Area Coverage in a Fixed-Obstacle Environment using Mobile Sensor Networks

Hamid Mahboubi, Amir G. Aghdam and Kamran Sayrafian-Pour

Abstract

In this paper, efficient deployment strategies for mobile sensor networks are proposed to improve the coverage area in target fields containing obstacles. The developed algorithms iteratively calculate and update the position of the sensors in order to improve the overall achievable coverage by the network. The *visibility-aware multiplicatively weighted Voronoi* (VMW-Voronoi) diagram is used to discover coverage gaps in networks that have sensors with different sensing capabilities. The sensors, then, reduce the size of the coverage gaps in the target field. The relocation strategy also considers possible existing obstacles on the field. Simulation results are provided to demonstrate the effectiveness of the proposed distributed deployment schemes.

I. Introduction

Autonomous mobile sensor networks (MSN) have received increasing attention in the past decade due to their many commercial and defense related applications such as health and environmental monitoring [1], [2], target tracking [3], [4], [5] and surveillance [6], [7]. Advances in Micro-Electro-Mechanical Systems (MEMS) are also helping in the low-cost and practical implementation of MSNs.

Field coverage is a major problem that arises in many of the MSN applications. In this problem, the mobile nodes are expected to provide sensory coverage of as much area as possible (ideally the entire area) in a given target

H. Mahboubi is with the Department of Electrical & Computer Engineering, McGill University, 845 Rue Sherbrooke Ouest, Montréal, Québec H3A 0G4, Canada, {hamid.mahboobi}@mail.mcgill.ca

A. G. Aghdam is with the Department of Electrical & Computer Engineering, Concordia University, 1455 de Maisonneuve Blvd. W., EV005.139, Montréal, Québec H3G 1M8 Canada, {aghdam}@ece.concordia.ca

K. Sayrafian-Pour is with the National Institute of Standards and Technology (NIST), 100 Bureau Drive, Stop 8910 Gaithersburg, MD 20899 USA {ksayrafian}@nist.gov

This work has been supported by the National Institute of Standards and Technology (NIST), under grant 70NANB8H8146.

field. Given the mobility feature of nodes in an MSN, it would be desirable to have autonomous networks that can achieve maximal field coverage. Therefore, intelligent and decentralized relocation algorithms are extremely important in mobile sensor network field coverage problems. Design of efficient relocation algorithms are quite challenging due to the limited energy resources in such networks. Constraints such as node's energy consumption (due to motion or data communication) as well as limited communication and sensing ranges of the sensors must be taken into account.

A lot of research has been focused in this area. For example, in [8], gradient descent algorithms are proposed for a class of utility functions that increase network coverage. In [9], a sensor deployment strategy is proposed to solve coverage problem on a complicated surface in 3D space. A collaborative coverage algorithm using a combination of mobile and static sensors has been discussed in [10], where mobile sensors try to compensate for possible coverage gaps between static sensors. In [11], distributed control laws are presented to achieve convex equi-partition configuration in mobile sensor networks. The field coverage strategy in [12] is based on a localized Voronoi diagram, where each sensor uses the local information of the neighboring sensors to construct its own Voronoi region. A coordination algorithm and performance analysis have been presented in [13] using a class of aggregate objective functions based on the geometry of the Voronoi partitions and proximity graphs.

A Delaunay graph has been used in [14] to propose distributed gradient-descent coverage algorithms. An optimal algorithm is proposed in [15] to monitor an environmental boundary with mobile agents, where the boundary is approximated by a polygon. The problem of sensor deployment in a network with non-uniform coverage priority has been considered in [16], [17]. Several efficient deployment algorithms have also been proposed in [18] to increase the coverage area based on an iterative method.

Using Voronoi diagram, three sensor deployment algorithms (i.e. VEC, VOR and Minimax) have been introduced in [19] to discover and reduce coverage gaps throughout the field. In [20], the LRV (Least Recently Visited) algorithm has been presented to simultaneously solve the problem of coverage, exploration and sensor deployment. The coverage problem in three-dimensional space has been addressed in [21]; and, a distributed algorithm has been proposed for achieving full field coverage. Efficient network coverage strategies that do not use simple sensing models or Voronoi partitions are presented in [22]-[26]. Distributed gradient-descent algorithms for optimal coverage control are presented in [22], [23]. These algorithms exploit cooperation among sensors and optimize a probabilistic detection metric.

In [24], distributed algorithms for optimal field coverage in the presence of polygonal obstacles and limited sensors field-of-view are proposed. The problem of distributed convergence to a Nash equilibrium in mobile sensor networks is investigated in [25]. In [26], a field coverage strategy has been developed to maximize the probability of detecting events which occur in a given region. The approach prolongs the network lifetime by properly reducing the communications costs. Distributed control laws are provided in [27] for the disk-covering and sphere-packing problems using non-smooth gradient flows. In [28], an efficient procedure for sensor relocation is introduced to minimize the maximum error variance and extended prediction variance.

In this paper, two different distributed algorithms are presented for deployment and relocation of sensors in an MSN. It is assumed that the nodes in the network have different sensing capabilities; and also, they are operating on a flat field containing obstacles. The approach in our proposed algorithms is based on using the *visibility-aware multiplicatively weighted Voronoi* (VMW-Voronoi) diagram. The effect of obstacles on sensors' sensing capabilities (i.e. visibility area of each sensor) is taken into consideration in the proposed algorithms. The VMW-Voronoi diagram is used for discovering coverage gaps and sensing radii of sensors are used as node weights in the construction of this diagram. In this work, it is assumed that if the line-of-sight between a point and a sensor is blocked with an obstacle, then the sensor is not able to sense any object located at that point. This is an acceptable assumption and has been used in the literature previously ([29], [30]).

Using VMW-Voroni diagram, the following two algorithms are presented in this paper: *Obstructed Farthest Point* (OFP) and *Obstructed Minmax Point* (OMP) algorithms.

By iterative application of these algorithms, a gradual improvement in the overall coverage can be obtained. At each iteration, a new candidate coordinate for sensor relocation is calculated based on the current position of each sensor and its VMW-Voronoi region. The decision to move each sensor to the calculated candidate coordinate is made after comparing the value of its local coverage at the current and candidate location. If the sensor's local coverage cannot be improved, it will remain in its current position; otherwise it will move to the new calculated coordinate. The algorithm terminates when none of the sensors can improve their local coverage by moving to their respective candidate positions.

