following kinematic equations:

$$a_j = w^c v_j^c + w^t v_j^t + w^a v_j^a + w^m v_j^m + w^r v_j^r \quad (1)$$

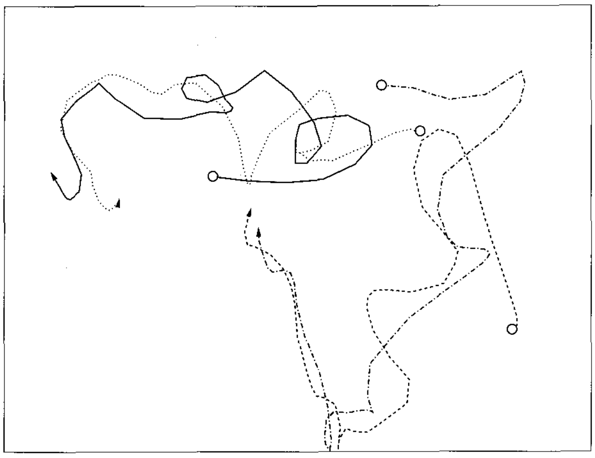
$$v_j = \alpha v_j + \min(a_j, \langle a_{\max}, \tan^{-1} a_j \rangle) \quad (2)$$

$$p_j = \beta p_j + \min(v_j, \langle v_{\max}, \tan^{-1} v_j \rangle)\Delta T, \quad (3)$$

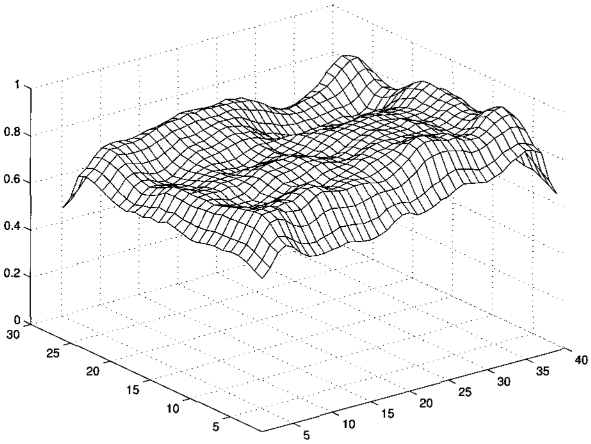
where $\langle r, \tan^{-1} v \rangle$ is a vector in a polar coordination whose length is r and angle is identical to that of vector v. $a_{\max}$ and $v_{\max}$ are pre-defined constants to indicate the maximum acceleration and the maximum speed of the node. α and β decide the rate of change from old to new. A small α and β will result in large possible change in a new velocity.

D. Complexity

The time complexity of the SGM simulation for n nodes is $O(n^2)$, because each node has to consider all other nodes, that is, a node needs the positional information of all nodes, even if only to determine whether the nodes are within the range or not. A real node, however, moves without considering the whole population. Instead, it considers only nearby neighbors. The question is how to make a simulated node sense and consider only nearby nodes even without accessing information of distant nodes. A simple solution is to order particles based on either x-position and/or y-position. Assuming that nodes are ordered on x-position, a node at (p_x, p_y) investigates neighbors in the range of $p_x \pm d_s$ from the ordered list, where d_s is the sensing distance. The effect of the range is to divide the space into a vertical strip. Even though the strip can reduce the number of particles under consideration, the computation complexity for maintaining the ordered list is not trivial because a node needs to retrieve the ordered list to find the correct location, to update its order list for for each move of a particle. Another approach to mimic the local retrieval is to partition the space into grids with a fixed interval, and to create a dynamic association of a node position and a grid cell. By choosing the grid interval as d_s, for example, a node in a grid cell (i, j) only needs to retrieve nodes in nine nearby cells of the range $(i \pm 1, j \pm 1)$ to find the set of its neighbors.



