Coverage by Directional Sensors

Jing Ai and Alhussein A. Abouzeid
Electrical, Computer and Systems Engineering Department, Rensselaer Polytechnic Institute,
Troy, New York 12180 Email: aij@rpi.edu, abouzeid@ecse.rpi.edu

Abstract

In this paper, we study a novel "coverage by directional sensors" problem with tunable orientations on a set of discrete targets. We propose a Maximum Coverage with Minimum Sensors (MCMS) problem in which coverage in terms of the number of targets to be covered is maximized whereas the number of sensors to be activated is minimized. We present its exact Integer Linear Programming (ILP) formulation and an approximate (but computationally efficient) centralized greedy algorithm (CGA) solution. These centralized solutions are used as baselines for comparison. Then we provide a distributed greedy algorithm (DGA) solution. By incorporating a measure of the sensors' residual energy into DGA, we further develop a Sensing Neighborhood Cooperative Sleeping (SNCS) protocol which performs adaptive scheduling on a larger time scale. Finally we evaluate the proposed solutions and protocol in terms of providing coverage and maximizing network lifetime through extensive simulations.

I. INTRODUCTION

sensing coverage reflects how well the environment is monitored, and serves as a basis for applications such as physical phenomenon monitoring and target tracking/detection. Due to the diversity of the sensor network applications, the concept of sensing coverage is subject to a wide range of interpretations. Nevertheless, only *isotropic sensors* have been studied in the literature. For example, in barrier coverage (e.g., [1], [2]), the sensing ability of sensors depends only on the distance from the point to the sensor. In area or point coverage (e.g., [3]–[8]), sensing ability of sensors is abstracted as a circular region (or disk) and an event or target is detected in a binary sense depending on whether it is inside such a sensing disk or not.

To the best of our knowledge, no research work on coverage by directional sensors, such as image or video sensors, has been done in the community of wireless sensor networks. Intuitively, compared to the isotropic sensors, directional sensors are obviously distinct from them in that *coverage region of a directional sensor is determined by both its location and orientation.* It can be best illustrated by an example, shown in Fig. 1.

In this paper, we study the problem of coverage by directional sensors with tunable orientations under the random deployment strategy. To compensate for the lack of exact positioning and improve the fault tolerance, nodes are deployed in excess, and thus redundant sensors usually arise. Furthermore, sensors are usually powered by batteries and it may not be possible to recharge or replace the batteries after deployment, especially in military applications. In addition, target locations may change even after initial deployment, thus changing the optimal solution to the coverage problem. In this paper, we develop solutions that maximize the number of targets to be covered while minimizing the number of sensors to be activated at any instant. We also present solutions that include sleep scheduling for nodes.

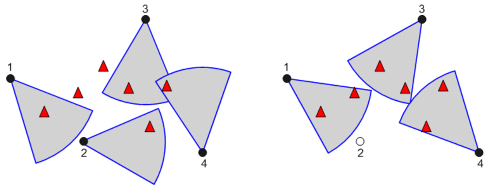

Fig. 1. Two cases of four directional sensor nodes (black balls) deployed to cover six targets (red triangles) in a sensor field. [left] Case I: all four nodes are active while two targets are uncovered. [right] Case II: three nodes are active with no targets uncovered; node 2 (small circle) is in sleep mode to conserve energy.

II. Related Work

There are two main threads of research, though dealing with the circular coverage by isotropic sensors, related to our work.

