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Maximum Lifetime Strategy for Target Monitoring with Controlled Node Mobility in Sensor Networks with Obstacles

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***Abstract*—Consider a mobile sensor network that is used to monitor a moving target in a field with obstacles. In this paper, an efficient relocation technique that simultaneously maximizes the network lifetime is proposed. The main sources of energy consumption in the network are sensing, communication, and movement of the sensors. To account for this energy consumption, a graph is constructed with edges that are weighted based on the remaining energy of each sensor. This graph is subsequently employed to address the lifetime maximization problem by solving a sequence of shortest path problems. The proposed technique determines a near-optimal relocation strategy for the sensors as well as an energy-efficient route to transfer information from the target to destination. This near-optimal solution is calculated in every time instant using the information obtained through the previous time step. It is shown that by choosing appropriate parameters, sensors' locations and the communication route from target to destination can be arbitrarily close to their corresponding optimal choices at each time instant. Simulation results confirm the effectiveness of the proposed technique.**

I. Introduction

Recently, mobile sensor networks (MSN) have received considerable attention in the literature due to their applications in emerging technologies such as health monitoring [1], environmental monitoring [2], [3], intrusion detection [4], [5], surveillance [6], [7] and target tracking [8], [9]. In [8], the problem of underwater target tracking is investigated, where it is desired to minimize the energy consumption of the sensors. In [9], it is aimed to activate the minimum number of sensors in the network to track a moving target. The mobility of sensors allows a sensor network to adaptively compensate for variations in the environment, and therefore address the intended application more efficiently. In particular, mobile sensor networks can be very effective in tracking and monitoring moving (or otherwise changing) targets. The sensors are required to collaboratively route the target information to a designated destination node.

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The MSNs (and other types of sensor networks, in general) are heavily constrained by limitations in resources such as energy and processing capability. Such constraints should be taken into account in the design of efficient motion-planning algorithms in a practical setting. In [10], a network of mobile sensors is used for structural health monitoring while addressing challenges such as adaptability and resource limitations. The authors in [11] develop a wireless sensor network for measuring various bio-parameters such as ECG, EEG and EMG. Adding the mobility feature to such networks will create an intelligent environment that can pervasively monitor the health of elderly patients regardless of their position in hospitals or care centers.

Many researchers have investigated the problem of energy minimization in MSNs. The authors in [12] propose an approach for maintaining connectivity in a network of static and mobile backbone nodes. The strategy aims at minimizing the number of backbone nodes and controlling their mobility. A distributed control scheme is proposed in [13] to position the aerial vehicles in such a way that the signal-link quality among a team of ground and air vehicles is optimized. The air vehicles position themselves such that the communication-link quality is optimized. The ground vehicles, on the other hand, perform a collaborative task independent of the air vehicles. The problem of distributed tracking of a maneuvering target using a sensor network is investigated in [14]. It is assumed that the sensing range of the sensors is limited. It is also assumed that the target can only be observed by a small group of sensors, and it is hidden from most of them. A message-passing version of the Kalman-Consensus filter is then proposed to track a maneuvering target effectively. Note that mobile sensors are often powered by small batteries which might be difficult to replace because of the harsh environmental conditions or even cost given the relatively high number and frequency of the required replacements in a typical network. Therefore, minimizing the energy consumption of the sensors while maintaining the network-level objectives are essential in the design of an efficient MSN. A technique is presented in [15] to transform the problem of designing an energy-efficient target tracking MSN to the popular shortest path problem. The above work tackles the energy minimization problem in an obstacle-free environment, while in [16] the same problem is investigated in the presence of obstacles. In addition to minimizing the energy consumption of each individual sensor, it is often desired to maximize the lifetime of the network.

It is important to note that although the lifetime maximization problem is closely related to the energy minimization problem, they have important differences as demonstrated by simulations in Section V. In other words, minimizing the energy consumption of sensors does not necessarily imply maximizing network lifetime. In [17], the problem of energy imbalance in many-to-one sensor networks is investigated, and a general model is proposed for maximizing network lifetime. An analytical framework is presented in [18] to study coverage and lifetime in an MSN using a two-dimensional Gaussian distribution model.

Another class of strategies for increasing the lifetime of the MSNs uses a mobile sink instead of moving all sensors. For example, the authors in [19] plan the mobility of a sink node by solving a mixed integer linear programming problem in order to prolong the network lifetime. As another example, in [20] a distributed strategy is presented to find the optimal information flow vector in a network consisting of battery powered static sensors and a mobile sink. In [21], the NP-hard problem of planning the optimal trajectory of a mobile sink for collecting data from sensors is converted to a convex problem which can be solved efficiently to maximize the lifetime of the network (note that typically sending the collected information from all sensors to a fixed sink requires a large amount of energy). The authors in [22] introduce a sensor network with k mobile sinks, each of which can travel a limited distance, receive data through a predetermined number of hops, and plan the trajectory of the mobile sinks using a joint optimization problem. A distributed algorithm is developed in [23] to maximize the lifetime of the network for the case when data is transfered to a mobile sink and some delay can be tolerated in the process. Some other techniques have also been presented in the literature which take the movement energy of the sensors into consideration. For instance, the authors in [24] propose a target tracking strategy in an MSN to increase the lifetime of the network in an obstacle-free environment but the results cannot be easily extended to the case of an environment with obstacles.

Although several papers have investigated the problem of network lifetime maximization, most of the existing results only consider communication and/or sensing in the energy consumption model, and the mobility of the sensors is often neglected in the formulation in order to simplify the analysis [8]-[25]. In fact, in most applications sensor movement is the dominant source of energy consumption. To the best of the authors' knowledge, there is no result on target monitoring in the literature, where the movement of the sensors is considered in the energy consumption model. In this paper, the problem of tracking and monitoring a moving target in a field with obstacles is investigated. It is assumed that the main sources of energy consumption of sensors in the network are sensing, communication, and movement. It is also assumed that the obstacles in the field can limit the communication and sensing capabilities of the sensors by blocking the path between them. The main objective is to develop an efficient motion strategy for the sensors such that the network lifetime is maximized, while any possible obstacles are avoided. To this end, an energy-efficient route is obtained to transfer information from the target to destination using a shortest path algorithm. The sensors move to their new locations and the algorithm is repeated after a prescribed time interval (which is set based on the target's maximum speed). The important properties of the proposed strategy in relation to the lifetime of the network are discussed in detail. The main contribution of the present work with respect to the existing literature is that it investigates the problem in the presence of obstacles, and that it uses an accurate model for energy consumption. These issues add significant complexity to problem analysis. Preliminary results of this work have been published in [24], [26].

The plan of the remainder of the paper is as follows. In Section II, a modified form of the conventional Voronoi diagram reflecting the energy consumption of the sensors is introduced. The problem statement is provided in Section III, along with some important assumptions and definitions. In Section IV, an energy-efficient monitoring strategy for mobile sensors in the presence of obstacles is presented, as the main contribution of this work. Simulation results are provided in Section V to demonstrate the effectiveness of the proposed strategy. Finally, some concluding remarks are given in Section VI.

II. Residual Energy-Based Voronoi Diagram

Consider a set of n distinct weighted nodes denoted by $\mathbf{S} = \{(S_1, e_1), (S_2, e_2), \ldots, (S_n, e_n)\}$ in a 2D plane, where $e_i > 0$ is the weighting factor associated with the i-th node S_i, for any $i \in \mathbf{n} := \{1, 2, \ldots, n\}$. Let a distance function between an arbitrary point Q in the above plane and the weighted node (S_i, e_i) be given; denote this function by $f(S_i, e_i, Q)$. The *extended Voronoi diagram* is defined as a partitioning of the plane into n regions in such a way that the nearest node (in terms of the distance function given above) to any point inside a region is the node assigned to that region. The mathematical description of each region obtained by the above partitioning is as follows:

$$\Pi_i = \{Q \in R^2 | f(S_i, e_i, Q) \leq f(S_j, e_j, Q),\ \forall j \in \mathbf{n} \backslash \{i\}\} \tag{1}$$

Note that for certain functions $f(.)$ and weighting factors e_i, some regions may be empty (contain no points).

Now, consider n sensors in a field, and let them be represented by the nodes $S_1, S_2, \ldots, S_n$ described above. The weight of the node S_i in (1) is set to be the remaining energy of that sensor (hence, it varies with time). Furthermore, let $f(S_i, e_i, Q)$ be equal to the difference between the initial energy of the i-th sensor, denoted by $E_{i,0}$, and the remaining energy of that sensor after traveling to point Q. Without loss of generality, assume that the initial energy of every sensor is the same, and denote it by E_0. Assume also that the sensor movement energy is proportional to the travel distance. Then, one can write:

$$f(S_i, e_i, Q) = (E_{i,0} - e_i) + e_s + \beta d(S_i, Q) \tag{2}$$

where β is a known constant whose value depends on the mechanical characteristics of the sensor. In fact, the energy consumption of a motion actuator (e.g., a motor) is, approximately, proportional to the moving distance. The coefficient β reflects this dependency. Also, e_s is the energy required

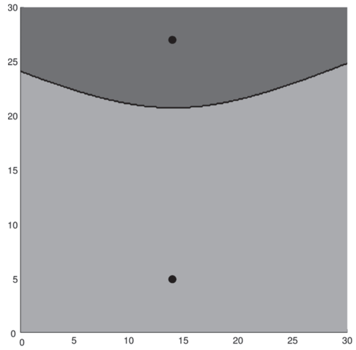


Fig. 1: An example of the residual energy-based Voronoi diagram for 2 sensors with different amounts of energy.

to overcome the static friction (when the sensor starts to move) which is assumed to be the same for all sensors. Furthermore, $d(S_i, Q)$ is the Euclidean distance between S_i and Q. Given the specific distance function $f(.)$ used in this paper, the extended Voronoi diagram will hereafter be referred to as the *residual energy-based Voronoi (RE-Voronoi) diagram*. Note that this diagram is constructed based on the residual energy of the sensors, and is completely different from the energy Voronoi diagram introduced in [16], which is constructed based on the energy consumption of the sensors. Some important characteristics of the RE-Voronoi diagram are described in the sequel.