The rest of this paper is organized as follows. Section II proposes visibility-aware multiplicatively weighted

Voronoi diagram as an extension of the conventional Voronoi diagram. The proposed algorithms for sensor relocation are proposed in Section III. Simulation results that demonstrate the effectiveness of our approach are provided in Section IV. Finally, conclusions and future works are discussed in Section V.

II. Visibility-aware Multiplicatively Weighted Voronoi Diagram

Let $\mathbf{F} \subset \mathbb{R}^{\mathbf{2}}$ represent a 2D target field. Consider $\mathbf{S} = (S_1, w_1), (S_2, w_2), \ldots, (S_n, w_n)$ to be a set of n distinct weighted nodes within the field $\mathbf{F}$. $w_i > 0$ is the weighting factor associated with the node S_i, for any $i \in \mathbf{n} := \{1, 2, \ldots, n\}$. The *visible set* of an arbitrary point $Q \in \mathbf{F}$ is defined as the largest subset of $\mathbf{S}$ with a non-obstructed line of sight view from all of its elements to the point Q. Let $\mathbf{Indx}_Q$ represent the indices of the nodes in this subset. In presence of obstacles in the field and depending on the location of point Q, the set $\mathbf{Indx}_Q$ may have between 0 to n elements. In particular, Q is called an *invisible point* if $\mathbf{Indx}_Q$ is an empty set, otherwise it is called a *visible point*. The set of all invisible points in the field $\mathbf{F}$ is called the invisible region and will be denoted by $\Theta_{\mathbf{S}}$. The invisible region is highly dependent on the positions of the nodes S_i and the obstacles on the field.

Definition 1. The weighted distance of a point Q from a node (S_i, w_i), $i \in \mathbf{n}$ is defined as:

$$d_w(Q, S_i) = \frac{d(Q, S_i)}{w_i}$$

where $d(Q, S_i)$ indicates the Euclidean distance between the point Q and the node S_i in the 2D field $\mathbf{F}$.

It is desired now to partition the visible area of the field ($\mathbf{F} \backslash \Theta_{\mathbf{S}}$) into n regions such that:

- Each region contains only one node, and
- the closest node, in the sense of weighted distance, to any point inside a region is the node assigned to that region.

The mathematical characterization of the invisible region and each visible region is given by:

$$\Theta_{\mathbf{S}} = \left\{Q \in \mathbb{R}^2 \mid \mathbf{Indx}_Q = \emptyset\right\} \tag{1}$$

$$\Pi_i = \left\{Q \in \mathbb{R}^2 \mid i \in \mathbf{Indx}_Q,\ d_w(Q, S_i) \le d_w(Q, S_j), \forall j \in \mathbf{Indx}_Q - \{i\}\right\} \tag{2}$$

The diagram obtained by partitioning the field $\mathbf{F}$ into the invisible region and the above-mentioned n regions is called the *visibility-aware multiplicatively weighted Voronoi* (VMW-Voronoi) diagram [31]. According to (2), any point Q in the i-th VMW-Voronoi region Π_i has the following property:

$$\frac{d(Q,S_i)}{d(Q,S_j)} \leq \frac{w_i}{w_j}, \quad \forall i,j \in \mathbf{Indx}_Q, \; i \neq j \tag{3}$$

Definition 2. Similar to conventional Voronoi diagram [32], the nodes S_i and S_j $(i, j \in \mathbf{n},\; i \neq j)$ in a VMW-Voronoi diagram are called *neighbors* if $\Pi_i \cap \Pi_j \neq \emptyset$. The set of all neighbors of S_i, $i \in \mathbf{n}$, is denoted by $\mathbf{N}_i$ and is formulated as:

$$\mathbf{N}_i = \{S_j \in \mathbf{S} \,|\, \Pi_i \cap \Pi_j \neq \emptyset, \; \forall j \in \mathbf{n} - \{i\}\} \tag{4}$$

The VMW-Voronoi diagram is the main tool for developing the sensor deployment strategy in this paper. A circle is used to characterize the sensing area of each sensor. The size of these circles could be different for different sensors. Consider the position of each sensor in the field as a node with a weight equal to the sensor's sensing radius, and sketch the VMW-Voronoi region for each sensor; the resultant diagram, together with the invisible region, covers the entire field $\mathbf{F}$.

Definition 3. Consider the sensor S_i with the sensing radius r_i and the corresponding VMW-Voronoi region $\Pi_i,\; i \in \mathbf{n}$, and let Q be an arbitrary point inside Π_i. The intersection of the region Π_i and a circle of radius r_i centered at Q is referred to as the *i-th coverage area w.r.t. Q*, and is denoted by $\beta^Q_{\Pi_i}$. The i-th coverage area w.r.t. the location of the sensor S_i is called the *local coverage area* of that sensor, and is denoted by β_{Π_i}.

From the characterization of the VMW-Voronoi regions provided in (2), it can be easily shown that if a sensor cannot detect a point in its corresponding region, no other sensor can detect it either. This means that in order to find the coverage gaps (i.e., the undetectable points in $\mathbf{F}$), it is sufficient to compare the VMW-Voronoi region of every sensor with its local coverage area. A VMW-Voronoi diagram with 3 sensors S_1, S_2 and S_3 with the sensing radii 10m, 18m, and 18m, respectively, is depicted in Fig. 1.

Definition 4. Consider an arbitrary point Q inside the VMW-Voronoi region Π_i, $i \in \mathbf{n}$. The area inside the VMW-Voronoi region Π_i which lies outside the i-th coverage area w.r.t. Q is referred to as the *i-th coverage gap w.r.t. Q*, and is denoted by $\theta^Q_{\Pi_i}$. The i-th coverage gap w.r.t. the location of the sensor S_i is called the *local coverage gap* of that sensor, and is denoted by θ_{Π_i}.

Assumption 1. The sensors are able to obtain their own positions with sufficient accuracy in the target field (using, for instance, the methods proposed in [33], [34]).

Assumption 2. The communication range of the sensors is limited (and possibly different for different nodes). This limitation could potentially prevent sensors from communicating with their neighbors, and can result in wrong VMW-Voronoi regions around some sensors. Consequently, such a limitation can have a negative impact on the detection of coverage gaps. Since the number of sensors in a mobile sensor network is typically large (or more precisely, there is a sufficient number of sensors per area unit) [35], [36], it is assumed that the graph representing sensors' communication topology is connected [37]. Hence, each sensor can obtain the information about the locations and sensing radii of the other sensors (and in particular its neighbors) through proper communication routes. Also it is assumed that the obstacles' locations are known by each sensor as *a priori* information. As a result, each sensor can calculate its VMW-Voronoi region accurately.

