Toward Autonomous Mobile Sensor Networks Technology

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***Abstract*—Mobile sensor networking technology has attracted considerable attention in various research communities in recent years due to their widespread applications in civilian and military environments. One objective when using mobile sensors is to obtain maximum field coverage by properly deploying sensor nodes. In many real-world applications a priori knowledge about the best deployment position for the sensors is not available. However, the motion capability of the sensors could allow each node to adjust its position (i.e. relocate) so that a better (and ultimately maximal) coverage is achieved. In this paper, a novel autonomous joint sensing range and relocation control algorithm is presented that achieves improved coverage and network lifetime at the same time. In the proposed algorithm, the sensing range of each sensor is adjusted iteratively based on its residual energy. At the same time, the sensor is directed to move within its corresponding multiplicatively weighted Voronoi (MW-Voronoi) region to ultimately increase sensing coverage in the field. Simulation results demonstrate the efficacy of the technique.**

I. Introduction

Large networks of mobile sensor devices, each capable of a combination of sensing, computing and communication are predicted to provide an unprecedented fine-grained interface between the physical and virtual worlds. The use of such networks of embedded systems could well dwarf previous milestones in the information technology revolution with major impact on the consumer electronics market. One vision for mobile wireless sensor networks involves end-users buying collection of sensor nodes, powering them up, and spreading them across the desired environment. The nodes then automatically form a network, relocate autonomously to better positions for optimal network operation, sense their environment, and report readings back to a central location for further processing or decision making.

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Recent developments in micro-electro-mechanical systems (MEMS) technology have provided us with a wealth of inexpensive, customizable, embedded sensor systems capable of wireless communication among each other. As a result of these developments, a broad spectrum of sensor network applications is currently being investigated. These include environmental monitoring, civil structure, health monitoring, industrial process monitoring and military and defense related applications [1]–[10].

A mobile sensor network (MSN) is typically comprised of wireless mobile nodes equipped with battery powered sensors. Each node in a mobile sensor network usually has limited mobility and data processing capability. Limitations on the physical resources of each individual node e.g. energy consumption, bandwidth and mobility make optimization of the network performance a critical condition in ability of the network to complete its mission. In addition to the limited resources and capabilities, lack of centralized control, and dynamic and unpredictable nature of the network and the environment contribute to challenges in the performance optimization and evaluation of such networks and their interaction with their surrounding environment.

With the wide spectrum of application for sensor networks, mobility adds another dimension of flexibility and at the same time complexity in the design of such networks. Despite this complexity, mobility will open the door to a variety of pervasive applications for autonomous sensor networks and smart environments. For example, optimal autonomous deployment of mobile sensor nodes in constantly changing radio environments and the relevant possible trade-offs between coverage, connectivity, information sensing, as well as network lifetime and maintenance issues have fundamental technology impact on mass commercialization of such networks.

In the MSN coverage problem, the objective is to obtain maximum field coverage by properly deploying sensor nodes. In many real-world applications a priori knowledge about the best deployment position for the sensors is not available. However, the motion capability of the sensors potentially allows each node to adjust its position (i.e. relocate) so that a better (and ultimately maximal) coverage is achieved.

This relocation ability of the nodes in a MSN creates new possibilities for intelligent control of their individual motion in order to optimize the performance of the whole network. However, mobility could add additional burden to an already scarce resource in such networks, i.e. energy. For example, in the coverage problem, relocating each node to an appropriate position could lead to a much better global coverage throughout the field by the network. However, this comes at the cost of higher energy consumption, and since each node has limited amount of battery power, excessive movements for a node could deplete its remaining energy supply faster. This, in turn, results in an early termination of its sensing function, hence reducing the overall covered area. Therefore, relocation of nodes in a mobile sensor network has to be done very judiciously. Other than node's position in the field, sensing range of each sensor directly affects the network coverage. However, larger sensing range requires higher energy consumption. Any practical relocation strategy for providing maximal field coverage by a mobile sensor network should take energy limitation of individual sensors into consideration. In fact, the solution should strive for maximal coverage while ensuring maximum network lifetime. In addition, it is desirable for the relocation strategy to be autonomous and have a decentralized structure so that each sensor can make its decision without much communication overhead.

In recent years, there has been a burst of research activities in mobile sensor networking. This research has been mostly concentrated on potential architectures, lacking several fundamental technology issues and specifically potential advantages of position control for mobile nodes.

A Voronoi-based approach [11] is presented for network coverage in a MSN, which does not require any global location assurance condition for the sensors. Fang et al [12] proposed an energy-efficient cooperative communication technique for improving data transmission in wireless sensor networks. The scheme utilizes the overhearing capability of the nodes and can decrease the number of transmissions times. An algorithm [13] is proposed to monitor an environmental boundary with mobile agents, where the boundary is optimally approximated with a polygon. Hong et al [14] proposed a localization algorithm which has an indefinite traveling direction and can estimate positions by a small number of anchors. Lee et al [15] introduced an approach for solving the energy-efficient coverage of wireless sensor networks using an ant colony optimization algorithm. Kwok et al [16] provided a gradient-descent coverage algorithm using the Delaunay graph. A multi-objective algorithm [17] is proposed for sensor deployment and power assignment. The algorithm decomposes the optimization problem into a number of scalar single-objective subproblems, which are solved simultaneously. In [18], [19] cost-effective resource management techniques are designed for prolonging network lifetime. Kaur et al [20] proposed a cluster-based technique for increasing the lifetime of the wireless sensor networks. The approach is particularly very effective for heterogeneous networks.

