2012 American Control Conference
Fairmont Queen Elizabeth, Montréal, Canada
June 27-June 29, 2012

Maximum Life Span Strategy for Target Tracking in Mobile Sensor Networks

Hamid Mahboubi, Walid Masoudimansour, Amir G. Aghdam, Kamran Sayrafian-Pour and Vladimir Marbukh

Abstract— **In this paper, an energy-efficient technique is proposed for tracking a target in a field using a network of mobile sensors while maximizing the life span of the network. The most important energy consumption sources in a mobile sensor network (MSN) are sensing, communication and movement of the sensors. In the proposed technique, first the field is divided into a grid of arbitrarily small cells. This grid is then used to obtain a graph with properly weighted edges. The weight assignment is done in such a way that it results in a close estimate of the maximum lifetime for the network. Finally, using a shortest path algorithm, an efficient route is found to transfer information from the target to destination.**

I. INTRODUCTION

Significant progress in micro-electro-mechanical systems (MEMS) has made the fabrication of small flexible mobile sensors possible. These small sensors, can work collaboratively in a distributed fashion to collect information more efficiently [1], [2], [3], [4]. Some of the diverse range of applications of sensor networks include monitoring [5], [6], intrusion detection [7] and surveillance [8]. One of the important applications of such networks is target tracking. Mobile sensor networks (MSN) can be very effective in detecting and tracking dynamic targets. In this type of application, a group of sensors are assigned to track the target, and work collaboratively with other sensors to route its information to a designated fixed point called destination. Some important constraints need to be taken into consideration in the design of efficient motion-planning algorithms for an MSN in a practical setting. Such constraints include, for example, communication and sensing limitations of sensors, their processing capabilities, and limited energy.

In [9], a novel technique is introduced for target tracking and density management of sensors in an MSN. A protocol is designed in [10] to improve the accuracy of multiple target tracking in sensor networks. A decentralized multiple target tracking scheme is proposed in [11] to minimize energy consumption by partitioning the sensor nodes to clusters. In [12], a dynamic sleep schedule is used to prolong the lifetime of a target-tracking sensor network. This is carried out by dividing the sensors into two groups of border sensors and interior sensors, and putting the interior sensors into sleep mode in the absence of target. A number of existing results also use different sleep-mode strategies to deactivate certain sensors in the tracking process in order to maximize the network lifetime (e.g, see [13], [14]).

In the present work, the problem of tracking a moving target in a sensing field is investigated. The main objective is to develop a proper motion strategy for the sensors such that the life span of the network is maximized. It is assumed that the main sources of energy consumption in the network are sensing, communication, and movement of sensors. First, the sensing field is divided into a grid, where the sensors and the target represent the nodes of the grid. The grid nodes are then transformed to the vertices of a graph, whose edges are weighted properly in terms of the location of the corresponding nodes in order to formulate the energy consumption in the network. The proposed technique finds an energy-efficient route to transfer information from the target to the destination using a shortest path algorithm. It is shown that under certain conditions the shortest path is a good candidate for the sensors to take in order to maximize the life span of the network.

The organization of this work is as follows. In Section II, a modified form of the conventional Voronoi diagram is introduced which reflects energy consumption of sensors in the network. Section III presents the problem statement, which is followed by some important assumptions and definitions. In Section IV, an energy-efficient tracking strategy is presented for mobile sensors, as the main contribution of the paper. Simulation results are provided in Section V to demonstrate the effectiveness of the proposed algorithm. Finally, Section VI gives a brief summary of the results.