The first thread has in common the idea of turning off the redundant nodes online according to an off-duty eligibility rule derived based on geometric properties. Huang and Tseng [3] provide a solution on how nodes utilize localized information to determine whether every point in its service area is covered by at least k sensors, where k is a predefined value, and it can be easily incorporated into distributed protocols as the off-duty eligibility rule. Tian and Nicolas [5] design a back-off based node scheduling scheme to guarantee the complete coverage, where the off-duty eligibility rule is based on the concept of "sponsored area." Wang *et al.* [6] first investigate the relationship between coverage and connectivity and then utilize an off-duty eligibility rule based on the analysis of intersection points by sensing disks to design the CCP which can dynamically configure the network to provide different degrees of coverage as requested by applications. Zhang and Hou [7] also observe that coverage infers connectivity if the transmission range is at least twice the sensing range. They proposed OGDC where the off-duty eligibility rule is built upon the optimal conditions of minimizing sensing overlap and they show it can result in less working nodes to maintain coverage and connectivity compared to CCP. Though the schemes along this line can be naturally implemented in a distributed way, most of them (except OGDC) do not reveal the optimal performance that can be achieved.

The second thread deals with the sensing coverage as a discrete problem in which nodes are usually organized in a power-aware way offline. Megrian and Potkonjak [9] present several ILP formulations and strategies to reduce overall energy consumption while maintaining guaranteed 0/1 coverage. Slijepcevic and Potkonjak [4] propose the SET K-COVER problem to maximize the number K of disjoint set covers which can be activated successively along the time, where a set cover is defined as a set of nodes that can completely cover the monitored area. Abrams *et al.* [10] present three approximation algorithms (i.e., randomized, distributed and centralized algorithms) for a variation of the SET K-COVER problem. Cardei and Du [8] propose the Maximum Disjoint Set Cover problem which shares the same notion as [4] in a different scenario where a set of targets with known locations need to be covered. By further relaxing the constraint of disjoint set covers, i.e. that one node can be in multiple set covers, Cardei *et al.* [11] improve the network lifetime. Although it is valuable to derive the optimal scheduling

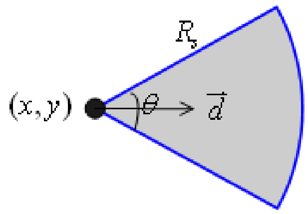

Fig. 2. Angular sensing model of a directional sensor node in a two-dimensional plane.

by mathematical programming techniques and related approximate or heuristic algorithms, most of the solutions (except the distributed greedy algorithm in [10]) are impractical to be realized in wireless sensor networks since they do not scale.

Our work differs from the prior work in several ways. First, the desired configuration of directional sensors and orientations at any instant is formulated as the MCMS problem, which can be solved exactly by an ILP formulation in a small scale and approximately by CGA in a large scale as the baselines. Second, we also provide the distributed solution (i.e., DGA) for the MCMS problem; moreover, the SNCS protocol can maintain sensing coverage and prolong the network lifetime simultaneously even on a large time scale with varying network conditions. Finally, our proposed framework to deal with coverage by directional sensors with tunable orientations can treat the coverage by isotropic sensors as a special case (we show comparisons against OGDC for this case in the results section).

III. The MCMS Problem Statement

Please note that, throughout the rest of the paper, unless otherwise mentioned, "sensor" refers to a directional sensor, as defined in the following section.

A. The Sensing Model of A Directional Sensor

Unlike an isotropic sensor, a directional sensor has a finite angle of view and thus can not sense the whole circular area. Hence, by a simple geometrical abstraction, its sensing region can be viewed as a sector in a two-dimensional plane which is shown in Fig. 2.

The following parameters completely characterize the sensing sector of a directional sensor node (please refer to Fig. 2). (x, y): the Cartesian coordinates that denote the location of the sensor in a two-dimensional plane; θ: the field of view (FOV), describing the maximum angle of sensing achieved by directional sensor; R_s: maximum sensing range of the sensor, beyond which a target will not be detected in a binary detection sense; $\vec{d}$: a unit vector which cuts the sensing sector into half. This parameter defines the orientation of the directional sensor (i.e., the direction it is looking).

