Cost-Efficient Routing with Controlled Node Mobility in Sensor Networks

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Abstract

In this paper, an energy-efficient strategy is proposed for tracking a moving target in a mobile sensor network. The energy expenditure of the sensors in the network is assumed to be due to communication, sensing and movement. First, the target area is divided into a grid of sufficiently small rectangular cells in order to search for near optimal locations for the sensors in different time instants. The grid is then converted to a graph with properly weighted edges. A shortest-path algorithm is subsequently applied to route the information flow from the target to destination using a subset of sensors.

I. INTRODUCTION

Wireless sensor networks are widely used in a broad range of civilian and military applications. Such applications include wildlife monitoring, tracking vehicles, security surveillance and battlefield communication, to name only a few [1], [2], [3], [4], [5]. Target tracking is one of the most important problems concerning mobile sensor networks [6]. In this type of problems, it is desired to track a moving target by properly moving some or all of the sensors in the field to create a route from the target to destination, where the network information is collected. There has been considerable progress recently in developing efficient deployment algorithms for mobile sensor networks [7], [8]. On the other hand, communication, sensing and movement are sources of energy consumption in mobile sensors [9]. Hence, limited energy resources of the sensors need to be taken into consideration in designing sensor deployment algorithms in real-world applications. Furthermore, due to the distributed structure of the network, a decentralized decision-making configuration is often more desirable. It is important to note that a strategy which takes these limitations into account and achieves the design specifications does not necessarily exist.

In [10], the desired sensing and communication radii of sensors as well as their locations at each instant is calculated in a network consisting of sensors which are collaboratively tracking a target, maximizing the durability of the network. However, in this work, a part of the energy consumption due to sensor movement is not included, and energy consumption is assumed to be just due to sensing and communication. Multi-target tracking problem is investigated in [11], where a decentralized detection strategy with low energy consumption is proposed for target tracking.

The problem of collaborative tracking of mobile nodes in wireless sensor networks is studied in [12]. It combines target tracking and node selection procedures to identify the effective sensors for an energy efficient strategy. In [13], an algorithm is provided to estimate the position of the target, while optimizing the quantization level for the minimum transmission power. A distributed energy optimization technique is proposed in [14] for target tracking in wireless sensor networks. Sensor nodes are clustered properly, and the sensing area is partitioned for parallel sensor deployment optimization. Grid exclusion and Dijkstra’s algorithms are employed for coverage and energy metrics, respectively. The coverage is then maximized while minimizing the energy consumption.

In the present work, an energy-efficient routing technique is introduced to track a target in a mobile sensor network, while optimizing the energy consumption. It is assumed that the main sources of energy consumption in the network are communication, sensing, and movement. The field is first divided into a grid (which discretizes the problem), and then each sensor is directed to a proper node in the grid. A graph is subsequently derived from this grid, and its edges are weighted properly based on the parameters of the energy consumption model. This graph is used to find the optimal route to transfer the information from the target to destination. Then, the graph is redrawn in such a way that the minimum energy problem is translated to the constrained shortest path from the target to destination. This is a well-known problem in network and routing, and several algorithms exist in the literature to handle it. Due to the simplicity and effectiveness of Dijkstra’s algorithm it will be adopted in this paper to solve the underlying problem.

The organization of the paper is as follows. In Section II the problem is introduced and important assumptions and definitions are provided. Section III presents the proposed routing technique as the main contribution of the paper. In Section IV complexity and performance of the algorithm are discussed. Simulations are presented in Section V to support the theoretical findings. Finally, a brief summary is given in Section VI.

II. PROBLEM STATEMENT

Consider a group of $n$ mobile sensors $S_1, \ldots, S_n$ aimed to track a moving target. The sensors are distributed in a field where the target moves, and their mission is to preserve connectivity between target and destination (a fixed location where the network information is collected). Furthermore, in selecting those sensors which create a route from the target to destination, H. Mahboubi, W. Masoudi and A. G. Aghdam are with the Department of Electrical & Computer Engineering, Concordia University, 1455 de Maisonneuve Blvd. W., EV005.139, Montréal, Québec H3G 1M8 Canada. {h.mahbo, w.masou, aghdam}@ece.concordia.ca
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cost-effectiveness must be taken into account. This cost is concerned with the energy consumed to establish connectivity, and depends mainly on movement, sensing and communication.

