An Energy-Efficient Target Tracking Strategy for Mobile Sensor Networks

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***Abstract*—In this paper, an energy-efficient strategy is proposed for tracking a moving target in an environment with obstacles, using a network of mobile sensors. Typically, the most dominant sources of energy consumption in a mobile sensor network are sensing, communication and movement. The proposed algorithm first divides the field into a grid of sufficiently small cells. The grid is then represented by a graph whose edges are properly weighted to reflect the energy consumption of sensors. The proposed technique searches for near optimal locations for the sensors in different time instants to route information from the target to destination, using a shortest path algorithm. Simulations confirm the efficacy of the proposed algorithm.**

I. Introduction

Wireless sensor networks have recently emerged as an increasingly important area of research due to their wide range of applications such as environmental monitoring, security surveillance, traffic management and intrusion detection, to name only a few [1], [2], [3]. Target tracking is one of the topics of interest in mobile sensor networks (MSN), where it is desired to track a moving target by properly positioning some or all of the sensors in the field to create a route from the target to the destination node (which collects information) [4]. Several sensor deployment algorithms have recently been developed for this type of network to tackle the target-tracking problem [5], [6].

In a practical MSN deployment algorithm, limited energy of sensors needs to be taken into consideration [7]. The main sources of energy consumption in a mobile sensor are communication, sensing and movement [8]. Furthermore, due to the distributed structure of the network, a decentralized decision-making configuration is often more desirable. This problem is addressed in [9] by considering kinematics of the target and temporarily deactivating sensors which are not involved in tracking process. In [10], the desired sensing and communication radii of sensors as well as their locations at each instant are calculated in a network consisting of sensors which collaboratively track a target in such a way that the network lifetime is maximized. The main shortcoming of the method, however, is that it only takes the communication and sensing energies into account (neglecting the movement energy). In [11], various approaches are investigated for target tracking in five different categories, namely hierarchical, tree-based, prediction-based, and mobicast message-based tracking as well as hybrid methods. A method for predicting target motion using its movement history, current location, velocity and motion direction is presented in [12].

The problem of collaborative tracking of mobile nodes in wireless sensor networks is studied in [13], where target tracking and node selection procedures are employed together to identify proper sensor locations and information route for an energy-efficient tracking strategy. In [14], an algorithm is provided to estimate the position of the target, while optimizing the quantization level for the minimum transmission power. A distributed energy optimization technique is proposed in [15] for target tracking in wireless sensor networks, where sensor nodes are clustered properly and the sensing area is partitioned for parallel sensor deployment optimization. Grid exclusion and Dijkstra's algorithm are subsequently employed for coverage and energy metrics, respectively. The coverage is then maximized while minimizing energy consumption. In [16] and [17], the authors present efficient algorithms to maximize the lifetime of a sensor network with and without obstacles, respectively. It is to be noted that while the lifetime maximization and energy minimization problems are closely related, they also have fundamental differences (this issue has been pointed out in detail later in the paper).

In the present work, an energy-efficient algorithm is developed for target tracking in a field with obstacles using a mobile sensor network. It is assumed that the main sources of energy consumption in the network are communication, sensing, and movement. First, the field is divided into a grid, and the candidate sensor positions are calculated in discrete time instants. A graph is subsequently derived from this grid, and its edges are weighted properly based on the proposed algorithm to model the energy consumption in the network. This graph is used to find a close estimate of the optimal path for routing information from the target to destination. Then, the graph is redrawn in such a way that the minimum energy problem is translated to a constrained

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shortest path problem from the target to destination. This is a well-known problem in network and routing, for which several algorithms exist in the literature. A preliminary version of this work has been published in [18].

The organization of the paper is as follows. In Section II, energy Voronoi diagram is introduced and the problem statement is provided. Section III presents a target tracking algorithm as the main contribution of this work. Simulation results are given in Section IV, which confirm the effectiveness of the proposed technique. Finally, conclusions are drawn in Section V.

II. Problem Formulation

A. Energy Voronoi Diagram

Let $\mathbf{S}$ be a set of n sensors $S_1, \dots, S_n$ in a 2D field. For any arbitrary point A, denote the minimum required energy for S_i to travel to point A by $E_{min}(S_i, A)$. In the case where there is no obstacle in the field, in order to minimize the movement energy, the sensor S_i must move toward point A in a straight line. In the presence of obstacles, however, the direct path may be obstructed.

Now, it is desired to partition the field into n regions $\Lambda_1, \dots, \Lambda_n$, such that for any arbitrary point Q in region Λ_i, the sensor requiring minimum energy to travel to point Q be S_i (this implies that every region contains only one sensor). The diagram obtained by the partitioning described above is called the *energy Voronoi diagram*, and the corresponding regions are called the *energy Voronoi regions*. The mathematical characterization of each energy Voronoi region obtained by the above partitioning is as follows:

$$\Lambda_i = \{Q \in R^2 | E_{min}(S_i, Q) \le E_{min}(S_j, Q), \forall j \in \mathbf{n} - \{i\}\} \tag{1}$$

for any $i \in \mathbf{n}$, where $\mathbf{n} := \{1, 2, \dots, n\}$.

Definition 1. Similar to conventional Voronoi diagram, the sensor S_i and S_j $(i, j \in \mathbf{n}, i \neq j)$ in an energy Voronoi diagram are called neighbors if $\Lambda_i \cap \Lambda_j \neq \emptyset$. The set of all neighbors of S_i, $i \in \mathbf{n}$, is denoted by N_i and is formulated below:

$$\mathbf{N}_i = \{S_j \in \mathbf{S} \mid \Lambda_i \cap \Lambda_j \neq \emptyset, \ \forall j \in \mathbf{n}\} \tag{2}$$

Definition 2. In the remainder of the paper, the distance between two points A and B is defined as the length of the shortest path connecting these two points, and is denoted by $d_{A,B}$. Obviously, in a field without obstacles this length is equal to the Euclidean distance.

Remark 1. Note that in the absence of obstacles, the energy Voronoi diagram is, in fact, the same as the conventional Voronoi diagram.

Fig. 1 shows the energy Voronoi diagram for a field with obstacles. In this figure, it is assumed that the energy required for any sensor to move to a specific point is linearly proportional to the distance between the sensor and that point.

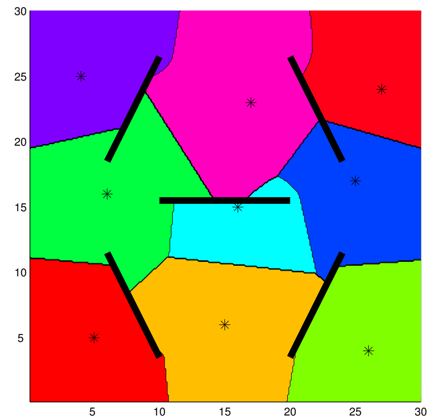


Fig. 1: An example of the energy Voronoi diagram for a group of 9 sensors in a field with obstacles.

B. Problem Statement

Consider a group of n mobile sensors $S_1, \dots, S_n$, a fixed access point (or destination point), and a moving target. The objectives of this paper are described below.

Problem Definition: It is desired to develop a strategy to: (i) monitor a moving target and send its information to the destination point, and (ii) minimize the energy consumption of the network. In other words, the objective is to find proper positions for the sensors at any point in time such that some desired specifications are satisfied, while the total energy consumption of the sensors is minimized. Note that limitations in the sensing and communication ranges of the sensors are formulated as some constraints which are taken into account in the construction of the energy digraph introduced in the next section.