Consider sensors 1 and 2 with the remaining energies e_1 and e_2, respectively. If $f(S_1, e_1, Q) = f(S_2, e_2, Q)$, then:

$$\begin{aligned}
&(E_0 - e_1) + e_s + \beta d(S_1, Q) = (E_0 - e_2) + e_s + \beta d(S_2, Q) \\
&\Rightarrow e_1 - e_s - \beta d(S_1, Q) = e_2 - e_s - \beta d(S_2, Q) \\
&\Rightarrow d(S_1, Q) - d(S_2, Q) = \frac{e_1 - e_2}{\beta} \qquad (3)
\end{aligned}$$

(i.e., the difference between the two distances is constant). Therefore, any point Q for which $f(S_1, e_1, Q) = f(S_2, e_2, Q)$ lies on one branch of a hyperbola (in the special case when $e_1 = e_2$, this branch turns out to be the perpendicular bisector of the segment S_1S_2) [26]. To construct the RE-Voronoi region associated with a node in the network, first the branches of the above-mentioned hyperbolae between that node and all other nodes are drawn. The smallest region containing the node is, in fact, the region assigned to that node. Fig. 1 shows the RE-Voronoi diagram for 2 sensors with different amounts of energy.

Now, consider a 2D field with obstacles. When an obstacle intersects the line connecting a sensor to its candidate location, then the sensor cannot move on a straight line to arrive at that position. In addition, obstacles can significantly perturb the communication and sensing reach of the sensor. In particular, in this work it is assumed that the communication and detection signals of the sensors are completely blocked by obstacles [27]. Fig. 2 shows an example where the target cannot be detected by the sensor because of the way the obstacle is positioned. Since the obstacle is blocking the line-of-sight between the points S and Q, the sensor can, for instance, move along the segments $\overline{SA}, \overline{AQ}$, which represent

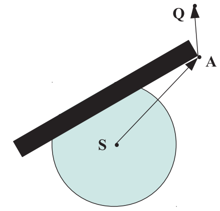


Fig. 2: An example of a sensor near an obstacle with blocked sensing reach.

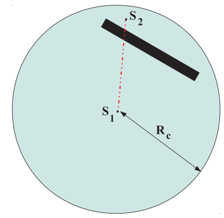


Fig. 3: An example of a sensor near an obstacle with blocked communication reach.

the shortest distance in this case. In this work, the shortest distance is used instead of conventional Euclidean distance $d(S, Q)$ to calculate the movement energy of any sensor in the formulation of the RE-Voronoi diagram. Furthermore, as Fig. 3 shows, two sensors located on opposite sides of an obstacle cannot communicate even if they are distanced within each others normal communication range. Fig. 4 depicts the RE-Voronoi diagram in the presence of obstacles for two sensors, which will hereafter be referred to as the *obstructed* residual energy-based Voronoi (ORE-Voronoi) diagram. As it can be observed from this figure, the boundaries of the ORE-Voronoi regions in this case are not necessarily branches of hyperbolae, and their shapes are highly dependent on the configuration of obstacles. It is important to note that, In general, the computation of the residual energy-based Voronoi diagram is much more complex than that of the conventional Voronoi diagram [28], [29].

III. Problem Statement

Consider a group of n mobile sensors $S_1, \ldots, S_n$, a moving target, and a fixed access point (also referred to as the destination point). The main objective of this work is defined below.

Sensor Coordination Problem: It is desired to develop an algorithm to: (i) monitor the target such that it remains in the sensing range of at least one sensor at all times; (ii) transmit information from the target to destination point, and (iii) maximize the lifetime of the network. More precisely, the objective is to compute the new locations of sensors at each time instant such that a set of prescribed specifications are met. These specifications include end-to-end connectivity preservation from the target to a fixed destination (through the sensing and communication links), while the durability of the sensors is maximized.

In order to develop an energy-efficient sensor deployment strategy, it is required to adopt a proper model for the energy consumption of sensors. In general, the energy consumption of mobile sensors is mainly due to communication, sensing,

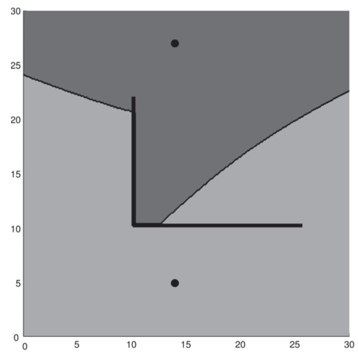


Fig. 4: An example of the obstructed residual energy-based Voronoi diagram for two sensors with different amounts of energy.

and movement. Although minimizing energy consumption is of great importance in an MSN, in many applications it is more desirable to maximize the lifetime of the sensors instead, in order to increase the durability of the overall network (note that energy minimization and lifetime maximization are closely-related but not identical problems). An effective strategy to maximize the lifetime of a sensor network is to deploy sensors in such a way that the ones with smaller residual energy consume less power. To this end, sensors must operate in a collaborative fashion in order to determine for each of them the best location as well as the most efficient routing path to transmit information from the target to destination. Since the analytical solution of this problem is complex in general, as an efficient alternative approach, the sensing field is divided into a grid first. The grid cells are chosen sufficiently small such that the sensors and target can be assumed to be located on some nodes of the grid at every time instant. Construct a directed graph (digraph) whose vertices are the grid nodes, and let the edges be weighted in terms of the above-mentioned three sources of energy consumption as described later. This digraph will hereafter be called the *energy consumption digraph*.

Definition 1. Network lifetime is the time it takes for the first sensor to completely deplete its energy. It is to be noted that different definitions are given for network lifetime in the literature and the one adopted here is consistent with that in [30], [31] and [32].

Notation 1. Throughout this paper, the nearest sensor to node Q in terms of energy consumption, referred to as *EC-nearest* sensor to node Q, is denoted by S_Q^1 and characterized by:

$$f(S_Q^1, e_{S_Q^1}, Q) \leq f(S_j, e_j, Q),\ S_Q^1 \in \mathbf{S},\ S_j \in \mathbf{S}\backslash\{S_Q^1\} \quad (4)$$

where $e_{S_Q^1}$ is the remaining energy of sensor S_Q^1. Also, the i-th nearest sensor to node Q (again in terms of energy consumption) is referred to as the i-th EC-nearest sensor to Q, and is denoted by S_Q^i. This can be formulated as:

$$f(S_Q^i, e_{S_Q^i}, Q) \leq f(S_j, e_j, Q),\ S_Q^i \in \mathbf{S}\backslash \bigcup_{h=1}^{i-1}\{S_Q^h\},$$
$$S_j \in \mathbf{S}\backslash \bigcup_{h=1}^{i}\{S_Q^h\} \quad (5)$$

where $e_{S_Q^i}$ is the remaining energy of sensor S_Q^i. Furthermore, the residual energy of the i-th EC-nearest sensor to Q, after traveling to this point will be denoted by $E_{r,Q}^i$.

Assumption 1. It is assumed that the sensor assigned to sense the target at any time instant is the EC-nearest sensor to it, which is hereafter called the *monitoring sensor* at that time instant. Note that this sensor is not necessarily fixed (i.e., it may change from time to time). A subset of other sensors can be employed accordingly to create an information route from the target to destination.

In the definition of the EC-nearest sensor to the target the residual energy of sensors as well as the distance between the sensors and target are taken into consideration. That is why this notion is used to select the monitoring sensor such that the reliability and durability of target monitoring is improved (note that a sensor near the target which has sufficient amount of energy would be an ideal choice for the monitoring sensor).

Denote the monitoring sensor by S_T (note that $S_T \in \{S_1, S_2, \ldots, S_n\}$ at any time instant) and the destination point by P_D. Denote also the target node and the RE/ORE-Voronoi region containing it by P_T and Π_T, respectively. The following assumption and definition are borrowed from [15].

Assumption 2. It is assumed that the target is at a reachable distance from the destination point through other sensors at all times, i.e. $d(P_T, P_D) \leq nR_c + R_s$, where $d(.,.)$ denotes the shortest distance between two points. Also, n, R_c and R_s denote the number of sensors, their communication radius and sensing radius, respectively.

Note that the condition in Assumption 2 is intuitive in the sense that if the distance between the target and destination point exceeds $nR_c + R_s$, then transferring information from the target to destination is impossible and meaningless.