II. EXTENDED VORONOI DIAGRAM

Consider a set of n distinct weighted nodes denoted by $\mathbf{S} = \{(S_1, w_1), (S_2, w_2), \ldots, (S_n, w_n)\}$, where $w_i > 0$ is the weighting factor associated with S_i, for any $i \in \mathbf{n} := \{1, 2, \ldots, n\}$. Let the distance between an arbitrary point Q and the weighted node (S_i, w_i) be denoted by $f(S_i, w_i, Q)$. The *extended Voronoi diagram* is defined as a partitioning of the plane into n regions with the property 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 characterization of each region obtained

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

K. Sayrafian-Pour and V. Marbukh are with the National Institute of Standards and Technology (NIST), 100 Bureau Drive, Stops 8920 and 8910 Gaithersburg, MD 20899 USA {ksayrafian, marbukh}@nist.gov

This work has been supported by the National Institute of Standards and Technology (NIST), under grant 70NANB8H8146.

by the above partitioning is as follows:

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

Note that for certain functions $f(.)$ and weighting factors $w(i)$'s, some regions may contain no points.

Consider now n sensors in a field, and let them be represented by the nodes $S_1, S_2, \ldots, S_n$. The weight of the node S_i is considered as the remaining energy of that sensor, and is denoted by $e_i,\ \forall i \in \mathbf{n}$. Furthermore, let $f(S_i, e_i, Q)$ be equal to the difference between the initial energy of the i-th sensor, $E_{i,0}$, and the remaining energy of that sensor after traveling to point Q. Assuming the required energy for traveling distance d is proportional to d^α, one can write:

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

where α and β are known constants, e_s is the energy required to overcome the static friction (when the sensor starts to move), and is assumed to be the same for all sensors. Furthermore, $d(S_i, Q)$ is the Euclidean distance between S_i and Q. In this case, the extended Voronoi diagram will be referred to as the *α-residual rate Voronoi diagram*. In the sequel, the α-residual rate Voronoi diagram is described for two different cases of α. Note that, without lose of generality, the initial energy of the sensors can be assumed to be equal. This energy will be referred to as E_0 hereafter.

i) α=1

Consider two sensors located at S_1 and S_2 with the remaining energies e_1 and e_2, respectively. If $f(S_1, e_1, Q) = f(S_2, e_2, Q)$, then

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

Therefore, the loci of every point Q for which $f(S_1, e_1, Q) = f(S_2, e_2, Q)$ is a branch of a hyperbola. In the special case when $e_1 = e_2$, this loci is the perpendicular bisector of the segment S_1S_2.

To construct the 1-residual rate Voronoi region associated with a node in the network, first the branches of the above-mentioned hyperbolas of that node and the other nodes are drawn. The smallest region containing each node is, in fact, the Voronoi region of that node. Fig. 1 shows the α-residual rate Voronoi diagram for 6 sensors with different amounts of remaining energy.

ii) α=2

Similar to the previous case, consider two sensors S_1 and S_2 with the remaining energies e_1 and e_2. If $f(S_1, e_1, Q) = f(S_2, e_2, Q)$, then

$$\begin{aligned} &E_0 - e_1 + e_s + \beta[d(S_i, Q)]^2 = E_0 - e_2 + e_s + \beta[d(S_j, Q)]^2 \\ &\Rightarrow [d(S_1, Q)]^2 - [d(S_2, Q)]^2 = \frac{e_1 - e_2}{\beta} = const. \end{aligned} \tag{4}$$

Therefore, in this case, the loci of every point Q for which $f(S_1, e_1, Q) = f(S_2, e_2, Q)$ is a line perpendicular to the segment S_1S_2. If $e_1 = e_2$, then this line is the perpendicular bisector of S_1S_2.

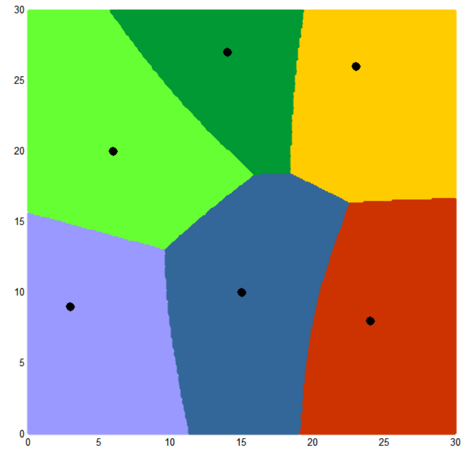


Fig. 1. An example of the 1-residual rate Voronoi diagram for a group of 6 sensors with different amounts of remaining energy.

