A Mobility Prediction (MP)-based Phenomenon Monitoring in an Unbounded Area

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***Abstract*—The task of monitoring a moving phenomenon in an unbounded area using a mobile sensor network (MSN) brings out several challenges due to the high movement speed of phenomenon, the limited sensing/communication capabilities of mobile sensor nodes. To address the challenges and achieve a high weighted sensing coverage, in this paper we propose a monitoring algorithm, namely VirFID-MP (Virtual Force (VF)-based Interest-Driven moving phenomenon monitoring with Mobility Prediction). In VirFID-MP, the movement of phenomenon is first predicted based on its previous movements. Then, the predicted information is used to determine a global virtual force, which is utilized to speed up the MSN toward the moving phenomenon. Simulation results show that VirFID-MP outperforms original VirFID in terms of weighted coverage efficiency, when the MSN monitors a moving phenomenon.**

***Index Terms*—Mobile sensor nodes; moving phenomenon; virtual forces; mobility prediction**

I. INTRODUCTION

In this paper, we study the use of multiple mobile sensor (MS) nodes (e.g., mobile robots, unmanned aerial vehicles (UAVs)) to form a mobile sensor network (MSN) [1], [2], [3], [4], [5] for monitoring a moving phenomenon in an unknown and unbounded area. For example, MS nodes can be deployed to monitor an area of interest, such as flood, polluted area or disaster area, where the phenomenon of interest (e.g., gas/radiation leakage, radioactivity substance, toxic pollutants) may change its position and distribution over time.

Our goal is to control the movements of MS nodes so that they can quickly and reliably monitor and follow the phenomenon while maintaining the maximum sensing coverage and the network connectivity for long-term monitoring. However, designing such a phenomenon monitoring algorithm involves a lot of challenges due to the unpredictable changes of phenomenon and the limited sensing/communication capabilities of MS nodes.

In order to achieve these objectives of phenomenon monitoring, a few monitoring algorithms using MS nodes have been proposed in [6], [7]. For example, the authors in [6] proposed a cluster creation-based monitoring algorithm, namely Causataxis that makes the MSN to grow toward the phenomenon of interest by continuously creating new clusters at the high interest area, and rotting clusters at low interest area. However, the MSN under Causataxis fails to maintain a high sensing coverage when it monitors a moving phenomenon due to its low network growth speed, as a result of cluster creation overhead.

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In addition, Virtual Force (VF)-based Interest-Driven moving phenomenon monitoring (VirFID) schemes were proposed in [7] to achieve a better sensing coverage with the moving phenomenon. In VirFID, the movement of each MS node is driven by the sum of virtual forces, which is determined using the local and global information sharing among nodes. The use of virtual force enables the MSN to achieve a higher sensing coverage compared with Causataxis, particularly when the MSN follows a moving phenomenon.

However, in VirFID, the MSN firsts detects the movement of phenomenon based on the change of interest values of nodes, then responses to it by updating the nodes' movements using the virtual forces. Therefore, when the phenomenon moves at high speed, the MSN may become behind the phenomenon, and can not maintain a desired weighted sensing coverage.

To overcome the limitations of VirFID, in this paper we propose VirFID-MP (VirFID with Mobility Prediction) that performs the prediction of the future movement of the phenomenon to speed up MS nodes toward the phenomenon. More specifically, in VirFID-MP, the movement (i.e., movement speed and direction) of the phenomenon is periodically determined based on the movement information of nodes in the MSN at every time interval.

Then, the future movement of phenomenon is predicted using the information on its current and previous movements. The predicted information is used to determine a global force, called mobility prediction (MP)-based global virtual force. This global virtual is exerted on all MS nodes to make the MSN faster to follow the moving phenomenon.

The rest of the paper is organized as follows. In Section II, we present the system model considered in this paper. Section III presents our preliminary work. In Section IV, the proposed algorithm is described in detail. In Section V, simulation setup and performance analysis are discussed. Finally, Section VI gives the conclusion of the paper.

II. System Model

In this paper, the system under consideration consists of multiple mobile sensor (MS) nodes (e.g., mobile robots, unmanned aerial vehicles (UAVs)). MS nodes (or referred to as simply nodes) are equipped with sensing devices to collect interest data on the phenomenon (e.g., a radioactivity level, the temperature, or the concentration level of toxic pollutants).

Each MS node is also equipped with a communication device to exchange the cooperative task-related information with other nodes or relay the collected data to the center for further analysis.