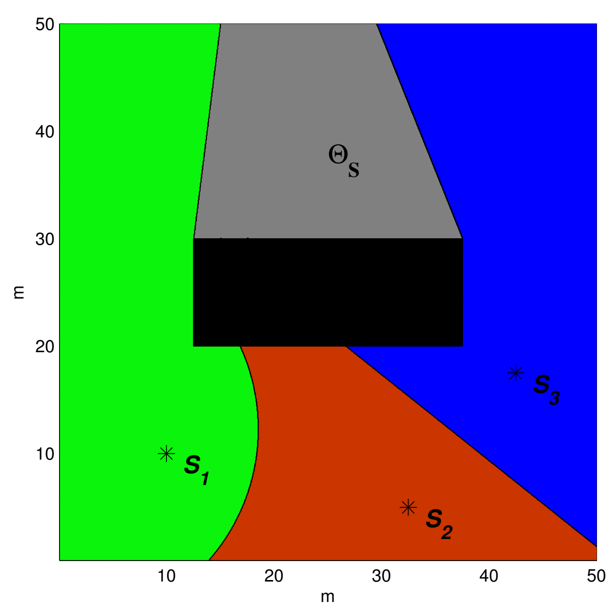


Fig. 1: An example of the VMW-Voronoi diagram for a group of 3 non-identical sensors in a field with obstacles [31].

III. Deployment Protocols

In this section, two different deployment protocols are developed for a network of non-identical sensors in the presence of obstacles. The proposed techniques are iterative, where in each iteration every sensor S_i, $i \in \mathbf{n}$, first broadcasts its sensing radius r_i and position P_i to other sensors. Thus, every sensor is able to construct its own VMW-Voronoi region based on the information received from other sensors in the network. Then, every sensor detects coverage gaps in its region. When a coverage gap is discovered, the corresponding sensor calculates its new position using one of the proposed algorithms. The new position is calculated with the aim of eliminating the coverage gap or reducing its size after the sensor relocates to that position. Once the new location $\acute{P}_i$ is calculated, the coverage area w.r.t. this new location, i.e., $\beta_{\Pi_i}^{\acute{P}_i}$ is evaluated and compared to the current coverage area, i.e., $\beta_{\Pi_i}^{P_i}$. The sensor moves to the new location only if the resultant coverage area is greater than the present value, i.e. $\beta_{\Pi_i}^{\acute{P}_i} > \beta_{\Pi_i}^{P_i}$; otherwise, it does not move in this iteration. In order to have a termination criterion for the algorithms, a proper threshold ϵ is defined; if no sensor can improve its coverage area by this threshold, the algorithm is terminated.

The following theorem shows that any sensor deployment strategy which follows the scheme described in the previous paragraph is guaranteed to increase the total coverage.

Theorem 1. *Let the positions of the sensors in the set* $\mathbf{S}$ *be represented by* $\mathbf{P} = \{P_1, P_2, \ldots, P_n\}$ *with the corresponding VMW-Voronoi regions* $\Pi_1, \Pi_2, \ldots, \Pi_n$. *Let also the invisible region be denoted by* $\Theta_{\mathbf{P}}$. *Assume the sensors move to new positions* $\acute{\mathbf{P}} = \{\acute{P}_1, \acute{P}_2, \ldots, \acute{P}_n\}$ *with the corresponding VMW-Voronoi regions* $\acute{\Pi}_1, \acute{\Pi}_2, \ldots, \acute{\Pi}_n$ *such that* $\acute{P}_i \neq P_i$ *for all* $i \in \mathbf{k}$, *where* $\mathbf{k}$ *is a non-empty subset of* $\mathbf{n}$. *If the* i*-th coverage area w.r.t.* $\acute{P}_i$ *in the previously constructed VMW-Voronoi region* Π_i *is greater than the previous* i*-th local coverage area (i.e.,* $\beta_{\Pi_i}^{\acute{P}_i} > \beta_{\Pi_i}^{P_i}$*) for all* $i \in \mathbf{k}$, *then the total coverage in the network increases.*

Proof: Denote the total uncovered area (coverage gap) of the field when the sensors are located in $\mathbf{P}$ and $\acute{\mathbf{P}}$ with θ and $\acute{\theta}$, respectively. It is deduced from the characterization of the VMW-Voronoi diagram that:

$$\theta = \Theta_{\mathbf{P}} + \sum_{i=1}^{n} \theta_{\Pi_i}^{P_i} \tag{5}$$

It can be easily shown that by increasing the coverage area in $\Pi_i,\ i \in \mathbf{k}$, the corresponding coverage gap will be decreased. Since it is assumed that the i-th coverage area w.r.t. $\acute{P}_i$ is greater than the i-th local coverage area for any $i \in \mathbf{k}$, one can conclude that:

$$\theta_{\Pi_i}^{\acute{P}_i} < \theta_{\Pi_i}^{P_i}, \quad \forall i \in \mathbf{k} \tag{6}$$

On the other hand, it is possible that some of the points in $\theta_{\Pi_i}^{\acute{P}_i}$ and $\Theta_{\mathbf{P}}$ are also covered by other mobile sensors at $\acute{\mathbf{P}}$. Hence:

$$\acute{\theta} \leq \Theta_{\mathbf{P}} + \sum_{i=1}^{n} \theta_{\Pi_i}^{\acute{P}_i} \tag{7}$$

Using the last two relations and noting that for any $i \in \mathbf{n} \backslash \mathbf{k}$ by definition $\theta_{\Pi_i}^{\acute{P}_i} = \theta_{\Pi_i}^{P_i}$, one can obtain the following inequality:

$$\acute{\theta} < \Theta_{\mathbf{P}} + \sum_{i=1}^{n} \theta_{\Pi_i}^{P_i} \tag{8}$$

Now, it is concluded from (5) and (8) that:

$$\acute{\theta} < \theta \tag{9}$$

which means that the total coverage area increases under this deployment scheme. ■

The above-mentioned procedure will be used in the next two subsections to develop two algorithms, namely, OFP and OMP.