I order to construct the i-th 2-residual rate Voronoi region, the above-mentioned perpendicular lines of the node S_i and the other nodes are drawn first. The smallest polygon (created by these perpendicular lines) containing the i-th node is, in fact, the i-th 2-residual rate Voronoi region. An example of a 2-residual rate Voronoi diagram with 6 sensors is sketched in Fig. 2.

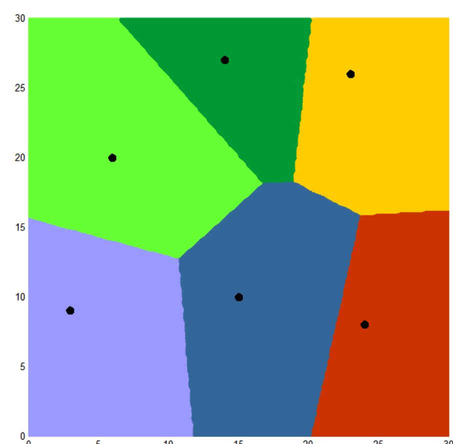


Fig. 2. An example of the 2-residual rate Voronoi diagram for a group of 6 sensors with different amounts of remaining energy.

III. Problem Statement

Consider a group of n mobile sensors $S_1, \ldots, S_n$. Consider also a moving target and a fixed access point (also referred to as the destination point). In order to ensure target tracking at all times, it is essential to maintain connectivity (in terms of sensing and communication) between target and destination point.

In order to develop energy-efficient sensor deployment strategies, it is required to adopt a proper model for the energy consumption of sensors. In general, the energy consumption of mobile sensors is due to communication, sensing, and movement. Although minimizing energy consumption is of great importance in MSNs, in many applications it is more desirable that the life span of the sensors is maximized, in order to increase the durability of the overall network. An effective strategy to maximize the life span of the network is that sensors with small residual energy consume small amounts of energy such that the residual energy of the sensor with minimum remaining energy is maximized. To this end, sensors must operate in a collaborative fashion in order to determine the best location and routing path for each sensor to transmit the information from target to destination. Since the analytical solution of this problem is complicated in general, as an efficient alternative approach, divide the sensing field into a grid. Assume that the target and sensors are located on some nodes of the grid in each time instant. Then, a graph is constructed whose vertices are the grid nodes, and whose edges are properly weighted, to model the three sources of energy consumption in the network. This graph will be referred to as the *energy consumption digraph*. The following notation will prove convenient in the development of the main results.

Notation 1. Throughout this paper, the j-th nearest sensor to node P_i will be denoted by $S^j_{P_i}$, for any $j \in \mathbf{n}$ and any node P_i in the grid (note that the term "nearest" is used here based on the definition of distance in the previous section). For example, $S^1_{P_2}$ represents the nearest sensor to node P_2. Furthermore, E^j_{r,P_i} denotes the residual energy of the j-th nearest sensor to P_i, after traveling to this point.

Assumption 1. In each time instant, it is assumed that the sensor assigned to sense the target is the one with the smallest distance to it. This sensor is referred to as the *tracking sensor*, and 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 target to destination.

The tracking sensor will be denoted by S_T (note that $S_T \in \{S_1, S_2, \ldots, S_n\}$ at any time instant). Furthermore, the target node and the α-residual rate Voronoi region containing it will be denoted by P_T and Π_T, respectively. In addition, the destination point will be denoted by P_D.

Definition 1. In the remainder of this paper, any node on the grid which belongs to Π_T and a sensor can sense the target from that point is called a *sensing node*. Furthermore, any node of a given path P excluding target and destination is referred to as a *path node*.

IV. MAIN RESULTS

A technique is provided in the sequel to find candidate locations for the sensors such that a sensor with the lowest residual energy at the beginning of a time step, will consume minimum energy during that time step.