Assumption 1. It is assumed that one sensor is properly selected to sense the target, and all other sensors can potentially be used to create an information route to the destination at any time instant. This sensor is referred to as the tracking sensor, and is not necessarily fixed. The tracking sensor at any point in time is selected based on the target position and the energy-efficient deployment strategy discussed later.

Let the tracking sensor be denoted by $S_T$, with the maximum sensing radius $R_S$ (note that $S_T \in \{S_1,S_2,...,S_n\}$ at any time instant). This means that if the target is within a circle of radius $R_S$ centered at $S_T$, then it can be detected by this sensor.

Assumption 2. The target is assumed to be within a reachable distance from the destination at all times, i.e. $x(t) \leq nR_C + R_S, \forall t$, where $x$ is the distance between the target and destination, $R_C$ is the maximum communication radius of each sensor, and $n$ is the number of sensors.

To minimize the energy consumption, the sensors must operate in a collaborative fashion in order to determine the best locations for sensors, and the best routing path to communicate the information. The energy loss due to movement is assumed to be proportional to the distance. The energy loss due to communication and sensing between two nodes $P$ and $Q$, on the other hand, is proportional to $d(P,Q)^{x}$ and $d(P,Q)^{y}$, respectively, where $d(P,Q)$ is the distance between $P$ and $Q$. Moreover, $\lambda$ and $\gamma$ are positive real values which depend on the characteristics of the environment (typically $\gamma > \lambda$).

To develop the energy-efficient routing technique, the field is first divided into a grid, and it is assumed that the sensors are located on the nodes of the grid at any time instant. Three different graphs are then constructed, whose vertices are the grid nodes, and whose edges are weighted properly, in accordance with the available models for the three sources of energy consumption.

The three weighted graphs (which are, in fact, directed) are subsequently combined to obtain the overall energy consumption graph, which will be referred to as the combined energy digraph. The following notation and definitions will prove convenient in the development of the main results.

Notation 1. Throughout this paper, the $j$-th nearest sensor to node $P$ will be denoted by $S^j_P$, for any $j \in n := \{1,2,...,n\}$. For example, $S^1_P$ represents the nearest sensor to node $P$. Furthermore, $d^j_P$ denotes the distance between $S^j_P$ and $P$.

Definition 1. In this paper, the term path nodes refers to all the nodes on a given path connecting the target to destination, excluding the target and destination themselves.

III. MAIN RESULTS

In this section, a strategy is presented to properly place the sensors in the field at any time instant in such a way that the total energy consumption due to the sensing, communication and movement of the sensors is sufficiently close to its minimum value.

Consider $n$ sensors which can move on the surface of a field. Let the field be divided into a grid of a given size. Partition also the field into a Voronoi diagram [15] with $n$ regions (each region associated with one sensor). Let the $j$-th region of the Voronoi diagram be denoted by $\Lambda_j$, for any $j \in n$. Three different graphs are constructed in the sequel.

1) Communication energy digraph: Construct a directed graph (digraph) in which the edges are properly weighted to model the communication cost between the sensors. In this digraph, there is an edge from the node $P_i$ to $P_j$ if $P_j$ is in the communication range of $P_i$, i.e., if the distance between them is less than or equal to $R_C$. It is to be noted that all edges in this digraph are bidirectional.

Definition 2. The region containing the target and the node on which the target resides will hereafter be denoted by $\Lambda_T$ and $P_T$, respectively. In addition, the destination will be denoted by $P_D$.