Cost-effective resource management techniques [21], [22] are designed for prolonging network lifetime. Cortes et al [23] developed coordination algorithms to increase coverage, and also provide a performance analysis using a class of aggregate objective functions. Zhang et al [24] proposed a novel localization technique for a network of wireless sensors in a noisy environment and in the presence of obstacles. The scheme is distributed and range-independent, and is efficient in terms of energy consumption and computational complexity.

In this paper, a joint sensing range and relocation control strategy is introduced that leads to better overall coverage while maximizing the network lifetime. The sensors movement adjustments are iteratively calculated. At each iteration, sensors also adjust their sensing ranges based on their residual energies. Every sensor then moves in a direction that leads to a larger covered area. To accomplish this, the multiplicatively weighted Voronoi (MW-Voronoi) diagram (see Appendix) is used to find the coverage gaps. A weight proportional to the sensing radius is assigned to each sensing node [25], and the sensor relocates to a new location only if (i) it has sufficient energy to move to the new location, and (ii) the covered area in its new location is larger. If any one of these conditions is not met, then the senor remains in its current position. It is shown that the proposed algorithm increases the covered area while maximizing network lifetime.

The organization of the remainder of the paper is as follows. The problem is formally introduced in Section II, along with our assumptions and some useful definitions. The main contributions of the paper are presented in Section III, where a novel algorithm for efficient sensor deployment is presented. Simulations are given in Section IV, and finally the conclusions of the work are summarized in Section V.

II. Problem Statement

Given a group of n nonidentical mobile sensors in a flat field, let the position of each sensor be represented by a node with a weight equal to its sensing range. The sensors are randomly distributed in a 2D field, and the position of sensor i is denoted by P_i, for any $i \in \mathbf{n}$.

One of the common design specifications in any sensor network is energy efficiency [26]. It is known that power consumption of a mobile sensor is mainly due to sensing, communication, and movement. Note that a signal can be transmitted from node i to node j if and only if the corresponding signal-to-interference-plus-noise ratio SINR exceeds certain threshold χ. This can be mathematically expressed as:

$$SINR_{ij} = \frac{P_{ij}\xi_{ij}}{\eta_j + \sum_{(n,k)\neq(i,j),n\neq i,j} P_{nk}\xi_{nj}} > \chi \qquad (1)$$

where P_{ij} is the power required to transmit information from node i to node j, ξ_{ij} is the propagation *path loss* from node i to node j, $\sum_{(n,k)\neq(i,j),n\neq i,j} P_{nk}\xi_{nj}$ is the overall interference power, and η_j is the noise power at node j. For simplicity, assume that the interference power is negligible, and that the noise power η_j is equal to 1, for all $j \in \mathbf{n}$. Then, using (1) the following minimum power consumption by node i is obtained for direct communication with node j:

$$P_{ij} = \frac{\chi}{\xi_{ij}}$$

The path loss is inversely proportional to some power of the distance d between nodes i and j, i.e. d^γ. The power exponent

γ is typically between 2 and 4, and is closer to 4 for low-lying antenna and near-ground channels, as in most sensor network applications [27], [28]. The communication radius of sensor i at time instant t, denoted by $R_{ci}(t)$, is equal to the radius of the largest circle around the location of the i-th sensor $P_i(t)$, such that the corresponding SINR from $P_i(t)$ to any point inside the circle is greater than the threshold χ. On the other hand, the power required for sensing is typically greater than the communication power. This power is also proportional to d^{λ}, where d is distance and $\lambda \geq 2$. For example in a passive RFID system, to sense an RFID tag a signal is transmitted from the RFID reader to the object containing the tag and reflected back to the sensor. As a result, the path loss for sensing an object that is away from the reader by distance d is inversely proportional to $d^{2\gamma}$ [29]. Therefore, the minimum power consumption by the i-th sensor such that any point inside its sensing range R_i can be sensed is proportional to R_i^{λ}. On the other hand, an energy consumption model for sensor relocation is given by

$$E_i^{reloc}(P_i, \acute{P}_i) = \eta \widetilde{\acute{P}_i P_i} \tag{2}$$

where η is a constant, $\acute{P}_i$ is the i-th sensor's position after relocation, and $\widetilde{\acute{P}_i P_i}$ is its traveling distance [30]. In this paper, it is assumed that the sensors can adjust their sensing ranges. Moreover, a sensors consume energy for stopping or starting to move (the latter is because of static friction). It is assumed in this work that the energy required for stopping a mobile sensor and then overcoming its static friction after a complete stop is equivalent to the energy required for continuously moving the sensor 1m [26].