B. Target In Sector (TIS) Test

To make the problem tractable, we assume that a directional sensor can only take a finite set of orientations. For instance, in the example shown in Fig. 3, a directional sensor with $\frac{\pi}{4}$ of FOV can pick eight orientations with

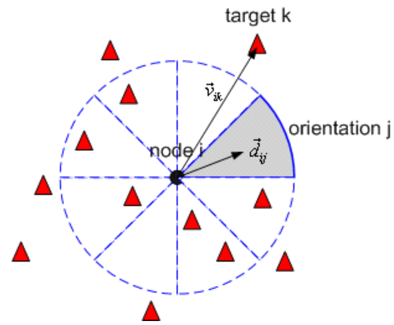

Fig. 3. A finite set of orientations for a directional sensor (black ball) covering targets (red triangles). The shadowed area is the current sensing sector of the directional sensor. A directional sensor can only choose one active sector at any time instant.

mutually disjoint sensing sectors which can be combined to generate the full circular view of an isotropic sensor.

With each choice of orientation, a certain subset of targets are covered by the directional sensor. The relationship between a directional sensor, its orientation and a target can be determined by a Target in Sector (TIS) test.

The TIS test can be described as follows. Consider a target k located at $\vec{t}_k$ and a directional sensor i located at $\vec{l}_i$. In order to determine whether the target k can be sensed by the directional sensor i with the j-th orientation, we follow the following steps: (1) calculate the distance vector $\vec{v}_{ik}$ pointing from the directional sensor i to the target k, $\vec{v}_{ik} = \vec{t}_k - \vec{l}_i$. (2) Check whether the resulting distance vector is within the FOV of the directional sensor i by performing the inner product operation $\vec{d}_{ij}^T \cdot \vec{v}_{ik} \geq \| \vec{v}_{ik} \|_2 \cos(\frac{\theta}{2})$ with equality when the target k is along the two edges of node i sensing sector. (3) Verify whether or not target k is within the sensing range of the directional sensor i or not by checking $\| \vec{v}_{ik} \|_2 \leq R_s$ with equality when the target k is on the arc of the sensing sector of the directional sensor i. (4) If both (2) and (3) hold, the result of the TIS test is true (i.e., node i covers the target k if it sets its orientation to j); otherwise, it is false.

Let Φ_{ij} denote the set of targets that are covered by sensor i when its orientation is j. Then we can determine all the sets $\Phi_{ij} \forall i, j$, by running the TIS test for every i, j.

C. Maximum Coverage with Minimum Sensors (MCMS) Problem

Under the random deployment strategy, not all targets are covered by the initial deployment. Further, all sensors are active. Our goal is to change the initial orientations in order to cover as many targets as possible while activating as few sensors as possible, at any time instant. We call this the MCMS problem. The MCMS problem can be formally stated as follows:

Given: A set of targets $\mathcal{S} = \{s_1, s_2, \ldots, s_m\}$ to be covered; a set of n homogenous directional sensors, each of which has p possible orientations, randomly deployed in a two-dimensional plane. Hence, a collection of subsets $\mathcal{F} = \{\Phi_{ij}, 1 \leq i \leq n, 1 \leq j \leq p\}$) can be generated based on TIS test, where each element Φ_{ij} is a subset of $\mathcal{S}$.

Problem: Find a subcollection $\mathcal{Z}$ of $\mathcal{F}$, with the constraint that at most one Φ_{ij} can be chosen for the same i, to maximize the cardinality of the union of chosen $\bigcup_{(i,j)} \Phi_{ij}$ (i.e., the number of covered targets) while minimizing the cardinality of $\mathcal{Z} = \{\Phi_{ij}, (i,j) \text{ is chosen}\}$ (i.e., the number of activated directional sensors).

The following theorem shows the complexity of the MCMS problem.

Theorem 3.1: The MCMS problem is $\mathcal{NP}$-complete.

IV. Centralized Solutions of the MCMS Problem

A. ILP Formulation

The parameters used for the formulation can be summarized as follows. n: the number of directional sensors; m: the number of targets; p: the number of orientations available for each directional sensor.