Definition 3. Throughout this paper, the nearest sensor to point P, denoted by S'_P, is the sensor with the following property:

$$E_{min}(S'_P, P) \le E_{min}(S_i, P), \ \forall i \in \mathbf{n}$$

In addition, the second nearest sensor to point P, denoted by S''_P, is the sensor with the following properties:

$$E_{min}(S''_P, P) \ge E_{min}(S'_P, P)$$

$$E_{min}(S''_P, P) \le E_{min}(S_i, P), \ \forall S_i \neq S'_P$$

For convenience of notation, in the rest of the paper $E_{min}(S'_P, P)$ and $E_{min}(S''_P, P)$ will be denoted by $E_{min}(S'_P)$ and $E_{min}(S''_P)$, respectively.

Assumption 1. It is assumed that the target is in a reachable distance from the destination through the sensors at all times. In other words, the sensors can be positioned such that despite their sensing and communication limitations, they can cooperatively transfer information about the target to destination. Additionally, the nearest sensor to the target, which is referred to as the *tracking sensor*, is assigned to detect the target. This sensor is not necessarily fixed, and may change from time to time, as the target moves. A subset of the other sensors is used along with the tracking sensor to route information from the target to destination.

The sensors operate collaboratively to minimize the overall energy consumption of the network by finding the optimal locations for them and the best routing path for information transmission. The problem of energy-efficient target tracking using a mobile sensor network is very complicated in its general form. In the next section, a strategy is presented to place the sensors in proper positions at any time instant such that the total energy consumption of the sensors (due to sensing, communication and movement) is sufficiently close to its minimum value.

III. MAIN RESULTS

Consider a field with obstacles, and a group of n sensors in it. The energy-efficient target monitoring problem introduced in the preceding section cannot be solved analytically, in general. As a feasible alternative, the field is represented by a grid whose nodes are chosen sufficiently close to each other, such that the target and every sensor can be assumed to be located at some node of the grid at all times. In the rest of the paper, the nodes where the destination and target are located at are referred to as the *destination node* and *target node*, respectively. The following notation and definitions will prove convenient in the development of the main results.

Notation 1. The tracking sensor will be denoted by S_T (note that $S_T \in \{S_1, S_2, \ldots, S_n\}$ at any time instant). In addition, the target node and the energy Voronoi region containing it will be denoted by P_T and Λ_T, respectively, and the destination node will be denoted by P_D. Note that the destination node is fixed, but S_T, P_T and Λ_T can change with time.

Definition 4. Throughout this paper, any node in Λ_T from which a sensor can detect the target, is referred to as a *sensing node*.

Definition 5. Given a path Π connecting the target to the destination, any node on the path except for the target and destination will hereafter be referred to as a *regular node*.

The *energy digraph* is introduced in the sequel, which will be used later in the deployment strategy.

Construct a directed graph (digraph) whose vertices are the grid nodes, and whose edges are weighted properly to model the three sources of energy consumption, i.e. sensing, communication and movement. In this digraph, there is an edge from P_T to P_j if and only if P_j is a sensing node. The weight of this edge is equal to the required sensing energy for a sensor at P_j to detect the target, and is denoted by $\omega_s(T, j)$. Fig. 2 demonstrates the directed edges connecting P_T to sensing nodes in a given energy Voronoi diagram. In this figure, the blue square represents the target located at P_T, and the red circle around it contains all nodes from which the target can be detected (i.e., the target is in their sensing range). In addition, there is an edge from a node $P_i \neq P_T$ to P_j if and only if P_j is not a sensing node and a sensor located at P_i is able to communicate with a sensor at P_j. The weight of this directed edge depends on the locations of the two nodes, and is denoted by $w(i, j)$. The following procedure is used to determine this weight.

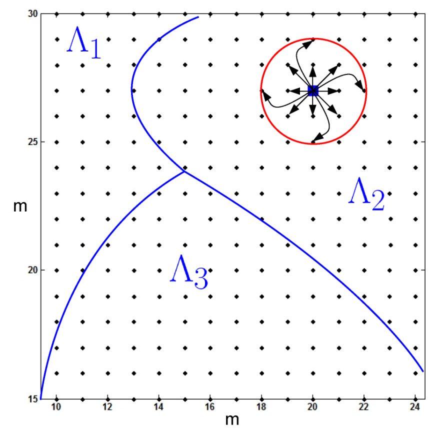


Fig. 2: Directed edges connecting the target to sensing nodes for a given energy Voronoi diagram.

Case 1) Consider the case where P_i and P_j are in different energy Voronoi regions OR P_j is the destination node.

i) If the target and P_i are in the same region AND P_i is not a sensing node, then:

$$w(i, j) = E_{min}(S''_{P_i}) + \omega_c(i, j)$$

where $\omega_c(i, j)$ is the communication cost from node P_i to node P_j.

ii) If the target and P_i are in different regions OR P_i is a sensing node, then:

$$w(i, j) = E_{min}(S'_{P_i}) + \omega_c(i, j)$$

Case 2) Consider the case where P_i and P_j are in the same energy Voronoi region AND P_j is not the destination node.

i) If the target and P_i are in the same region AND P_i is not a sensing node, then:

$$w(i, j) = E_{min}(S''_{P_i}) + \omega_c(i, j)$$

ii) If the target and P_i are in different regions, then:

$$w(i, j) = min[E_{min}(S'_{P_i}) + E_{min}(S''_{P_j}), E_{min}(S'_{P_j}) + E_{min}(S''_{P_i})] - E_{min}(S'_{P_j}) + \omega_c(i, j)$$

iii) If P_i is a sensing node, then:

$$w(i, j) = E_{min}(S'_{P_i}) + \omega_c(i, j)$$

Notice that the above weight assignment in the energy digraph is done in such a way that the sum of the weights

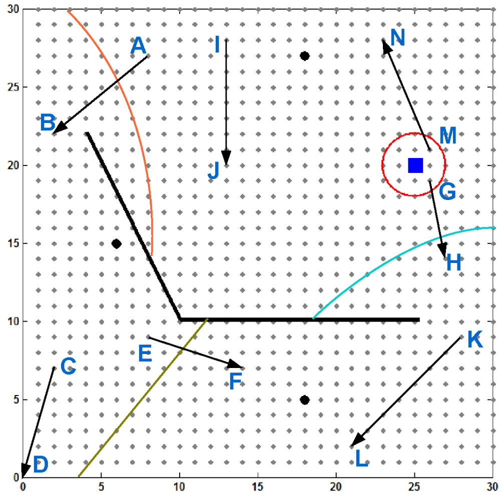


Fig. 3: An illustrative example of the two cases introduced for the energy digraph.

allocated to the edges of any arbitrary path from target to destination is an approximation of the minimum energy required for a subset of sensors to move to some regular node locations and route information to the destination node. It is desired to find the shortest weighted path connecting the target to destination in the energy digraph, subject to the constraint that the number of nodes in the path is less than or equal to n. It will be shown that this path provides a cost-effective route, which can, under some conditions, be optimal (Theorem 3).

Fig. 3 is an illustrative example of the above cases, where similarly to Fig. 2, the blue square represents the target and the red circle around it shows the reachability area of the target. Also, nodes A and B in this figure satisfy the conditions of case 1(i). The edges CD, EF and GH satisfy the conditions of case 1(ii). Node D (associated with the edge CD) is the destination, and node G (associated with the edge GH) is a sensing node. Furthermore, node E and the target are *not* in the same region. The edge IJ satisfies the conditions of case 2(i), as I is not a sensing node and does not lie in the same region as the target. The edge KL satisfies the condition of case 2(ii), and the nearest sensor to K in this case is also the nearest sensor to L. Finally, M is a sensing node and the edge MN satisfies the conditions of case 2(iii).