While maximizing coverage area is an important objective in a MSN, in most applications it is also desirable to maximize the lifetime of the sensors and consequently increase the durability of the entire network. Let the sensing range of sensor i at time instant t be a circle of radius $R_i(t)$, centered at the position of that sensor. It is desired to move the sensors and place them in proper locations in the field and adjust their sensing ranges using a distributed deployment strategy such that while the covered area increases, the lifetime of the network is also increased as much as possible. Different definitions are provided for network lifetime in the literature [31], [32]. Here, network lifetime is defined as the time when 20% of the nodes in the network deplete their energy supply completely, and therefore stop functioning.

Assumption 1. The sensors are capable of localizing themselves in the field with sufficient accuracy (e.g., using the techniques proposed in [33].

Definition 1. Consider a sensor S_i, $i \in \mathbf{n}$, and let its sensing radius and MW-Voronoi region be denoted by $R_i(t)$ and $\Pi_i(t)$, respectively. Let also Q be a point inside $\Pi_i(t)$. Throughout this paper, the intersection of $\Pi_i(t)$ and a circle of radius $R_i(t)$ centered at Q is called the *i-th coverage area w.r.t. Q at time t*, and is denoted by $\beta_{\Pi_i}^{Q}(t)$. In particular, the i-th coverage area w.r.t. the location of the sensor S_i at time t is called the *i-th local coverage area at time t*, and is denoted by $\beta_{\Pi_i}(t)$. Furthermore, the total covered area of the field by all sensors at time t is referred to as the *total coverage area at time t*, and is denoted by $\beta(t)$.

In what follows, a performance criterion is defined, which accounts for both the MSN coverage area and lifetime associated with non-renewable energy consumption of the sensor battery.

Definition 2. Throughout this paper, the expected value of the i-th local coverage area over the time interval $[t_a, t_b]$ is called the *i-th average coverage area over $[t_a, t_b]$*, and is denoted by $\beta_i[t_a, t_b]$. Also, the expected value of the total covered area over the time interval $[t_a, t_b]$ is called the *average total coverage area*, and is represented by $\beta[t_a, t_b]$.

Definition 3. Consider an arbitrary point Q inside the MW-Voronoi region $\Pi_i(t)$, $i \in \mathbf{n}$. The area inside $\Pi_i(t)$ which lies outside the i-th coverage area w.r.t. Q at time t is referred to as the *i-th coverage hole w.r.t. Q at time t*, and is denoted by $\theta_{\Pi_i}^{Q}(t)$. The i-th coverage hole w.r.t. the location of the sensor S_i at time t is called the *i-th local coverage hole at time t*, and is denoted by $\theta_{\Pi_i}(t)$. Furthermore, the total uncovered area of the field at time t is called the *total coverage hole at time t*, and is denoted by $\theta(t)$.

Assumption 2. In this paper, it is assumed that the summation of the coverage area of all sensors is fixed for all times before the network dies. In other words, the sensing ranges of sensors satisfy the following constraint:

$$\sum_{i=1}^{n} \pi R_i^2(t) = \mu \tag{3}$$

where $R_i(t)$ is the sensing radius of the i-th sensor at time t and μ is a prescribed constant.

Remark 1. The communication range of every sensor in the network is bounded. This practical limitation can prevent a sensor from communicating with its neighbors, which, in turn, leads to the wrong MW-Voronoi region around that sensor. Note that this can negatively affect the detection of coverage holes. However, since the number of sensors in a MSN is typically large [34], [35], the likelihood of having one (or several) sensors isolated from the rest of the nodes is very low. Therefore, it is often realistic to assume the corresponding communication graph of the network is connected [36]. As a result, each sensor can obtain the information of all other sensors, and subsequently adjust its sensing range and calculate its MW-Voronoi region accurately. The results of the present paper, however, can be extended to the case where the communication graph of the network is not connected, using the method provided in [23].

III. Joint Relocation and Sensing Range Control Algorithm

A novel sensor relocation algorithm referred to as the *lifetime maximization farthest point boundary (LMFPB)* algorithm will be introduced in this section for efficient coverage and improved lifetime of the network. The main characteristic of this algorithm is that the movement of sensors and adjustment of their sensing ranges are performed iteratively until the network dies. Each round in the proposed algorithm consists of five phases. The algorithm is run at the time instants t_0, $t_1 := t_0 + \Delta T$, $t_2 := t_0 + 2\Delta T$, $\ldots$, where ΔT is the time it takes to complete the computations and relocate the sensors accordingly. The details of the k-th iteration in the time interval $[t_k, t_{k+1}]$ are discussed below.