2) Sensing energy digraph: From the properties of the Voronoi diagram, it is known that the closest sensor to any point in a Voronoi region is the sensor associated with that region. The target is assumed to be tracked by the closest sensor to it. This implies that the target and the sensor which tracks it at any point in time, are in the same Voronoi region. Every node of the grid whose distance from the target is less than $R_S$ and is in $\Lambda_T$ is connected to the target by a directed edge (from the target to the node) with a weight proportional to the corresponding sensing energy. Moreover, any node on the grid which is in $\Lambda_T$ and is within a distance of $R_S$ from $P_T$ will be referred to as a sensing node. Figure 1 shows a sample position of the target and the sensor energy digraph edges. $R_S$ is assumed to be 2 in this figure, and the target is connected to any point in the grid in the region $\Lambda_T$ and enclosed in the circle with radius of $R_S$ centered at the target.

3) Movement energy digraph: Construct a directed graph in which the edges are appropriately weighted to model the energy required for the sensors to move to a proper location in order to transmit information from the target to destination. This directed graph is called movement energy digraph. The weight of the directed edge from $P_i$ ($P_i \neq P_T$) to $P_j$ is denoted by mov($i,j$), which depends on the locations of the two nodes. The following procedure is used to find this weight.
Consider the case where $P_i$ and $P_j$ are in different Voronoi regions, OR $P_j$ is the destination node.

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

$$mov(i, j) = \beta \cdot d^2_{P_i}$$

where $\beta$ is a constant coefficient.

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

$$mov(i, j) = \beta \cdot d^1_{P_i}$$

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:

$$mov(i, j) = \beta \cdot d^2_{P_i}$$

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

$$mov(i, j) = \beta \cdot [\min(d^1_{P_i} + d^2_{P_j}, d^1_{P_j} + d^3_{P_i}) - d^1_{P_j}]$$

iii) If $P_i$ is a sensing node, then:

$$mov(i, j) = \beta \cdot d^1_{P_i}$$

It is important to notice that, our algorithm tries to allocate weights to the movement energy digraph such that in any arbitrary path from target to destination, the sum of the allocated weights to the path edges by the algorithm is a lower limit which is as close as possible to the minimum movement energy required for a subset of sensors to move to path nodes and start routing the information. As simulation results will show, our proposed method is successful in a high percent of cases. Figure 2 gives an illustration of the above cases for edges which each are assumed to belong to an arbitrary path. For example, in this figure, nodes $B$ and $C$ satisfy the conditions of part (i) of the second case and the edge $BC$ is assigned a weight of $\beta \cdot d^2_{BC} = \beta \cdot d(S_4, B)$ where $d(S_4, B)$ is the distance between $S_4$ and $B$. Edges $AD$, $EF$ and $GH$ satisfy part (ii) of the first case. In the edge $AD$, node $P_j = D$ is the destination. For $EF$, $P_i = E$ and the target are in different regions and in $GH$, $P_i = G$ is a sensing node, therefore they will be assigned the weights $\beta \cdot d^1_{AD} = \beta \cdot d(S_3, A)$, $\beta \cdot d^1_{EF} = \beta \cdot d(S_1, E)$ and $\beta \cdot d^1_{GH} = \beta \cdot d(S_2, G)$ respectively. The edge $KL$ is an example of part (i) of the second case in which $P_i = K$ and the target are in different regions and $K$ is not a sensing node. The algorithm assigns the weight $\beta \cdot d^2_{KL} = \beta \cdot d(S_1, K)$ to it. The edge $MN$ satisfies part (iii) of the second case. In this case, the nearest sensor to $M$ and $N$ is the same and the algorithm assigns the weight $\beta \cdot [\min(d^1_{MN} + d^2_{MN} + d^3_{MN}) - d^1_{MN}] = \beta \cdot [\min(d(S_4, M) + d(S_3, N), d(S_4, N) + d(S_2, M)) - d(S_4, N)]$ to this edge. Finally, the edge $IJ$ is an example of part (iii) of the second case. In this case, since $P_i = I$ is a sensing node, the weight of this edge is $\beta \cdot d^1_{IJ} = \beta \cdot d(S_2, I)$.

