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

Hamid Mahboubi, *Senior Member, IEEE,* Walid Masoudimansour, *Student Member, IEEE,*
Amir G. Aghdam, *Senior Member, IEEE,* and Kamran Sayrafian-Pour, *Senior Member, IEEE*

Abstract—In this paper, an efficient technique is proposed for a mobile sensor network used to monitor a moving target in a field with obstacles while the network lifetime is maximized. The main sources of energy consumption of the sensors in the network are sensing, communication, and movement. A graph is constructed and its edges are weighted properly 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, which can be solved using existing methods. 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 of the previous time step. It is shown that by choosing appropriate parameters, sensors' locations and the communication route from target to destination obtained by the proposed algorithm can be arbitrarily close to the optimal locations and route 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], [2], environmental monitoring [3], [4], intrusion detection [5], [6], surveillance [7], [8] and target tracking [9], [10]. In [9], the problem of underwater target tracking is investigated, where it is desired to minimize the energy consumption of the sensors. In [10], 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 efficient and flexible in tracking and monitoring moving (or otherwise changing) targets. The

H. Mahboubi is with the Department of Electrical & Computer Engineering, McGill University, 845 Rue Sherbrooke O, Montréal, Québec H3A 0G4 Canada.   E-mail: hamid.mahboubi@mail.mcgill.ca

W. Masoudimansour and A. G. Aghdam are with the Department of Electrical & Computer Engineering, Concordia University, 1455 de Maisonneuve Blvd. W., EV012.179, Montréal, Québec H3G 1M8 Canada. E-mail: {w_masou,aghdam}@ece.concordia.ca

K. Sayrafian-Pour is with the National Institute of Standards and Technology (NIST), 100 Bureau Drive, Stop 8920 Gaithersburg, MD 20899 USA. E-mail: ksayrafian@nist.gov

sensors are required to collaboratively work in order to route the target information to a designated destination node.

The MSNs (and 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 [11], a network of mobile sensors has been used for structural health monitoring while addressing challenges such as adaptability and resource limitations. Hu et al. [12] developed 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 been investigating the problem of energy minimization in MSNs. The authors in [13] propose an approach for maintaining connectivity in a network of regular 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 [14] 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 [15]. It is assumed that the sensing range of the sensors is limited and the target can only be observed by a few 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 due to the 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 [16] to transform the problem of designing an energy-efficient target tracking MSN to the popular shortest path problem. The authors in [17] and [16] propose efficient algorithms to tackle the energy minimization problem in a sensor network with and without obstacles, respectively. In addition to minimizing the energy consumption of each individual sensor, it is also important

to maximize the lifetime of the network. Note that minimum energy consumption does not necessarily imply maximum lifetime for the network. Several strategies are proposed in the literature to increase the lifetime of a sensor network but most of them do not consider the movement energy of the sensors, and many of them are developed for static ones. For example, in [18], the problem of energy imbalance in many-to-one sensor networks is investigated, and a general model is proposed for maximizing the network lifetime. An analytical framework is presented in [19] to study coverage and lifetime in an MSN using a two-dimensional Gaussian distribution model. Another class of strategies for increasing the lifetime of MSNs uses a mobile sink instead of moving all sensors. For example, the authors in [20] 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 [21] 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 [22], the NP-hard problem of planning the optimal trajectory of a mobile sink for gathering data from sensors is converted to a convex problem which is solved to maximize the lifetime of the network (note that typically sending the collected information from all sensors to a fixed sink is the major energy consumption source). The authors in [23] introduce a sensor network with k mobile sinks, each of which can travel a limited distance and can 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 [24] 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. A few methods have also been provided in the literature which take the movement energy of the sensors into consideration. For instance, the authors in [25] 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 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 model in order to simplify the analysis [9]-[26]. 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 are considered in the energy consumption model. Furthermore, the objective in [16], [17] is to minimize the energy consumption of the sensors, as noted before. Although this is closely related to the lifetime maximization problem considered in the present work, the two problems have important differences as elaborated in the simulations section of the paper. 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 the 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 channel 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 desired characteristics 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 [25], [27].

The organization 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 made in Section VI.

II. 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:

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

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 linearly proportional to the travel distance.

Then, one can write:

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

where β is a known constant which is related to the mechanical characteristics of the sensor. In fact, the energy consumption of a motion actuator (e.g., a motor) is, approximately, linearly related to the moving distance. β reflects this relation, and its value depends on the sensor and its moving mechanism. Also, e_s is the energy required 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. For the particular choice of the distance function and weighting factor in this paper, the extended Voronoi diagram will be referred to as the *energy-based Voronoi (E-Voronoi) diagram*. Some important characteristics of the E-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:

$$(E_0 - e_1) + e_s + \beta d(S_1, Q) = (E_0 - e_2) + e_s + \beta d(S_2, Q)$$
$$\Rightarrow e_1 - e_s - \beta d(S_1, Q) = e_2 - e_s - \beta d(S_2, Q)$$
$$\Rightarrow d(S_1, Q) - d(S_2, Q) = \frac{e_1 - e_2}{\beta} = \text{const.} \qquad (3)$$

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 $S_1 S_2$) [27]. To construct the E-Voronoi region associated with a node in the network, first the branches of the above-mentioned hyperbolae of that node and the other nodes are drawn. The smallest region containing a node is, in fact, the region assigned to that node. Fig. 1 shows the E-Voronoi diagram for 2 sensors with different amounts of energy.
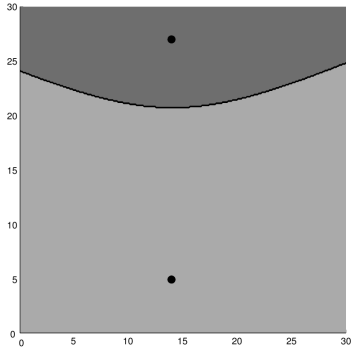

Fig. 1: An example of the energy-based Voronoi diagram for 2 sensors with different amounts of energy.