First phase: In this phase, every sensor S_i, $i \in \mathbf{n}$, at time t_k broadcasts its location $P_i(t_k)$ and residual energy $E_i(t_k)$ to other sensors and receives similar information from other sensor. According to Remark 1, each sensor is aware of the positions and residual energies of all other sensors. Note that the sensors only need to communicate to each other in a short period of time at the beginning of the iteration and the communication links between sensors do not need to be maintained for the rest of the time interval. It is also assumed that in each iteration the consumed energy of the sensors due to communication E^{com} is fixed. In order to simplify notations, the time argument of all time dependent variables will be omitted in the rest of the paper.

Second phase: In the second phase, each sensor adjusts its sensing range based on the remaining energy of all sensors in the network, and subsequently constructs its MW-Voronoi region. The sensing radius of every sensor is determined in this phase in such a way that a sensor which has less energy left consumes less power to increase the durability of the network. More precisely, the sensing radii are chosen in such a way that if the remaining energy of a sensor, say the i-th sensor, is m times larger than that of another sensor, say the j-th sensor, then the energy consumption rate of the i-th sensor due to sensing must be m times larger than that of the j-th sensor. Let the residual energy of the i-th sensor in the second phase be denoted by $\acute{E}_i = E_i - E^{com}$. As noted in the previous section, the power consumption of the i-th sensor due to sensing is proportional to R_i^{λ}, where R_i is its sensing radius. Choose the sensing radii of the sensors as follows:

$$R_i = \left[\frac{\frac{\nu}{\pi}(\acute{E}_i)^{\frac{2}{\lambda}}}{\sum_{i=1}^{n}(\acute{E}_i)^{\frac{2}{\lambda}}} \right]^{\frac{1}{2}} \tag{4}$$

where ν is a fixed parameter.

By choosing the sensing radii of the sensors as given in (4), if the residual energy of sensor i is m times larger than that of sensor j, then the energy consumption rate of the i-th sensor due to sensing is m times larger than that of the j-th sensor. To prove it, choose the sensing radii of the sensors according to (4). Then, the energy consumption rate of the i-th and j-th sensors due to sensing satisfy the following relation:

$$\frac{E_i^s}{E_j^s} = \frac{R_i^{\lambda}}{R_j^{\lambda}} = \frac{\left[\frac{\frac{\nu}{\pi}(\acute{E}_i)^{\frac{2}{\lambda}}}{\sum_{k=1}^{n}(\acute{E}_k)^{\frac{2}{\lambda}}} \right]^{\frac{\lambda}{2}}}{\left[\frac{\frac{\nu}{\pi}(\acute{E}_j)^{\frac{2}{\lambda}}}{\sum_{k=1}^{n}(\acute{E}_k)^{\frac{2}{\lambda}}} \right]^{\frac{\lambda}{2}}} \tag{5}$$

where E_i^s is the energy consumption rate of sensor i due to sensing. By simplifying the above relation one arrives at:

$$\frac{E_i^s}{E_j^s} = \frac{\acute{E}_i}{\acute{E}_j}$$

which is equal to m, by assumption.

One can show that:

$$\sum_{i=1}^{n} \pi R_i^2 = \sum_{i=1}^{n} \pi \left[\frac{\frac{\nu}{\pi}(\acute{E}_i)^{\frac{2}{\lambda}}}{\sum_{k=1}^{n}(\acute{E}_k)^{\frac{2}{\lambda}}} \right] = \frac{\pi \frac{\nu}{\pi} \sum_{i=1}^{n}(\acute{E}_i)^{\frac{2}{\lambda}}}{\sum_{k=1}^{n}(\acute{E}_k)^{\frac{2}{\lambda}}} = \nu$$

Now, it follows from the above observations that by using the sensing radii (4) for sensor i, $i \in \mathbf{n}$, with ν equal to μ (see Assumption 2) the objective of the second phase is achieved, while the constraint (3) is satisfied. Note that once the sensing radius of every sensor is determined, one can choose the weighting factor of each node equal to its sensing radius and construct the MW-Voronoi diagram accordingly.

Third phase: In this phase, each sensor checks its MW-Voronoi region to find the possible coverage hole. If a coverage hole exists, the sensor finds a target location for itself (but does not move there) using a proper scheme, such that by moving there the coverage hole would be eliminated, or at least its size would be reduced by a certain threshold. Various strategies are reported in the literature for finding the target location and any of them can be used in this phase (e.g. see [37], [38]). In this paper, the farthest point boundary (FPB) strategy proposed in [37] is adopted in this phase. In this strategy, each sensor first finds the farthest point in its MW-Voronoi region, which is denoted by $X_{i,far}$ for the i-th region. Then, a point on the segment connecting $X_{i,far}$ to the i-th sensor whose distance from $X_{i,far}$ is equal to R_i is chosen as the target location $\acute{P}$ for the i-th sensor. It is important to note that the sensors do not move in this phase.

Fourth phase: Once the new candidate location $\acute{P}_i$ is calculated, the coverage area w.r.t. this location, i.e. $\beta_{\Pi_i}^{\acute{P}_i}$, is obtained in this phase.