Definition 2. A *sensing node* is a node belonging to Π_T, from where a sensor can sense the target. Furthermore, any node of a given path P excluding the target and destination is referred to as a *path node* of P.

IV. Main Results

Consider a 2D field with some obstacles and n sensors. Partition the field into the ORE-Voronoi regions, and denote the j-th region by Π_j, for any $j \in \mathbf{n}$. A weight-assignment algorithm is provided in the sequel to find some candidate locations for the sensors in order to solve the sensor coordination problem. Construct a digraph where an edge from P_T to a node P_j exists if and only if P_j is a sensing node; the weight of this edge is considered to be 0. Fig. 5 demonstrates the edges originated from P_T for an RE-Voronoi diagram (no obstacles). Furthermore, there is an edge from node P_i ($P_i \neq P_T$) to another node P_j in this digraph if and only if a sensor located at P_i could transmit the information to a sensor located at P_j. Note that in the case where an obstacle is blocking the line-of-sight between P_i and P_j, there would be no edge between their corresponding vertices in the digraph. The following procedure is used for the weight assignment of the edges in the digraph.

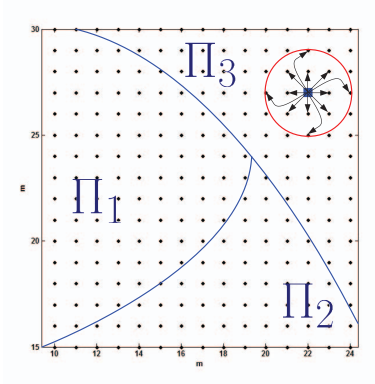


Fig. 5: Edges originating from the target to its adjacent sensing nodes in a residual energy-based Voronoi diagram.

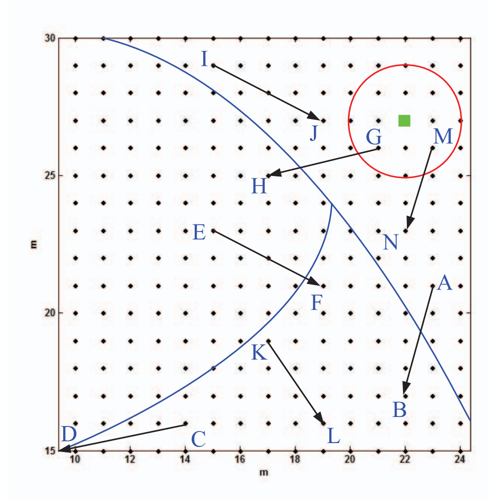


Fig. 6: Different types of edges for a field with three sensors.

Weight-Assignment Strategy

Case 1) Assume P_i and P_j are in different regions OR P_j is the destination node. Then:

i) If the target and P_i are in the same region AND P_i is not a sensing node, then the weight of the edge from P_i to P_j is given by:

$$w(i,j) = \left[\frac{E_0 - E^2_{r,P_i} + \omega_c(P_i,P_j)}{E_0}\right]^k$$

where $\omega_c(P_i,P_j)$ is the communication cost from node P_i to P_j, E^2_{r,P_i} is the residual energy of the second EC-nearest sensor to P_i after traveling to this point (see Notation 1), and k is a constant which will be introduced later.

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

$$w(i,j) = \left[\frac{E_0 - E^1_{r,P_i} + \omega_c(P_i,P_j)}{E_0}\right]^k$$

where E^1_{r,P_i} is the residual energy of the EC-nearest sensor to P_i after traveling to this point (see Notation 1).

iii) If P_i is a sensing node, then:

$$w(i,j) = \left[\frac{E_0 - E^1_{r,P_i} + \omega_c(P_i,P_j) + \omega_s(P_T,P_i)}{E_0}\right]^k$$

where $\omega_s(P_T,P_i)$ is the required sensing energy for a sensor at P_i to sense the target.

Case 2) Consider now the case where P_i and P_j are in the same 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:

$$w(i,j) = \left[\frac{E_0 - E^2_{r,P_i} + \omega_c(P_i,P_j)}{E_0}\right]^k$$

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

$$\begin{aligned} w(i,j) = max\Bigg(min\Bigg(&\left[\frac{E_0 - E^1_{r,P_i} + \omega_c(P_i,P_j)}{E_0}\right]^k + \left[\frac{E_0 - E^2_{r,P_j} + \omega_{min}}{E_0}\right]^k, \left[\frac{E_0 - E^1_{r,P_j} + \omega_c(P_i,P_j)}{E_0}\right]^k \\ &+ \left[\frac{E_0 - E^2_{r,P_i} + \omega_{min}}{E_0}\right]^k\Bigg) - \left[\frac{E_0 - E^1_{r,P_j} + \omega_{max}}{E_0}\right]^k, \left[\frac{E_0 - E^1_{r,P_i} + \omega_c(P_i,P_j)}{E_0}\right]^k\Bigg) \end{aligned}$$

where ω_{min} is the smallest amount of energy required by any sensor on a grid node to communicate with the nearest node to it in the grid, and ω_{max} is the largest amount of energy required by any sensor on a grid node to communicate with the farthest node in its communication range.

iii) If P_i is a sensing node, then:

$$w(i,j) = \left[\frac{E_0 - E^1_{r,P_i} + \omega_c(P_i,P_j) + \omega_s(P_T,P_i)}{E_0}\right]^k$$

Fig. 6 illustrates sample edges for each of the above cases for the sensor network of Fig. 5. In the edge AB, node A is not a sensing node but it is in the same region as the target and it is not in the same region as P_j. Thus, the edge AB is an example of case $1(i)$. On the other hand, CD and EF satisfy the conditions of case $1(ii)$ because EF has vertices in different regions while E is not in the target's region, and D is the destination node. The edge GH represents case $1(iii)$ as G is a sensing node. Moreover, the three edges IJ, KL and MN are examples of cases $2(i)$, $2(ii)$ and $2(iii)$, respectively.

Given an energy consumption digraph, it is desired now to find the shortest path connecting the target to destination, subject to the constraint that the number of nodes in the path is less than or equal to the number of sensors. This path provides an information route which is optimal for lifetime maximization under some conditions as discussed later. Algorithm 1 summarizes the proposed technique.

Algorithm 1

1) Divide the field to rectangular grid cells.
2) Partition the field using the obstructed residual energy-based Voronoi diagram.
3) Construct a digraph with the grid nodes as its vertices.
4) Assign proper weights to the edges of the constructed digraph using the proposed weighting strategy.
5) Find the shortest path connecting the target to the destination node.
6) Move the sensors to the nodes of the shortest path for establishing the information link.
7) Repeat the algorithm from step 2 after relocating the sensors.

As noted in [24], an efficient routing algorithm (such as Dijkstra) can be used to find the shortest path in an energy consumption digraph. If the number of nodes in the shortest path turns out to be greater than n, then one can switch to a constrained shortest path algorithm, which is typically slower than its unconstrained counterparts [33]. Note that although finding the shortest path subject to some constraints in a graph is, in general, an NP-hard problem [34], it can be solved in polynomial time in special cases, e.g., when the number of nodes on the path does not exceed a certain value [35].

Remark 1. The proposed algorithm is mainly dependent on the residual energy of sensors not their initial energy. Hence, the assumption that all sensors have the same initial energy, used in Section II, is only for simplicity of analysis (more precisely, it simplifies some of the expressions). If the initial energies are not the same, one can still use the simplified analysis by choosing a value that is greater than all initial energies and using it for all sensors in the equations.

Remark 2. The constant parameter β in (3) has significant impact on the shape of the regions in the residual energy-based Voronoi diagram. Since in the weight-assignment strategy (which is a very important part of the proposed algorithm) the regions' shapes and configuration play a key role, hence β is a very important parameter in the proposed algorithm.

Definition 3. A path P with at most n nodes which connects the target to destination is called a *feasible path*. The sum of the weights of the directed edges of a feasible path P is denoted by $W(P)$, and is referred to as the *path weight* of P.

Definition 4. Throughout this paper, the percentage of the total energy consumption of a sensor is referred to as the *consumed energy* of that sensor. In other words, consumed energy is equal to the ratio of the difference between the initial energy of a sensor and its residual energy, to its initial energy.

Definition 5. Consider a network of n mobile sensors $S_1, S_2, \ldots, S_n$, and a feasible path P with m nodes, denoted by the ordered set $(P_T, P_1, P_2, ..., P_m, P_D)$. Assume the EC-nearest sensor (among n sensors) to the target is assigned to P_1. For the rest of the sensors and the path nodes, there are $\binom{n-1}{m-1}$ (combination of $m-1$ out of $n-1$) possible sensor assignments, which together with the sensor assigned to P_1 can be used to transfer information from P_T to P_D in this case. Let the assignment of the distinct sensors $S_{i_1}, S_{i_2}, \ldots, S_{i_m}$ to the nodes $P_1, P_2, \ldots, P_m$, respectively, be denoted by the pair (P, S_P), where S_P represents the ordered set $(S_{i_1}, S_{i_2}, \ldots, S_{i_m})$. Furthermore, denote by (P, S_P^*) the sensor assignment for which the energy consumption of the sensor with the smallest residual energy (after relocating the sensors and transmitting information from the target to destination) is minimum, and call it the *optimal assignment*. Note that the optimal sensor assignment is not unique. Also, it is important to note that the optimal sensor assignment can change each time the sensors are relocated. However, to simplify notation, the time-dependence has not been explicitly shown in the above representation.