The variables in the ILP are as follows. ψ_k: a binary variable that has value one if target k is covered by any directional sensor, and zero otherwise; χ_{ij}: a binary variable that has value one if the directional sensor i uses the orientation j, and zero otherwise; ξ_k: an integer variable that counts the number of directional sensors covering the target k. Γ: an integer variable that denotes the total number of targets being covered. Λ: an integer variable that denotes the total number of directional sensors that are activated.

Under the random deployment, for each directional sensor i, there is an incidence matrix $\mathcal{A}^i_{(m\times p)}$ where each of its elements a^i_{kj} can be derived based on TIS test:

$$a^i_{kj} = \begin{cases} 1 & k \in \Phi_{ij} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

Therefore, ξ_k can be expressed as:

$$\xi_k = \sum_{i=1}^{n}\sum_{j=1}^{p} a^i_{kj}\chi_{ij} \tag{2}$$

Now the ILP for the MCMS problem can be states as:

$$\textbf{max} \ \sum_{k=1}^{m} \psi_k - \rho(\sum_{i=1}^{n}\sum_{j=1}^{p} \chi_{ij}) \tag{3}$$

subject to:

$$\frac{\xi_k}{n} \leq \psi_k \leq \xi_k \ \forall k = 1 \ldots m \tag{4}$$

$$\sum_{j=1}^{p} \chi_{ij} \leq 1 \ \forall i = 1 \ldots n \tag{5}$$

$$\psi_k = 0 \ or \ 1 \ \forall k = 1 \ldots m \tag{6}$$

$$\chi_{ij} = 0 \ or \ 1 \ \forall i = 1 \ldots n, \ \forall j = 1 \ldots p \tag{7}$$

The objective function in equation (3) maximizes the number of targets to be covered and imposes a penalty by multiplying the number of sensors to be activated by a penalty coefficient ρ whose value must be small enough ($\rho \ll 1$) to guarantee uniqueness of the solution. In addition, there are ($m + n \cdot p$) variables and ($2m + n + n \cdot p$) constraints for the ILP. Equation (4) represents a set of inequalities to indicate that whether any target k is covered or not: if none of the directional sensor covers target k, i.e., $\xi_k = 0$, then $\psi_k = 0$ to follow the right inequality; if target k is covered by any direction sensor, i.e., $\xi_k > 0$, since ξ_k is bounded by n, the total number of deployed sensors, $\frac{\xi_k}{n}$ is a real number less than one, then $\psi_k = 1$ to follow the left inequality. Equation (5) guarantees that one directional sensor has at most one orientation depending on whether it is activated or not.

B. Centralized Greedy Algorithm (CGA)

Although the solution of the ILP formulation provides the optimal solution for the MCMS problem, it is not scalable for large problem instances. Thus, we also present here a polynomial time algorithm for solving the MCMS problem.

The basic idea is based on the greedy principle and can be described as follows: we first construct $\mathcal{F}$, a collection of sets $\{\Phi_{ij}, 1 \leq i \leq n, 1 \leq j \leq p\}$, based on targets, directional sensors and all their possible orientations by TIS tests as an instance of the problem. CGA runs in loops, where initially, all nodes are inactive (i.e., not selected). In each loop, for each sensor i that has not yet been activated, the number of additional targets that would change from uncovered to covered for each possible orientation is calculated. Then, the inactive sensor and its orientation that maximizes the number of newly covered targets is activated. Any ties are broken by selecting one of the choices at random. If there are no more targets to be covered or no more unselected directional sensors remaining, the algorithm terminates; otherwise, directional sensors will be activated iteratively according to the above greedy rule.

For CGA, in the worst case, to perform the TIS test for all nodes requires mnp steps; followed in each loop to choose a desired (i, j), the running time is bounded by $O(np)$. Since there are at most n loops, the time complexity of CGA is $O((m + n)np)$ in the worst case.

V. A Distributed Solution for the MCMS Problem

In DGA, without global information available in a centralized location, we assume that each sensor make its decision independently based on the perfect local information, such as locations and orientations, gathered from the neighborhood confined by its maximum sensing range R_s via wireless communication. Moreover, every sensor has a unique variable, which we call “priority”. The priority needs to be unique only among its neighborhoods. Each sensor is in one of two states; *active* or *inactive* state.