Fifth phase: If the coverage area w.r.t. the new candidate location is less than or equal to the current local coverage area, i.e. $\beta_{\Pi_i}^{\acute{P}_i} \leq \beta_{\Pi_i}^{P_i}$, the sensor does not move to the new destination and remains at its current location. If on the other hand $\beta_{\Pi_i}^{\acute{P}_i} > \beta_{\Pi_i}^{P_i}$, one of the following three cases can happen:
i) $E_i \leq E^{com} + (\Delta T)E_i^s + E_i^f$
where E_i^f is the energy required to stop the i-th sensor and then start to move it as noted earlier. In this case, the i-th sensor does not move and remains in its current location.
ii) $E_i \geq E^{com} + (\Delta T)E_i^s + E_i^f + E_i^{reloc}(P_i, \acute{P}_i)$.
In this case, the i-th sensor moves to $\acute{P}_i$ (because it has enough energy to move, sense, and communicate).
iii) $E^{com} + (\Delta T)E_i^s + E_i^f < E_i < E^{com} + (\Delta T)E_i^s + E_i^f + E_i^{reloc}(P_i, \acute{P}_i)$.
In this case, the energy of the i-th sensor is not enough for moving to $\acute{P}_i$ (although it is enough for overcoming static friction). Hence, it obtains the point $\tilde{P}_i$ from the following

equality:

$$\tilde{P}_i = P_i + \left(\frac{E_i - E^{com} + (\Delta T) E_i^s + E_i^f}{E_i^{reloc}(P_i, \acute{P}_i)} \right) \overrightarrow{P_i \acute{P}_i}$$

and moves to $\tilde{P}_i$ if and only if $\beta_{\Pi_i}^{\tilde{P}_i} > \beta_{\Pi_i}^{P_i}$.

Different definitions are provided in the literature for network lifetime [31], [32]. In this paper, the network is said to be dead once 20% of the sensors completely deplete their energy, at which point the above algorithm is terminated.

Consider a set of n mobile sensors deployed in a 2D field. Construct the MW-Voronoi diagram by considering the sensing range of each sensor as its weighting factor. The following equalities hold:

i) $\beta = \sum_{i=1}^{n} \beta_{\Pi_i}$
ii) $\theta = \sum_{i=1}^{n} \theta_{\Pi_i}$
iii) $\beta[t_a, t_b] = \sum_{i=1}^{n} \beta_i[t_a, t_b]$
(The above parameters are introduced in Definitions 1-3).

Note that, if one sensor cannot cover a certain point inside its MW-Voronoi region, that point cannot be covered by any other sensor either. Equalities (i) and (ii) follow directly from this result. Equality (iii) can be easily concluded from (ii).

Similar to Theorem 1 of [39], one can show that by moving the sensors to their new destinations the total coverage increases.

Theorem 1. Consider a set of n mobile sensors $S_1, S_2, \ldots, S_n$ in a 2D plane, and let their positions be denoted by the set $\mathbf{P} = \{P_1, P_2, \ldots, P_n\}$ with the corresponding MW-Voronoi regions $\Pi_1, \Pi_2, \ldots, \Pi_n$. Assume the sensors move to new positions $\acute{\mathbf{P}} = \{\acute{P}_1, \acute{P}_2, \ldots, \acute{P}_n\}$ such that $\acute{P}_i \neq P_i$ if and only if $i \in \mathbf{k}$, where $\mathbf{k}$ is a non-empty subset of $\mathbf{n}$. If the i-th coverage area w.r.t. $\acute{P}_i$ in the previously constructed MW-Voronoi region Π_i is larger than the i-th local coverage area in Π_i (i.e., $\beta_{\Pi_i}^{\acute{P}_i} > \beta_{\Pi_i}^{P_i}$) for every $i \in \mathbf{k}$, then the overall network coverage increases.

Proof. As it was mentioned earlier, the following inequality holds:

$$\theta = \sum_{i=1}^{n} \theta_{\Pi_i}^{P_i} \tag{6}$$

It can be shown that if for any $i \in \mathbf{k}$ the coverage area in Π_i increases, then the i-th coverage hole decreases. Since the i-th coverage area w.r.t. $\acute{P}_i$ is assumed to be larger than the i-th local coverage area for every $i \in \mathbf{k}$, it can be concluded that:

$$\theta_{\Pi_i}^{\acute{P}_i} < \theta_{\Pi_i}^{P_i}, \quad \forall i \in \mathbf{k} \tag{7}$$

In addition, note that if $\acute{P}_i = P_i$, i.e. the i-th sensor did not move, then:

$$\theta_{\Pi_i}^{\acute{P}_i} = \theta_{\Pi_i}^{P_i}, \quad \forall i \in \mathbf{n} \backslash \mathbf{k} \tag{8}$$

Now, the area inside the i-th region Π_i, $i \in \mathbf{n}$, can be divided into the following three sub-areas [40]:

- The area $\beta_{\Pi_i}^{\acute{P}_i}$ which can be covered by sensor i if it moves to $\acute{P}_i$.
- The area which is not covered by sensor i if it moves to $\acute{P}_i$ but every point in this area is covered by at least one other sensor located for example at $\acute{P}_j$, $j \neq i$. Denote this area by $\acute{\varphi}_i$.
- The area which is not covered by any sensors after they move to the new locations $\acute{\mathbf{P}}$. Denote this area by $\acute{\gamma}_i$.