A. Obstructed Farthest Point (OFP) Strategy

The main idea behind this algorithm is to move every sensor to the farthest point in its VMW-Voronoi region such that any existing coverage gap is covered. If a sensor S_i detects a coverage gap in its corresponding VMW-Voronoi region, it calculates the farthest point $X_{i,far}$ in that region, and moves toward it until this point is covered. Fig. 2 shows a sample VMW-Voronoi region constructed by the sensor S_1. The segments g and e are generated due to the two neighboring sensors with sensing radii equal to that of S_1. The segments a and h are obstacle edges, and the segment c is formed because of the field boundary. The edge b, in fact, is constructed by the sight line of the sensor, and finally arcs d and f are formed by two neighboring sensors with larger and smaller sensing radii than that of S_1, respectively. As the figure illustrates, the OFP algorithm finds the farthest point to S_1, (i.e. $X_{1,far}$) as a candidate for the next location of the sensor. Since the local coverage of the sensor will increase by moving to

S_1', the sensor moves toward $X_{1,far}$ until it is covered.

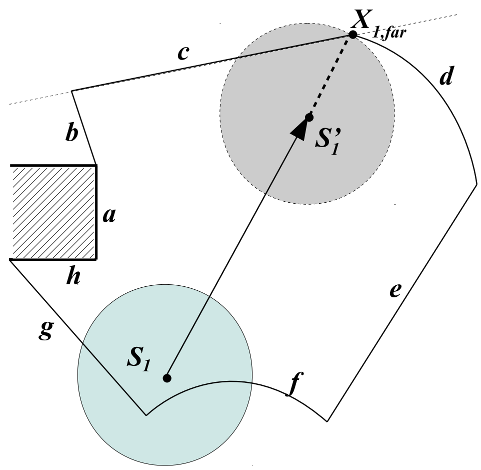


Fig. 2: A sample VMW-Voronoi region and a candidate point calculated using the OFP method.

Fig. 3 shows an example of coverage improvement as a result of using the OFP Algorithm. In this example, 27 mobile sensors with varying sensing ranges are randomly deployed in a 2D field of size $50\text{m} \times 50\text{m}$. Among these 27 sensors, 15 have sensing range of 6m, 6 with a radius of 5m, 3 with a radius of 7m and the remaining 3 sensors with a radius of 9m. The communication range of each sensor is assumed to be greater than its sensing range by a factor of $10/3$. Three snapshots of the field coverage are shown in Fig. 3. The circles represent the sensing area of each sensor. As observed, the coverage is 68.44% initially, but it increases to 81.31% after the first iteration of the presented algorithm (Fig. 3(b)). The final coverage is 95.32% (Fig. 3(c)).

B. Obstructed Minmax Point (OMP) Strategy

Although the OFP algorithm performed well in most simulated scenarios, there exist certain network setups and node configurations, where it might not be as effective. Fig. 4 shows such an example. The next candidate location for the sensor under the OFP algorithm does not lead to any improvement in the local coverage of the sensor. Thus, the mobile sensor remains in its previous location. However, there exit other potential positions for sensor relocation that can increase its local coverage. Another configuration for which the OFP algorithm is not as effective is when the calculated candidate point lies on a sight line connecting the sensor to an obstacle (e.g., see Fig. 5). These candidate points are, by definition, on the sight line; therefore, if the sensor moves to such a position, then there

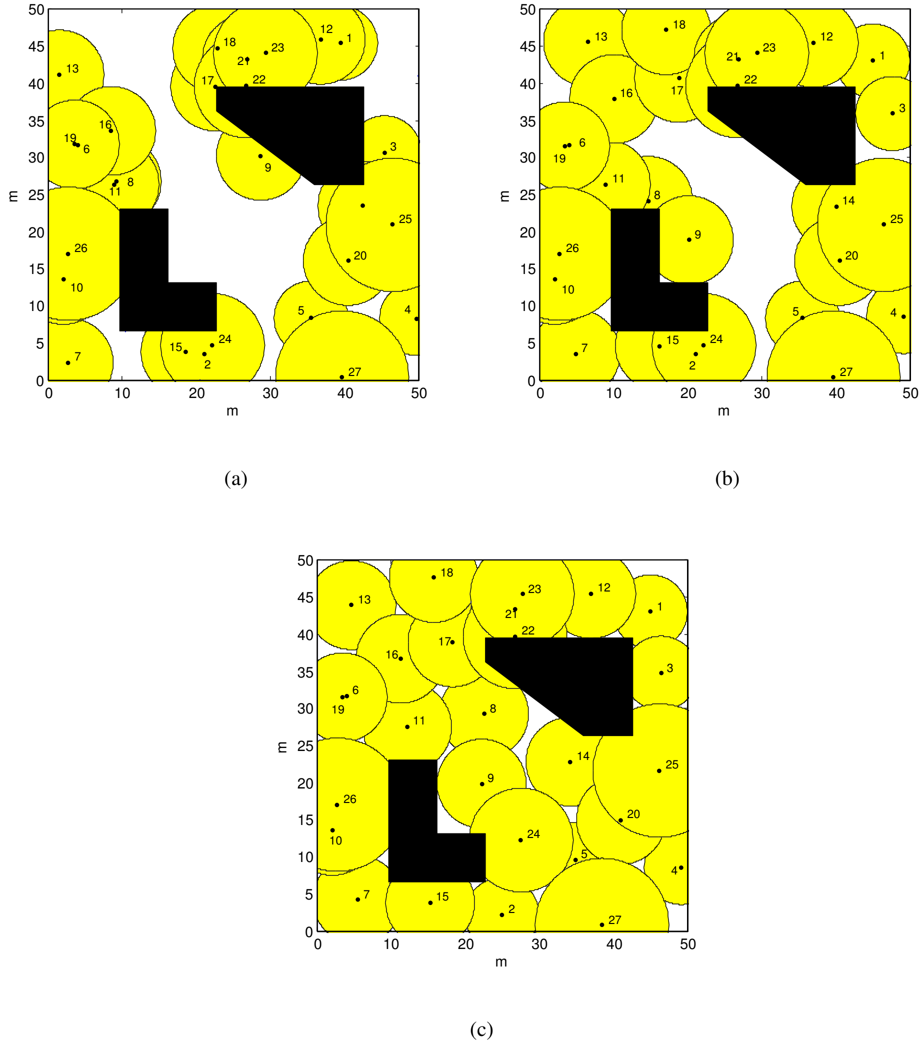


Fig. 3: Snapshots of the movement of the sensors under the OFP algorithm. (a) Initial coverage; (b) field coverage after the first round, and (c) final coverage.

is a good chance that part of the sensor's sensing capability is blocked in its corresponding region.