Now, consider a 2D field with obstacles. When an obstacle is located on the line connecting a sensor to its candidate location, then the sensor cannot move on a straight line, and, in addition, its sensing and communication capabilities are attenuated. In particular, in this work it is assumed that the obstacles completely block the communication and sensing range of the sensors [28]. 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 provide 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 for the sensor in the formulation of the E-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 E-Voronoi diagram in the presence of obstacles for two sensors, which will hereafter be referred to as the *obstructed* energy-based Voronoi (OE-Voronoi) diagram. As it can be observed from this figure, the boundaries of the OE-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, when there are obstacles in the field and/or the distances between nodes are not Euclidean, the computation of the energy-based Voronoi diagram would be much more complex than that of the conventional Voronoi diagram [29], [30].
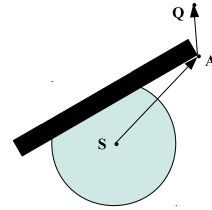

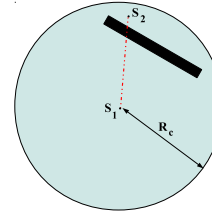**Fig. 2:** An example of a sensor near an obstacle with blocked sensing range.

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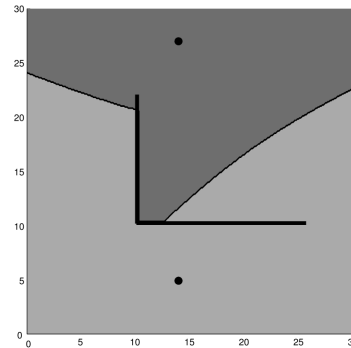

Fig. 4: An example of the obstructed energy-based Voronoi diagram for two sensors with different amounts of energy.

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.

Problem Definition: 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 the 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, 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 that sensors with smaller residual energy compared to other sensors consume less power. To this end, sensors must operate in a collaborative fashion in order to determine the best location and routing path for each of them to transmit the information from the target to destination. Since the analytical solution of this problem is complicated in general, as an efficient alternative approach, the sensing field is divided into a grid first. Let the grid cells be 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 according to 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 [31], [32] and [33].

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 the 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 the 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 its location, 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.

The most important parameters which need to be taken into consideration for selecting the monitoring sensor are the residual energy of the sensors and the distance between the sensors and the target. In the definition of the EC-nearest sensor to the target both of these parameters are considered, and 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 a perfect choice).

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 E/OE-Voronoi region containing it by P_T and Π_T, respectively.

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 range and sensing range, 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 a group of n sensors. Partition the field into the OE-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 maximize the network lifetime. 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 E-Voronoi diagram. 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.
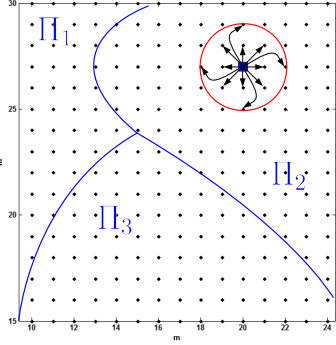

Fig. 5: Edges originating from the target to its adjacent sensing nodes in an energy-based Voronoi diagram.

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:

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

where $\omega_c(P_i, P_j)$ is the communication cost from the node P_i to P_j, E_{r,P_i}^2 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:

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

where E_{r,P_i}^1 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:

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

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:

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

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

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

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

iii) If P_i is a sensing node, then:

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

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 while it is in the same region as the target but 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.
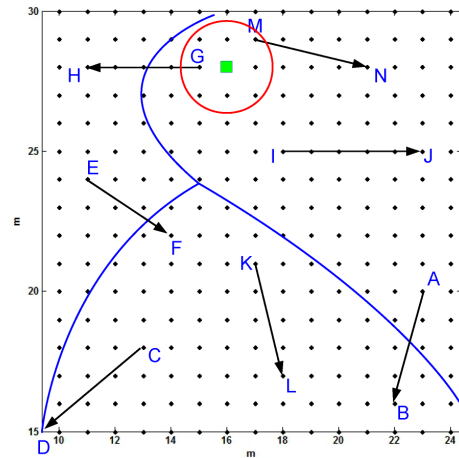

Fig. 6: Different types of edges for a field with three sensors.

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 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.

Remark 1. One can use an efficient routing algorithm (such as Dijkstra) 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 [25].

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 some number n [35].

Remark 2. Note that 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 terms used in in this work). 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 use it in the paper.

Remark 3. The constant parameter β in (3) has significant impact on the shape of the regions in the 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 sometimes 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 employed to transfer the 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 a mobile sensor network. The k-th power of the consumed energy of the sensor S_{i_j} after traveling to node P_j and exchanging information will be 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 will be called *path cost* of P, and will be denoted by $C(P)$.

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

Proof: Assume 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 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, $\forall 1 \leq i, j \leq h, j \neq i+1$. Partition P into h sub-paths as follows:

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

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, 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

the 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

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

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

$$\left.+ \left[\frac{E_0 - E_{r,P_i}^2 + \omega_{min}}{E_0}\right]^k\right) - \left[\frac{E_0 - E_{r,P_j}^1 + \omega_{max}}{E_0}\right]^k$$

or

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

Let the former be called *type A* edge and the latter *type B* edge. Divide the sub-path P^a to l sub²-paths as follows:

$$P^{a,1} = P_1^{a,1}, P_2^{a,1}, \dots, P_{m_1}^{a,1}, P_1^{a,2}$$
$$P^{a,2} = P_1^{a,2}, P_2^{a,2}, \dots, P_{m_2}^{a,2}, P_1^{a,3}$$
$$\vdots$$
$$P^{a,l} = P_1^{a,l}, P_2^{a,l}, \dots, P_{m_l}^{a,l}, P_1^{a+1,1}$$

such that the last edge in any sub²-path $P^{a,b}$, $b = 1, 2, \dots, l$, is a type B edge, and the rest of the edges in that sub²-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 sub²-path $P^{a,b}$, $1 \leq b \leq l$. In this case, the weight assigned to $P^{a,b}$ is:

$$W^b(a) = \sum_{q=1}^{m_b-1} \left[min\left(g(1, P_q^{a,b}, P_{q+1}^{a,b})\right.\right.$$

$$\left.+ g_{min}(2, P_{q+1}^{a,b}), g(1, P_{q+1}^{a,b}, P_q^{a,b}) + g_{min}(2, P_q^{a,b})\right)$$