The interest distribution of the phenomenon is modeled by a function $f(x, y, t)$ of coordinates of (x, y) and time of t. Using the equipped sensing device, at time t each MS node can obtain the interest value (i.e., sensed value) at its position of (x, y). Also, it is assumed that each MS node knows its geographic position using localization techniques [8]. Once an MS node decides to move to a target position, it uses an equipped navigation system to move towards the target position.

III. Preliminary Work

In order to enable the MSN to track and follow a moving phenomenon in an unbounded area for long-term monitoring, Virtual Force (VF)-based Interest-Driven moving phenomenon monitoring (VirFID) schemes were proposed in [7]. In VirFID schemes, the local neighborhood information and the global information sharing in the MSN are used to determine the virtual forces, which are then utilized to control the movements of nodes toward the phenomenon.

More specifically, the local information on neighborhood positions and interest values is used to calculate the local virtual force, which includes formation and interest forces. While the interest force enables nodes to track and follow the phenomenon, the formation force allows network connectivity among nodes by making neighboring nodes maintain a certain distance between them.

To determine the formation and interest virtual forces, each node maintains a list including positions and interest values of its neighboring nodes, which is performed using periodic beacon message exchange mechanism.

Let $f = (f_x, f_y)^T$ denote a column vector where f_x and f_y are x and y coordinates of f, respectively. If we denote (x_i, y_i) and (x_j, y_j) as positions of two neighboring nodes i and j, the formation force vector, f_{ij}^{form}, which is applied on node i by node j is calculated as

$$f_{ij}^{form} = \frac{\delta_{ij}}{d_{ij}} \big(x_j - x_i, y_j - y_i\big)^T \tag{1}$$

where $d_{ij} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$ is distance between two nodes i and j, and δ_{ij} can be expressed as

$$\delta_{ij} = \begin{cases} C_a(d_{ij} - d_{th}) & \text{if } d_{ij} \geq d_{th} \\ C_r(d_{ij} - d_{th}) & \text{o/w} \end{cases} \tag{2}$$

where C_a and C_r are attractive and repulsive constants, and d_{th} is distance threshold desired between two neighbor nodes. Under formation forces, two neighbor nodes are kept connected with a threshold distance.

Let denote I_i and I_j as the interest values of i and j, respectively. Then, the interest virtual force vector, f_{ij}^{int}, which is exerted on node i by node j is

$$f_{ij}^{int} = \frac{\xi_{ij}}{d_{ij}} \big(x_j - x_i, y_j - y_i\big)^T \tag{3}$$

where $\xi_{ij} = \text{sgn}\big(I_j - I_i\big) C_i e^{\frac{-1}{|I_i - I_j|}}$. Note that C_i is a interest constant, and *sgn(.)* denotes the sign function. As shown in (3), the interest force moves a node closer the neighbor having a higher interest value, and away from the neighbor of a lower interest value.

In VirFID, in addition to the local information, the global information on interest values and positions of nodes in the MSN is also used to determine an additional force, called global virtual force. By using the global force, the nodes in the MSN can more flexibly adjust their positions to explore uncovered area of higher interest value, and achieve higher performance.

In order to move toward the phenomenon, at every period t_m, each node first determines the sum of forces, including the local and global forces acting on it. Then, the calculated force is used to determine the next position to which the node should move after period t_m.

Moreover, depending on the level of information used to determine the virtual forces, three variants of VirFID were presented in [7], which are VirFID-LIB (Local Information-Based), VirFID-GHL (Global Highest and Lowest), and VirFID-IBN (Interest at Boundary Nodes). More specifically, while VirFID-LIB uses only the local information, VirFID-GHL and VirFID-IBN also use the global information. For example, VirFID-IBN uses the global information on interest values of boundary nodes to determine the global force, and achieves the highest weighted sensing coverage among three VirFID schemes.

IV. Mobility Prediction based Phenomenon Monitoring Algorithm

In order to improve the performance of VirFID algorithm for monitoring a high-speed moving phenomenon, we propose VirFID-MP (VirFID with Mobility Prediction). In VirFID-MP, the future movement (i.e, movement speed and direction) of phenomenon is first predicted based on the information on previous movement of phenomenon. The predicted information is then used to determine a global virtual force, which is utilized to speed up the MSN toward the phenomenon.