Definition 6. Consider the optimal assignment (P, S_P^*) for an MSN. The k-th power of the consumed energy of sensor S_{i_j} after traveling to node P_j and exchanging information is referred to as the *node cost* of P_j in path P, and will hereafter be denoted by $C_P(P_j)$. Furthermore, the sum of the node costs of all the path nodes of P is called *path cost* of P, and is denoted by $C(P)$.

Theorem 1. *For any feasible path P in an energy consumption digraph, the inequality $W(P) \leq C(P)$ holds.*

Proof: Assume that the feasible path $P = (P_T, P_1, P_2, \ldots, P_m, P_D)$ passes through regions $\Pi_1, \Pi_2, \ldots, \Pi_h$, and that the path has n_i nodes in region Π_i, $i = 1, 2, \ldots, h$. Note that Π_i and Π_j can be the same regions, $1 \leq i, j \leq h, j \neq i+1$. Partition P into h sub-paths as follows:

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

Now, it suffices to show that for any sub-path, the path weight is less than or equal to the corresponding path cost. If Π_a contains exactly one node for any $a = 1, 2, \ldots, h$, then the sub-path P^a contains only the edge (P_1^a, P_1^{a+1}) (note that P_1^{h+1} is, in fact, the destination node P_D). The weight assigned to this edge in the digraph is $\left[\frac{E_0 - E_{r,P_1^a}^1 + \omega_c(P_1^a, P_1^{a+1})}{E_0}\right]^k$ for $a \neq 1$ and $\left[\frac{E_0 - E_{r,P_1^a}^1 + \omega_c(P_1^a, P_1^{a+1}) + \omega_s(P_T, P_1^a)}{E_0}\right]^k$ for $a = 1$, which correspond to the assignment of the EC-nearest sensor to node P_1^a. It is important to note that in both cases the assigned weight is equal to the minimum combined cost of movement, communication, and sensing of a sensor after moving to P_1^a. If the EC-nearest sensor to P_1^a is also the EC-nearest sensor to some other nodes in the path, the weight is less than the cost.

On the other hand, if Π_a contains more than one node, then there will be two possibilities as follows:

Case 1: $a \neq 1$. In this case, the weight of every edge from P_i to P_j is either

$$min\left(\left[\frac{E_0 - E^1_{r,P_i} + \omega_c(i,j)}{E_0}\right]^k + \left[\frac{E_0 - E^2_{r,P_j} + \omega_{min}}{E_0}\right]^k, \left[\frac{E_0 - E^1_{r,P_j} + \omega_c(i,j)}{E_0}\right]^k + \left[\frac{E_0 - E^2_{r,P_i} + \omega_{min}}{E_0}\right]^k\right) - \left[\frac{E_0 - E^1_{r,P_j} + \omega_{max}}{E_0}\right]^k$$

or

$$\left[\frac{E_0 - E^1_{r,P_i} + \omega_c(i,j)}{E_0}\right]^k$$

Let the former be called *type A* edge and the latter *type B* edge. Divide the sub-path P^a to l sub^2-paths as follows:

$$P^{a,1} = P^{a,1}_1, P^{a,1}_2, \ldots, P^{a,1}_{m_1}, P^{a,2}_1$$
$$P^{a,2} = P^{a,2}_1, P^{a,2}_2, \ldots, P^{a,2}_{m_2}, P^{a,3}_1$$
$$\vdots$$
$$P^{a,l} = P^{a,l}_1, P^{a,l}_2, \ldots, P^{a,l}_{m_l}, P^{a+1,1}_1$$

such that the last edge in any sub^2-path $P^{a,b}$, $b = 1, 2, \ldots, l$, is a type B edge, and the rest of the edges in that sub^2-path are type A. Obviously, in any region Π_a there is at least one sub-path, and every sub-path contains at least one type B edge.

Assume now that the EC-nearest sensor to all nodes of Π_a is assigned to one of the nodes of a sub^2-path $P^{a,b}$, $1 \leq b \leq l$. In this case, the weight assigned to $P^{a,b}$ is:

$$W^b(a) = \sum_{q=1}^{m_b-1} \Big[min\Big(g(1, P^{a,b}_q, P^{a,b}_{q+1}) + g_{min}(2, P^{a,b}_{q+1}), g(1, P^{a,b}_{q+1}, P^{a,b}_q) + g_{min}(2, P^{a,b}_q)\Big) - g_{max}(1, P^{a,b}_{q+1})\Big] + g(1, P^{a,b}_{m_b}, P^{a,b+1}_1) \tag{6}$$

where $g(u, P_i, P_j) = \left[\frac{E_0 - E^u_{r,P_i} + \omega_c(P_i,P_j)}{E_0}\right]^k$, $g_{min}(u, P_i) = \left[\frac{E_0 - E^u_{r,P_i} + \omega_{min}}{E_0}\right]^k$, and $g_{max}(u, P_i) = \left[\frac{E_0 - E^u_{r,P_i} + \omega_{max}}{E_0}\right]^k$. From the properties of the ORE-Voronoi diagram, the EC-nearest sensor to all nodes of the sub^2-paths $P^{a,b}$ is the same, but the sensor can move to only one node. Thus, the cost of moving m_b sensors to m_b nodes of the sub^2-paths, denoted by $C^b(a)$, satisfies the following inequality:

$$C^b(a) \geq g(1, P^{a,b}_j, P^{a,b}_{j+1}) + \sum_{q=1, q\neq j}^{m_b} g(2, P^{a,b}_q, P^{a,b}_{q+1}), \quad \forall j \in \{1, 2, ..., m_b\} \tag{7}$$

It is straightforward now to derive the following relations:

$$\begin{aligned} W^b_{a,1} &= \sum_{q=1}^{j-1} g(1, P^{a,b}_{q+1}, P^{a,b}_{q+2}) + g_{min}(2, P^{a,b}_q) - g(1, P^{a,b}_{q+1}, P^{a,b}_{q+2}) \\ &\geq \sum_{q=1}^{j-1} min\Big(g(1, P^{a,b}_q, P^{a,b}_{q+1}) + g_{min}(2, P^{a,b}_{q+1}), g(1, P^{a,b}_{q+1}, P^{a,b}_{q+2}) + g_{min}(2, P^{a,b}_q)\Big) - g(1, P^{a,b}_{q+1}, P^{a,b}_{q+2}) \end{aligned} \tag{8}$$

$$\begin{aligned} W^b_{a,2} &= \left[\sum_{q=j}^{m_b-1} g(1, P^{a,b}_q, P^{a,b}_{q+1}) + g_{min}(2, P^{a,b}_{q+1}) - g(1, P^{a,b}_{q+1}, P^{a,b}_{q+2})\right] + g(1, P^{a,b}_{m_b}, P^{a,b+1}_1) \\ &\geq \left[\sum_{q=j}^{m_b-1} min\Big(g(1, P^{a,b}_q, P^{a,b}_{q+1}) + g_{min}(2, P^{a,b}_{q+1}), g(1, P^{a,b}_{q+1}, P^{a,b}_{q+2}) + g_{min}(2, P^{a,b}_q)\Big) - g(1, P^{a,b}_{q+1}, P^{a,b}_{q+2})\right] + g(1, P^{a,b}_{m_b}, P^{a,b+1}_1) \end{aligned} \tag{9}$$

By expanding the right side of the above relations and simplifying them, it is concluded that:

$$\begin{aligned} W^b_{a,1} + W^b_{a,2} &= g(1, P^{a,b}_j, P^{a,b}_{j+1}) + \sum_{q=1, q\neq j}^{m_b} g(2, P^{a,b}_q, P^{a,b}_{q+1}) \\ &\geq \sum_{q=1}^{m_b-1} \Big[min\Big(g(1, P^{a,b}_q, P^{a,b}_{q+1}) + g_{min}(2, P^{a,b}_{q+1}), g(1, P^{a,b}_{q+1}, P^{a,b}_{q+2}) + g_{min}(2, P^{a,b}_q)\Big) - g(1, P^{a,b}_{q+1}, P^{a,b}_{q+2})\Big] \\ &\quad + g(1, P^{a,b}_{m_b}, P^{a,b+1}_1) \end{aligned} \tag{10}$$

Since $g(u, P_i, P_j) \leq g_{max}(u, P_i)$ for any integer u and any points P_i and P_j, the following inequality is obtained:

$$\begin{aligned} &\sum_{q=1}^{m_b-1} \Big[min\Big(g(1, P^{a,b}_q, P^{a,b}_{q+1}) + g_{min}(2, P^{a,b}_{q+1}), g(1, P^{a,b}_{q+1}, P^{a,b}_{q+2}) + g_{min}(2, P^{a,b}_q)\Big) - g(1, P^{a,b}_{q+1}, P^{a,b}_{q+2})\Big] \\ &+ g(1, P^{a,b}_{m_b}, P^{a,b+1}_1) \geq \sum_{q=1}^{m_b-1} \Big[min\Big(g(1, P^{a,b}_q, P^{a,b}_{q+1}) + g_{min}(2, P^{a,b}_{q+1}), g(1, P^{a,b}_{q+1}, P^{a,b}_{q+2}) + g_{min}(2, P^{a,b}_q)\Big) \\ &- g_{max}(1, P^{a,b}_{q+1})\Big] + g(1, P^{a,b}_{m_b}, P^{a,b+1}_1) \end{aligned} \tag{11}$$