To simplify the description of the algorithm, we say a target is acquired by a sensor if the target was not covered by any higher priority sensor. Initially, each sensor is in the *active* state, assigns itself a priority, and has a random initial orientation. Each sensor starts to collect its neighborhood information, i.e., priorities, locations and orientations. Upon receiving such information, each sensor makes its decision independently as follows. It will calculate, for each of its possible orientations, the number of acquired targets. There are two cases: (a) If the maximum number of acquired targets is positive (i.e., not zero), it will choose the orientation corresponding to the maximum number (random choice in case of a tie). If a sensor i has to switch to a new orientation, it sends out a new message to inform its neighborhood. (b) If the maximum number of acquired targets is zero, the sensor activates a transition timer, with duration T_w. The timer is canceled if new information from its neighborhood arrives and changes the maximum number of acquired targets to a non-zero value. Otherwise the transition timer expires, and the sensor transitions from *active* to *inactive* state. Notice that the sensor does not switch to *inactive* state immediately in order to allow the decisions of its neighborhood to stabilize.

In DGA, since sensors make their local decisions based on gathered neighborhood information, two concerns may arise: (a) whether the algorithm terminate within a finite time and (b) whether, when the algorithm terminates, there exists any target which is left uncovered because of a "misunderstanding," where one sensor assumes the other sensor has covered the target, while it actually has not. We call such a target a "hidden" target. The following two theorems answer the above two questions.

Theorem 5.1: DGA terminates in finite time.

Theorem 5.2: DGA guarantees no "hidden" targets.

Theorem 5.3: The worst case message complexity of DGA is $O(n^2)$.

VI. Sensing Neighborhood Cooperative Sleeping Protocol

Assuming static priorities of sensors, DGA runs once and terminates, providing a solution to the MCMS problem. Since the objective of the MCMS problem is minimizing the number of active sensors, DGA provides an energy-efficient configuration in the network. However, without dynamic energy balancing consideration among sensors, those *active* sensors set by DGA will ultimately deplete their batteries. Therefore, we extend DGA so as to perform dynamic scheduling among sensors depending on the amount of residual energy. The new protocol is called the Sensing Neighborhood Cooperative Sleeping (SNCS) protocol.

The SNCS protocol works as follows. Each node continuously alternates between two phases; scheduling and sensing. In each scheduling phase, all sensors set their states to be *active* at the beginning and then perform DGA described above. At the end of the scheduling phase, as a result of running DGA, each sensor will be in one of two states; active or inactive. The *active* sensors will continue to be active in the followed sensing phase with its sensing and communication units turned on; whereas the *inactive* sensors will go to sleep immediately with its sensing and communication units turned off. In addition, these *inactive* sensors will reset themselves to be *active* state until the next scheduling phase.

In the scheduling phase of SNCS protocol, we assign the residual energy of a sensor as its priority in the DGA. Notice that the residual energy of sensors depends on their behaviors (i.e., transmit, receive, idle or sleep) and dynamically changes along the time, to maintain an unchanged order of priorities among sensors during one-time DGA execution to guarantee its termination, priorities are set to be the instantaneous value of residual energy of sensors only once in every scheduling phase. Moreover, to satisfy the uniqueness property of priorities in DGA, the residual energy of sensors are expected to be different. Even if the equalities appear, since we assume that sensors can not be located at the same coordinations in the two-dimensional plane, we can further incorporate the sensors' geographic location information to ensure the uniqueness of the priorities.