As it can be concluded from the above discussion, although the OFP algorithm is effective in many cases, one may find a proper location for the sensor in the special cases described above. The obstructed minmax point (OMP) strategy is proposed in the sequel to address this shortcoming of the OFP algorithm. The main idea behind the OMP strategy is that to achieve maximum coverage, no sensor should be too far from any point in its corresponding VMW-Voronoi region. The OMP strategy finds the location where its distance from the farthest point of the region is minimum and considers it as the candidate location for the sensor in the next step. This point is called the *OMP*

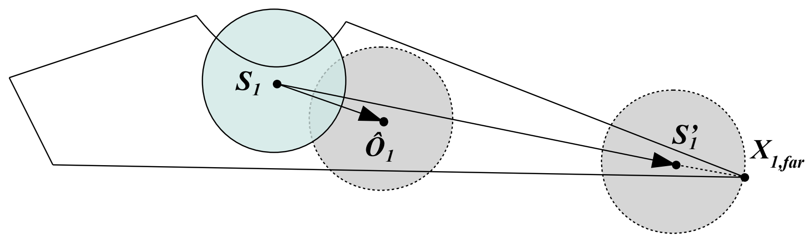


Fig. 4: A sample VMW-Voronoi region for which the OFP method performs poorly because of a narrow angle, while the OMP strategy finds a proper candidate location.

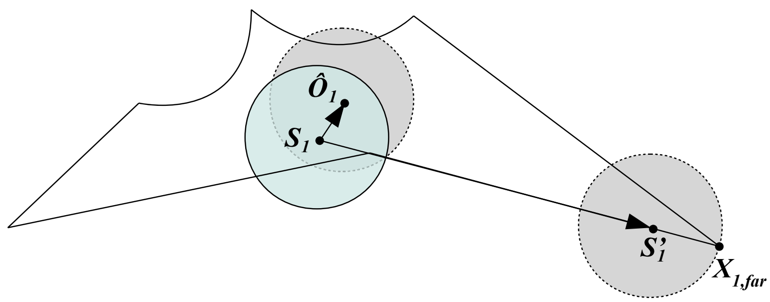
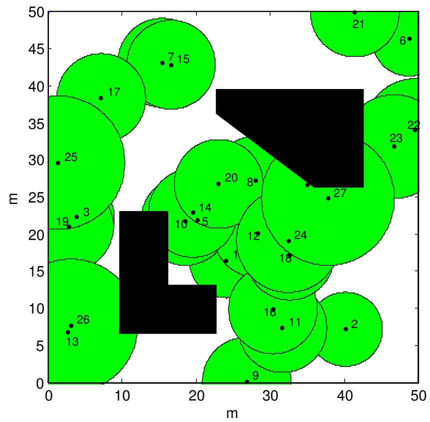


Fig. 5: A sample VMW-Voronoi region for which the OFP method performs poorly because of the sensor's sight line, while the OMP strategy finds a proper candidate location.

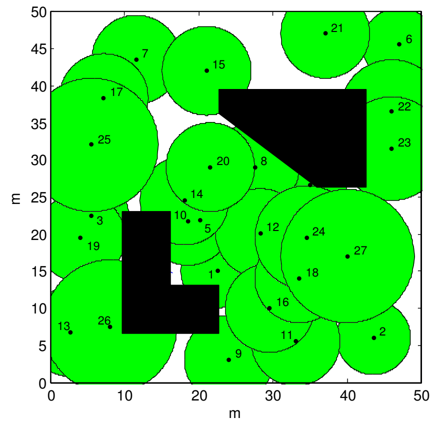
centroid, and is denoted by $\hat{O}_i$ for the i-th region, $i \in \mathbf{n}$. It is clear that the candidate point $\hat{O}_1$ in Fig. 4 yield better coverage compared to the one obtained by using the OFP technique. Also, in Fig. 5, the OMP strategy performs more efficiently than the OFP algorithm due to the specific shape of the region which makes the farthest point lie on the sight line of the sensor.

Consider the initial setting of Fig. 6(a), and let the OMP strategy be employed. The results are depicted in Figs. 6(b) and 6(c), where it is shown that after the first round the coverage increases from 67.09% to 84.94%, and that the final coverage is 97.62%.

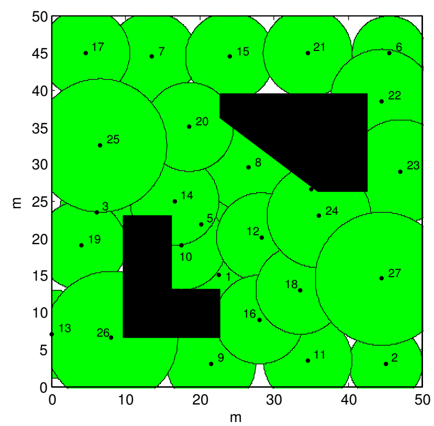
Remark 1. One of the important properties of the VMW-Voronoi diagram is that first of all it partitions the field, and more importantly there is exactly one sensor in each visible region. Since in the proposed algorithms the new location for each sensor is inside the corresponding VMW-Voronoi region and each sensor moves within its region, hence the sensors would not collide. Assume now that a sensor cannot communicate with some of its neighbors, and consequently it obtains a VMW-Voronoi region which some of its boundaries are different from the exact ones. As a result, the VMW-Voronoi regions do not necessarily partition the field in the sense that some of them overlap



(a)



(b)



(c)

Fig. 6: Snapshots of the movement of the sensors under the OMP algorithm. (a) Initial coverage; (b) field coverage after the first round, and (c) final coverage.

with each other. Such VMW-Voronoi regions can negatively affect the detection of coverage gaps. On the other hand, the overlapping of the VMW-Voronoi regions can lead to sensor collisions.

Remark 2. It is worth mentioning that the analytical solution to the optimal sensor deployment problem with respect to a prescribed coverage performance function is, in general, highly complex. Hence, to evaluate the performance of the algorithms proposed here, several simulations are performed using random settings [19], [38], [10]. This method of performance assessment is typically used to evaluate the effectiveness of any sensor deployment strategy.

In the next section, the performance of the proposed algorithms in terms of the coverage area, energy consumption of the sensors, rate of convergence, and computational complexity are investigated.

IV. Simulation Results

Consider a sensing field of size $50\mathrm{m} \times 50\mathrm{m}$ with two obstacles. Also consider a network of 36 mobile sensors with varying sensing radii i.e. out of these 36 mobile sensors, 20 sensors have a sensing radius of 6m, 8 have a radius of 5m, 4 have a radius of 7m. The communication radius of each sensor is assumed to be greater than its sensing radius by a factor of $10/3$; e.g., a sensor with a sensing radius of 6m has a communication radius of 20m.

Define the *coverage factor* as the ratio of the covered area to the total area in the field. The simulation results presented in this section are the average values obtained from 20 different random initial sensor deployments. Coverage factor under both algorithms is shown in Fig. 7. While both algorithms provide satisfactory coverage, the OMP technique exhibits a better performance in this example.