$$\left.- g_{max}(1, P_{q+1}^{a,b})\right] + g(1, P_{m_b}^{a,b}, P_1^{a,b+1})$$

$$\tag{6}$$

where $g(u, P_i, P_j) = \left[\frac{E_0 - E_{r,P_i}^u + \omega_c(P_i,P_j)}{E_0}\right]^k$, $g_{min}(u, P_i) = \left[\frac{E_0 - E_{r,P_i}^u + \omega_{min}}{E_0}\right]^k$, and $g_{max}(u, P_i) = \left[\frac{E_0 - E_{r,P_i}^u + \omega_{max}}{E_0}\right]^k$. From the properties of the OE-Voronoi diagram, the EC-nearest sensor to all nodes of the sub²-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 sub²-paths, denoted by $C^b(a)$, satisfies the following relation:

$$C^b(a) \geq g(1, P_j^{a,b}, P_{j+1}^{a,b}) + \sum_{q=1, q \neq j}^{m_b} g(2, P_q^{a,b}, P_{q+1}^{a,b}),$$

$$\tag{7}$$

$$\forall j \in \{1, 2, \dots, m_b\}$$

It is straightforward now to derive the following relations:

$$W_{a,1}^b = \sum_{q=1}^{j-1} g(1, P_{q+1}^{a,b}, P_{q+2}^{a,b})$$

$$+ g_{min}(2, P_q^{a,b}) - g(1, P_{q+1}^{a,b}, P_{q+2}^{a,b})$$

$$\geq \sum_{q=1}^{j-1} min\left(g(1, P_q^{a,b}, P_{q+1}^{a,b})\right.$$

$$\left.+ g_{min}(2, P_{q+1}^{a,b}), g(1, P_{q+1}^{a,b}, P_{q+2}^{a,b}) + g_{min}(2, P_q^{a,b})\right)$$

$$- g(1, P_{q+1}^{a,b}, P_{q+2}^{a,b})$$

$$\tag{8}$$

$$W_{a,2}^b = \left[\sum_{q=j}^{m_b-1} g(1, P_q^{a,b}, P_{q+1}^{a,b}) + g_{min}(2, P_{q+1}^{a,b})\right.$$

$$\left.- g(1, P_{q+1}^{a,b}, P_{q+2}^{a,b})\right] + g(1, P_{m_b}^{a,b}, P_1^{a,b+1})$$

$$\geq \left[\sum_{q=j}^{m_b-1} min\left(g(1, P_q^{a,b}, P_{q+1}^{a,b})\right.\right.$$

$$\left.+ g_{min}(2, P_{q+1}^{a,b}), g(1, P_{q+1}^{a,b}, P_{q+2}^{a,b}) + g_{min}(2, P_q^{a,b})\right)$$

$$\left.- g(1, P_{q+1}^{a,b}, P_{q+2}^{a,b})\right] + g(1, P_{m_b}^{a,b}, P_1^{a,b+1})$$

$$\tag{9}$$

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

$$W_{a,1}^b + W_{a,2}^b = g(1, P_j^{a,b}, P_{j+1}^{a,b}) + \sum_{q=1, q \neq j}^{m_b} g(2, P_q^{a,b}, P_{q+1}^{a,b})$$

$$\geq \sum_{q=1}^{m_b-1} \left[min\left(g(1, P_q^{a,b}, P_{q+1}^{a,b})\right.\right.$$

$$\left.+ g_{min}(2, P_{q+1}^{a,b}), g(1, P_{q+1}^{a,b}, P_{q+2}^{a,b})\right.$$

$$\left.\left.+ g_{min}(2, P_q^{a,b})\right) - g(1, P_{q+1}^{a,b}, P_{q+2}^{a,b})\right]$$

$$+ g(1, P_{m_b}^{a,b}, P_1^{a,b+1})$$

$$\tag{10}$$

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 relation is obtained:

$$\sum_{q=1}^{m_b-1} \left[min\left(g(1, P_q^{a,b}, P_{q+1}^{a,b}) \right. \right.$$
$$+ g_{min}(2, P_{q+1}^{a,b}), g(1, P_{q+1}^{a,b}, P_{q+2}^{a,b}) + g_{min}(2, P_q^{a,b}) \Big)$$
$$\left. - g(1, P_{q+1}^{a,b}, P_{q+2}^{a,b}) \right]$$
$$+ g(1, P_{m_b}^{a,b}, P_1^{a,b+1}) \geq \sum_{q=1}^{m_b-1} \left[min\left(g(1, P_q^{a,b}, P_{q+1}^{a,b}) \right. \right.$$
$$+ g_{min}(2, P_{q+1}^{a,b}), g(1, P_{q+1}^{a,b}, P_{q+2}^{a,b}) + g_{min}(2, P_q^{a,b}) \Big)$$
$$\left. - g_{max}(1, P_{q+1}^{a,b}) \right] + g(1, P_{m_b}^{a,b}, P_1^{a,b+1}) \tag{11}$$

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:

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

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 relation:

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

where $g_s(u, P_i, P_j) = \left[\frac{E_0 - E_{r,P_i}^u + \omega_c(P_i, P_j) + \omega_s(P_T, P_i)}{E_0} \right]^k$. 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 OE-Voronoi region is referred to as a *perfect path*. It is obvious that 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 $P_i P_{i+1}$. 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 will be that of the EC-nearest sensor 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 $P_i P_{i+1}$ 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 4. 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 n, x, θ, where $x, \theta \leq$*

1, *if* $k > \frac{ln(n)}{ln(1+\theta)}$ *then*

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

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

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

Since $x \leq 1$, thus

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

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

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:

$$E(\bar{P}, S_{\bar{P}}^*) > E(P^*, S_{P^*}^*) + \theta \Rightarrow$$
$$\left[E(\bar{P}, S_{\bar{P}}^*) \right]^k > \left[E(P^*, S_{P^*}^*) + \theta \right]^k \tag{14}$$

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:

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

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

Relations (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 5. An important (and novel) part of the proposed algorithm is the weight assignment procedure in the energy digraph for simulating the energy consumption of sensors. This is carried out in such a way 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).