Note that the right side of (11) is, in fact, equal to $W^b(a)$. From (7), (10) and (11), one arrives at:

$$C^b(a) \geq W^b(a)$$

Now, for the other sub[2]-path $P^{a,c}$, $c = 1, 2, \ldots, l$, $c \neq b$, one can write:

$$\begin{aligned} C^c(a) &\geq \sum_{q=1}^{m_c} g(2, P_q^{a,c}, P_{q+1}^{a,c}) \\ &\geq g(1, P_j^{a,c}, P_{j+1}^{a,c}) + \sum_{q=1, q\neq j}^{m_c} g(2, P_q^{a,c}, P_{q+1}^{a,c}), \\ &\quad \forall j \in \{1, 2, ..., m_c\} \end{aligned}$$

Using a similar approach:

$$C^c(a) \geq W^c(a)$$

Recall that the weight and cost of a sub-path in a region Π_a are the sum of the weights and costs of the sub[2]-paths of that region. Thus, for region Π_a:

$$C(a) \geq W(a), \quad a = 2, 3, \ldots, h$$

where $C(a)$ and $W(a)$ are the path cost and path weight of sub-path P^a, respectively.
Case 2: $a = 1$ *(the region contains the target)*. In this case, the EC-nearest sensor to the nodes of this region is assigned to detect the target, and hence, cannot be assigned to another node. Thus, the cost of the sub-path P^1 satisfies the following inequality:

$$C(1) \geq g_s(1, P_1^1, P_2^1) + \sum_{q=2}^{n_1} g(2, P_q^1, P_{q+1}^1)$$

where $g_s(u, P_i, P_j) = \left[\frac{E_0 - E^u_{r,P_i} + \omega_c(P_i,P_j) + \omega_s(P_T,P_i)}{E_0}\right]^k$. On the other hand, the proposed weight-assignment strategy yields:

$$W(1) = g_s(1, P_1^1, P_2^1) + \sum_{q=2}^{n_1} g(2, P_q^1, P_{q+1}^1)$$

and hence:

$$C(1) \geq W(1)$$

This completes the proof. ■

Definition 7. A *good path* is defined as a feasible path P with the following properties:
i) It has at most two nodes in the region Π_T and at most one node in other regions.
ii) If the region Π_T contains exactly two nodes of the path, say P_i and P_j, creating a directed edge from P_i to P_j, then the path P does not pass through the region containing the second EC-nearest sensor to P_j.
Moreover, a feasible path P with at most one node in each ORE-Voronoi region is referred to as a *perfect path*. Obviously, any perfect path is a good path as well.

Definition 8. Consider a network of n mobile sensors and a feasible path P with m nodes, and let the optimal assignment (P, S_P^*) be deployed. Let also the maximum energy consumption (from the initial time of the network operation) among all sensors once they move to their assigned nodes and transmit information from the target to destination be referred to as the *max-min energy consumption* w.r.t. the path P, and be denoted by $E(P, S_P^*)$.

Definition 9. Among all feasible paths, the one w.r.t. which the max-min energy consumption is minimum will be referred to as the *optimal path*. Let this path be denoted by P^*.

Theorem 2. *For any feasible good path, the path weight and path cost are equal.*

Proof: Consider the following two cases:

Case 1: Region Π_a, $a = 1, 2, \ldots, h$ *contains only one node.* In this case, it is important to note that in the optimal assignment of a good path, the EC-nearest sensor to node P_i in region Π_a is assigned to that node. On the other hand, the proposed weight-assignment strategy assigns the weight $g(1, P_i, P_{i+1})$ to the edge P_iP_{i+1}. Thus, the path cost and path weight for the edge in region Π_a are equal.

Case 2: Region Π_T *contains the sensing node* P_i *as well as the node* P_{i+1}. Since the EC-nearest sensor is always assigned to sense the target, in this case the optimal assignment is the one where the EC-nearest sensor is assigned to P_i and the second EC-nearest sensor to P_{i+1}. Note that, from the definition of a good path, the second EC-nearest sensor to P_{i+1} is not assigned to any other node. Moreover, the weights of the edges P_iP_{i+1} and $P_{i+1}P_{i+2}$ are $g_s(1, P_i, P_{i+1})$ and $g(2, P_{i+1}, P_{i+2})$, respectively. Therefore, the path cost and path weight are equal for this case as well.

From the above discussions (which are valid for any region), it is concluded that the path cost and path weight of a good path are equal. ■

Remark 3. Since any perfect path is also a good path, the result of Theorem 2 holds for any perfect path as well.

Definition 10. A feasible path P is said to be θ*-optimal* if the difference between $E(P, S_P^*)$ and $E(P^*, S_{P^*}^*)$ is at most equal to θ, i.e., $E(P, S_P^*) - E(P^*, S_{P^*}^*) \leq \theta$.

Lemma 1. *For any positive real numbers* ν, x, θ, *where* $x, \theta \leq 1$, *if* $k > \frac{ln(\nu)}{ln(1+\theta)}$ *then*

$$(x + \theta)^k > \nu x^k$$

Proof: The inequality $k > \frac{ln(\nu)}{ln(1+\theta)}$ yields

$$(1 + \theta)^k > \nu \tag{12}$$

Since $x \leq 1$, thus

$$(1 + \frac{\theta}{x})^k \geq (1 + \theta)^k \tag{13}$$

It results from (12) and (13) that $(1+\frac{\theta}{x})^k > \nu$, or equivalently $(x + \theta)^k > \nu x^k$. ■

Theorem 3. *Choose an arbitrary constant $k > \frac{ln(n)}{ln(1+\theta)}$ and apply the proposed weight-assignment strategy. If the shortest path $\bar{P}$ in the energy consumption digraph is a good path, then it is θ-optimal.*

Proof: Consider the shortest path $\bar{P}$ with the corresponding optimal assignment, and let the sensor that consumes the minimum energy $E(\bar{P}, S^*_{\bar{P}})$ be denoted by $\bar{S}_1$. The following two cases are investigated:

Case 1: $\bar{S}_1$ *is not assigned to any node of* $\bar{P}$. Consider the optimal path P^* and the corresponding optimal assignment $S^*_{P^*}$. If $\bar{S}_1$ is not assigned to any node of the optimal path P^* either, then $E(P^*, S^*_{P^*}) = E(\bar{P}, S^*_{\bar{P}})$. If, on the other hand, $\bar{S}_1$ is assigned to one of the nodes of the optimal path, then its energy consumption is greater than $E(\bar{P}, S^*_{\bar{P}})$. Note that the energy consumption of $\bar{S}_1$ is less than or equal to $E(P^*, S^*_{P^*})$, which implies that $E(\bar{P}, S^*_{\bar{P}}) \leq E(P^*, S^*_{P^*})$. By definition, this means that $\bar{P}$ is the optimal path. The proof is complete now on noting that any optimal path is θ-optimal as well.

Case 2: $\bar{S}_1$ *is assigned to a node of* $\bar{P}$. In this case, if $\bar{P}$ is not a θ-optimal path, then:

$$\begin{gathered} E(\bar{P}, S^*_{\bar{P}}) > E(P^*, S^*_{P^*}) + \theta \Rightarrow \\ \left[E(\bar{P}, S^*_{\bar{P}})\right]^k > \left[E(P^*, S^*_{P^*}) + \theta\right]^k \end{gathered} \tag{14}$$

Also, according to Lemma 1:

$$\left[E(P^*, S^*_{P^*}) + \theta\right]^k \geq n\left[E(P^*, S^*_{P^*})\right]^k \tag{15}$$

From the definition of path cost and max-min energy consumption and on noting that there are at most n sensors in any feasible path, one arrives at:

$$C(\bar{P}) \geq \left[E(\bar{P}, S^*_{\bar{P}})\right]^k \tag{16}$$

$$n\left[E(P^*, S^*_{P^*})\right]^k \geq C(P^*) \tag{17}$$

Inequalities (14), (15), (16) and (17) yield:

$$C(\bar{P}) > C(P^*) \tag{18}$$

On the other hand, from Theorem 1:

$$C(P^*) \geq W(P^*) \tag{19}$$

Also, since $\bar{P}$ is a good path, according to Theorem 2:

$$C(\bar{P}) = W(\bar{P}) \tag{20}$$

From (18), (19) and (20), it is concluded that $W(\bar{P}) > W(P^*)$, which is in contradiction with the fact that $\bar{P}$ is the shortest path. Therefore, $\bar{P}$ is a θ-optimal path. ■

Corollary 1. *Choose $k > \frac{ln(n)}{ln(1+\theta)}$; if the shortest path $\bar{P}$ is a perfect path, then it is θ-optimal too.*

Proof: The proof follows immediately from Theorem 3, on noting that any perfect path is a good path as well. ■

Remark 4. The proposed weight assignment is performed such that although there is no guarantee that the shortest path between the target and destination is a good path, most of the time it is (as verified by simulations). It can be shown that in some cases the shortest path is almost always a good path (i.e., only in some pathological cases the two paths would not be the same). For example, when the energy consumption of sensors due to movement is sufficiently greater than that due to communication, and also the communication ranges of sensors are relatively large such that they can communicate to each other with no need to change their positions, the shortest path would almost always be a good path (note that these are reasonable assumptions in most practical cases). Weight assignment is an important component of the proposed algorithm.