(a) Traces of 4 nodes in Swarm-group model



(b) Node spatial distribution

Fig. 1. Basic Characteristics of Swarm Group Model

IV. Experimentation

We conducted comprehensive simulations for the swarm group model as well as the random walk model and the random waypoint model to compare with the new group model. Each model consisted of 20 mobile hosts in 800m by 600m, and the nodes were randomly placed in the simulation region initially. The simulation of each model was run for 12 hours.

The traveling pattern of mobile nodes using the SGM model is shown in Figure 1(a), in which four mobile nodes were chosen for 600 seconds. The tracing characteristics of other mobility models can be found in [7]. The mobile node in our simulation were initially placed in random location indicated by small circles, but they formed two groups shortly after starting the simulation. Each mobile node moved wildly within the group depending on the behavioral model described previously.

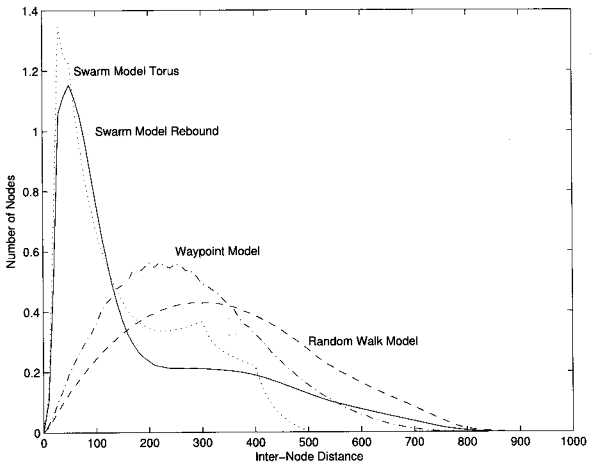
Figure 1(b) shows the normalized node spatial distribution of the SGM model with a rebound boundary, in which a node changes its direction oppositely when it reaches a boundary. The theoretical and experimental spatial distribution of the random walk and the random waypoint models can be found in [4], [13], [24]. The nodal distribution in the figure is almost uniform in the middle of the simulation region. However, it increases as it comes close to the boundary and decreases at the boundary. This distortion is caused by the clustering effect of the SGM. When a group of nodes rebound at the boundary, nodes in their leading group rebound naturally, but nodes in the succeeding group tend not only to move toward the boundary, but also to change their direction to the leading group directly. The nodes in the succeeding group can follow the leading group without rebounding to the boundary. As a result, the density close to the boundary is high, but the one at the boundary is low. To avoid the distortion of spatial distribution with a limited simulation region, a boundless simulation area can be adopted, in which a mobile node reaching one side of the boundary continues travelling and reappear on the opposite side of the boundary [7]. In addition, a node calculates the distance of its neighbor by considering a boundary wrapped around with its opposite boundary. For example, the distance $D_{<a,b>}$ between two nodes a and b, whose locations are (x_a, y_a) and (x_b, y_b), respectively, can be obtained as

$$D^2_{<a,b>} = \min(|x_a - x_b|, X_{\max} - |x_a - x_b|)^2 + \min(|y_a - y_b|, Y_{\max} - |y_a - y_b|)^2,$$

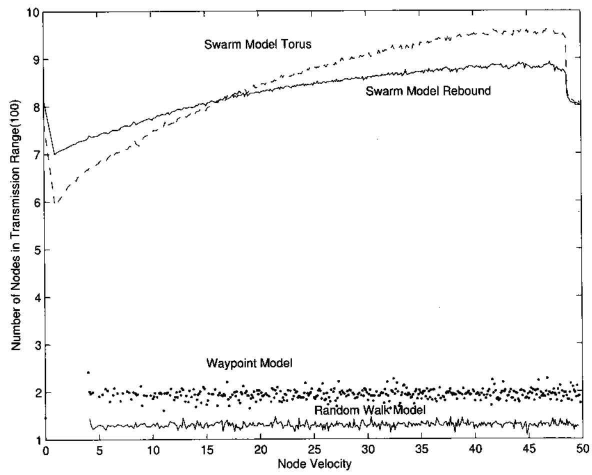
where $X_{\max}$ and $Y_{\max}$ are the size of simulation area. The boundless simulation eliminates the distortion in the spatial distribution, but its inter-nodal distribution, the essential characteristic for ad-hoc networks, is very similar to the result of a rectangular area.