Once the above three digraphs are constructed, derive a new digraph called combined energy digraph, in which the node $P_i$ is connected to $P_j$ if there is a directed edge from $P_i$ to $P_j$ in at least one of the three digraphs. The weight assigned to this edge is the sum of the weights of the corresponding existing edges in the three digraphs. Notice that, if the distance between any two grid points $P_i$ and $P_j$ is greater than $R_C$, the corresponding edge in the communication energy digraph has been assigned a weight of infinity, therefore making the corresponding edge in the combined energy digraph of infinite weight. It
is desired in this new graph to find the shortest weighted 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. It will be shown that this path provides a cost-effective route, which can, under some conditions, be optimal.

**Remark 1.** One can use a proper fast and efficient routing algorithm (such as Dijkstra) to find the shortest path. If in the end the number of nodes in the shortest path was greater than \( n \), then one can switch to a constrained shortest path algorithm, which is normally slower than unconstrained algorithms.

**Definition 3.** The sum of the weights of the directed edges of a path \( \Pi \) is referred to as the *path weight*, and is denoted by \( W(\Pi) \). Note that the path weight is, in fact, the sum of the weights of directed edges of the sensing energy digraph, communication energy digraph and movement energy digraph, which will hereafter be called the *sensing path weight*, *communication path weight*, and *movement path weight*, respectively.

**Definition 4.** Given a path \( \Pi = (P_T, P_1, P_2, \ldots, P_m, P_D) \) connecting the target to destination, the minimum energy required for any group of \( m \) sensors to be located at \( P_1, P_2, \ldots, P_m \) and transmit the information from the target to destination is called the *path cost*, and is denoted by \( C(\Pi) \). Note that the path cost is, in fact, the sum of the minimum energy required for the selected sensors to move to their designated locations on the path, sense the target, and communicate with each other on the path, which will hereafter be referred to as the *movement path cost*, *sensing path cost*, and *communication path cost*, respectively. However, to find this value, it suffices to consider the movement energy only, and add it to the fixed sensing and communication energy required to establish the underlying information link. This is due to the fact that all sensors are assumed to be identical in terms of sensing and also communication capabilities.

**Definition 5.** The *optimal path* in a combined energy digraph is a path consisting of at most \( n \) nodes, such that there exist a group of sensors which the cost of moving them to these nodes and establishing an information link from the target to destination is minimum, among all possible choices of paths and sensors. This path will be denoted by \( \Pi^* \).

**Theorem 1.** Consider a path \( \Pi \) which connects the target to destination such that:

i) \( \Pi \) has at most two nodes in each Voronoi region.
ii) If a region \( \Lambda_k \) contains exactly two nodes of the path, say \( P_i \) and \( P_j \), then the path \( \Pi \) does not pass through any other region containing the second nearest sensor to \( P_i \) or \( P_j \).

*Then, the path cost and path weight of \( \Pi \) are equal.*

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

**Case 1:** Region \( \Lambda_k \) contains only one node. To minimize the movement energy in this case, one can assign the nearest sensor of this node to it. From the weight assignment rule in the movement energy digraph, it follows that the movement path cost and movement path weight are equal.

**Case 2:** Region \( \Lambda_k \) contains the two nodes \( P_i \) and \( P_j \), but not the node \( P_T \) (target). Similar to the previous case, it results
from the weight assignment rule in the movement energy digraph that the sum of the weights of the edge from $P_i$ to $P_j$ and the edge coming out of $P_j$ is given by:

$$X_k = \beta \cdot \min (d_{P_i}^1 + d_{P_j}^1, d_{P_i}^2 + d_{P_j}^2) - d_{P_j}^1 + \beta \cdot d_{P_j}^1$$

$$= \beta \cdot \min (d_{P_i}^1 + d_{P_j}^1, d_{P_j}^2 + d_{P_j}^2)$$

(1)

Since $\Pi$ does not pass through the Voronoi regions containing the second nearest sensors to $P_i$ and $P_j$, the above value is the minimum energy required to place the sensors in these two nodes.