Consider a group of n sensors, and let the sensing field be divided into a grid of sufficiently small cells. Using α-residual rate Voronoi diagram, the field is partitioned into n regions. Denote the j-th region with Π_j, for any $j \in \mathbf{n}$.

Construct a directed graph (digraph) in which the edges are related to the energy consumption of the sensors. In this digraph, there is an edge from P_T to an arbitrary point P_j if and only if P_j is a sensing node; the weight of this edge is considered to be 0. Furthermore, the node P_i ($P_i \neq P_T$) is connected to node P_j in this digraph, if and only if a sensor located at P_i could communicate with a sensor located at P_j. The following procedure is used to find the weight of this edge, denoted by $w(i,j)$.

Case i) Consider the case where P_i is a sensing node. Then:

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

where $\omega_s(T,i)$ is the required sensing energy for a sensor at P_i to sense the target, $\omega_c(i,j)$ is the communication cost between the nodes P_i and P_j, and k is a constant which will be introduced later.

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

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

Case iii) Finally, if P_i and the target are in different regions, then:

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

It is desired in the energy consumption digraph 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. It will be shown that this path provides a route, which can, under some conditions, be optimal in the sense of maximizing the life span of the network.

Remark 1. One can use an efficient routing algorithm (such as Dijkstra) to find the shortest path in the energy consumption digraph. If eventually, the number of nodes in the shortest path is greater than n, then one can switch to a constrained shortest path algorithm, which is typically slower than the unconstrained counterparts.

Definition 2. A path P which has at most n nodes and connects target to destination will hereafter be referred to as a *feasible path*. Moreover, the sum of the weights of the directed edges of a feasible path P is referred to as the *path weight*, and is denoted by $W(P)$.

Definition 3. In the rest of the paper, the term *consumed energy* of a sensor refers to the percentage of the total energy consumption by that sensor. More precisely, consumed energy is equal to the ratio of the difference between the initial energy of the sensor and its residual energy, to its initial energy.

Definition 4. 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 $(P_T, P_1, P_2, ..., P_m, P_D)$. There are $\binom{n}{m}$ (combination of m out of n) possible sensor assignments which 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), where S represents the ordered set $(S_{i_1}, S_{i_2}, \ldots, S_{i_m})$. Furthermore, denote with (P, S^*) the sensor assignment for which the energy consumption of the sensor with the smallest residual energy (after relocating the sensors and transmitting information from target to destination) is minimum. This assignment will be referred to as the *optimal assignment*. It is important to note that the optimal sensor assignment can change each time the sensors are relocated, but for simplicity of notation the time dependence has not been explicitly shown in the above representation.

Definition 5. 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 collaborating in information transmission will be referred to as *node cost* of P_j in path P and will be denoted by $C_P(P_i)$ hereafter. Furthermore, the sum of node costs of all the path nodes of P will be called *path cost* of P and is denoted by $C(P)$.

The main results of the paper are presented in the sequel. The proofs are omitted due to space limitations.

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

Definition 6. A feasible path P is called a *good path* if it satisfies 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 nearest sensor to P_j.

Definition 7. 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 energy consumption of the sensor which consumes the maximum energy amongst all sensors once they move to their assigned nodes and transmit information from target to destination be denoted by $E(P, S_P^*)$, and referred to as the max-min energy consumption w.r.t. the path P.

Definition 8. 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* and denoted by P^*.

Definition 9. A feasible path P with at most one node in each α-residual rate Voronoi region is referred to as a *perfect path*. It is obvious that any perfect path is a good path as well.