Remark 6. 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 access to the above-mentioned information directly, and this information should be transmitted to the destination point 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 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 7. Note that with 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. Therefore, the complexity of the algorithm in this part is of order $O(1/\delta^4)$. However, note that 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 is an improvement in terms of 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 $O(E + V \log V)$ [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 is approximately $O(1/\delta^4)$. Therefore, the overall complexity of the algorithm is approximately $O(1/\delta^4)$. Note that the construction of the digraph and finding the shortest path, which are the most time consuming parts of the algorithm, do not depend on the number of sensors. 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.

The length of time steps, on the other hand, highly depends on the processing power of the central unit in 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 does not go out of the sensing range (see equation 26).

Remark 8. It is important to note that, there are 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.

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 the time instants t_0, $t_1 := t_0 + \Delta T$, $t_2 := t_0 + 2\Delta T$, ..., 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 $[t_j, t_{j+1}]$ ($j = 0, 1, 2, \ldots$) 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 also sent to this node. Note also that information of sensors which are not cooperating remains unchanged and is 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, let the position of the monitoring sensor be denoted by $P_M(t_j)$ and $P_M(t_{j+1})$ in the first and third execution cycles, respectively, and assume $\Omega(t_j) = \max_{t_j \leq t \leq t_{j+1}} \|P_T(t) - P_T(t_j)\|$. Then, the target is guaranteed to stay within the sensing range in the last cycle provided the sensing radius R_s of each sensor is chosen

less than its actual sensing range $R_{s,act}$. Furthermore, the inequality

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

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:

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

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 relations 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:

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

It is to be noted that 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 9. 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, note that 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 $\times$ 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 chosen as 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 P_i to point 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 10. Note that the size of the field and the number of sensors considered in the simulations here are within the ranges 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 $\times$ 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 assumed to be inversely proportional to the speed of the target). Note that 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 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 are required to move. Note that 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 11. Simulation results show that for different network setups 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.

To show the effectiveness of the proposed technique, it is now compared with the algorithm provided in [16], which minimizes the overall energy consumption of a sensor network. This algorithm is applied to the above network setup, and the energy consumption of all sensors are depicted in Fig. 8 along with those obtained by using the method developed in the present work. This figure shows that the proposed algorithm outperforms the one provided in [16] in terms of network
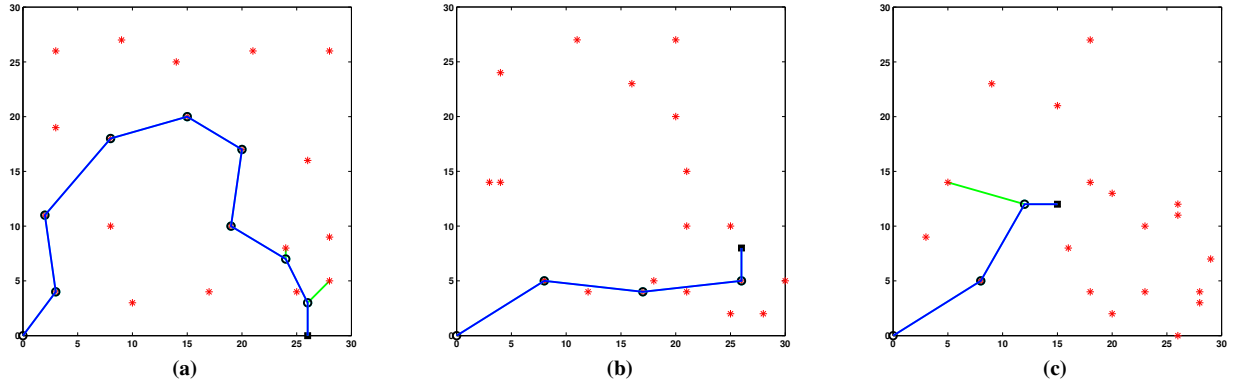
Fig. 7: Three snapshots of the sensors and target in the first scenario of Example 1. Blue segments indicate the energy-efficient routes under the proposed algorithm, while the green lines demonstrate the movement of the sensors from their current locations to the candidate points in case they are required to move.
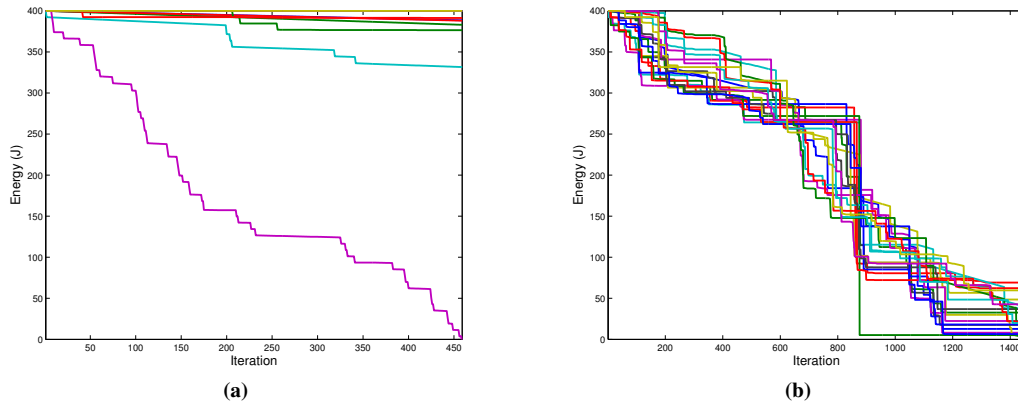

Fig. 8: The energy of sensors during the operation of the network in the first scenario of Example 1, using: (a) the tracking algorithm of [16], and (b) the proposed algorithm.

lifetime. More precisely, the algorithm in [16] iterates 459 times before the first sensor runs out of energy, while no sensor dies before 1450th iteration under the proposed algorithm. Note that 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 the 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 [16] 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 described above. 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, it will be compared with the algorithm in [17] 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 [17] and the one provided in this work, respectively.

These figures show that the algorithm introduced in this work increases the network lifetime by 69%. 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 12. It is important to note that if the target moves smoothly in the field, then under the technique proposed in [16] 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 [16] 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 changed in order to prevent it from depleting its energy fast.