Definition 6. Given a path $\Pi = (P_T, P_1, P_2, ..., P_m, P_D)$ connecting the target to destination, the minimum energy required for any group of m sensors to move to $P_1, P_2, ..., P_m$ and transmit information from the target to destination is called the *path cost*, and is denoted by $C(\Pi)$. In the path cost, the amounts of energy required for sensing the target, communicating information and moving the sensors to designated locations will hereafter be called *path-sensing cost*, *path-communication cost* and *path-movement cost*, respectively. In addition, the sum of the weights of the directed edges of a path Π in the energy digraph is referred to as the *path weight*, and is denoted by $W(\Pi)$. Two components of the path weight are $\omega_s(T, j)$ and $\omega_c(i, j)$, which will be referred to as the *path-sensing weight* and *path-communication weight*, respectively, and the remaining weight will be called the *path-movement weight*.

Definition 7. Consider an energy digraph with a path consisting of at most n nodes, such that there exists a group of sensors which the cost of moving them to these nodes and establishing an information link from the target to destination is minimum, among all possible choices of paths and sensors. This path will be referred to as the *optimal path*, and is denoted by Π^* [18].

Remark 2. To find the shortest path from the target node to the destination node in an energy digraph, one can use an efficient routing method such as Dijkstra's algorithm. Note that for the case where the number of nodes in the shortest path is greater than n, one can use a constrained shortest path first (CSPF) algorithm, which is normally slower than its unconstrained counterpart [19].

Remark 3. As noted in the weight assignment procedure, $\omega_c(i, j)$ is the communication cost from node P_i to node P_j. Therefore, after finding the shortest path from the target to destination, the sum of the communication costs of the edges in a path is, in fact, the path-communication cost. Similarly, $E_{min}(.)$ is the energy consumption due to movement, and consequently sum of the corresponding terms in a path reflects the path-movement cost. Finally, note that since only the tracking sensor consumes sensing energy, the term $\omega_s(T, j)$ only appears in edges from the target to sensing nodes.

Theorem 1. *For any path Π from the target to destination in an energy digraph, the relation $W(\Pi) \le C(\Pi)$ holds.*

Proof: Assume that the path Π passes through the regions $\Lambda_1, \Lambda_2, ..., \Lambda_\kappa$, and that the path has n_i nodes in region Λ_i, $\quad i \in \{1, 2, ..., \kappa\}$. Partition Π into κ sub-paths as follows:

$$\begin{aligned}
\Pi^1 &= (P_T, P_1^1, P_2^1, ..., P_{n_1}^1, P_1^2) \\
\Pi^2 &= (P_1^2, P_2^2, ..., P_{n_2}^2, P_1^3) \\
&\vdots \\
\Pi^\kappa &= (P_1^\kappa, P_2^\kappa, ..., P_{n_\kappa}^\kappa, P_D)
\end{aligned}$$

In any fixed path in the energy digraph, the path-communication cost and path-sensing cost are equal to the path-communication weight and path-sensing weight, respectively. Thus, to prove the theorem, it suffices to show that the path-movement cost is greater than or equal to the path-movement weight. To this end, it will be shown in the sequel that the path-movement weight of the sub-path Π^i is less than or equal to the corresponding path-movement cost, for any $i \in \{1, 2, ..., \kappa\}$.

If Λ_i contains exactly one node, then the sub-path Π^i contains only the edge (P_1^i, P_1^{i+1}) (note that $P_1^{\kappa+1}$ is, in fact, P_D). In the weight assigned to this edge in the energy digraph, the component corresponding to the movement energy is $E_{min}(S'_{P_1^i})$ (which is the energy required to move to the location of node P_1^i, the nearest sensor to it). Clearly, the minimum energy required to move a sensor to P_1^i is equal to $E_{min}(S'_{P_1^i})$ as well (note that the sensor assigned to move to a node is not necessarily its nearest sensor because that may be the nearest sensor to multiple nodes in the path). Therefore, in this case the path-movement weight of sub-path Π^i is less than or equal to the path-movement cost.

If Λ_i contains more than one node, there will be two possibilities as follows:

Case 1: $i = 1$ (the region contains the target). In this case, by assumption, the nearest sensor to the nodes of this region is assigned to detect the target, and hence cannot be assigned to another node simultaneously. As a result, the cost of moving n_1 sensors to n_1 nodes of the sub-path Π^1 is greater than or equal to Y defined below:

$$Y = E_{min}(S'_{P_1^1}) + \sum_{k=2}^{n_1} E_{min}(S''_{P_k^1})$$

On the other hand, the path-movement weight of the sub-path Π^1 in the energy digraph is:

$$X = E_{min}(S'_{P_1^1}) + \sum_{k=2}^{n_1} E_{min}(S''_{P_k^1})$$

This means that the path-movement weight of Π^1 is less than or equal to its path-movement cost.

Case 2: $i \neq 1$. In this case, the path-movement weight of the sub-path Π^i in the energy digraph is:

$$X = \sum_{k=1}^{n_i-1} \{min[E_{min}(S'_{P_k^i}) + E_{min}(S''_{P_{k+1}^i}), E_{min}(S'_{P_{k+1}^i}) + E_{min}(S''_{P_k^i})] - E_{min}(S'_{P_{k+1}^i})\} + E_{min}(S'_{P_{n_i}^i})$$

It is concluded from the properties of the energy Voronoi diagram that the nearest sensor to any node of the sub-path Π^i is the nearest sensor to all other nodes of this sub-path as well. However, this sensor can move to only one node; therefore, the cost of moving n_i sensors to the n_i nodes of the path which lie in region Λ_i is greater than or equal to:

$$Y = E_{min}(S'_{P_j^i}) + \sum_{k=1, k\neq j}^{n_i} E_{min}(S''_{P_k^i})$$

for any $j \in \{1, 2, ..., n_i\}$. Now, consider the following relations:

$$\begin{aligned} X_1 &= \sum_{k=1}^{j-1} \{[E_{min}(S'_{P_{k+1}^i}) + E_{min}(S''_{P_k^i})] - E_{min}(S'_{P_{k+1}^i})\} \\ &\geq \sum_{k=1}^{j-1} \{min[E_{min}(S'_{P_k^i}) + E_{min}(S''_{P_{k+1}^i}), E_{min}(S'_{P_{k+1}^i})] \\ &\qquad + E_{min}(S''_{P_k^i}) - E_{min}(S'_{P_{k+1}^i})\} \end{aligned} \tag{3}$$

$$\begin{aligned} X_2 &= \sum_{k=j}^{n_i-1} \{[E_{min}(S'_{P_k^i}) + E_{min}(S''_{P_{k+1}^i})] - E_{min}(S'_{P_{k+1}^i})\} \\ &\qquad + E_{min}(S'_{P_{n_i}^i}) \\ &\geq \sum_{k=j}^{n_i-1} \{min[E_{min}(S'_{P_k^i}) + E_{min}(S''_{P_{k+1}^i}), E_{min}(S'_{P_{k+1}^i}) \\ &\qquad + E_{min}(S''_{P_k^i})] - E_{min}(S'_{P_{k+1}^i})\} + E_{min}(S'_{P_{n_i}^i}) \end{aligned} \tag{4}$$

By expanding and simplifying (3) and (4), one can conclude that:

$$\begin{aligned} Y &= X_1 + X_2 \\ &\geq \sum_{k=1}^{n_i-1} \{min[E_{min}(S'_{P_k^i}) + E_{min}(S''_{P_{k+1}^i}), E_{min}(S'_{P_{k+1}^i}) \\ &\qquad + E_{min}(S''_{P_k^i})] - E_{min}(S'_{P_{k+1}^i})\} + E_{min}(S'_{P_{n_i}^i}) = X \end{aligned} \tag{5}$$

Since Y is less than or equal to the path-movement cost of the sub-path Π^i, it results from the above relation that the path-movement weight of this sub-path is less than or equal to its path-movement cost.