Since the union of $\Pi_1, \Pi_2, \ldots, \Pi_n$ is the entire field and their intersection is the empty, the overall uncovered area after the sensors move to the new locations $\acute{\mathbf{P}}$ is, in fact, the union of the uncovered areas described as the third sub-area category mentioned above, i.e.:

$$\acute{\theta} = \sum_{i=1}^{n} \acute{\gamma}_i, \qquad i \in \mathbf{n} \tag{9}$$

Furthermore, it follows from Definition 3 that with the partitioning $\Pi_1, \Pi_2, \ldots, \Pi_n$, the i-th coverage hole w.r.t. $\acute{P}_i$ can be expressed as:

$$\theta_{\Pi_i}^{\acute{P}_i} = \acute{\varphi}_i + \acute{\gamma}_i, \quad \forall i \in \mathbf{n} \tag{10}$$

It is concluded from the above equation that:

$$\acute{\gamma}_i \leq \theta_{\Pi_i}^{\acute{P}_i}, \quad \forall i \in \mathbf{n} \tag{11}$$

Now, (9) and (11) yield:

$$\acute{\theta} \leq \sum_{i=1}^{n} \theta_{\Pi_i}^{\acute{P}_i} \tag{12}$$

In addition, it follows from (7), (8) and (12) that:

$$\acute{\theta} < \sum_{i=1}^{n} \theta_{\Pi_i}^{P_i} \tag{13}$$

It is now concluded from (6) and (13) that:

$$\acute{\theta} < \theta \tag{14}$$

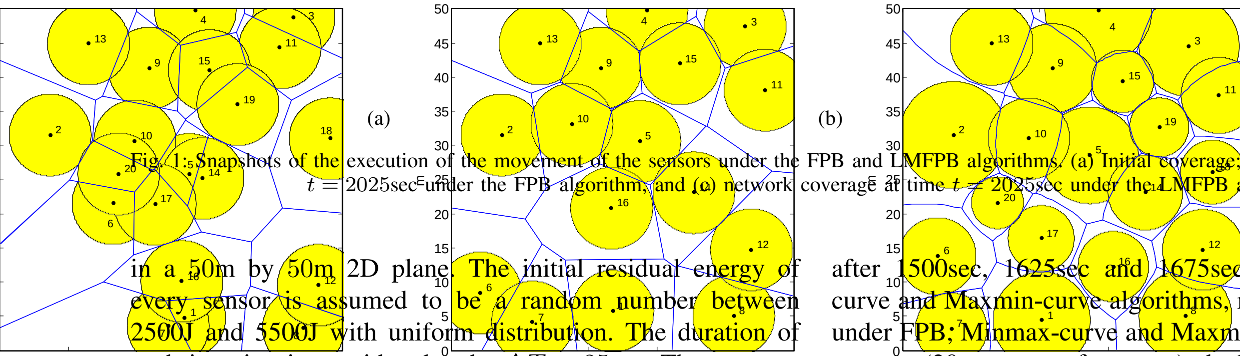
This means that the total coverage area increases using the underlying relocation scheme. □

One of the important features of the proposed sensor deployment strategy described in this paper is that every sensor moves to its new candidate location only if its coverage area w.r.t. the new location in the current MW-Voronoi region (corresponding to the positions of the sensors before moving) increases. Consequently, according to Theorem 1 of [39] by moving the sensors to their new destinations the total coverage increases. Note that once the sensors adjust their sensing ranges, the total coverage may change.

Note that the LMFPB algorithm uses the FPB strategy for searching target locations. However, by adjusting the sensing ranges of the sensors and using the relocation technique outlined above, LMFPB outperforms the FPB strategy in terms of network coverage and lifetime. This will be shown in the next section.

IV. Simulation Results

Example 1. In this example, consider 20 mobile sensors with the initial sensing range of 6m randomly distributed



(a) (b) (c)

Fig. 1: Snapshots of the execution of the movement of the sensors under the FPB and LMFPB algorithms. (a) Initial coverage; (b) network coverage at time $t = 2025$sec under the FPB algorithm, and (c) network coverage at time $t = 2025$sec under the LMFPB algorithm.

in a 50m by 50m 2D plane. The initial residual energy of every sensor is assumed to be a random number between 2500J and 5500J with uniform distribution. The duration of each iteration is considered to be $\Delta T = 25$sec. The constant coefficient α and power exponent of the sensing radius (λ) in the energy consumption model for sensing are assumed to be $\alpha = 0.032$J/m^2, and $\lambda = 2$, respectively. In addition, the constant coefficient η in the energy consumption due to relocation of sensors is taken to be $\eta = 40$J/m. Assume that the energy requirement of each sensor for communication at each iteration is $E^{com} = 10$J. Also, assume that the amount of additional energy needed to stop and then start the movement of a sensor is equal to $E_i^f = 40$J. This is considered to be identical to the energy that is needed to continuously move a sensor by 1m [26].