Scenario 3: In this last scenario, the same setup of Scenario 2 has been used with different types of obstacles to verify the performance of the algorithm in this configuration. 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 algorithm in [17] using simulation results. Figs. 12 (a) and (b) show the remaining energy of
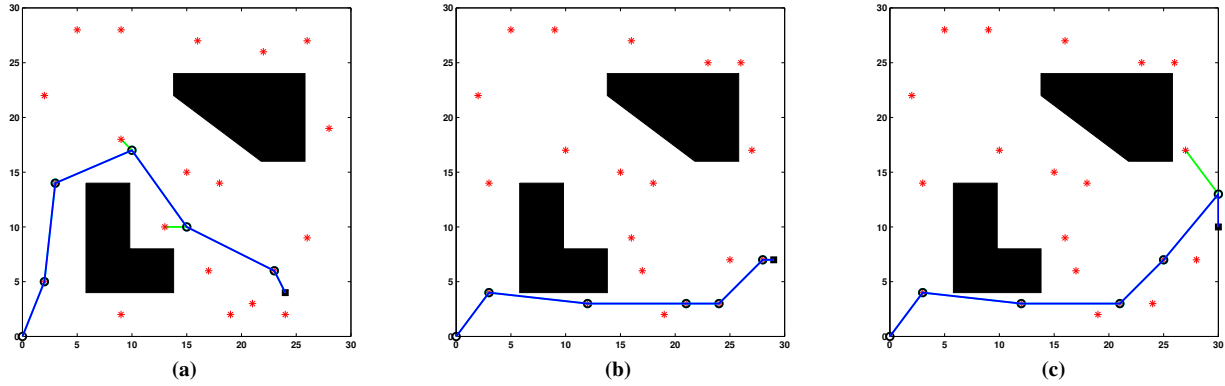
Fig. 9: Three snapshots of the network configuration obtained by using the proposed technique in the second scenario of Example 1.
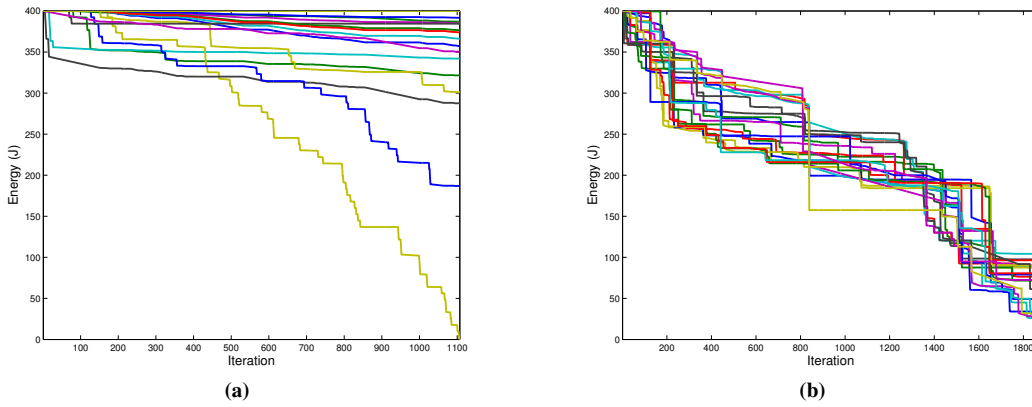

Fig. 10: The energy of sensors during the operation of the network in the second scenario of Example 1, using: (a) the tracking algorithm of [17], and (b) the proposed algorithm.

the sensors in 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 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 (note that 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 the following advantages compared to [45]:

i) In [45], it is assumed that the communication graph of the network does not change if the sensors change their locations. In fact, as stated in [45], this is an acceptable assumption when the communication range of the sensors is comparable to the field size. The method proposed in the present work, on the other hand, tackles the problem in the general form without making such an assumption.

ii) The execution time of the proposed method is less than that in [45]. Note that the authors in [45] formulate an optimization problem and solve it using a method which includes two nested loops. As mentioned in [45], due to these nested loops, the algorithm has a long execution time. Note also that, this optimization problem must be solved in every time step if the algorithm is to be used for monitoring a moving target.

iii) The method proposed in this paper can find a near-optimal solution in the presence of obstacles, while the method in [45] is only for an obstacle-free environment.

VI. CONCLUSIONS

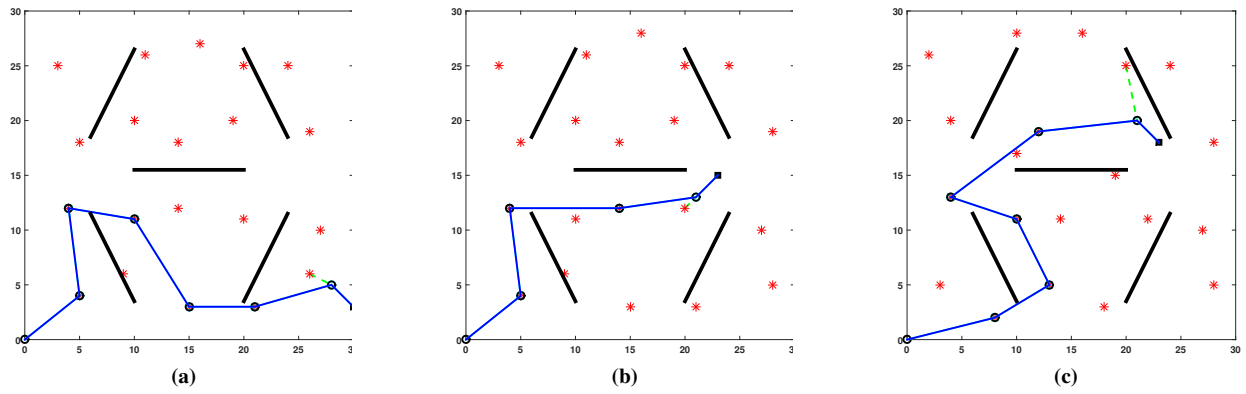A novel technique is proposed to prolong the lifetime of a mobile sensor network which is deployed to monitor a