On the other hand, the path-movement weight and path-movement cost of Π are, respectively, the sum of the path-movement weights and path-movement costs of its sub-paths. It can be concluded from this fact and the results of the above two cases that the path-movement weight of the path is less than or equal to its path-movement cost. This completes the proof. ■

Theorem 2. *Consider a path Π from the target to destination such that:*

i) *it has at most two regular nodes in each energy Voronoi region it passes through, and*
ii) *if a region contains exactly two regular nodes of the path, then Π does not pass through any other region containing the second nearest sensor to these two nodes.*

Then the path cost and path weight of Π are equal.

Proof: Since the path-communication and path-sensing costs for any fixed path are equal to the path-communication and path-sensing weights, respectively, it suffices to show that the path-movement cost and path-movement weight are equal. To this end, consider the following three cases:

Case 1: An energy Voronoi region containing only one regular node. To minimize the movement energy in this case, one can assign the nearest sensor of this node to it. From the weight-assignment rule in the energy digraph, it follows that the path-movement cost and path-movement weight are equal in this case.

Case 2: An energy Voronoi region containing P_T (target) as well as two regular nodes. In this case, the sum of the movement weights of the corresponding edges is:

$$E_{min}(S'_{P_i}) + E_{min}(S''_{P_j}) \tag{6}$$

where P_i and P_j are the two regular nodes in the above region. Since Π does not pass through the region containing the second nearest sensor to P_j, thus (6) gives the minimum energy required to place two sensors in P_i and P_j.

Case 3: An energy Voronoi region containing two regular nodes, but not P_T. Denote the two regular nodes in this region by P_i and P_j. Similar to the previous case, it results from the weight-assignment rule in the energy digraph that the sum of the movement weights of the edge from P_i to P_j and the edge coming out of P_j is given by:

$$\begin{aligned} X_k = & min[E_{min}(S'_{P_i}) + E_{min}(S''_{P_j}), E_{min}(S'_{P_j}) \\ & + E_{min}(S''_{P_i})] - E_{min}(S'_{P_j}) + E_{min}(S'_{P_j}) \\ = & min[E_{min}(S'_{P_i}) + E_{min}(S''_{P_j}), E_{min}(S'_{P_j}) \\ & + E_{min}(S''_{P_i})] \end{aligned} \tag{7}$$

Since Π does not pass through the energy Voronoi regions containing the second nearest sensors to P_i and P_j (according to the statement of the theorem), the above value is the minimum energy required to place the sensors in these two nodes.

Since the above discussions apply to every energy Voronoi region, one can conclude that the path-movement cost and path-movement weight are equal, which implies that the path cost and path weight of Π are also equal, as pointed out earlier. ■

Corollary 1. *Consider a path Π connecting the target to destination in a given energy digraph. If Π has exactly one node in any region it passes through, then the path cost and path weight of Π are equal.*

Proof: The proof follows immediately from Theorem 2, as a special case. ■

Theorem 3. *Assume the shortest path $\bar{\Pi}$ from the target to destination in a given energy digraph has the following properties:*

i) *it has at most two regular nodes in each energy Voronoi region it passes through, and*
ii) *if Λ_k contains exactly two regular nodes, then $\bar{\Pi}$ does not pass through any other region containing the second nearest sensor to these two nodes.*

Then $\bar{\Pi}$ is the optimal path.

Proof: Suppose the shortest path $\bar{\Pi}$ and the optimal path Π^* are not the same. Then:

$$C(\Pi^*) < C(\bar{\Pi}) \tag{8}$$

From Theorem 1:

$$W(\Pi^*) \leq C(\Pi^*) \tag{9}$$

Also, from Theorem 2:

$$W(\bar{\Pi}) = C(\bar{\Pi}) \tag{10}$$

Combining the three relations given above, one arrives at the following inequality:

$$W(\Pi^*) < W(\bar{\Pi})$$

which contradicts the fact that $\bar{\Pi}$ is the shortest path. Thus, $\bar{\Pi}$ is the same as Π^*. ■

The following corollary follows directly from Theorem 3.

Corollary 2. *If the shortest path $\bar{\Pi}$ connecting the target to destination in the energy digraph has exactly one regular node in each energy Voronoi region it passes through, then $\bar{\Pi}$ is, in fact, the optimal path.*

It is worth mentioning that the energy Voronoi diagram plays a key role in developing the algorithm. In fact, the weight assignment procedure, which is one of the most important parts of the algorithm, highly depends on the energy Voronoi regions. Also, by partitioning the field into n energy Voronoi regions based on equation (1), the nearest sensor (in terms of energy consumption) to the points of any region is identified. Hence, after finding the shortest path from target to destination, the nearest sensors can move to the corresponding shortest path nodes. Note that if an energy Voronoi region includes exactly one node of the shortest path, then the corresponding sensor of that region is assigned to move to that node. Otherwise, if it includes two nodes of the shortest path, then the corresponding sensor of the region is assigned to move to the nearest node, and the second nearest sensor to the remaining node is assigned to move there.

Remark 4. It is to be noted that weight assignment in the energy digraph is a challenging problem. In fact, the proposed weight assignment procedure in the energy digraph is an important (and novel) part of the algorithm, and is carried out in such a way that it models the three sources of energy consumption (i.e. sensing, communication and movement). It is also carried out such that not only is the path weight always less than or equal to the path cost for any arbitrary path, but the shortest path from target to destination generically satisfies the conditions of Theorem 3, and consequently it is the optimal path too. In other words, using the proposed weight assignment procedure, the problem of finding the optimal path is simplified to finding the shortest path from the target to destination.

Remark 5. To the best of the authors' knowledge, the problem of target tracking using a wireless sensor network with a sufficiently accurate energy-consumption model is not studied in the general form in a continuous-time setup. In fact, using the strategy proposed in this work, one can divide the field into a grid in order to transform the problem to the discrete-time domain, where efficient techniques are available to solve it. One can use a larger grid (smaller cells) which leads to a more accurate solution to the underlying problem at the expense of higher computational complexity. The proposed strategy can also be very effective in dealing with constrained trajectory tracking problems (e.g., involving obstacle avoidance constraints).

Remark 6. The proposed method transforms a highly complex problem to a series of shortest path problems which can be solved efficiently. To clarify this point, consider a field with 16 sensors and 900 nodes (similar to Example 1). In order to find the optimal sensor configuration using a brute force method (instead of using the proposed approach) in this case, one needs to check all combinations of 16 out of 900 nodes in each iteration (more than 7×10^{33} combinations), which is not possible practically.

The weight-assignment and the shortest-path procedures are the most complex parts of the proposed algorithm. Given a field of size $L \times W$, let δ denote the distance between every pair of neighboring nodes in the grid. The complexity of the procedure for determining the weight of the edges connecting every pair of nodes in the weight-assignment technique is of order $O(1/\delta^4)$. Different methods can be used, however, to reduce the execution time significantly. For instance, if the communication range of sensors is R_c, then for every node in the grid one needs to check only the nodes whose distance from it is less than R_c (to simplify the implementation, one can choose a $2R_c \times 2R_c$ square centered at that particular node). This would reduce the computational complexity, as R_c/δ is typically smaller than L/δ and W/δ. Note also that these computations can be performed in parallel for all edges, to further reduce the execution time.

The complexity of the shortest path algorithm, on the other hand, is of order $O(E+VlogV)$ [20], where V and E are the number of vertices and edges of the energy digraph, respectively. Following a discussion similar to that given in the preceding paragraph, the complexity of the shortest path algorithm is of order $O(1/\delta^4)$, approximately. Thus, the overall order of complexity of the proposed algorithm is about $O(1/\delta^4)$.