Fig. 1 shows three snapshots of the network configuration under the FPB and LMFPB algorithms for the above-mentioned set-up. In each snapshot, the coverage area of every sensor is depicted by a filled circle around it. Since all sensors have the same sensing radius initially (as can be observed in the first snapshot) and also in the final deployment at time $t = 2025$sec (second snapshot) under the FPB algorithm, the corresponding regions are polygons, as in conventional Voronoi diagram. On the other hand, since the sensors do not have the same sensing radius under the LMFPB algorithm, the regions are not polygons in the third snapshot and are, in fact, MW-Voronoi regions. The initial coverage in this set-up is 56.8%. As it can be seen from the second snapshot, under the FPB algorithm four sensors die at $t = 2025$sec, at which point the network coverage is 62.9%. Finally, Fig. 1(c) shows that at time $t = 2025$sec all sensor are still operating under the LMFPB algorithm, and the network coverage is 77.5%.

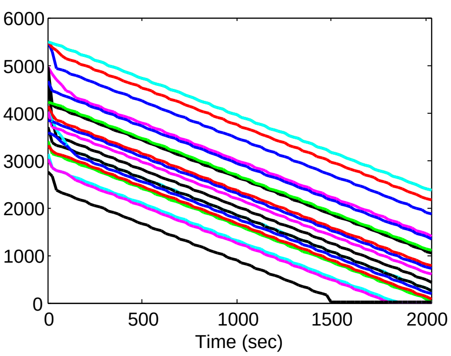
Figs. 2(a)-(c) shows the residual energy of all sensors versus time under the FPB [37], Minmax-curve and Maxmin-curve algorithms [40] without adjusting the sensing radii of the sensors. As observed, the first sensor runs out of energy after 1500sec, 1625sec and 1675sec under FPB, Minmax-curve and Maxmin-curve algorithms, respectively. In addition, under FPB, Minmax-curve and Maxmin-curve algorithms four sensors (20 percent of sensors) deplete their energies after 2025sec, 1950sec and 1850sec respectively. This is equivalent of network lifetime under those algorithms. In comparison, Fig. 2(d) exhibits the residual energy of each sensor under the proposed strategy. It is observed from the figure that all sensors run out of energy almost at $t = 2450$sec. From these figures, it is concluded that under the LMFPB algorithm the network operates 21.0%, 25.6% and 32.4% longer compared to the FPB, Minmax-curve and Maxmin-curve algorithms, respectively.

The coverage factor (defined as the ratio of the covered area to the overall area) of the network versus time is depicted in Fig. 3 for all FPB, Minmax-curve, Maxmin-curve and LMFPB algorithms. As observed, under the FPB, Minmax-curve and Maxmin-curve algorithms some sensors start to run out of energy earlier; and, this negatively impacts the coverage factor. However, under the LMFPB algorithm all sensors are still operating at $t = 2025$sec, and the coverage factor of the network is satisfactory. The average total coverage area of the network $\beta[0, t]$ (Definition 2) for all algorithms is shown in Fig. 4. It is observed from this figure that the LMFPB algorithm also outperforms all FPB, Minmax-curve and Maxmin-curve algorithms in terms of average coverage.

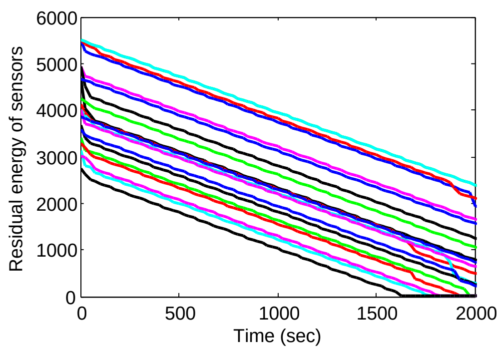
Example 2. Consider 25 sensors randomly deployed in a 50m by 50m 2D plane. Let the parameters Δ, λ, α, η, E^{com} and E^f be equal to the values given in the previous example. The performance of the proposed algorithm is investigated for two different scenarios.