Assigning the value of residual energy to the priority variables in DGA is essential for the SNCS protocol to achieve a trade-off between coverage and network lifetime. In each scheduling phase, residual energy of sensors act as priorities in DGA to solve the MCMS problem. The sensors which have higher priorities (i.e., residual energy) are more likely to be selected to be *active* by the DGA to contribute to coverage, while the sensors with lower residual energy are more likely to go to sleep so as to conserve their energy. Since *active* sensors have larger energy dissipation rates than that of *inactive* sensors in the following sensing phase(s), those *active* sensors will, after a certain time, have less residual energy than that of *inactive* sensors. As a result, these *inactive* sensors may be turned to *active* by DGA when the residual energy of the neighboring active sensors depletes to a level that is lower than that of the inactive sensors. Thus, by using the residual energies of nodes as the priorities in the SNCS protocol, the SNCS protocol dynamically changes the states of the sensors (between *active* and *inactive*) so as to achieve energy balancing across the network while providing a solution to the MCMS problem.

VII. Performance Evaluation

We conduct four sets of experiments to study the performance of proposed solutions and protocol.

In the first experiment, we evaluate the affect of various parameters (m, n, p, R_s) on the solution of the MCMS problem. First, given m and n, we identify the effect of size of sensing sector only on ILP solutions under different p and R_s. As expected, the coverage ratio (number of covered targets divided by the total number of targets) increases/the number of *active* sensors decreases with the increase of the size of sensing sector which is determined by both p and R_s. Note that this is true in most (but not all) cases, due to the integer nature of the solution. Second, given p, R_s and m, we compare solutions for the MCMS problem of ILP, CGA and DGA by changing n. With the increase of sensors deployed, both the coverage ratio and active nodes for all three schemes increase linearly until n approaches a certain value; upon passing such a value, the number of active nodes increases slowly or even decrease whereas the coverage ratios continuously increase and then become saturated when n is above some threshold. To state the differences: for the coverage ratio, ILP always behaves the best among the other two schemes and DGA tracks closely with that of CGA with all n values; for the number of sensors activated which is a bit complicate after n is more than some certain value stated above, DGA activates the largest number of sensors in most of cases; while the curves depicting the number of active sensors by ILP and CGA may cross at some points but ILP stabilizes at a lower value than that of CGA.

In the second experiment, we compare the performance of DGA with OGDC in [7] for the special case of circular coverage. Though OGDC provides area coverage rather than target coverage, there are two reasons for choosing OGDC for comparison. First, as mentioned in [12], by configuring the set of targets as a set of regular grid points with a certain density, target coverage can be approximated as area coverage. Second, as stated in [7], OGDC outperforms other existing distributed algorithms [13], [5], [6] in terms of the above interested performance metrics. Our results show that, by appropriately configuring the density of targets as a set of regular grid points, the performance of DGA is comparable to that of OGDC. The reason is that to maximize the number of acquired targets with a certain granularity in DGA is in the same spirt of minimizing the overlaps among sensing disks in OGDC.

In the third experiment, we evaluate the performance of the SNCS protocol in terms of coverage and network lifetime. Given n, p R_s and a simplified energy consumption model, we consider different density of targets by varying m to examine the network lifetime, which is defined as the time until half of the sensors deplete their energy. For any m, the curve of coverage ratio stabilizes at a high level for a relative long period and then drops sharply toward some lower level. Moreover, with the increase of m, both network lifetime and coverage ratio decrease. A similar "cutoff" property is also observed in the curves of active ratio of sensors. However, unlike the trend for the coverage ratio, the active ratio of sensors increases with the increase of m.

In the fourth experiment, we reevaluate the performance of the SNCS protocol by relaxing the assumptions we made before on acquiring perfect local neighborhood information. Specifically, we introduce the following: (a) the sensors no longer know their exact location information (b) orientation errors are also introduced and (c) wireless communications may result in corrupted messages. To study the impacts of the above three factors, we evaluate the performance of the SNCS protocol under each of them independently and then compare the results with an ideal scenario. In the first two cases, the coverage ratio decreases with the increase of localization errors while the ratio of active sensors and network lifetime are insensitive to these errors, respectively. In the third case, the coverage ratios are insensitive to packet loss ratio while the ratio of active sensors increases proportionally with such a class of error.