Remark 5. It is to be noted that the optimality of the proposed solution depends on θ. Although theoretically there is no limit on the value of k, and a choice of large k will result in a small θ, a large k could cause numerical problems. More precisely, for a large value of k, the weight of the directed edges in the energy digraph might be truncated to zero, and as a result finding the shortest path between the target and destination (θ-optimal path) would be meaningless. Therefore, although theoretically there is no limit on the value of k, there is a tradeoff between the optimality and computational limitation which needs to be taken into account when choosing this parameter.

It is important to note that the proposed algorithm is centralized, and all the processing is performed in a central unit in the destination point. Also, note that the network connectivity is not necessary for performing the proposed algorithm. The only requirement is that the target should be at a reachable distance from the destination point through other sensors at all times (see Assumption 2). This condition is far less restrictive than the network connectivity condition which is often required in different sensor network applications. To perform the proposed algorithm, each sensor needs the information about the position of the target and other sensors, as well as their residual energies. Sensors used in an MSN are typically small, and have limited communication and sensing capabilities. Due to these limitations, it is possible that the communication graph of the network will be disconnected at certain time intervals, and consequently, some sensors will not have information about the target and other sensors (note that this information is required for the implementation of the algorithm). These types of sensors are typically not equipped with powerful processing modules. Note that the destination node (which acts as the central unit) does not have the position information described above directly, and this information should be transmitted to this node through a subset of mobile sensors. Note also that usually the destination node has a more powerful processor and battery, as well as a strong transmitter capable of sending information about the newly calculated locations of sensors and the optimal route to the entire network. 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 $[t_i, t_i + \Delta T]$ positions of the target and also the sensors collaborating in target monitoring (as well as their residual energies) change. Since a unidirectional multihop communication link is available from target to destination by the collaborating sensors, hence information about the target and these sensors can be transferred to the destination. On the other hand, the position and residual energy of any sensor that is not part of the 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 sends them to all sensors.

Remark 6. Using a finer grid (higher resolution) the sensors can be placed closer to the optimal locations at the expense of higher computational complexity. In addition, the size of the time steps is lower-limited by the computational power of the destination node.

In terms of complexity, the most demanding parts of the proposed method are weight assignment and shortest path determination. Consider a field of length L and width W, and let the distance between each pair of the neighboring grid nodes be δ. A decision should be made for every pair of nodes to classify the corresponding edge in the weight assignment part of the algorithm. Following an argument similar to the one presented in [16], the complexity of the algorithm in this part is of order $O(1/\delta^4)$. However, from the implementation point of view, several methods can be used to decrease the execution time considerably. For example, assume that the communication range of the sensors is R_c. In this case, for each node, only the nodes within a neighborhood of radius R_c need to be checked (for a simple implementation, this can be a $2R_c \times 2R_c$ square centered at that particular node). Since R_c/δ is typically smaller than L/δ or W/δ, this reduces the computational complexity. Also, this part of the algorithm can be executed in parallel for all sensors, which, again, improves the execution time.

On the other hand, the complexity of the shortest path algorithm is of order $O(E+VlogV)$ [36], where E and V are the number of edges and vertices of the energy digraph, respectively. Following a discussion similar to the one provided in the previous paragraph, the complexity of the shortest path algorithm in terms of the size of the cells is approximately $O(1/\delta^4)$. Therefore, the overall complexity of the algorithm is approximately $O(1/\delta^4)$. This means that in the construction of the energy digraph and finding the shortest path (which are the most time consuming parts of the algorithm) the number of sensors is not important. In fact, the effect of the number of sensors on the complexity of the algorithm is negligible compared to the procedures mentioned above. Hence, the algorithm is scalable with respect to the number of sensors. However, in terms of the size of the field and fineness of the grid, one should take the above complexity order into account [16].

The length of time steps, on the other hand, highly depends on the processing power of the central unit (i.e., the destination node) as well as the velocity of the target. In fact, one can reduce the time step as long as the central unit is computationally powerful enough to calculate the candidate locations and information route in the time interval between the iterations. Also, the time interval can be increased as long as the target remains within the sensing range of the monitoring sensor (see equation 26).

Remark 7. There are different methods which can be used to reduce the sensing and communication requirements (e.g., using event-triggered and self-triggered techniques) in order to further prolong the network lifetime. This includes, for example, event-triggered and self-triggered techniques.

In the sequel, the approach in [37] is borrowed to investigate the real-time implementation of the proposed algorithm, and address some important practical issues. Let the algorithm be executed at time instants t_0, $t_1 := t_0 + \Delta T$, $t_2 := t_0 + 2\Delta T$, $\ldots$, where ΔT is the time interval required to complete the corresponding computations, relocate the sensors, and obtain a near-optimal route from the target to destination.

Real-time implementation of the algorithm requires information about the residual energies of all sensors, as well as the location of the target and all sensors be shared between the destination point and sensors. Three execution cycles are considered in $[t_j, t_{j+1}]$ ($j = 0, 1, 2, \ldots$) along with two time steps δt_1, δt_2 ($\delta t_1 < \delta t_2$) as follows:

i) $[t_j, t_j + \delta t_1]$: In this cycle, the residual energies and positions of sensors cooperating in monitoring the target and transferring its information to the destination node are sent to this node. Moreover, the information of sensors which are not cooperating remains unchanged, and hence, is also available at the destination point. All the required computations are then performed, and information about new locations of the sensors and transferring route is shared between all sensors in this cycle.

ii) $[t_j + \delta t_1, t_j + \delta t_2]$: In this cycle, the values obtained in the previous cycle are used to properly place the sensors in the field (this is the only cycle in which the sensors move).

iii) $[t_j + \delta t_2, t_{j+1}]$: In this cycle, the objective is to maintain connectivity and send information from the target to destination point. Therefore, the target has to be in the sensing range of the monitoring sensor.

A sufficient condition is given next, which guarantees the target remains in the sensing range of the monitoring sensor. Assume the target is detected by the monitoring sensor at time t_j, and let the target position at times t_j and t_{j+1} be denoted by $P_T(t_j)$ and $P_T(t_{j+1})$, respectively. Moreover, denote the position of the monitoring sensor in the first and third execution cycles by $P_M(t_j)$ and $P_M(t_{j+1})$, respectively, and define $\Omega(t_j) = \max_{t_j \le t \le t_{j+1}} \|P_T(t) - P_T(t_j)\|$, and let the actual sensing range of each sensor be denoted by $R_{s,act}$. Then, the target is guaranteed to stay within the sensing range in the last cycle provided the sensing radius R_s is chosen less than every sensor's actual sensing range $R_{s,act}$. Furthermore, the inequality

$$\|P_T(\acute{t}) - P_M(t_{j+1})\| \le R_{s,act} \tag{21}$$

Needs to be satisfied for all $\acute{t} \in [t_j + \delta t_2, t_{j+1}]$. Now, it results from the triangle inequality that:

$$\|P_T(\acute{t}) - P_M(t_{j+1})\| \le \|P_T(t_j) - P_M(t_{j+1})\| + \|P_T(\acute{t}) - P_T(t_j)\| \tag{22}$$

On the other hand:

$$\|P_T(t_j) - P_M(t_{j+1})\| \leq R_s \tag{23}$$

$$\|P_T(\acute{t}) - P_T(t_j)\| \leq \Omega(t_j) \tag{24}$$

It follows from the above inequalities that (21) holds if:

$$\Omega(t_j) \leq R_{s,act} - R_s \tag{25}$$

Let the maximum speed of the target in the time interval $[t_j, t_{j+1}]$ be denoted by $v(t_j)$. One can verify that (25) holds if:

$$\Delta T v(t_j) \leq R_{s,act} - R_s \tag{26}$$

In order for the condition in (26) to be satisfied for a faster target, R_s (which is a design parameter) should be sufficiently small. This, however, can reduce the efficiency of the monitoring sensor.

Remark 8. It is worth mentioning that the proposed algorithm is a greedy optimization approach, which provides a near-optimal solution at each time step. Solving the problem over multiple time steps is a very challenging problem, and can be considered as a future work for a given target movement model. Also, although the proposed algorithm provides a near-optimal solution at each time step independently, its performance is investigated over the lifetime of the network (multiple time steps) in the next section.