**Case 3:** Region $\Lambda_k$ contains the two nodes $P_i$ and $P_j$, as well as the node $P_T$. In this case, the sum of the weights of the corresponding edges is:

$$\beta \cdot d_{P_i}^1 + \beta \cdot d_{P_j}^1$$

(2)

Since $\Pi$ does not pass through the region containing the second nearest sensor to $P_j$, thus (2) gives the minimum energy to place two sensors in $P_i$ and $P_j$.

Since the discussions given above are valid for all Voronoi regions, one can conclude that the path cost and path weight of $\Pi$ are equal.

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

**Proof:** The proof follows immediately from Theorem 1, as a special case.

**Theorem 2.** For any path $\Pi$ connecting the target to destination in a combined energy digraph, the relation $W(\Pi) \leq C(\Pi)$ holds.

**Proof:** Since for any fixed path the communication and sensing path costs are equal to communication and sensing path weights, respectively, it suffices to show that the movement path cost is greater than or equal to the movement path weight. To this end, assume that the path $\Pi$ passes through the regions $\Lambda_1, \Lambda_2, \ldots, \Lambda_k$, and that the path has $n_i$ nodes in region $\Lambda_i$, $i \in \{1, 2, \ldots, k\}$. Partition $\Pi$ into $k$ sub-paths as follows:

$$\Pi^1 = (P_{i_1}, P_{i_1}^1, P_{i_2}, P_{i_2}^1, \ldots, P_{i_n}^1, P_T^1)$$

$$\Pi^2 = (P_{i_1}^2, P_{i_2}^2, \ldots, P_{i_n}^2, P_T^1)$$

$$\vdots$$

$$\Pi^k = (P_{i_1}^k, P_{i_2}^k, \ldots, P_{i_n}^k, P_T^k)$$

Now, it suffices to show that the movement path weight of the sub-path $\Pi^i$ is less than or equal to the corresponding movement path cost, for any $i \in \{1, 2, \ldots, k\}$. If $\Lambda_i$ contains exactly one node, then the sub-path $\Pi^i$ contains only the edge $(P_{i_1}^i, P_{i_1}^{i+1})$ (note that $P_{i_1}$ is, in fact, $P_{i_1}^{i+1}$). The assigned weight to this edge in the movement energy digraph is $\beta \cdot d_{P_{i_1}}^1$, which is the energy required to move to the node $P_{i_1}$, the nearest sensor to it. It is obvious that the minimum required energy for a sensor to move to $P_{i_1}$ is equal to $\beta \cdot d_{P_{i_1}}^1$ as well (note that sometimes the sensor assigned to a node is not necessarily its nearest sensor, because that may be the nearest sensor to multiple nodes in the path). Therefore, in this case, the movement path weight of sub-path $\Pi^i$ is less than or equal to the movement path cost.

If $\Lambda_i$ contains more than one node, there will be two possibilities as follows:

**Case 1:** $i \neq 1$. In this case, the weight assigned to the sub-path $\Pi^i$ in the movement energy digraph is:

$$X = \beta \cdot \left[ \sum_{k=1}^{n_i-1} \min (d_{P_{i_1}}^1 + d_{P_{i_1}}^2, d_{P_{i_1}}^3 + d_{P_{i_1}}^4) - d_{P_{i_1}}^1 \right] + \beta \cdot d_{P_{i_1}}^1$$

From the properties of the Voronoi diagram, the nearest sensor to all nodes of the sub-path $\Pi^i$ is the same. However, this sensor can move to only one node; therefore, the cost of moving $n_i$ sensors to the $n_i$ nodes of the path which lie in the region $\Lambda_i$ is greater than or equal to:

$$Y = \beta \cdot \left[ d_{P_{i_1}}^1 + \sum_{k=1, k \neq j}^{n_i} d_{P_{i_1}}^2 \right]$$

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

$$X_1 = \beta \cdot \left[ \sum_{k=1}^{j-1} \left( d_{P_{i_1}}^1 + d_{P_{i_1}}^2 \right) - d_{P_{i_1}}^1 \right]$$

$$\geq \beta \cdot \left[ \sum_{k=1}^{j-1} \min (d_{P_{i_1}}^1 + d_{P_{i_1}}^2, d_{P_{i_1}}^3 + d_{P_{i_1}}^4) - d_{P_{i_1}}^1 \right]$$