Since the complexity of the algorithm is highly dependent on the fineness of the grid, the number of grid nodes should be chosen carefully, taking into account the tradeoff between the computational complexity of the algorithm and the accuracy of the results. In summary, with a finer grid (higher resolution) the sensors can be placed closer to the optimal locations at the cost of higher computational complexity.

Remark 7. Although the algorithm proposed in this paper is cost-efficient in terms of energy consumption, it may have some practical limitations in terms of processing capability of sensors. To address this limitation, some of the computations (e.g., finding ω_c and the distance between different pairs of nodes, as defined in Definition 2) can be performed off-line. On the other hand, the shortest path subroutine, which is an important part of the proposed strategy, can be handled efficiently using the Dijkstra algorithm. Furthermore, there is a trade-off between the accuracy and computational complexity of the algorithm, as noted earlier, which needs to be taken into consideration when choosing the size of the grid.

To perform the proposed algorithm, each sensor needs to know the information about the positions of the other sensors, as well as the position of the target. The destination node is usually equipped with a transmitter capable of sharing the information with other sensors, and hence the required information is transmitted to all sensors as soon as the destination node receives it. Assume at time t_i the destination node has information about the target and all sensors (and subsequently all sensors also have this information). At time interval $[t_i, t_i + \Delta T]$ the positions of the target and the sensors collaborating to track it change. Since a unidirectional multihop communication link is available from the target to destination through the collaborating sensors, information about the target and these sensors can be transferred to the destination. On the other hand, the position of any sensor that is not involved in the communication link from the target to destination does not change in the above time interval, and hence the destination node still has this information. As a result, the destination node has all the required information at time t_{i+1}, and consequently could process it and send the results to all sensors.

IV. Simulation Results

In this section, simulations are performed using MATLAB to test the proposed algorithm. All the parameters in the simulations (the size of the field, the number of sensors as well as their sensing and communication ranges) are chosen close to the ones used in the literature [21], [22], [23], [24], [25]). The chosen values are also consistent with existing sensor prototypes such as Smart Dust (University of California, Berkeley), CTOS dust, and Wins (Rockwell) [26]. Also, the value chosen for the coefficient β which specifies the movement energy consumption per unit distance (and highly depends on the friction factor of the surface on which the sensor is moving) is similar to that used in [27], [28]. All other coefficients corresponding to the communication model (α and λ) are similar to those in [28].

In the first three examples of this section, a 30m $\times$ 30m rectangular field with obstacles is considered, and the field is divided into a 30×30 grid. The effect of obstacles on sensing, communication and movement of the sensors can be considered using several models. For example, they can attenuate electromagnetic sensing and communication signals or can entirely block them, thus preventing the sensors from communicating and sensing in specific directions. In this section, it is assumed that any pair of nodes whose line of sight is blocked by an obstacle cannot communicate with each other. Moreover, if the line of sight from the target to a sensor is blocked by an obstacle, the target cannot be detected by that sensor. Other models for the effect of obstacles can also be used in the proposed algorithm.

Example 1. As the first example, consider 16 identical sensors in the field. The network is aimed to track a target with an unpredictable movement pattern, by routing information from it to the destination node. The communication and sensing ranges are assumed to be 10m and 1.5m, respectively, for all sensors. Let also the respective movement, communication, and sensing energy consumptions be:

$$E_{min}(S_i, A) = \beta \times d_{S_i,A}, \quad \omega_c(i,j) = \alpha \times d^{\lambda}_{P_i,P_j}$$
$$\omega_s(T,j) = \theta \times d^{\gamma}_{P_T,P_j}$$

where the constant coefficients in the above relations are $\alpha = 10^{-7}$, $\beta = 7.54$, $\theta = 0.1$, $\lambda = 2$, and $\gamma = 2$. Moreover, d_{P_i,P_j} is the distance between nodes P_i and P_j as specified in Definition 2. Assume that the target moves randomly from one node to another within the interval $[-7\text{m}, 7\text{m}]$ in both horizontal and vertical directions. The proposed technique is used to determine the target-to-destination route and the new locations of the sensors for the next time instant. Note that data is assumed to be processed in discrete time instants, where the corresponding time interval is chosen based on the target's movement characteristics such as velocity.

Let initially the sensors be distributed randomly with a uniform distribution along the horizontal and vertical axes. Let also the destination be located at the origin, and assume that the sensors' maximum velocity is $0.5\frac{\text{m}}{\text{s}}$. Thus, in order to maintain the connectivity of a route from the target to destination, every time step is assumed to be 20s. Fig. 4 illustrates the locations of the target (black square) and sensors as well as the shortest path between the target and destination (blue lines) for three consecutive steps. Green lines show the movement of the sensors from their previous locations to their current positions whenever they need to move. Furthermore, the previous locations of the sensors are shown by asterisks, while the present locations of the sensors on the shortest path are depicted by small circles. A comparison of the network energy consumption under the method proposed in this paper with the one presented in [16] (which, similar to the proposed method, considers movement, communication and sensing as the dominant energy consumption sources for maximizing the life-span of the network) is provided in Fig. 5. This figure shows the sum of the residual energies of all sensors versus time in the proposed minimum energy consumption (solid curve) and that in the maximum life-span strategy in [16] (dotted curve). It can be observed from this figure that after 2720s, the sum of the residual energies of the sensors in the proposed method is 71% greater than that in the maximum life-span strategy.

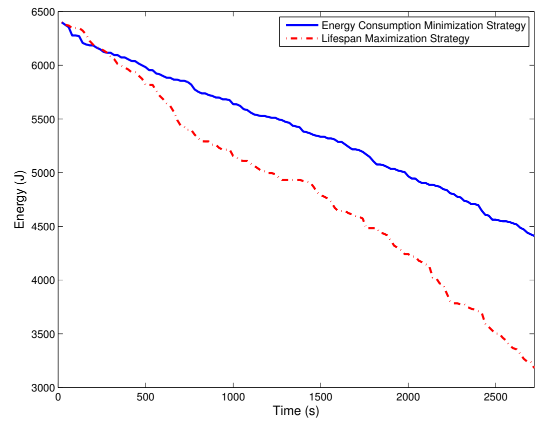


Fig. 5: The total residual energy of all sensors in Example 1.

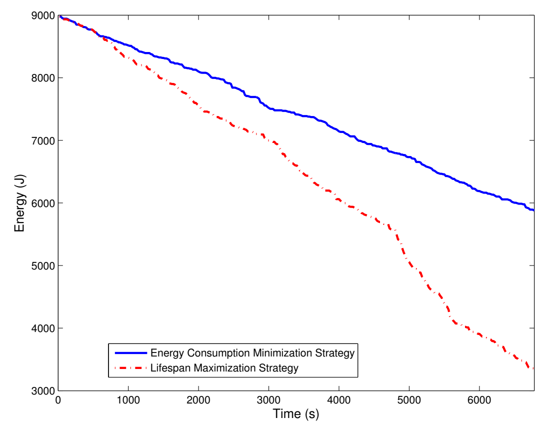
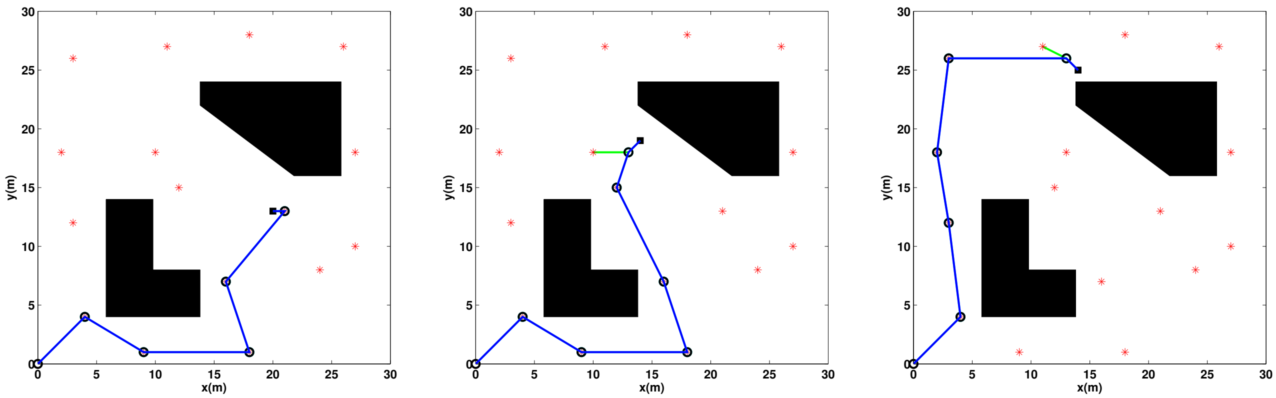