V. Simulation Results

Example 1. Consider 20 identical sensors randomly deployed in a 30m × 30m field. It is desired to monitor a moving target and route its information to the destination point. Let the field be represented by a 2D plane with the destination point located at the origin. Suppose that the communication and sensing radii of each sensor are 10m and 3m, respectively. Let also the energy required for a sensor at point P_i to communicate with another sensor at point P_j be equal to $\omega_c(P_i, P_j) = \mu[d(P_i, P_j)]^\lambda$, where λ is a given constant. Furthermore, the energy required for a sensor at point P_i to sense the target at P_T is equal to $\omega_s(P_T, P_j) = \zeta[d(P_T, P_j)]^\gamma$, for a given constant γ. Assume also that the energy a sensor consumes to move from the point P_i to P_j is equal to $\beta\bar{d}(P_i, P_j)$, where $\bar{d}(P_i, P_j)$ is the smallest distance a sensor at P_i should move to reach P_j, and β is a given constant. It is important to note that in the presence of obstacles, $\bar{d}(P_i, P_j)$ is not necessarily the Euclidean distance between P_i and P_j. Let θ be chosen as 0.15, which yields $k > 21.43$ (according to Theorem 3).

Remark 9. The size of the field and the number of sensors considered in the simulations here are close to those used in the literature (e.g., see [38], [39], [40], [41], [42]). In addition, the sensing and communication ranges considered in this section are comparable with those considered in [43], [38] (6m and 20m, respectively), and other sensor prototypes such as Smart Dust, CTOS dust, and Wins (Rockwell) [44].

Partition the field into a 30 × 30 grid, and let the target move either one meter forward/backward randomly along each axis or stay still at each time step (the length of this time step is considered to be inversely proportional to the speed of the target). The target is assumed to stay in the field at all times, and if it reaches the boundary of the field, its direction will change such that the boundary is not crossed. Let also the system parameters be $\mu = 10^{-3}$, $\zeta = 10^{-3}$, $\beta = 7.54$, $\lambda = 2$, and $\gamma = 2$. The candidate location of every sensor along with the desired route is determined by using Algorithm 1.

Scenario 1:

In this scenario, it is assumed that there is no obstacle in the field. Figs. 7(a), (b), (c) demonstrate the route and candidate locations of the sensors at three different time instants, using the proposed algorithm. In each snapshot, the location of the target and sensors as well as the shortest path in the constructed energy consumption digraph are depicted. The current location of the sensors are shown by asterisks, while their calculated candidate locations to move to are depicted by small circles. The location of the target is shown by a square, and the shortest path is indicated by blue segments. Furthermore, green lines show the movement of the sensors from their current locations to the candidate points, in case they should move. Under the proposed algorithm, the nearest sensors to the path nodes in the sense of Euclidean distance are not necessarily assigned to those nodes (see Fig. 7(a), (c)). Also, it can be observed from this figure that the proposed algorithm does not necessarily provide the shortest possible communication route. This is due to the fact that the algorithm tends to employ those sensors that have higher residual energies.

Remark 10. Simulation results show that for different network settings with different number of sensors and specifications, in most cases the shortest path in the proposed algorithm is either a good path or a perfect path, which according to Theorem 3 is θ-optimal as well.

The Proposed strategy is now compared with the algorithm provided in [15], which minimizes the overall energy consumption of a sensor network. This algorithm is applied to the above network setting, and the energy consumption of every sensor is depicted in Fig. 8 along with the energy consumption curves obtained by using the method developed in the present work. This figure shows that the proposed algorithm outperforms the one given in [15] in terms of network lifetime. More precisely, the algorithm in [15] iterates 459 times before the first sensor runs out of energy, while no sensor dies before 1450th iteration under the proposed algorithm. Since the algorithm introduced in the present work takes the remaining energy of the sensors into consideration (which means a sensor with more energy would be more likely to transmit information), the amount of energy of every sensor is more or less the same throughout the operation of the network. Furthermore, the tracking sensor in [15] can remain unchanged for a relatively long period of time (specially if the target moves slowly) but under the proposed algorithm this sensor can change frequently if it depletes large amount of energy abruptly in order to monitor the target.

Scenario 2:

Assume now that there are two obstacles in the field.

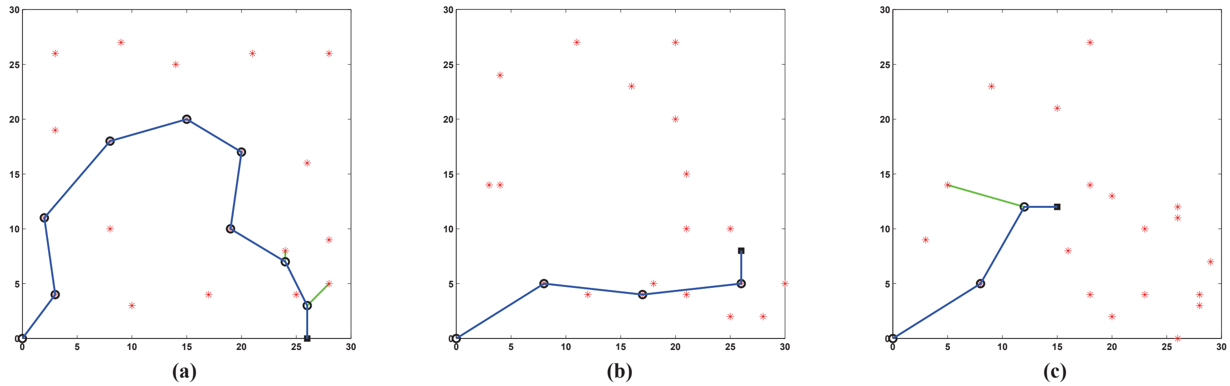


Fig. 7: Three snapshots of the sensors and target in the first scenario of Example 1. Blue segments indicate the energy-efficient routes under the proposed algorithm, while the green lines demonstrate the movement of the sensors from their current locations to the candidate points in case they should move.

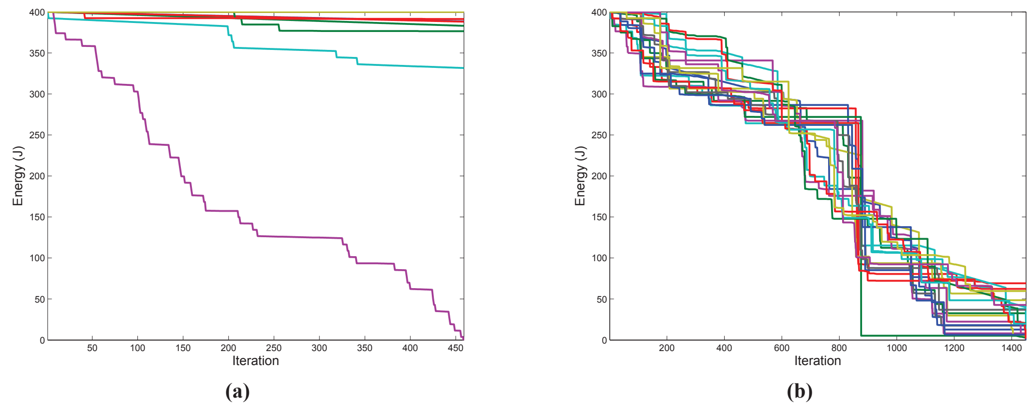


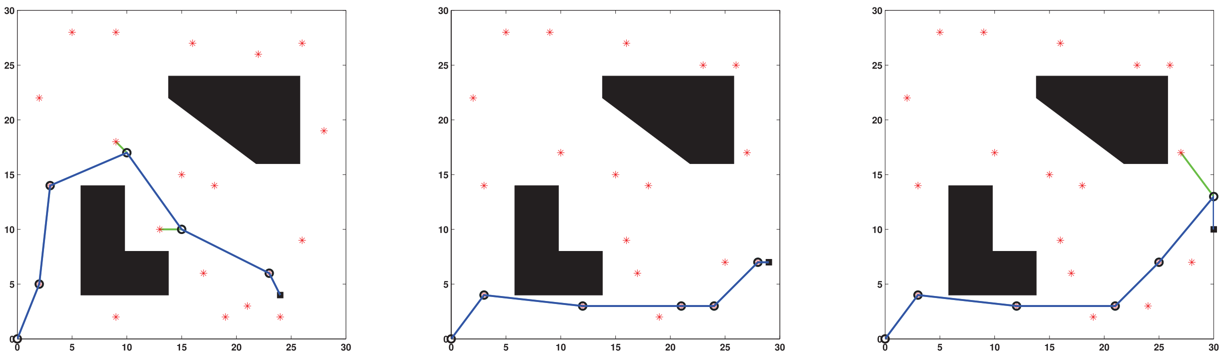
Fig. 8: The energy of sensors during the operation of the network in the first scenario of Example 1, using: (a) the tracking algorithm of [15], and (b) the proposed algorithm.

Using Algorithm 1, the results shown in Fig. 9 are obtained, analogously to Fig. 7. To assess the performance of the proposed technique in the presence of obstacles, the results will be compared with those obtained by using the algorithm in [16], which minimizes the overall energy consumption of a sensor network with obstacles. Figs. 10 (a) and (b) depict the remaining energy of every sensor v.s. iteration number under the algorithm given in [16] and the one provided in this work, respectively. These figures show that under the algorithm introduced in this work, the network operates 69% longer than that under the algorithm in [16]. They also show that the consumption of energy across the nodes is more balanced under the proposed algorithm, which further demonstrates the efficiency of the method.

Remark 11. If the target moves smoothly in the field, then under the technique proposed in [15] the tracking sensor does not change frequently, as it continues to be the nearest sensor to the target. As a result, the tracking sensor in [15] runs out of energy relatively fast. However, since in the method proposed here the EC-nearest sensor to the target is defined based on the residual energy of sensors, the monitoring sensor can be reassigned. This prevents the sensor from depleting its energy fast.