(3)
\[ X_2 = \beta \left[ \sum_{k=1}^{n-1} (d_{k+1}^1 + d_{k+1}^2) - d_{k+1}^1 \right] + \beta d_{p_j}^1 \]
\[ \geq \beta \left[ \sum_{k=1}^{n-1} \min(d_{k+1}^1 + d_{k+1}^2, d_{k+1}^1 + d_{k+1}^2) - d_{k+1}^1 \right] + \beta d_{p_j}^1 \]

By expanding and simplifying the last two inequalities, one can conclude that:

\[ Y = X_1 + X_2 \]

Hence:

\[ Y = X_1 + X_2 \]
\[ \geq \beta \left[ \sum_{k=1}^{n-1} \min(d_{k+1}^1 + d_{k+1}^2, d_{k+1}^1 + d_{k+1}^2) - d_{k+1}^1 \right] + \beta d_{p_j}^1 = X \]

Since \( Y \) is less than or equal to the movement path cost of the sub-path \( \Pi^1 \), it results from the above relation that the movement path weight of this sub-path is less than or equal to its movement path cost.

Case 2: \( i = 1 \) (the region contains the target). In this case, the nearest sensor to the nodes of this region is clearly assigned to detect the target, and hence cannot be assigned to another node simultaneously. As a result, the cost of moving \( n_1 \) sensors to \( n_1 \) nodes of the sub-path \( \Pi^1 \) is greater than or equal to:

\[ Y = \beta \left[ \sum_{k=2}^{n_1} d_{p_i}^2 \right] \]

On the other hand, the weight assigned to the sub-path \( \Pi^1 \) in the movement digraph is:

\[ X = \beta \left[ d_{p_i}^1 + \sum_{k=2}^{n_1} d_{p_i}^2 \right] \]

This means that the movement path weight of \( \Pi^1 \) is less than or equal to its movement path cost.

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

\[ \square \]

Theorem 3. Assume the shortest path \( \bar{\Pi} \) connecting the target to destination in a given combined energy digraph has the following properties:

i) \( \bar{\Pi} \) has at most two nodes in each Voronoi region it passes through.

ii) If \( \Lambda_k \) contains the nodes \( P_i \) and \( P_j \), then \( \bar{\Pi} \) does not pass through the regions containing the second nearest sensor to \( P_i \) or \( P_j \).

Then, \( \bar{\Pi} \) is the optimal path.

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

\[ C(\Pi^*) < C(\bar{\Pi}) \]  
(6)

From Theorem 1:

\[ W(\bar{\Pi}) = C(\bar{\Pi}) \]  
(7)

Also, from Theorem 2:

\[ W(\Pi^*) \leq C(\Pi^*) \]  
(8)

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

\[ W(\Pi^*) < W(\bar{\Pi}) \]

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

\[ \square \]

Corollary 2. If the shortest path \( \bar{\Pi} \) connecting the target to destination in the combined energy digraph has exactly one node in each Voronoi region it passes through, then \( \bar{\Pi} \) is, in fact, the optimal path.
Proof: The proof is straightforward, on noting that this is a special case of Theorem 3.

Remark 2. To the best of the authors’ knowledge, the problem of target tracking using a wireless sensor network with a sufficiently accurate energy-consumption model is not studied in the general form in a continuous-time setup. However, using the strategy proposed here, one can divide the field to a grid in order to transfer the problem to the discrete domain, where efficient techniques are available to solve it. One can use a larger grid to obtain smaller cells, which in turn leads to a more accurate solution to the underlying problem at the expense of higher computational complexity. Furthermore, the proposed strategy can also be quite effective in constrained trajectory tracking problems (e.g., obstacle avoidance).