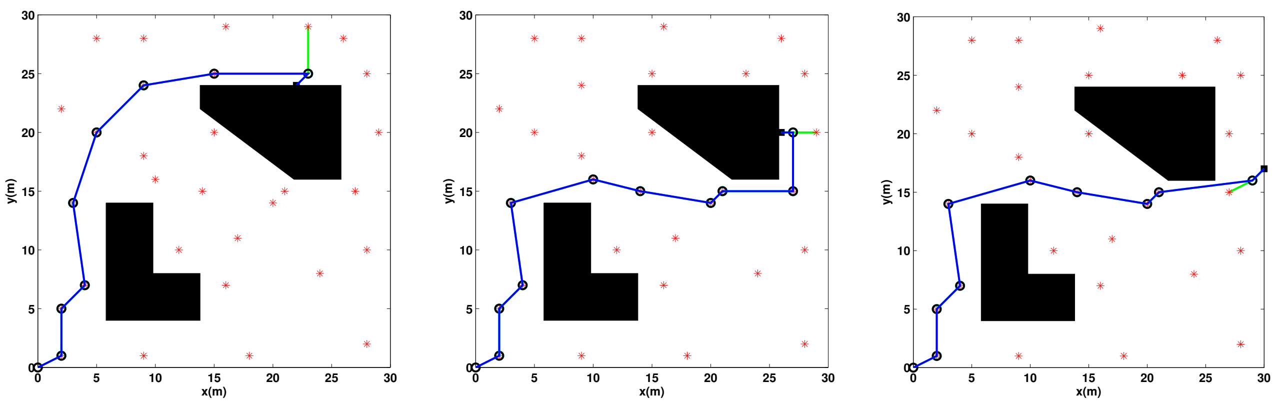
Fig. 7: The total residual energy of all sensors in Example 2.

Example 2. In this example, the performance of the proposed algorithm is evaluated with a higher number of sensors. Consider 30 sensors with the same specifications as in the previous example. The simulation results for this case are given in Fig. 6, where it can be observed that usually not many sensors other than the one assigned to detect the target are required to move under the proposed technique. This is not surprising, as the link from the target to destination can be established through different routes, and hence there is no need to move the sensors in order to track the target (note that the movement energy is typically greater than sensing and communication energies). It can be observed from Fig. 7 that after 6780s, the sum of the residual energies of the sensors in the proposed method is 43% greater than that in the maximum life-span strategy.



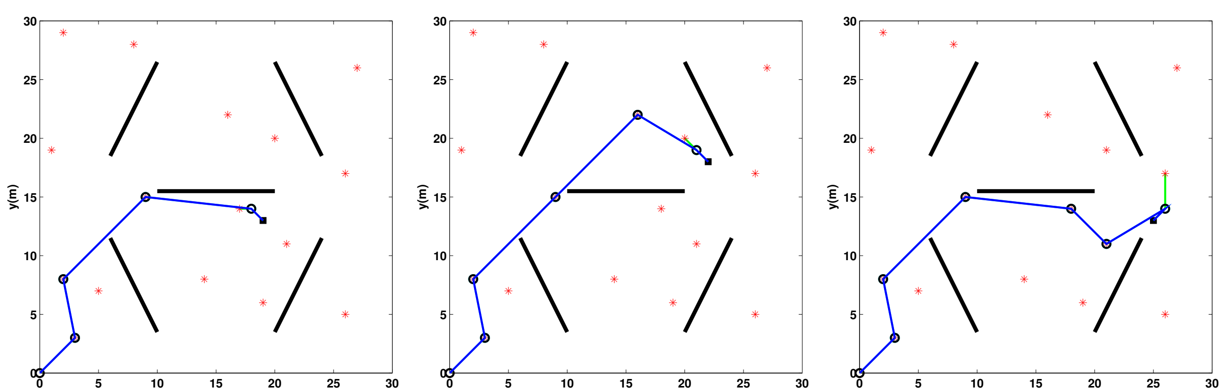
(a) (b) (c)

Fig. 4: Snapshots of the network configuration obtained by the proposed technique for 16 sensors in three consecutive steps of Example 1: (a) 22^{nd} step; (b) 23^{rd} step, and (c) 24^{th} step.



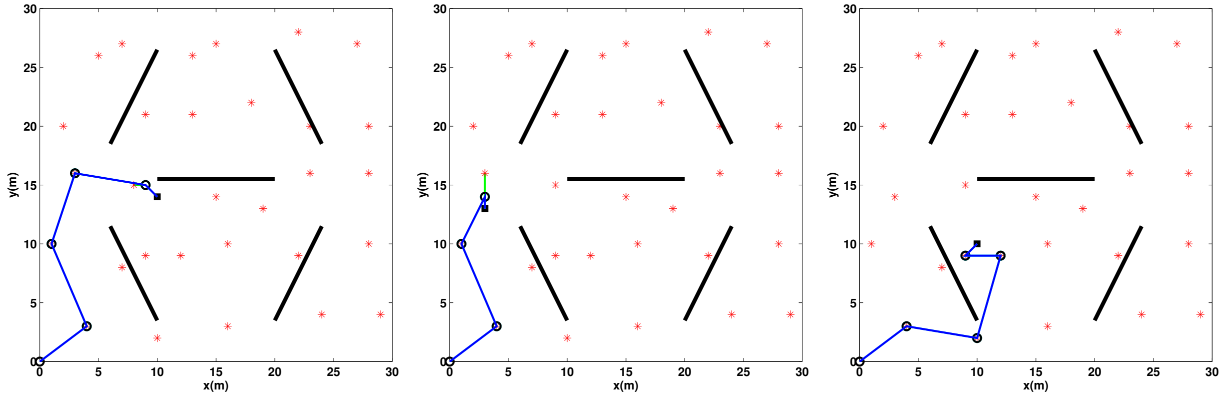
(a) (b) (c)

Fig. 6: Snapshots of the network configuration obtained by the proposed technique for 30 sensors in three consecutive steps of Example 2: (a) 28^{th} step; (b) 29^{th} step, and (c) 30^{th} step.