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

Remark 2. Since any perfect path is also a good path, the result of Theorem 2 holds for any feasible 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*

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

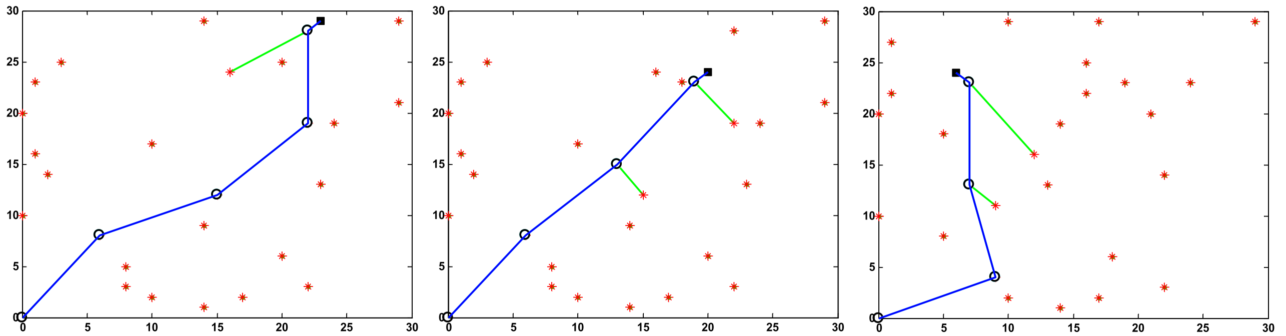
Theorem 3. *Choose a constant $k > \frac{ln(n)}{ln(1+\theta)}$ and apply the proposed algorithm. If the shortest path $\bar{P}$ in the energy consumption digraph is a good path, then it is θ-optimal.*

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.*

V. Simulation Results

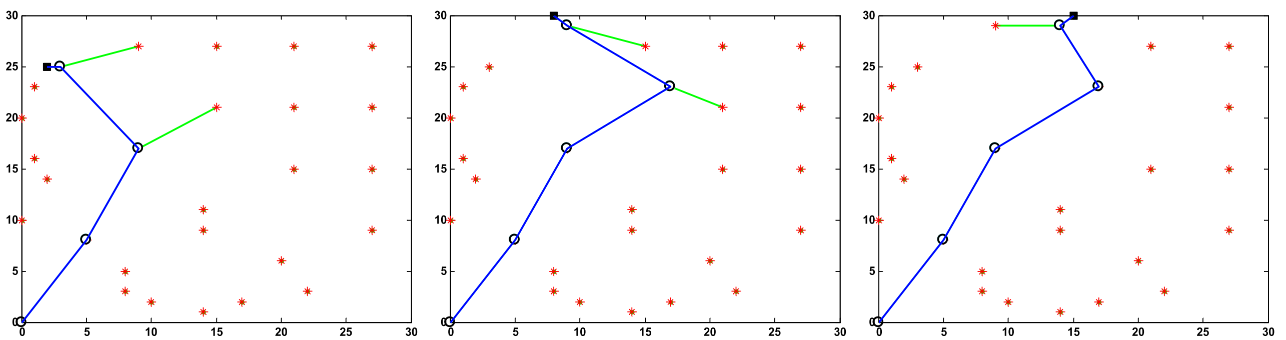
Consider 25 identical sensors which are randomly deployed in a field of size 30m $\times$ 30m. A target is moving in the field, and the sensors are to track it and route its information to the destination point which is assumed to be in the origin. Suppose all sensors have communication and sensing ranges of 10m and 1.5m, respectively. Communication and sensing energies are assumed to be $\omega_c(i,j) = \mu[d(P_i, P_j)]^\lambda$ and $\omega_s(T,j) = \zeta[d(P_T, P_j)]^\gamma$, respectively, where $d(P_i, P_j)$ is the Euclidean distance between the points P_i and P_j, as noted before. It is also assumed that the required energy for a sensor to travel from a point P_i to another point P_j is equal to $\beta d(P_i, P_j)$, resulting in a 1-residual rate Voronoi diagram. In addition, θ is considered to be 0.05 which yields $k > 65.97$.