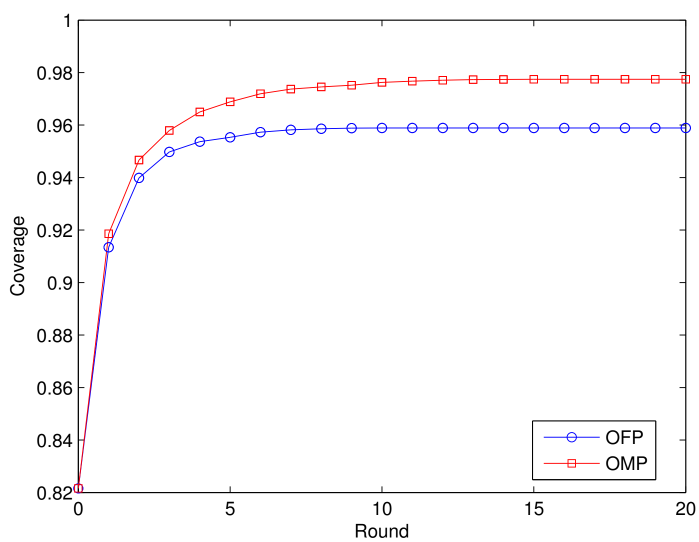


Fig. 7: Total normalized field coverage per round for 36 sensors.

To investigate the effect of the number of sensors on the performance of the algorithms, we considered four more setups: n=9, 18, 27, and 45, in addition to n=36 discussed above. It is assumed that the changes in the number of identical sensors in the new setups are proportional to the changes in the total number of sensors. For example, for n=27 there will be 15 sensors with sensing radius of 6m, 6 with sensing radius of 5m, 3 with sensing radius of 7m, and 3 with sensing radius of 9m. Fig. 8 shows the resulting final coverage versus number of sensors. Both algorithms yield satisfactory results with the OMP strategy still performing better.

An important factor in the performance evaluation of different deployment strategies is the time it takes for each strategy to reach the desired termination criteria. Assuming that both relocation strategies require the same deployment time in each round of algorithm execution, then, the number of rounds to reach a predetermined termination criteria is a good measure of the deployment speed of each algorithm.

Fig. 9 shows that under both algorithms the number of rounds required to meet a certain termination condition increases with the number of sensors. This is the case up to certain number of sensors and then beyond that the number of required rounds decreases. The reason can be explained as follows. When the number of sensors is small, the sizes of their corresponding VMW-Voronoi regions are relatively larger than their coverage circles. And, it will be likely for some sensors that their entire coverage circles are enclosed within their VMW-Voronoi regions. Therefore, further relocation of each sensor in its region would not increase the coverage level. On the other hand, when the number of sensors is relatively large, the size of their corresponding VMW-Voronoi regions will be small. And, with a high likelihood, the coverage circles of most sensors enclose their VMW-Voronoi regions. This in turn implies that the termination criteria is satisfied in smaller number of rounds. Fig. 9 shows that the convergence rate of the OFP algorithm is faster than that of the OMP; therefore, it is a better candidate for field coverage if higher deployment speed is required.

Another important factor in performance evaluation of deployment algorithms in mobile sensor networks is energy-efficiency. Movement of a sensor, more precisely, the distance it travels and also the number of times it stops (impact of static friction) are the dominant sources of energy consumption. Fig. 10 shows the average distance traveled by a sensor versus number of sensors in the network. As observed, the average traveled distance for a large number of sensors is small. For large number of sensors, the distance between each sensor's position and its candidate location in its corresponding VMW-Voronoi region decreases. Therefore, the average traveling distance required by a sensor decreases. This, in turn, leads to a reduction in energy consumption. Also, it can be seen from Fig. 10 that the OFP algorithm is more efficient than the OMP strategy for a larger number of sensors. Fig. 11 shows the number of relocations versus the number of sensors in the network. In both algorithms, and up to certain value, the number of relocations increases with the number of sensors, and then decreases after that. Again, this can

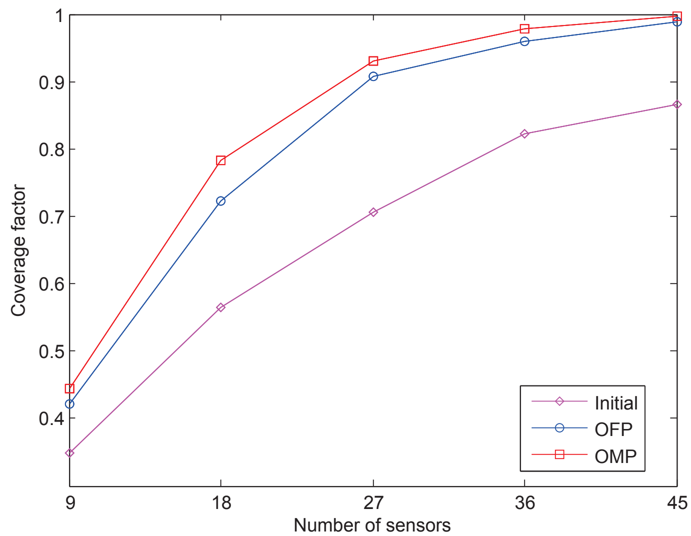


Fig. 8: The coverage factor versus number of sensors under the proposed algorithms.

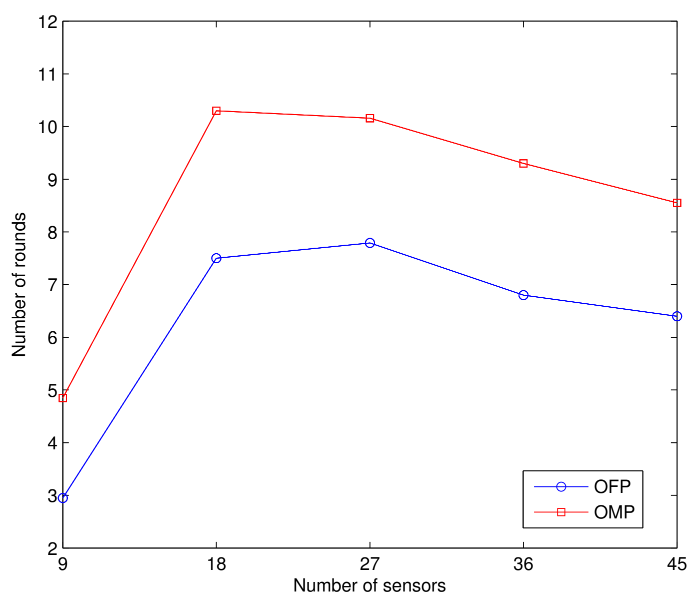


Fig. 9: Number of rounds needed to reach the termination criteria for different number of sensors using the proposed algorithms.

be justified based on the relative sizes of the sensors coverage circles versus their VMW-Voronoi regions. Figs. 10 and 11 clearly demonstrate that the OFP algorithm outperforms the OMP strategy in energy consumption.