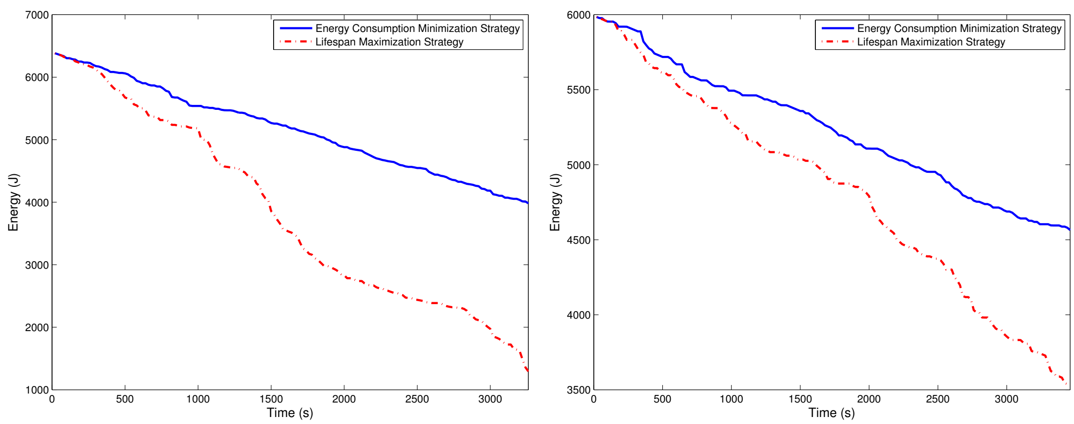
(a) (b) (c)

Fig. 8: Snapshots of the network configuration obtained by the proposed technique for 16 sensors in three consecutive steps of Example 3: (a) 89^{th} step; (b) 90^{th} step, and (c) 91^{st} step.



(a) (b) (c)

Fig. 9: Snapshots of the network configuration obtained by the proposed technique for 30 sensors in three consecutive steps of Example 3: (a) 55^{th} step; (b) 56^{th} step, and (c) 57^{th} step.



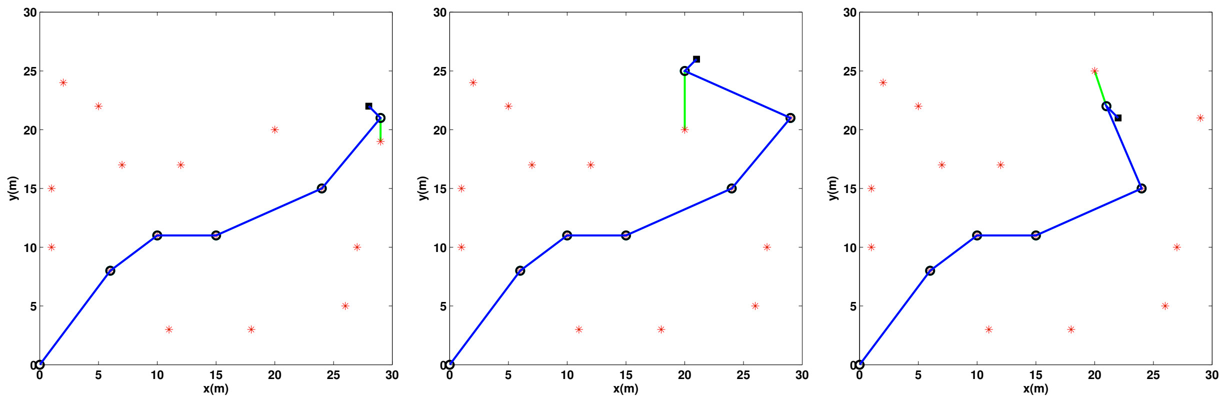
(a) (b)

Fig. 10: The total residual energy of all sensors in Example 3 for (a) 16 sensors, and (b) 30 sensors.

Example 3. In this example, two different sensor configurations and a different structure for the obstacles are considered in the field. The sensor specifications are the same as the previous examples. Figs. 8 and 9 show the field with 16 and 30 sensors, respectively, in three consecutive snapshots of the network, confirming the results discussed so far. Fig. 10, on the other hand, demonstrates that the algorithm proposed in this paper outperforms the one in [16] by 67% and 22% for 16 and 30 sensors, respectively, as far as the network energy consumption is concerned. Simulation results show that in most cases (and different settings), the shortest path obtained using the proposed algorithm satisfies the conditions of Theorem 3, which means it is the optimal path as well.

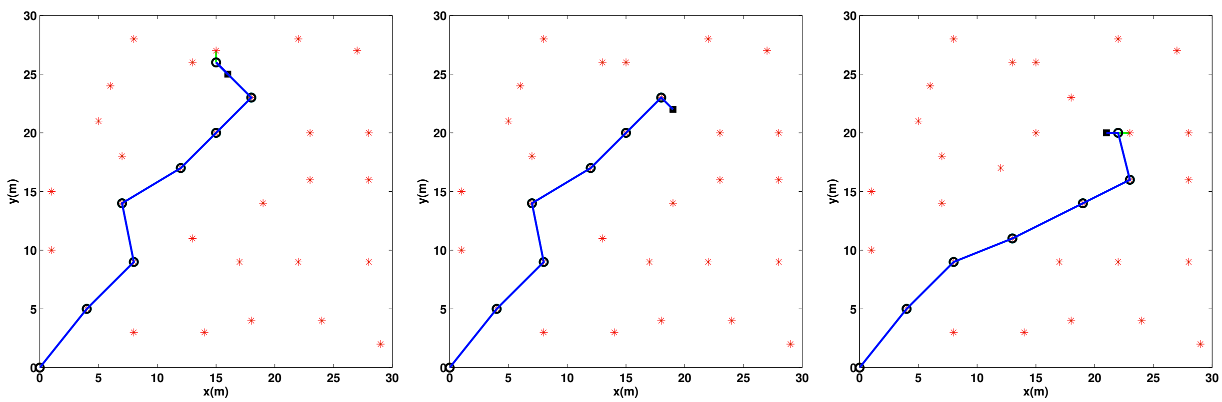
Example 4. In this example, the size of the field is assumed to be the same as the previous example, but no obstacle exists in the field. The chosen route and sensors for information transmission from the target to destination are depicted for 16 and 30 sensors in Figs. 11 and 12, respectively, for three different snapshots. Then in Fig. 13, the results obtained using the proposed algorithm in this case are compared to those obtained by using the method in [17] which maximizes the life-span of the network when there is no obstacles in the field. It can be seen from Fig. 13(a) that at $t = 2620$s, the sum of the residual energies of the sensors under the proposed technique is 80% greater than that under the maximum life-span strategy. Furthermore, Fig. 13(b) shows that the proposed algorithm outperforms the algorithm in [17] by more than 60% after $t = 2840$s.

Remark 8. The simulation results provided in this section demonstrate that the effectiveness of the proposed algorithm in finding the optimal path highly depends on the number of sensors as well as their configuration, their communication and sensing ranges, and the configuration of obstacles. Simulations also show that in most configurations the



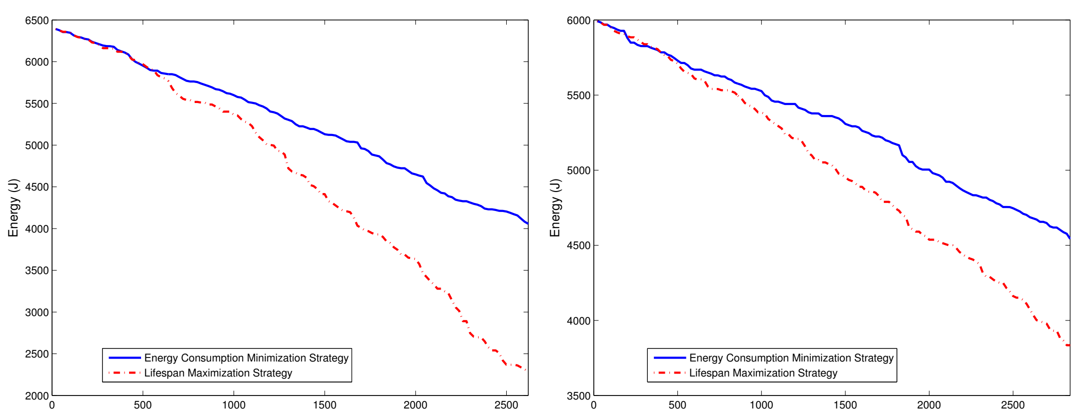
(a) (b) (c)

Fig. 11: Snapshots of the network configuration obtained by the proposed technique for 16 sensors in three consecutive steps of Example 4: (a) 70^{th} step; (b) 71^{st} step, and (c) 72^{nd} step.