Figure 2(a) shows the nodal distribution depending on the inter-node distance for the four mobility models. Note that the distributions are normalized to fairly compare among the models. To the study of ad hoc wireless networks, the relation between the number of mobile hosts and their distance is the major concern rather than the spatial distribution, because communication occurs between the mobile hosts but not between a base-station and a mobile host. Although both the Random Walk model and the boundless SGM have uniform spatial distributions, the movement pattern and aggregated behavior of mobile hosts in the SGM generate an extremely different result from the Random Walk model. More properly, the boundless SGM holds a similarity with the rebounding SGM regarding the inter-node distribution.

The nodal distribution of inter-node distance is the feature of ad hoc wireless communication networks for estimating a node connectivity among its neighbors and optimizing the power consumption of a mobile host. For example, assume that it is sufficient for a node to maintain 4-connectivity in average by adapting its transmission power. Note that the simulation was conducted with 20 mobile hosts so that 4 nodes can be considered as 20% of population. If the mobile hosts are assumed to move in the Random Walk model, a node must maintain its transmission power for 200m from the distribution of Figure 2(a). In the meanwhile, a node can transmit with the power of no more than 100m if the nodes are assumed to follow the SGM models.



(a) Nodal distribution of inter-node distance



(b) Dependency of the number of nodes in a transmission range and node speed

Fig. 2. Inter-nodal distribution and velocity dependency

In Figure 2(b), we show the relation between node speed and the number of nodes within a transmission range of 100m. As we can expect, the Random Walk and Random Waypoint models indicate no relationship and the numbers of nodes in the transmission range are very low because nodes wander in the simulation space independently without any collaboration. The number of nodes for the Random Waypoint model is slightly larger than the number of nodes for the Random Walk model because of the border effect, or non-uniform spatial distribution, in which the node density in the mid-space is higher than the one at the boundary.

In both SGM models, however, the number of neighbors increases as the node speed increases, which indicates that the higher speed nodes move, the higher tendency the nodes aggregate each other. As described earlier, a node moves as a result of a combination of five forces in conjunction with its current speed. The combined forces have relatively more impact to the node movement in a slow speed than in a high speed so that the opposite forces, such as collision-avoidance tendency and the random navigating, cause the group of nodes to scatter. Another reason is that the force of velocity-matching becomes low as the nodes move slowly, so that the impact of this positive force, or an aggregating force, is not intense at the low speed. Comparing the boundless and rebounding SGMs, the boundless SGM has higher aggregation that the rebounding SGM because a node follows its group at a boundary in the former model without any obstables so that nodes are aggreagated each other for a logner time.

V. Conclusion

In this paper, we proposed a group mobility model named Swarm Group Mobility model. The model generated the realistic motion of living creatures or objects controlled by living creatures by mimicking perception, physics, and psychological behaviors. The model simplified and parameterized the behavioral models. The model can be easily utilized for ad hoc wireless communication networks, in which the traditional Random Walk or Random Waypoint mobility models are not sufficient because they do not explain the correlation of node movements and the assumption of uniform randomness. Extensive simulation was conducted to compare the new mobility model with the traditional models. A couple of new features were extracted from the simulation, which are adequate for applying the ad hoc mobile network to the study of optimizing peer connectivty and transmission power.

There are several directions to the future work of the SGM model. Parameters used in the model, such as the sensing model, weight of behavioral models, need to be optimized for real group motion. By tracing real mobile host, a set of features in mobility needs to be developed so that the simulation and its parameters can be optimized to match to the feature set. A terrain model must be also considered for evaluating wireless communication in hills/valley, highways, 3D indoor and metropolitan pedestrians.

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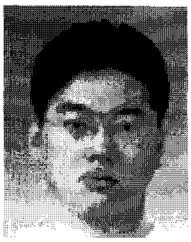

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