It is assumed that nodes are initially deployed around the highest interest point of the phenomenon. When the phenomenon moves to another location, the nodes also move along the movement direction of the phenomenon to follow it using the interest force in (3). Therefore, the movement of the phenomenon can be represented based on the movements of nodes.

Suppose that the time is divided into intervals of t_m, and each interval begins at $t_j = jt_m$ $(j = 0, 1, 2, \ldots)$. Let

$\{(x_i^0, y_i^0), (x_i^1, y_i^1), \ldots, (x_i^j, y_i^j)\}$ denote the movement trajectory of node i ($i = 1, \ldots, N$) up to time t_j, where N is the number of nodes in the MSN. Also, let $d_i^j = (d_x, d_y)^T$ denote the movement vector of node i at time t_j, which is expressed as

$$d_i^j = \frac{1}{\Gamma_i^j}\big(x_i^j - x_i^{j-1}, y_i^j - y_i^{j-1}\big)^T \tag{4}$$

where Γ_i^j is distance between two positions (x_i^{j-1}, y_i^{j-1}) and (x_i^j, y_i^j).

If we denote χ_i^j is the interest gain of node i by moving from position (x_i^{j-1}, y_i^{j-1}) to position (x_i^j, y_i^j) at t_j, the value of χ_i^j is calculated as

$$\chi_i^j = \begin{cases} \frac{I_i^j}{I_i^{j-1}} & \text{if } I_i^{j-1} > 0 \\ I_i^j & \text{if } I_i^{j-1} = 0 \end{cases} \tag{5}$$

We define $Z^j = (z_x^j, z_y^j)^T$ as the movement vector of the phenomenon. Then, Z^j can be determined based on the movement vectors of nodes as

$$Z^j = D^j \chi^j \tag{6}$$

where $D^j = (d_1^j, d_2^j, \ldots, d_N^j)$, and $\chi^j = (\chi_1^j, \chi_2^j, \ldots, \chi_N^j)^T$.

Let θ^j represent the movement direction angle of the vector Z_j from the x-axis. Then the value of θ^j is

$$\theta^j = \arctan\left(\frac{z_y^j}{z_x^j}\right) \qquad (0 \le \theta^j \le 2\pi) \tag{7}$$

Since θ^j does not represent the relative angle change between two consecutive movement vectors of the phenomenon, we define $\theta_d^j = \theta^j - \theta^{j-1}$ as the different angle i.e, the movement direction change of the phenomenon between time t_j and t_{j-1}.

In addition, let us denote v_i^j as the movement speed of node i at time t_j and $v_i^j = \frac{\Gamma_i^j}{t_m}$. If we denote v^j as the movement speed of the phenomenon, the value of v_j is calculated as

$$v^j = \|D^j V^j\| \tag{8}$$

where $V^j = (v_1^j, v_2^j, \ldots, v_N^j)^T$, and $\|.\|$ denotes *Euclidean* norm of a vector.

Up to time t_j, the movement history data of the phenomenon can be represented by two data series:

$$\begin{cases} \Theta = \{\theta_d^0, \theta_d^1, \theta_d^2, \ldots, \theta_d^j\} \\ V = \{v^0, v^1, v^2, \ldots, v^j\} \end{cases} \tag{9}$$

Note that $\theta_d^0 = 0$ and $v^0 = 0$.

Based on the movement history of the phenomenon in (9), in this study the future movement of phenomenon is predicted using a similar way to Heuristics EXP-AVG model in [9]. More specifically, the future movement is estimated using a certain number of movement history data points and a different weight is assigned to each point, which results in a different effect on the predicted value.

Let $\hat{\theta}_d^{j+1}$ and $\hat{v}^{j+1}$ denote the predicted values of the angle difference and the movement speed of the phenomenon at time t^{j+1}, respectively. Then, the values of $\hat{\theta}_d^{j+1}$ and $\hat{v}^{j+1}$ are calculated as

$$\begin{cases} \hat{\theta}_d^{j+1} = \sum_{k=0}^{M-1} w_k \theta_d^{j-k} \\ \hat{v}^{j+1} = \sum_{k=0}^{M-1} w_k v_d^{j-k} \end{cases} \tag{10}$$

where M is number of history data points used for prediction, and w_k ($k = 0, 1, \ldots, M-1$) is weight factor, which is expressed as

$$w_k = \frac{M-k}{\sum_{i=1}^{M} i} \tag{11}$$

Note that $\sum w_k = 1$. As shown in (10) and (11), the most recent movement history data point has a highest weight factor on the predicted value.