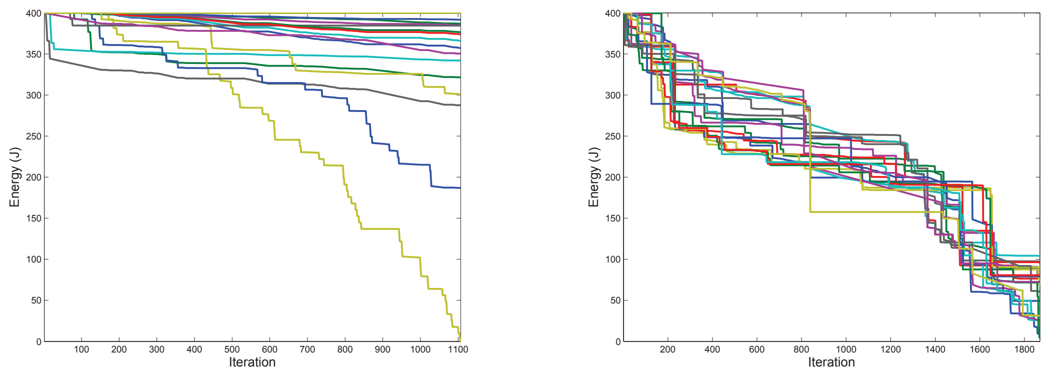
Scenario 3: In this last scenario, the same setting of scenario 2 is considered with different types of obstacles to verify the performance of the algorithm. Fig. 11 shows three snapshots of the network, which demonstrate the effectiveness of the proposed algorithm in tracking the target in this case. As in the previous scenario, the proposed algorithm is compared with the one in [16] by simulations. Figs. 12 (a) and (b) show the remaining energy of the sensors under both algorithms. It can be observed from these figures that the proposed algorithm demonstrates superior performance, as the balanced energy consumption increases the lifetime of the network substantially.

Example 2. In this example, the proposed technique is compared with the strategy given in [45], where a set of mobile sensors operate collaboratively to transmit information from multiple sources (whose locations are fixed) to a designated sink. Also, the energy consumption of sensors in [45] is due to both communication and movement. For this comparison, 12 sensors are considered with an initial energy of 800J each, and all other parameters are assumed to be the same as those in scenario 1 of Example 1. It is worth mentioning that to compare these two algorithms, it is required to solve the problem using the method in [45], then after relocating the sensors and calculating their residual energies and also considering the new location of the target, the problem must



(a) (b) (c)

Fig. 9: Three snapshots of the network configuration obtained by using the proposed technique in the second scenario of Example 1.



(a) (b)

Fig. 10: The energy of sensors during the operation of the network in the second scenario of Example 1, using: (a) the tracking algorithm of [16], and (b) the proposed algorithm.

be solved using the same algorithm again (in other words, the method in [45] is used to monitor a moving source or target). Figs. 13(a) and (b) demonstrate the results obtained by using the technique in [45] and the ones obtained by the proposed strategy, respectively. These figures show that the proposed method outperforms the one in [45] significantly in terms of network lifetime (the iteration time intervals are the same in both methods). In addition to the superiority of the proposed method in terms of network lifetime, it also has some other important advantages compared to [45]. For example, unlike the method in [45], the present technique does not assume that the communication graph remains fixed while the sensors move. Furthermore, the execution time of the proposed method is faster (because unlike the algorithm in [45] there is no nested loop in the algorithm here). Finally, the method in this work is developed in general for an environment with obstacles while that in [45] is only for an environment without obstacles.

VI. Conclusions

A novel relocation technique is proposed that simultaneously prolongs the lifetime of a mobile sensor network deployed to monitor a moving target in a field with possible obstacles. The methodology involves a digraph that is constructed by mapping the field into a grid. The vertices of the digraph are the grid nodes, and its edges are weighted based on the remaining energy of sensors. Using this digraph, the lifetime maximization problem is addressed by solving a sequence of shortest path problems. Detailed simulations demonstrate the effectiveness of the proposed strategy in finding the best locations for the mobile sensors at different points in time, as well as the best route to transmit the target information. Solving the investigated problem over multiple time-steps based on a realistic model for target motion can be considered as a natural extension of this work. Also, it is conjectured that adaptive sensing and communication range based on the remaining energy of each sensor can have a significant impact on the network lifetime. The authors plan to study this impact in the future.

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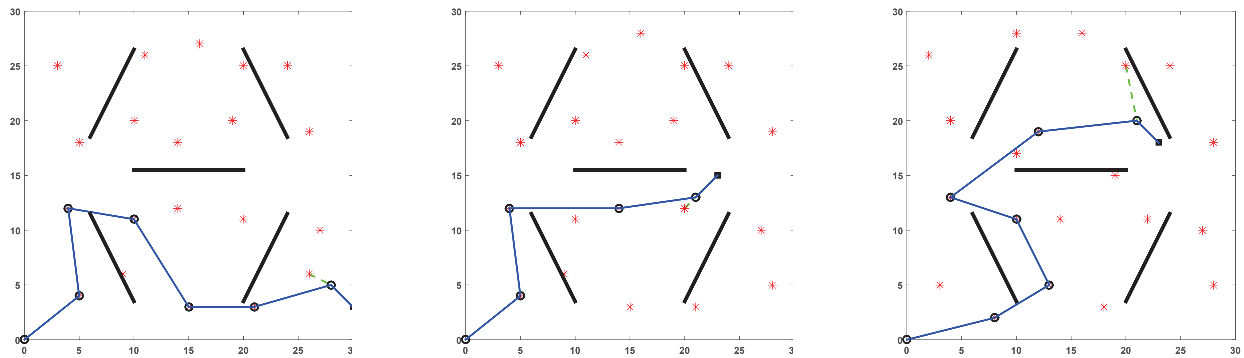
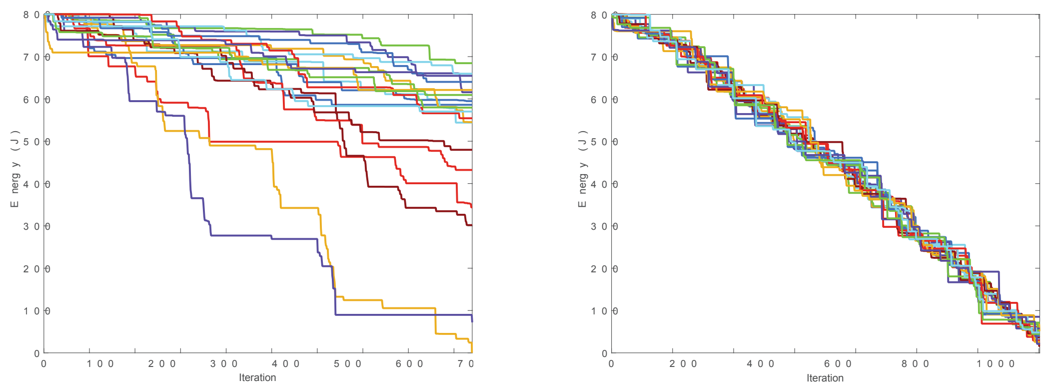


(a) **(b)** **(c)**

Fig. 11: Three snapshots of the network configuration obtained by using the proposed technique in the third scenario of Example 1.



(a) **(b)**

Fig. 12: The energy of sensors during the operation of the network in the third scenario of Example 1, using: (a) the tracking algorithm of [16], and (b) the proposed algorithm.

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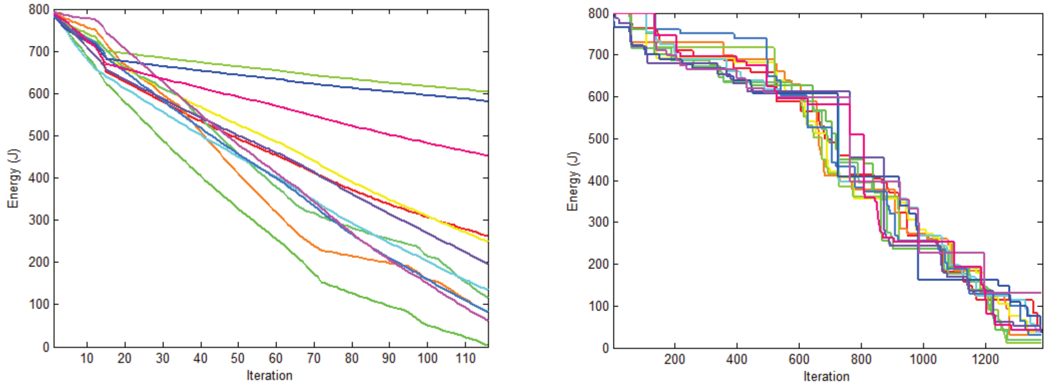

(a) **(b)**

Fig. 13: The energy of sensors during the operation of the network in Example 2, using: (a) the method given in [45], and (b) the proposed algorithm.

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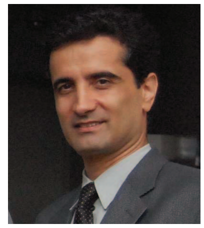

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