Remark 3. Note that the algorithms proposed in this paper differ only in the way the new locations of the sensors are determined. Since the complexity of finding the new location of the i-th sensor in the OFP strategy is more than that in OMP, hence the OFP algorithm outperforms the OMP algorithm as far as the computational complexity is concerned.

The above discussion is summarized below:

1) The OMP algorithm is more preferable as far as network coverage is concerned.
2) The OFP algorithm is more desirable when:
   - the deployment time is the main concern.
   - the energy consumption is the main concern.
   - the computational complexity is concerned.

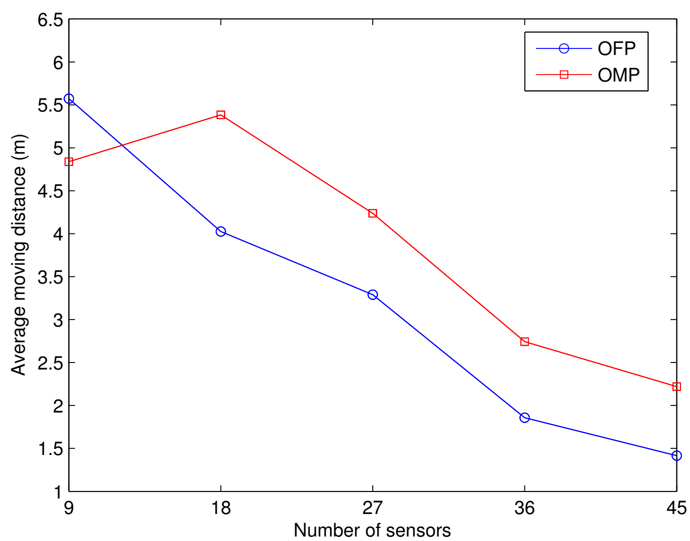


Fig. 10: Average traveled distance by each sensor versus number of sensors under proposed algorithms.

V. Conclusions and Future Works

In this paper, two efficient distributed sensor relocation techniques are proposed to increase field coverage of mobile sensor networks. The algorithms are applicable to networks having non-identical mobile sensors and target coverage fields with obstacles. To account for the existence of obstacles, an extension of MW-Voronoi diagram, namely visibility-aware MW-Voronoi (VMW-Voronoi) diagram has been proposed as a tool to allow enhancement in sensor's local coverage. The iterative implementation of the algorithms provides gradual maximization of the overall

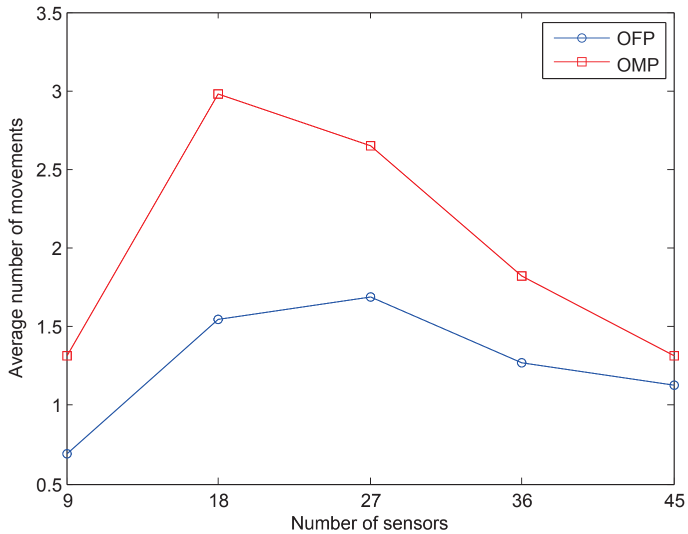


Fig. 11: Average number of movements required for different number of sensors, using the proposed algorithms.

network coverage. Simulation results confirm the effectiveness of the proposed techniques for different number of sensors. There are a number of related problems that can be investigated in the future. For example, adding static sensors to the field and proposing new deployment algorithms to maximize network coverage, investigating the effect of communication delay and link failure on network coverage are some of the open problems in this area.

VI. Acknowledgment

The authors would like to thank Dr. Kaveh Moezzi and Mr. Walid Masoudimansour for helpful discussions and suggestions.

References

[1] M. Moh, B. J. Culpepper, L. Dung, T.-S. Moh, T. H., and C.-F. Su, "On data gathering protocols for in-body biomedical sensor networks," in *Proceedings of IEEE Global Communications Conference*, 2005, pp. 2991–2996.

[2] A. Talukder, A. Panangadan, and A. Herrington, "Autonomous adaptive resource management in sensor network systems for environmental monitoring," 2008, pp. 1–9.

[3] H. Mahboubi, W. Masoudimansour, A. G. Aghdam, and K. Sayrafian-Pour, "Cost-efficient routing with controlled node mobility in sensor networks," in *Proceedings of IEEE Multiconference on Systems and Control*, 2011, pp. 1238–1243.

[4] A. Oka and L. Lampe, "Distributed scalable multi-target tracking with a wireless sensor network," 2009, pp. 6 pp. –.

[5] H. Mahboubi, A. Momeni, A. G. Aghdam, K. Sayrafian-Pour, and V. Marbukh, "Optimal target tracking strategy with controlled node mobility in mobile sensor networks," in *Proceedings of American Control Conference*, 2010, pp. 2921–2928.

[6] A. Olteanu, Y. Xiao, K. Wu, and X. Du, "An optimal sensor network for intrusion detection," 2009.

[7] M. Huntwork, A. Goradia, N. Xi, C. Haffner, C. Klochko, and M. Mutka, "Pervasive surveillance using a cooperative mobile sensor network," 2006, pp. 2099–2104.

[8] J. Cortes, S. Martinez, T. Karatas, and F. Bullo, "Coverage control for mobile sensing networks," *IEEE Transactions on Robotics and Automation*, vol. 2, pp. 243–255, 2004.