Equation (10) gives the predicted movement speed and different angle of the phenomenon at time t_{j+1}. Then, the predicted movement direction of phenomenon, $\hat{\theta}^{j+1}$, at time t_{j+1} is calculated as

$$\hat{\theta}^{j+1} = \hat{\theta}_d^{j+1} + \theta^j \tag{12}$$

At time t_j, using the predicted movement direction and speed of the phenomenon for time t_{j+1}, an additional force, called mobility prediction (MP)-based virtual force, f^{mp}, is determined to exert on every node in the MSN. This force can be expressed as

$$f^{mp} = \eta \hat{v}^{j+1}\big(\cos\hat{\theta}^{j+1}, \sin\hat{\theta}^{j+1}\big) \tag{13}$$

where η is a constant. As shown in (13), using the mobility prediction (MP)-based virtual force, the node moves toward the predicted movement direction of the phenomenon.

In VirFID-MP, to determine the mobility prediction (MP)-based virtual force, at every time interval t_m, each node in the MSN sends its current position and interest value to the *root* node using a tree-based routing protocol. Note that the root can be selected at initial deployment phase of the MSN.

Upon receiving the positions and interest values from nodes, the root first calculates the current speed and direction of the phenomenon, and performs the prediction to estimate the future movement of the phenomenon using the current information and the stored previous information on the movement of the phenomenon. Then, the predicted movement speed and direction of the phenomenon is flooded to all nodes in the MSN.

Once a node receives the predicted values from the root, it calculates the mobility prediction (MP)-based global virtual force. Then, the node uses this global force, in addition to the local force acting on node by its neighboring nodes to update its movement.

V. Performance Study

In this section, we first present simulation setup that is used to evaluate the performance of the proposed algorithm. Then, we compare the performance of proposed VirFID-MP

TABLE I
SIMULATION PARAMETERS AND VALUES

Parameters	Values
Communication range R_c	400 m
Sensing range R_s	100 m
Attractive force constant C_a	1
Repulsive force constant C_r	40
Interest force constant C_i	200
MP-based force constant η	200
Number of used history data M	10

with variants of original VirFID in terms of weighted coverage efficiency.

A. Simulation Setup

In order to evaluate the performance of VirFID-MP, we consider an MSN consisting of multiple MS nodes which are deployed in an open area. The communication range of R_c and the sensing range of R_s of each node is set to 400 m and 100 m, respectively.

System parameters are set as follows. For formation force, constants C_a and C_r are set to 1 and 40, respectively. The distance threshold d_{th} is set to the distance between two neighboring nodes in hexagonal pattern, which maximizes the sensing coverage while reducing coverage holes [10], i.e., $d_{th} = \sqrt{3}R_s$. Also, for interest force, C_i is set to 200.

For mobility prediction model, we use 10 the most recent movement data points to predict the future movement of the phenomenon i.e., $M = 10$. The value of η is set to 200. Also, a network simulator Qualnet 5.1 [11] is used to simulate the communication and movement of MS nodes. Some important simulation parameters are shown in the Table I.

To evaluate the performance of VirFID-MP, we use weighted coverage efficiency (WCE) metric, which indicates that how effectively MS nodes can cover the area of interest. More specifically, WCE is defined as the ratio of the interest values of all unit squares (1m × 1m) covered by MS nodes to the interest values of the entire area that has the interest value greater than 0. Moreover, we compare VirFID-MP with two variants of original VirFID (VirFID-LIB and VirFID-IBN).

On the other hand, the movement of the phenomenon is simulated using Gauss-Markov mobility model [12], [13]. More specifically, the movement direction and speed of the phenomenon is periodically updated at every time interval of τ. The values of movement speed (s_n) and direction (d_n) at the n^{th} interval is calculated based on values of s_{n-1} and d_{n-1} at