IV. DISCUSSION ON ALGORITHM PERFORMANCE AND EFFICIENCY

In this paper, we proposed a centralized algorithm which is used by the network to find a cost-efficient route for the information from target to destination. In practice, sensors have limited power and processing capabilities, and this makes the motivation to avoid heavy computations by the sensors during network action. However, since the present algorithm is centralized, significant parts of the computations can be done off-line easily. In fact, the communication energy digraphs can be fully constructed off-line. In addition, Although sensing and movement energy digraphs depend on target and sensors positions and they have to be updated in each time interval, parts of this update process still can be done off-line. One of the most important parts of the algorithm is the shortest path subroutine, which finds the shortest path connecting the target to the destination in the combined energy digraph. There are several algorithms to find this path in graphs. One of the most efficient algorithms among all, especially when the graph is not sparse, is Dijkstra algorithm, which we have used in our simulations. Results show that the algorithm finds the path in a reasonable time for the network to react. Simulation results, also, show that in more than 95 percent of the steps, the resulting shortest path satisfies the conditions of Theorem 3, thus, it is the optimal path. Furthermore, the algorithm is flexible in case more precision is needed for sensor locations, and this is achievable easily by increasing the number of grid points. In fact, one can make a trade off between the computational load and the precision of the algorithm by changing the number of the grid points.

V. SIMULATION RESULTS

Consider a rectangular 30m \( \times \) 20m field, and divide it into a 30 \( \times \) 20 grid. Assume that there are 6 sensors in the field which are to follow the target and route the data from it to the destination in an energy-efficient manner. Assume also that all sensors have communication and sensing ranges of 10m and 1.5m, respectively. Let the respective movement, communication, and sensing energy consumption be:

\[
W_m = \beta d_{i,j}, \quad W_c = \alpha d_{i,j}^\beta, \quad W_s = \theta d_{i,j}^\gamma
\]

where \( \alpha, \beta, \) and \( \theta \) are given constants, and \( d_{i,j} \) is the distance between nodes \( i \) and \( j \) (whose edge is to be weighted using the proposed procedure). For the simulations, assume \( \alpha = 1, \beta = 50, \theta = 10, \lambda = 2, \) and \( \gamma = 4. \)

Let the movement of the target be random integer steps in the interval \([−7,7] \) for both horizontal and vertical axes. The network processes the data in discrete time instants. This means that the proposed technique can be used at any time instant to determine the route and the new locations of the sensors to move to. The time interval between the consecutive time instants is chosen based on the target’s speed.

Let the initial locations of the sensors be chosen randomly, with a uniform distribution on both horizontal and vertical axes. Let also the destination be at the origin. Simulations are performed for 50 steps of the target. Figure 3 shows the random movement of the target, and Figure 4 illustrates the tracking process in three snapshots: steps 1, 33 and 50. In each snapshot, the locations of the target and sensors, along with the shortest path and the Voronoi regions are depicted. The present locations of the sensors are shown by small circles, while their previous locations are depicted by asterisks. Moreover, the location of the target is shown by a solid square in each snapshot, and the shortest path obtained is drawn in dotted line. Figure 5 depicts the results for three consecutive steps in the tracking process. It can be observed from this figure that the sensors are relocated properly in order to track the target continuously.

![Random movement of the target (50 steps).](image)
Remark 4. It can be verified that in all of the snapshots provided in the simulations, the shortest path is the same as the optimal path. This is not a coincidence, and is true for typical network configurations (where, for example, one Voronoi regions is not significantly larger than another one).
VI. CONCLUSIONS

A novel energy-efficient tracking technique is proposed in this paper for wireless sensor networks. The field is first divided into a grid, and is then mapped into a graph. Proper weights are subsequently assigned to the edges of the graph to model the energy consumption due to sensing, communication and movement, as the main sources of energy expenditure in this type of network. The problem of finding a proper route and selecting the corresponding sensor locations for an energy-efficient tracking is translated to the well-known shortest path problem. This is carried out by partitioning the field into Voronoi regions and investigating different scenarios in terms of network configuration. Simulations demonstrate the efficacy of the proposed tracking strategy.

REFERENCES