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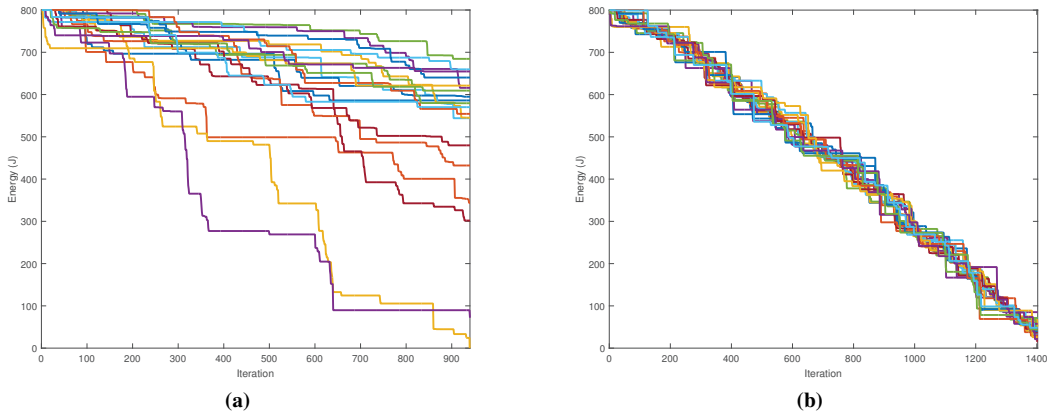

Fig. 12: The energy of sensors during the operation of the network in the third scenario of Example 1, using: (a) the tracking algorithm of [17], and (b) the proposed algorithm.
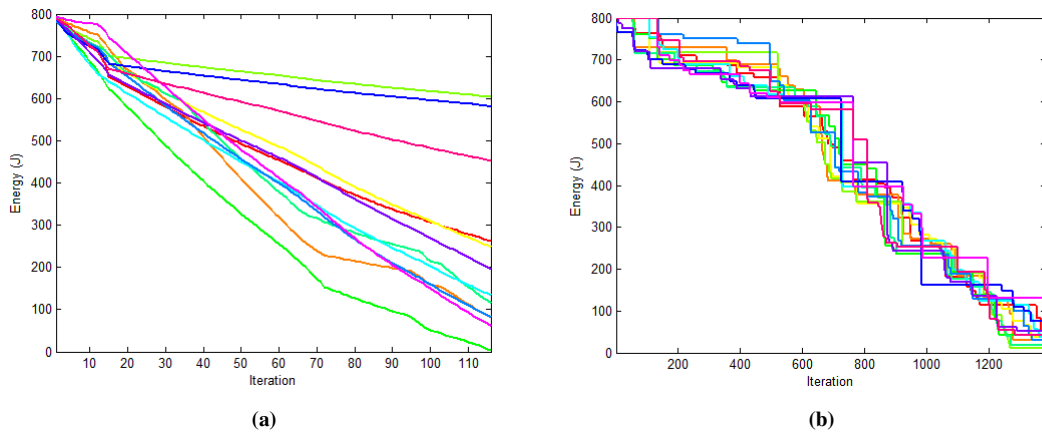

Fig. 13: The energy of sensors during the operation of the network in Example 2, using: (a) the method given in [45], and (b) the proposed algorithm.

moving target in a field with or without obstacles. A digraph is constructed by mapping the field to a grid, where 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. Simulations demonstrate the effectiveness of the proposed strategy in finding best location for the mobile sensors at different points in time, as well as the best route to transmit the target information. Adaptive sensing and communication range for each sensor with regard to its remaining energy can have a significant impact on the network lifetime, which is considered as a future work. Also, solving the investigated problem over multiple time-steps based on a realistic model for target motion can be considered as a future work.

REFERENCES

[1] J. Meyer, R. Bischoff, G. Feltrin, and M. Motavalli, "Wireless sensor networks for long-term structural health monitoring," *Smart Structures and Systems*, vol. 6, no. 3, pp. 263–275, 2010.

[2] F. Agyei-Ntim and K. Newman, "Lifetime estimation of wireless body area sensor network for patient health monitoring," in *Proceedings of 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society: Engineering the Future of Biomedicine*, 2009, pp. 1659–1662.

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

[4] F. Ingelrest, G. Barrenetxea, G. Schaefer, M. Vetterli, O. Couach, and M. Parlange, "Sensorscope: Application-specific sensor network for environmental monitoring," *ACM Transactions on Sensor Networks*, vol. 6, no. 2, pp. 1–32, 2010.

[5] A. Olteanu, Y. Xiao, K. Wu, and X. Du, "An optimal sensor network for intrusion detection," in *Proceedings of IEEE International Conference on Communications*, 2009.

[6] S. Shin, T. Kwon, G.-Y. Jo, Y. Park, and H. Rhy, "An experimental study of hierarchical intrusion detection for wireless industrial sensor networks," *IEEE Transactions on Industrial Informatics*, vol. 6, no. 4, pp. 744–757, 2010.

[7] X. Chang, R. Tan, G. Xing, Z. Yuan, C. Lu, Y. Chen, and Y. Yang, "Sensor placement algorithms for fusion-based surveillance networks," *IEEE Transactions on Parallel and Distributed Systems*, vol. 22, no. 8, pp. 1407–1414, 2011.

[8] J. Lu and T. Suda, "Differentiated surveillance for static and random mobile sensor networks," *IEEE Transactions on Wireless Communications*, vol. 7, no. 11, pp. 4411–4423, 2008.

[9] G. Isbitiren and O. B. Akan, "Three-dimensional underwater target tracking with acoustic sensor networks," *IEEE Transactions on Vehicular Technology*, vol. 60, no. 8, pp. 3897–3906, 2011.

[10] S. Misra and S. Singh, "Localized policy-based target tracking using wireless sensor networks," *ACM Transactions on Sensor Networks*, vol. 8, no. 3, pp. 1–30, 2012.

[11] B. Chen and W. Liu, "Mobile agent computing paradigm for building a flexible structural health monitoring sensor network," *Computer-Aided Civil and Infrastructure Engineering*, vol. 25, no. 7, pp. 504–516, 2010.

[12] F. Hu, Y. Xiao, and Q. Hao, "Congestion-aware, loss-resilient bio-monitoring sensor networking for mobile health applications," *IEEE Journal on Selected Areas in Communications*, vol. 27, no. 4, pp. 450–465, 2009.

[13] A. Srinivas, G. Zussman, and E. Modiano, "Mobile backbone networks - construction and maintenance," in *Proceedings of the 7th ACM international symposium on Mobile ad hoc networking and computing*, 2006, pp. 166–177.