(a) (b) (c)

Fig. 12: Snapshots of the network configuration obtained by the proposed technique for 30 sensors in three consecutive steps of Example 4: (a) 49^{th} step; (b) 50^{th} step, and (c) 51^{st} step.



(a) (b)

Fig. 13: The total residual energy of all sensors in Example 4 for (a) 16 sensors, and (b) 30 sensors.

shortest path found by the proposed algorithm is the optimal path.

Example 5. In this example, the same setting as Example 1 is used to demonstrate the robustness and effectiveness of the algorithm. The simulations are repeated with 20 different random sensor deployments. Fig. 14 shows the minimum, maximum, and average values of the total residual energy over all 20 simulations in each iteration (for the first 100 iterations). It can be observed from this figure that the proposed algorithm is robust, and the results are in a close neighborhood of the average value. Note that in all iterations the shortest path satisfies the conditions of Theorem 3, and therefore, it is the optimal path too.

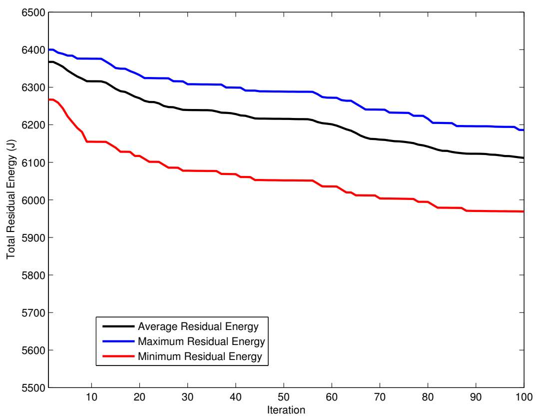


Fig. 14: The average, minimum, and maximum of the total residual energy of the network for 20 different random deployments of the sensors.

Example 6. In this example, the performance of the proposed algorithm is compared with the technique given in [28], where a set of mobile sensors operate collaboratively to transmit information from multiple sources (whose locations are fixed) to a designated sink. The authors in [28] consider both movement and communication as sources of energy consumption. For this comparison, 12 sensors are considered with initial energy of 800J. It is worth mentioning that in order to compare these two algorithms, the problem is solved using the method in [28]. Then, after relocating the sensors and calculating their residual energies and also taking the new location of the target into consideration, the problem is solved again using the same algorithm (this is how the method in [28] is used to track a moving source or target). Fig. 15 shows the remaining energy of individual sensors in the network obtained by using the method proposed in this paper (Fig. 15(b)) as well as [28] (Fig. 15(a)). In addition, Fig. 16 shows the total residual energy of the network for 100 iterations under both methods. These figures show that the method provided in the present work outperforms the one in [28] as under the proposed method the remaining energy of the sensors after 100 iterations is greater than that under the method in [28]. Note that due to the efficiency of the algorithm, the total residual energy of the network under the proposed method drops very slightly (from 9600J to 9542J). As it can be seen from Fig. 15(b), the energy of one sensor is dropped in iterations 58 to 64. The reason is that in those iterations the sensor positions and target movement are such that this sensor (which is assigned as the tracking sensor) should move to track the target, and consequently consumes energy due to movement in addition to sensing and communication.

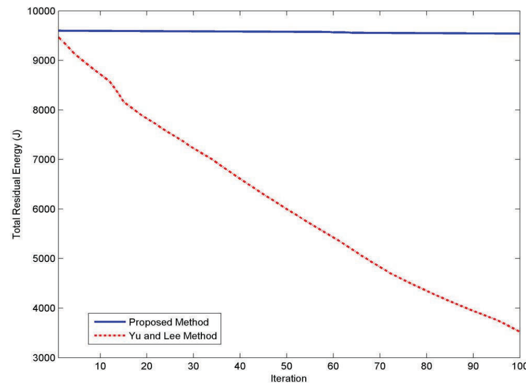


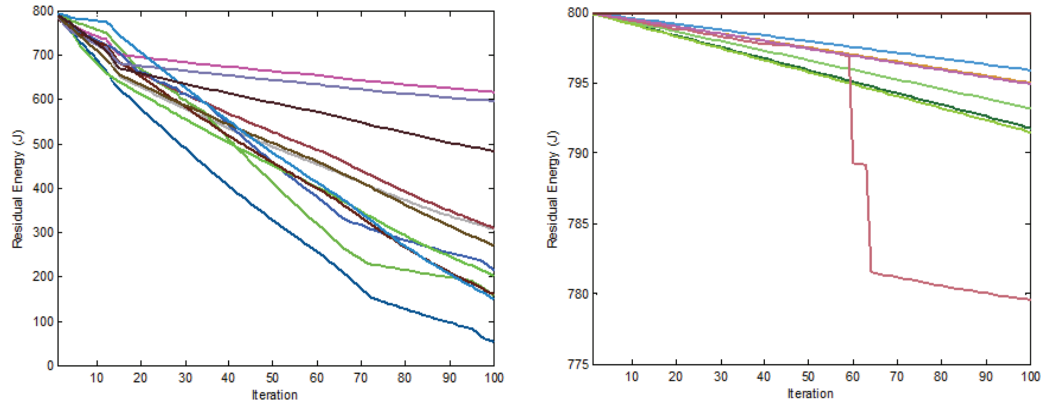
Fig. 16: The total residual energy of the network after 100 iterations under the proposed method (solid curve) and the one in [28] (dashed curve).

Furthermore, the method proposed in this paper has the following advantages compared to [28]:

- In [28], the authors assume that the communication graph of the network does not change if the sensors change their locations. As stated in [28], this is an acceptable assumption when the communication range of the sensors is comparable to the size of the field. The algorithm presented in this paper, however, tackles the problem in the most general form without such a restrictive assumption.
- The execution time of the proposed method is typically less than the one in [28]. In fact, the authors in [28] formulate an optimization problem and solve it using a method which includes two nested loops. As noted in [28], due to these nested loops, the algorithm has a long execution time. Note that this optimization problem must be solved in every time step if it is aimed to track a moving target.
- The proposed method can find the optimal route in the presence of obstacles, while the method in [28] is only for an obstacle-free environment.

V. Conclusions

A novel energy-efficient tracking technique is proposed in this paper for wireless sensor networks in the presence of obstacles. The field is first divided into a grid, and is then converted to a graph. Proper weights are subsequently assigned to the edges of the graph to efficiently model the energy consumption due to sensing, communication and movement, as the main sources of energy expenditure in



(a) (b)

Fig. 15: The residual energy of individual sensors in Example 6 after 100 iterations under: (a) the method in [28], and (b) the proposed method.

this type of network. The problem of finding a proper route and selecting the corresponding sensor locations for energy-efficient tracking is translated to the well-known shortest-path problem by partitioning the field into energy Voronoi regions and considering different network configurations. Simulations demonstrate the efficacy of the proposed tracking strategy and its superior performance compared to other methods. As future work, one can develop a distributed counterpart of the proposed scheme, which would be more desirable in many applications due to reduced information exchange requirement and higher reliability (at the cost of higher amount of computations for each sensor).

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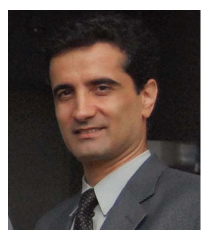

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