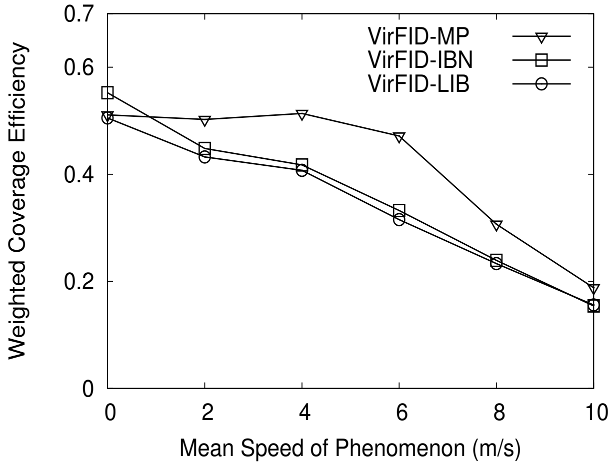

Fig. 1. Monitoring a moving phenomenon with 40 nodes

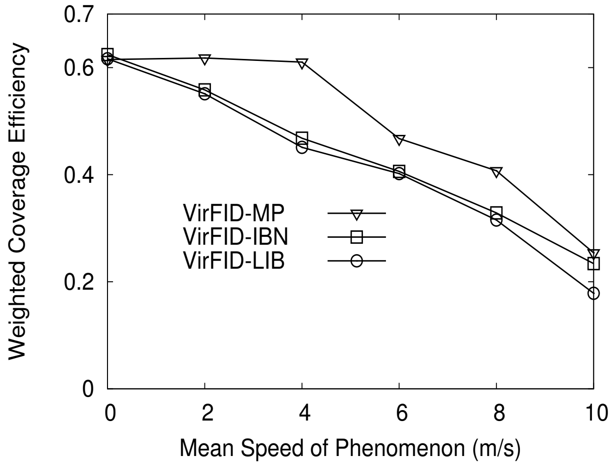

Fig. 2. Monitoring a moving phenomenon with 60 nodes

previous interval $(n-1)^{th}$ as

$$\begin{cases} d_n = \alpha d_{n-1} + (1-\alpha)\mu_d + \sqrt{1-\alpha^2}w^d_{n-1} \\ s_n = \alpha s_{n-1} + (1-\alpha)\mu_s + \sqrt{1-\alpha^2}w^s_{n-1} \end{cases} \quad (14)$$

where $0 \leq \alpha \leq 1$, μ_d and μ_s are asymptotic mean of direction and speed as $n \to \infty$, and w^d_n and w^s_n are uncorrelated and stationary Gaussian processes with zero-mean and variance σ^2. In our simulations, we use $\tau = 50s$, $\alpha = 0.6$, $\sigma = 1$, and $\mu_d = \pi/2$. Also, the value of μ_s is varied to change the movement speed of the phenomenon.

B. Performance Analysis

Figures 1, 2, and 3 show the WCE of VirFID-MP, VirFID-IBN, and VirFID-LIB when the mean movement speed of the phenomenon (μ_s) is varied from 0 to 10 mps. The WCE is collected 300 s after the phenomenon starts moving. The results

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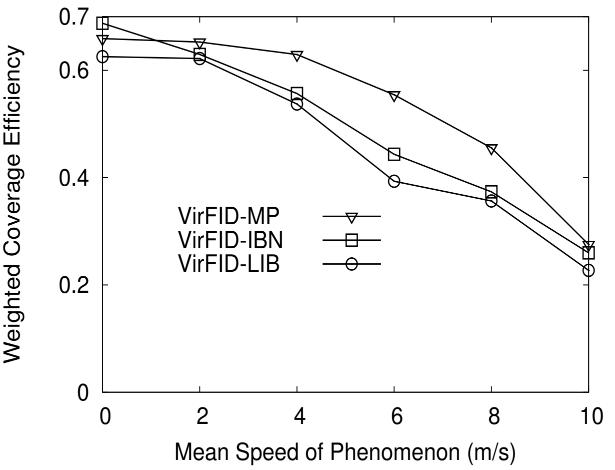

Fig. 3. Monitoring a moving phenomenon with 80 nodes

using a number of nodes of 40, 60, and 80 are presented in Figs. 1, 2, and 3, respectively.

As shown in Figs. 1, 2, and 3, as the movement of phenomenon increases, the WCE of three algorithm decreases. Also, when the speed of phenomenon is greater than 0, for all case of number of nodes, VirFID-MP consistently has the highest WCE among three algorithms. For example, in Fig. 2, when number of nodes is 60 and the speed of phenomenon is 4 mps, the WCE of VirFID-MP is 0.61 while the values of VirFID-IBN and VirFID-LIB are 0.47 and 0.45, respectively.