The following values are used for system parameters in the simulations: $\mu = 10^{-7}$, $\zeta = 0.1$, $\beta = 7.54$, $\lambda = 2$ and $\gamma = 4$. It is also assumed that the target moves in random integer steps in the interval $[-7, 7]$ along both horizontal and vertical axes. The field is divided to a grid of size 30×30. The algorithm determines the route and the new candidate locations for the sensors in discrete time instants. The time interval between these instants is chosen based on the target's speed. Simulation is performed for 100 time instants. Fig. 3 demonstrates the route and the candidate locations of the sensors for three different time instants: 41st, 46th and 81st. In each step, the location of the target and sensors as well as the shortest path 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 drawn in dotted line. Furthermore, green lines show the movement of the sensors from their current locations to the candidate points in case they need to move. Fig. 4 depicts three consecutive steps of the tracking process. Note that under the proposed algorithm, the nearest



(a) (b) (c)

Fig. 3. Snapshots of the network configuration obtained by the proposed technique for 25 sensors in three different steps: (a) 41^{st} step; (b) 46^{th} step, and (c) 81^{st} step.



(a) (b) (c)

Fig. 4. Snapshots of the network configuration obtained by the proposed technique for 25 sensors in three consecutive steps: (a) 20^{th} step; (b) 21^{st} step, and (c) 22^{nd} step.

sensor to the path nodes in the sense of Euclidean distance is not necessarily assigned to them (e.g., see Fig. 4(a)).

Remark 3. Simulation results show that for different network setups with different number of sensors and specification, in most of the 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 assess the performance of the proposed technique, it will be compared to the algorithm developed in [15] for minimizing the overall energy consumption of a sensor network. Consider the setup of the previous example, but with 9 sensors instead of 25. Let the initial energy of each sensor be 9000J. It is desired to compared the life span of the network, which is the time it takes for the first sensor to run out of energy as defined in [16], [17], [18], under the proposed method and the method in [15]. Fig. 5 depicts the remaining energy of sensors v.s. iteration number under the proposed algorithm, while Fig. 6 provides analogous results under the algorithm given in [15]. These figures show that under the algorithm introduced in this work the life span of the network increases by 22.6%. They also show that the consumption of energy in different nodes is more balanced under the proposed algorithm, which further demonstrates the efficiency of the method.

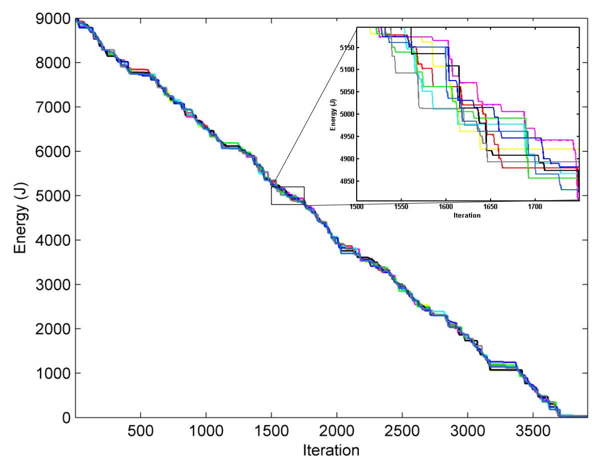


Fig. 5. Remaining energy of the sensors for different iterations using the algorithm proposed in this work for life span maximization.

Remark 4. It is important to note that if the target is moving smoothly in the field, then under the technique proposed in [15] the tracking sensor does not change frequently, as it continues to be the nearest sensor to the target. As a result, the energy of the tracking sensor in [15] is depleted fast. However, since in the method proposed here, the nearest sensor to the target is defined based on the residual energy

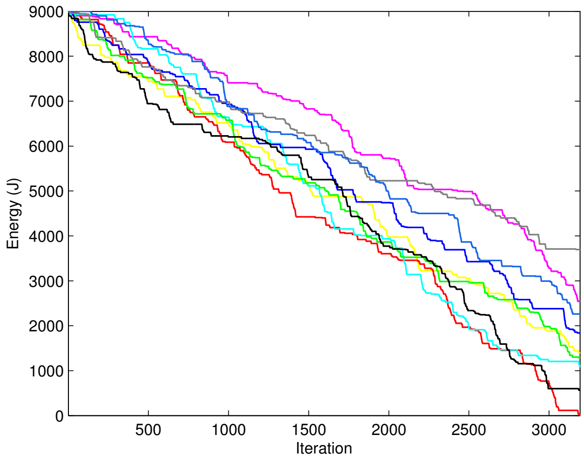


Fig. 6. Remaining energy of the sensors for different iterations using the overall energy consumption minimization algorithm from [15].

of the sensors, the tracking sensor can be changed appropriately. This prevents each sensor from quickly depleting its energy.