[14] S. Gil, M. Schwager, B. J. Julian, and D. Rus, "Optimizing communication in air-ground robot networks using decentralized control," in *Proceedings of 2010 IEEE International Conference on Robotics and Automation*, 2010, pp. 1964–1971.

[15] R. Olfati-Saber and N. Sandell, "Distributed tracking in sensor networks with limited sensing range," in *Proceedings of American Control Conference*, 2008, pp. 3157–3162.

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

[17] ——, "An energy-efficient target tracking strategy for mobile sensor networks in the presence of obstacles," *Concordia University Technical Report*, 2012 (available online at www.ece.concordia.ca/∼aghdam/TechnicalReports/techrep2012_2.pdf).

[18] Z. Cheng, M. Perillo, and W. Heinzelman, "General network lifetime and cost models for evaluating sensor network deployment strategies," *IEEE Transactions on Mobile Computing*, vol. 7, no. 4, pp. 484–497, 2008.

[19] D. Wang, B. Xie, and D. Agrawal, "Coverage and lifetime optimization of wireless sensor networks with gaussian distribution," *IEEE Transactions on Mobile Computing*, vol. 7, no. 12, pp. 1444–1458, 2008.

[20] W. Liang, J. Luo, and X. Xu, "Prolonging network lifetime via a controlled mobile sink in wireless sensor networks," in *Proceedings of 2010 IEEE Global Communications Conference*, 2010, pp. 1–6.

[21] M. Gatzianas and L. Georgiadis, "A distributed algorithm for maximum lifetime routing in sensor networks with mobile sink," *IEEE Transactions on Wireless Communications*, vol. 7, no. 3, pp. 984–994, 2008.

[22] F. Tashtarian, M. Yaghmaee Moghaddam, K. Sohraby, and S. Effati, "On maximizing the lifetime of wireless sensor networks in event-driven applications with mobile sinks," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 7, pp. 3177–3189, July 2015.

[23] W. Liang and J. Luo, "Network lifetime maximization in sensor networks with multiple mobile sinks," in *IEEE 36th Conference on Local Computer Networks*, Oct 2011, pp. 350–357.

[24] Y. Yun, Y. Xia, B. Behdani, and J. Smith, "Distributed algorithm for lifetime maximization in a delay-tolerant wireless sensor network with a mobile sink," *IEEE Transactions on Mobile Computing*, vol. 12, no. 10, pp. 1920–1930, Oct 2013.

[25] H. Mahboubi, W. Masoudimansour, A. G. Aghdam, and K. Sayrafian-Pour, "Maximum life span strategy for target tracking in mobile sensor networks," in *Proceedings of American Control Conference*, 2012, pp. 5096–5101.

[26] J. Teng, H. Snoussi, C. Richard, and R. Zhou, "Distributed variational filtering for simultaneous sensor localization and target tracking in wireless sensor networks," *IEEE Transactions on Vehicular Technology*, vol. 61, no. 5, pp. 2305–2318, 2012.

[27] W. Masoudimansour, H. Mahboubi, A. G. Aghdam, and K. Sayrafian-Pour, "Maximum lifetime strategy for target monitoring in a mobile sensor network with obstacles," in *Proceedings of 51th IEEE Conference on Decision and Control*, 2012, pp. 1404–1410.

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

[29] K. E. Hoff, III, J. Keyser, M. Lin, D. Manocha, and T. Culver, "Fast computation of generalized voronoi diagrams using graphics hardware," in *Proceedings of the 26th Annual Conference on Computer Graphics and Interactive Techniques*, 1999, pp. 277–286.

[30] S. Bhattacharya, R. Ghrist, and V. Kumar, "Multi-robot coverage and exploration in non-euclidean metric spaces," in *Proceedings of the Tenth Workshop on the Algorithmic Foundations of Robotics*, 2013, pp. 245–262.

[31] J. Park and S. Sahni, "An online heuristic for maximum lifetime routing in wireless sensor networks," *IEEE Transactions on Computers*, vol. 55, pp. 1048–1056, 2006.

[32] J. Kim, X. Lin, N. B. Shroff, and P. Sinha, "On maximizing the lifetime of delay-sensitive wireless sensor networks with anycast," in *Proceedings of IEEE INFOCOM*, 2008, pp. 1481–1489.

[33] C.-C. Hung, K. C.-J. Lin, C.-C. Hsu, C.-F. Chou, and C.-J. Tu, "On enhancing network-lifetime using opportunistic routing in wireless sensor networks," in *Proceedings of International Conference on Computer Communications and Networks*, 2010.

[34] A. Juttner, B. Szviatovski, I. Mecs, and Z. Rajko, "Lagrange relaxation based method for the qos routing problem," in *Proceedings of 20th IEEE INFOCOM*, 2001, pp. 859–868.

[35] I. Dumitrescu and N. Boland, "Algorithms for the weight constrained shortest path problem," *International Transactions in Operational Research*, vol. 8, no. 1, pp. 15–29, 2001.

[36] M. L. Fredman and R. E. Tarjan, "Fibonacci heaps and their uses in improved network optimization algorithms," *Journal of the ACM*, vol. 34, no. 3, pp. 596–615, 1987.

[37] H. Mahboubi, A. Momeni, A. G. Aghdam, K. Sayrafian-Pour, and V. Marbukh, "An efficient target monitoring scheme with controlled node

mobility for sensor networks," *IEEE Transactions on Control Systems Technology*, vol. 20, no. 6, pp. 1522–1532, 2012.

[38] G. Wang, G. Cao, and T. F. L. Porta, "Movement-assisted sensor deployment," *IEEE Transactions on Mobile Computing*, vol. 5, pp. 640–652, 2006.

[39] A. Galllais, J. Carle, D. Simplot-Ryl, and I. Stojmenovic, "Localized sensor area coverage with low communication overhead," *IEEE Transactions on Mobile Computing*, vol. 7, no. 5, pp. 661–672, 2008.

[40] R. S. Chang and S. H. Wang, "Self-deployment by density control in sensor networks," *IEEE Transactions on Vehicular Technology*, vol. 57, no. 3, pp. 1745–1755, 2008.