VIII. Conclusions

In this paper, we study the problem of coverage by directional sensors in randomly deployed wireless sensor networks. To characterize the desired node and orientation configuration at any instant, we first propose the MCMS problem, which is proved to be $\mathcal{NP}$-complete. Then we present its exact solution by an ILP formulation and approximate solution by CGA in a centralized fashion, respectively. Followed we provide the distributed solution of the MCMS problem by DGA and show its properties. Furthermore, to maximize the network lifetime in a larger time scale, we develop the SNCS protocol based on DGA with residual energy consideration of sensors to achieve energy balancing across the network as well. Finally, we systematically evaluate the performance of proposed solutions and protocol through extensive simulations.

To be noted, some components in our model may not be practical, such as the sensing region of a directional sensor with a binary detection model. However, our proposed framework can be easily generalized to accommodate other practical sensing and detection model of a sensor as long as we can measure the coverage and establish the relationship between sensing regions of sensors and the objects (e.g., target, region and volume and so on) to be covered.

REFERENCES

[1] S. Megrian, F. Koushanfar, M. Potkonjak, and M. Srivastava, "Coverage problems in wireless ad-hoc sensor networks," in *Proceedings of 20th Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM)*, Anchorage, AK, United States, April 2001.

[2] S. Megrian, F. Koushanfar, G. Qu, and M. Potkonjak, "Exposure in wireless ad-hoc sensor networks," in *Proceedings of the Annual International Conference on Mobile Computing and Networking (MOBICOM)*, Rome, Italy, July 2001.

[3] C.-F. Huang and Y.-C. Tseng, "The coverage problem in a wireless sensor network," San Diego, CA, United States, September 2003.

[4] S. Slijepcevic and M. Potkonjak, "Power efficient organization of wireless sensor networks," in *IEEE International Conference on Communications (ICC)*, Helsinki, Finland, June 2001.

[5] D. Tian and N. D. Georganas, "A coverage-preserving node scheduling scheme for large wireless sensor networks," in *Proceedings of the ACM International Workshop on Wireless Sensor Networks and Applications (WSNA)*, Atlanta, GA, United States, 2002.

[6] X. Wang, G. Xing, Y. Zhang, C. Lu, R. Pless, and C. Gill, "Integrated coverage and connectivity configuration in wireless sensor networks," in *Proceedings of the First International Conference on Embedded Networked Sensor Systems (SenSys)*, Los Angeles, CA, United States, 2003.

[7] H. Zhang and J. C. Hou, "Maintaining sensing coverage and connectivity in large sensor networks," *The Wireless Ad Hoc and Sensor Networks: An International Journal*, 2005.

[8] M. Cardei and D.-Z. Du, "Improving wireless sensor network lifetime through power aware organization," *ACM Wireless Networks*, 2005.

[9] S. Megrian and M. Potkonjak, "Low power 0/1 coverage and scheduling techniques in sensor networks," University of California, Los Angeles, Department of Computer Science, Tech. Rep. 030001, January 2003.

[10] Z. Abrams, A. Goel, and S. Plotkin, "Set k-cover algorithms for energy efficient monitoring in wireless sensor networks," in *Third International Symposium on Information Processing in Sensor Networks (IPSN)*, Berkeley, CA., United States, April 2004.

[11] M. Cardei, M. T. Thai, Y. Li, and W. Wu, "Energy-efficient target coverage in wireless sensor networks," in *Proceedings of 24th Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM)*, Miami, FL, United States, March 2005.

[12] T. Yan, T. He, and J. A. Stankovic, "Differentiated surveillance for sensor networks," in *Proceedings of the First International Conference on Embedded Networked Sensor Systems (SenSys)*, Los Angeles, CA, United States, 2003.

[13] F. Ye, G. Zhong, J. Cheng, S. Lu, and L. Zhang, "Peas: a robust energy conserving protocol for long-lived sensor networks," in *Proceedings of 23rd International Conference on Distributed Computing Systems (ICDCS)*, Providence, RI, United States, May 2003.