VI. Conclusions

A novel technique is proposed in this paper to prolong the lifetime of a network of mobile sensors while tracking a dynamic target. The field is first divided into a grid, which is then translated to a graph. The edges of the graph are then weighted properly to model the energy consumption of the network which is assumed to be mainly due to sensing, communication, and movement of the sensors. Then, a shortest path problem is solved to find candidate locations for the sensors, and the best route to transfer the information. Simulations demonstrate the effectiveness of the proposed strategy.

References

[1] W. Wang, N. Wang, E. Jafer, M. Hayes, B. O'Flynn, and C. O'Mathuna, "Autonomous wireless sensor network based building energy and environment monitoring system design," in *Proceedings of 2nd Conference on Environmental Science and Information Application Technology*, 2010, pp. 367–372.

[2] H. Mahboubi, A. Momeni, A. G. Aghdam, K. Sayrafian-Pour, and V. Marbukh, "Optimal target tracking strategy with controlled node mobility in mobile sensor networks," in *Proceedings of American Control Conference*, 2010, pp. 2921–2928.

[3] B. Barbagli, I. M. G. Manes, A. Manes, G. Langer, and M. Bacchi, "A distributed sensor network for real-time acoustic traffic monitoring and early queue detection," in *Proceedings of 4th International Conference on Sensor Technologies and Applications*, 2010, pp. 173–178.

[4] H. Mahboubi, K. Moezzi, A. G. Aghdam, K. Sayrafian-Pour, and V. Marbukh, "Self-deployment algorithms for coverage problem in a network of mobile sensors with unidentical sensing range," in *Proceedings of IEEE Global Communications Conference*, 2010.

[5] 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.

[6] Y. Tselishchev and A. Boulis, "Wireless sensor network tesbed for structural health monitoring of bridges," in *Proceedings of IEEE Sensors*, 2009, pp. 1796–1799.

[7] 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.

[8] P. K. Biswas and S. Phoha, "A sensor network test-bed for an integrated target surveillance experiment," in *Proceedings of Conference on Local Computer Networks*, 2004, pp. 552–553.

[9] M. Hamdi, N. Boudriga, and M. Obaidat, "Designing a wireless sensor network for mobile target localization and tracking," in *Proceedings of IEEE Global Communications Conference*, 2006.

[10] H. O. Sanli and H. Cam, "Joint coverage scheduling and identity management for multiple-target tracking in wireless sensor networks," in *Proceedings of IEEE Global Communications Conference*, 2008, pp. 453–458.

[11] X. Zhang, "Decentralized sensor-coordination optimization for mobile multi-target tracking in wireless sensor networks," in *Proceedings of IEEE Global Communications Conference*, 2010.

[12] N. Vasanthi and S. Annadurai, "Energy saving schedule for target tracking sensor networks to maximize the network lifetime," in *Proceedings of 1st International Conference on Communication System Software and Middleware*, 2006.

[13] A. Alfieri, A. Bianco, P. Brandimarte, and C.-F. Chiasserini, "Exploiting sensor spatial redundancy to improve network lifetime," in *Proceedings of IEEE Global Communications Conference*, 2004, pp. 3170–3176.

[14] Y. Pal, L. Awasthi, and A. Singh, "Maximize the lifetime of object tracking sensor network with node-to-node activation scheme," in *Proceedings of IEEE International Advance Computing Conference*, 2009, pp. 1200–1205.

[15] 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 International Conference on Control Applications (CCA), in Proceedings of the IEEE Multi-Conference on Systems and Control (MSC)*, 2011, pp. 1238–1243.

[16] 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.

[17] 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.

[18] 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.