[41] C. H. Caicedo-Nez and M. Zefran, "Distributed task assignment in mobile sensor networks," *IEEE Transactions on Automatic Control*, vol. 56, no. 10, pp. 2485–2489, 2011.

[42] K. Ma, Y. Zhang, and W. Trappe, "Managing the mobility of a mobile sensor network using network dynamics," *IEEE Transactions on Parallel and Distributed Systems*, vol. 19, no. 1, pp. 106–120, 2008.

[43] "Berkeley sensor and actuator center," September 2014. [Online]. Available: http://www-bsac.eecs.berkeley.edu

[44] G. Wang, G. Cao, P. Berman, and T. F. L. Porta, "A bidding protocol for deploying mobile sensors," *IEEE Transactions on Mobile Computing*, vol. 6, pp. 563–576, 2007.

[45] S. Yu and C. S. G. Lee, "Mobility and routing joint design for lifetime maximization in mobile sensor networks," in *Proceedings of IEEE International Conference on Intelligent Robots and Systems*, 2011, pp. 2300–2305.

Amir G. Aghdam (SM'05) received his Ph.D. in electrical and computer engineering from the University of Toronto in 2000 and is currently a Professor in the Department of Electrical and Computer Engineering at Concordia University. He is a member of Professional Engineers Ontario and a senior member of the IEEE.

Dr. Aghdam is a member of the Conference Editorial Board of IEEE Control Systems Society, Co-Editor-in-Chief of the IEEE Systems Journal, an Associate Editor of the IEEE Transactions on Control Systems Technology, European Journal of Control, IET Control Theory & Applications, and Canadian Journal of Electrical and Computer Engineering. He has been a member of the Technical Program Committee of a number of conferences including IEEE Conference on Systems, Man and Cybernetics (IEEE SMC), IEEE Conference on Decision and Control (IEEE CDC), and IEEE Multiconference on Systems and Control (IEEE MSC). Since August 2013, he has been a member of Natural Science and Engineering Research Council of Canada (NSERC) ECE Evaluation Group. He is a recipient of the 2009 IEEE MGA Achievement Award and 2011 IEEE Canada J. J. Archambault Eastern Canada Merit Award. Dr. Aghdam is 20142015 President of IEEE Canada and Director (Region 7), IEEE Inc., and is also a member of IEEE Awards Board for this period. His research interests include multi-agent networks, distributed control, optimization and sampled-data systems.

Hamid Mahboubi (S'08, M'14, SM'15) is a recipient of the Governor General of Canada Academic Gold Medal in 2015. He is also a recipient of the Gold Medal in the 1999 National Math Olympiad in Iran. He was awarded an honorary admission to Sharif University of Technology, Tehran, Iran, where he received his B.Sc. degree in Electrical Engineering in 2003. He received his M.A.Sc. degree in Electrical and Computer Engineering from the University of Tehran, Tehran, Iran, in 2006. He received his Ph.D. degree in 2014 from Concordia University, Montreal, Canada. He is currently a postdoctoral fellow in the Department of Electrical and Computer Engineering at McGill University, Montreal, Canada. Dr. Mahboubi is the recipient of Concordia University Distinguished Doctoral Dissertation Prize in Engineering and Natural Science, Doctoral Prize in Engineering and Computer Science, Fonds qubcois de la recherche sur la nature et les technologies (FQRNT) Post-Doctoral Award, Bourse d'Etudes Hydro Quebec Scholarship, Power Corporation of Canada Graduate Fellowship, and Canadian National Award in Transportation.

Dr. Mahboubi has served as Chair of the Control Systems Chapter of the IEEE Montreal Section since January 2012. He is a member of Editorial Board of IEEE SigView (IEEE Signal Processing Society) and a senior member of the IEEE. He also was a member of the Technical Program Committee of 2015 IEEE International Conference on Wireless for Space and Extreme Environments. His research interests include mobile sensor networks, multi-agent systems, hybrid systems, networked control systems, smart grids, and optimization.

Kamran Sayrafian-Pour (SM'05) holds Ph.D., M.S. and B.S. degrees in Electrical & Computer Engineering from University of Maryland, Villanova University and Sharif University of Technology, respectively. He is currently a Senior Scientist at the Information Technology Laboratory of the National Institute of Standards and Technology (NIST) located in Gaithersburg, Maryland where he leads a strategic program related to the application of Pervasive Technology in Health care Information Systems. Prior to this, he was the co-founder of Zagros Networks, Inc. a fabless semiconductor company based in Rockville, Maryland where he served as President and Senior Member of the architecture team. Dr. Sayrafian has been an adjunct faculty of the University of Maryland since 2003.

Dr. Sayrafian-Pour was the Technical Program Committee and Executive Co-Chair of the IEEE PIMRC 2014. He has also been the organizer and invited TPC member of several IEEE ComSoc Conferences and workshops focused on the applications of wireless communication in health care. His research interests include medical body area networks, mobile sensor networks and RF-based indoor positioning. He has published over 100 conference and journal papers, and book chapters in these areas. He was the recipient of the IEEE PIMRC 2009 and SENSORCOMM 2011 best paper awards. He is also a member of the editorial board of the IEEE Wireless Communications Magazine, and guest editor for a number of journal special issues focusing on the pervasive health care technologies and wireless sensor networks. Dr. Sayrafian was the US Embassy Science Fellow in Croatia in 2014. He was a contributing member of the European COST Action IC1004 "Cooperative Radio Communications for Green Smart Environments"; and, his research results have been included in the final report of this Action. He was also a contributing member and the co-editor of the channel modeling document of the IEEE802.15.6 international standard on body area networks. Dr. Sayrafian is the co-inventor/inventor of four US patents; and, the recipient of the 2015 US Department of Commerce Bronze Medal award for his contribution to the field of body area networks.

Walid Masoudimansour has received his B.Sc. in Electrical Engineering in 2003 from Sharif University of Technology, Tehran, Iran and his M.A.Sc. degree in Electrical Engineering from Concordia University, Montreal, QC, Canada in 2012. He is currently a Ph.D. candidate in Electrical Engineering department of Concordia University, Montreal, QC, Canada. Mr. Masoudimansour has received the Fonds de Recherche du Quebec - Nature et Technologies (FRQNT) award in 2014, and his research interests currently are Machine Learning, Artificial Intelligence, and Big Data.