[9] M.-C. Zhao, J. Lei, M.-Y. Wu, Y. Liu, and W. Shu, "Surface coverage in wireless sensor networks," in *Proceedings of 28th IEEE INFOCOM*, 2009, pp. 109–117.

[10] G. Wang, G. Cao, P. Berman, and T. F. L. Porta, "A bidding protocol for deploying mobile sensors," *IEEE Transactions on Mobile Computing*, vol. 6, no. 5, pp. 563–576, 2007.

[11] M. Pavone, E. Frazzoli, and F. Bullo, "Distributed policies for equitable partitioning: Theory and applications," in *Proceedings of 47th IEEE Conference on Decision and Control*, 2008, pp. 4191–4197.

[12] A. Boukerche and X. Fei, "A Voronoi approach for coverage protocols in wireless sensor networks," in *Proceedings of IEEE Global Communications Conference*, 2007, pp. 5190–5194.

[13] J. Cortes, S. Martinez, and F. Bullo, "Spatially-distributed coverage optimization and control with limited-range interactions," *ESAIM. Control, Optimization and Calculus of Variations*, vol. 11, pp. 691–719, 2005.

[14] A. Kwok and S. Martinez, "Unicycle coverage control via hybrid modeling," *IEEE Transactions on Automatic Control*, vol. 55, no. 2, pp. 528–532, 2010.

[15] S. Susca, F. Bullo, and S. Martinez, "Monitoring environmental boundaries with a robotic sensor network," *IEEE Transactions on Control Systems Technology*, vol. 16, no. 2, pp. 288–296, 2008.

[16] F. Bullo, J. Cortes, and S. Martinez, *Distributed Control of Robotic Networks*. Princeton University Press, 2009.

[17] J. Cortes, "Coverage optimization and spatial load balancing by robotic sensor networks," *IEEE Transactions on Automatic Control*, vol. 55, no. 3, pp. 749–754, 2010.

[18] H. Mahboubi, K. Moezzi, A. G. Aghdam, and K. Sayrafian-Pour, "Self-deployment algorithms for field coverage in a network of nonidentical mobile sensors: Vertex-based approach," in *Proceedings of American Control Conference*, 2011, pp. 3227–3232.

[19] G. Wang, G. Cao, and T. F. L. Porta, "Movement-assisted sensor deployment," *IEEE Transactions on Mobile Computing*, vol. 5, no. 6, pp. 640–652, 2006.

[20] M. A. Batalin and G. S. Sukhatme, "The design and analysis of an efficient local algorithm for coverage and exploration based on sensor network deployment," *IEEE Transactions on Robotics*, vol. 23, no. 4, pp. 661–675, 2007.

[21] M. K. Watfa and S. Commuri, "The 3-dimensional wireless sensor network coverage problem," in *Proceedings of IEEE International Conference on Networking, Sensing and Control*, 2006, pp. 856–861.

[22] W. Li and C. G. Cassandras, "Distributed cooperative coverage control of sensor networks," in *Proceedings of the IEEE Conference on Decision and Control, and the European Control Conference*, vol. 2005, 2005, pp. 2542–2547.

[23] C. G. Cassandras and W. Li, "Sensor networks and cooperative control," *European Journal of Control*, vol. 11, no. 4-5, pp. 436–463, 2005.

[24] M. Zhong and C. G. Cassandras, "Distributed coverage control and data collection with mobile sensor networks," *IEEE Transactions on Automatic Control*, vol. 56, no. 10, pp. 2445–2455, 2011.

[25] M. S. Stankovic, K. H. Johansson, and D. M. Stipanovic, "Distributed seeking of nash equilibria in mobile sensor networks," in *Proceedings of the IEEE Conference on Decision and Control*, 2010, pp. 5598–5603.

[26] M. Zhong and C. G. Cassandras, "Asynchronous distributed optimization with event-driven communication," *IEEE Transactions on Automatic Control*, vol. 55, no. 12, pp. 2735–2750, 2010.

[27] J. Cortes and F. Bullo, "Coordination and geometric optimization via distributed dynamical systems," *SIAM Journal on Control and Optimization*, vol. 44, no. 5, pp. 1543–1574, 2006.

[28] R. Graham and J. Cortes, "Asymptotic optimality of multicenter voronoi configurations for random field estimation," *IEEE Transactions on Automatic Control*, vol. 54, no. 1, pp. 153–158, 2009.

[29] H. Tan, Y. Wang, X. Hao, Q.-S. Hua, and F. Lau, "Arbitrary obstacles constrained full coverage in wireless sensor networks," in *Proceedings of 5th International Conference of Wireless Algorithms, Systems and Applications*, 2010, pp. 1–10.

[30] Y.-C. Wang, C.-C. Hu, and Y.-C. Tseng, "Efficient deployment algorithms for ensuring coverage and connectivity of wireless sensor networks," in *Proceedings of 1st International Conference on Wireless Internet*, 2005, pp. 114–121.

[31] H. Mahboubi, F. Sharifi, A. G. Aghdam, and Y. M. Zhang, "Distributed coordination of multi-agent systems for coverage problem in presence of obstacles," in *Proceedings of American Control Conference*, 2012, pp. 5252–5257.

[32] A. Okabe, B. Boots, K. Sugihara, and S. N. Chiu, *Spatial Tessellations: Concepts and Applications of Voronoi Diagrams*. Wiley, 2000.

[33] D. Niculescu and B. Nath, "Ad hoc positioning system (APS) using AOA," in *Proceedings of IEEE INFOCOM. 22nd Annual Joint Conference of the IEEE Computer and Communications Societies*, 2003, pp. 1734–1743.

[34] C. Intanagonwiwat, R. Govindan, and D. Estrin, "Directed diffusion: A scalable and robust communication paradigm for sensor networks," in *Proceedings of 6th Annual International Conference on Mobile Computing and Networking*, 2000, pp. 56–67.

[35] Y.-C. Wang and Y.-C. Tseng, "Distributed deployment schemes for mobile wireless sensor networks to ensure multilevel coverage," *IEEE Transactions on Parallel and Distributed Systems*, vol. 19, no. 9, pp. 1280–1294, 2008.

[36] 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, 2011.

[37] A. Kwok and S. Martinez, "A distributed deterministic annealing algorithm for limited-range sensor coverage," *IEEE Transactions on Control Systems Technology*, vol. 19, no. 4, pp. 792–804, 2011.

[38] A. Howard, M. J. Matarić, and G. S. Sukhatme, "An incremental self-deployment algorithm for mobile sensor networks," *Autonomous Robots*, vol. 13, no. 2, pp. 113–126, 2002.