The reason for higher WCE of VirFID-MP than VirFID-LIB and VirFID-IBN is the usage of mobility prediction. Using the predicted movement of the phenomenon, the MSN can detect the future movement of the phenomenon and adjust its movement direction fast enough to closely follow the phenomenon and maintain a high weighted sensing coverage. In addition, as shown in Figs. 1, 2, and 3, all algorithms greatly lose WCE when the mean movement speed of the phenomenon becomes higher than 8 mps.

Note that as shown in Figs. 1, 2, and 3, when the mean speed of the phenomenon is zero, VirFID-MP exhibits a similar WCE to VirFID-LIB and a lower WCE than VirFID-IBN. This is because when the mean speed of the phenomenon is zero, the mobility prediction (MP)-based global force approximates to zero. Therefore, nodes in VirFID-MP are only driven by the local virtual force, which is the same as in VirFID-LIB.

VI. Conclusions

In this paper, we have proposed a phenomenon monitoring algorithm, called VirFID-MP (VirFID with Mobility Prediction), which enables MS nodes to form an MSN for monitoring a moving phenomenon in an open area. In VirFID-MP, the future movement of the phenomenon is predicted to determine a global virtual force, which moves MS nodes toward the movement direction of the phenomenon. Using this global virtual force, MS nodes can speed up their movements toward the phenomenon, and maintain a high weighted sensing coverage when they monitor a moving phenomenon. Simulation results have shown that VirFID-MP can achieve a higher weighted coverage efficiency than variants of original VirFID in case of monitoring a high-speed moving phenomenon.

References

[1] I. F. Akyildiz and I. H. Kasimoglu, "Wireless sensor and actor networks: Research challenges," *Ad Hoc Networks*, vol. 2, no. 4, pp. 351–367, May 2004.

[2] B. J. Julian, M. Angermann, M. Schwager, and D. Rus, "Distributed robotic sensor networks: An information-theoretic approach," *International Journal of Robotics Research*, vol. 31, no. 10, pp. 1134–1154, Sept. 2012.

[3] J. Cortes, S. Martinez, T. Karatas, and F. Bullo, "Coverage control for mobile sensing networks," *IEEE Transactions on Robotics and Automation*, vol. 20, no. 2, pp. 243–255, Apr. 2004.

[4] lker Bekmezci, O. K. Sahingoz, and amil Temel, "Flying ad-hoc networks (FANETs): A survey," *Ad Hoc Networks*, vol. 11, no. 3, pp. 1254 – 1270, May 2013.

[5] D. Bhadauria, V. Isler, A. Studenski, and P. Tokekar, "A robotic sensor network for monitoring carp in minnesota lakes," in *IEEE International Conference on Robotics and Automation*, May 2010, pp. 3837–3842.

[6] S. Yoon, O. Soysal, M. Demirbas, and C. Qiao, "Coordinated locomotion and monitoring using autonomous mobile sensor nodes," *IEEE Transactions on Parallel and Distributed Systems*, vol. 22, no. 10, pp. 1742–1756, Oct. 2011.

[7] D. V. Le, H. Oh, and S. Yoon, "VirFID: A virtual force (VF)-based interest-driven moving phenomenon monitoring scheme using multiple mobile sensor nodes," *Ad Hoc Networks*, vol. 27, pp. 112 – 132, Apr. 2015.

[8] N. A. Alrajeh, M. Bashir, and B. Shams, "Localization techniques in wireless sensor networks," *International Journal of Distributed Sensor Networks*, vol. 2013, 9 pages, Jun. 2013.

[9] Y. Xu, J. Winter, and W.-C. Lee, "Prediction-based strategies for energy saving in object tracking sensor networks," in *Proc. 2004 IEEE International Conference on Mobile Data Management*, Jan. 2004, pp. 346–357.

[10] J. Li, B. Zhang, L. Cui, and S. Chai, "An extended virtual force-based approach to distributed self-deployment in mobile sensor networks," *International Journal of Distributed Sensor Networks*, vol. 2012, pp. 1–14, Feb. 2012.

[11] http://web.scalable networks.com/content/qualnet.

[12] B. Liang and Z. Haas, "Predictive distance-based mobility management for pcs networks," in *Proc. IEEE INFOCOM '99*, Mar. 1999, pp. 1377–1384.

[13] T. Camp, J. Boleng, and V. Davies, "A survey of mobility models for ad hoc network research," *Wireless Communications and Mobile Computing (WCMC): Special Issue on Mobile Ad Hoc Networking: Research, Trends and Applications*, vol. 2, pp. 483–502, Step. 2002.