Scenario 1: In this scenario all sensors are assumed to have the same initial energy (4000J) and also same initial sensing range (6m). Fig. 5 shows the residual energy of sensors versus time for the FPB and LMFPB algorithms. Under the FPB

(a) (b)

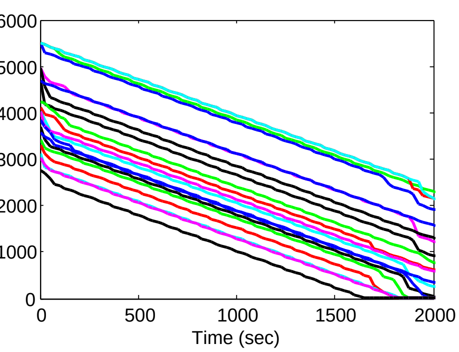


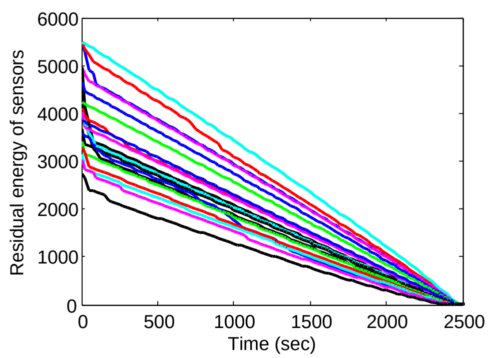
(c)



(d)

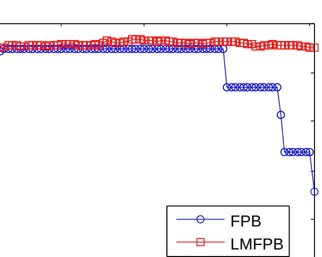
Fig. 2: Residual energy of sensors under (a) the FPB algorithm, (b) the Minmax-curve algorithm, (c) the Maxmin-curve algorithm, and (d) the LMFPB algorithm.

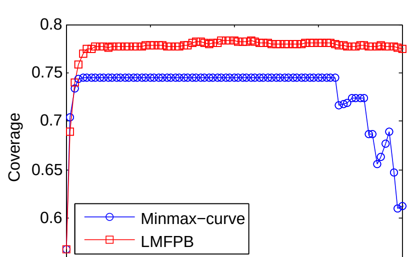


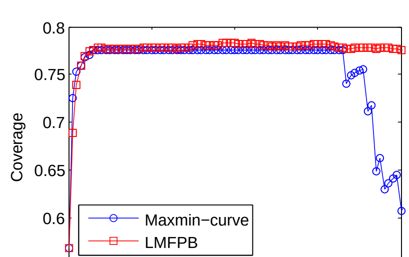


(a) (b) (c)

Fig. 3: Resultant coverage factor versus time under (a) FPB and LMFPB algorithms, (b) Minmax-curve and LMFPB algorithms, and (c) Maxmin-curve and LMFPB algorithms.

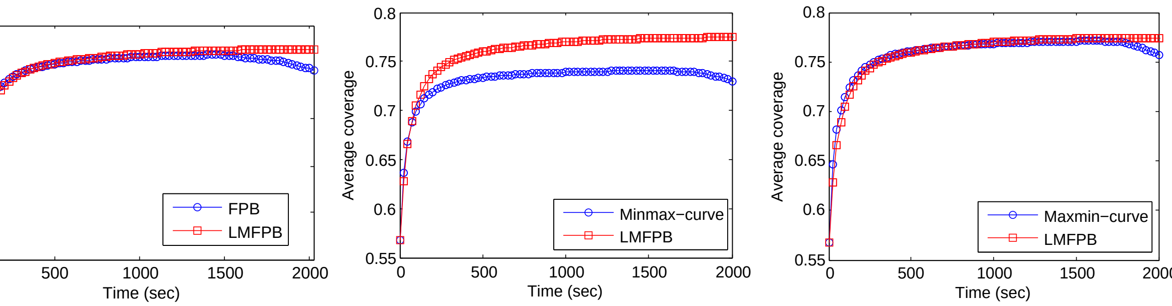






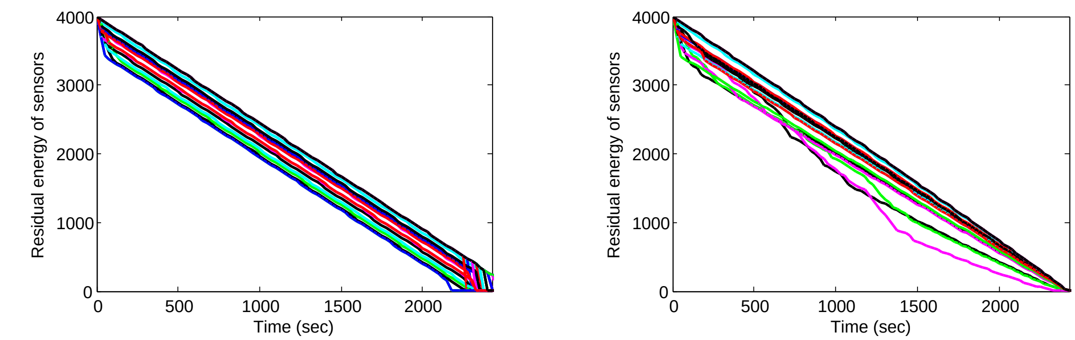
(a) (b) (c)

Fig. 4: Resultant average coverage versus time under (a) FPB and LMFPB algorithms, (b) Minmax-curve and LMFPB algorithms, and (c) Maxmin-curve and LMFPB algorithms.



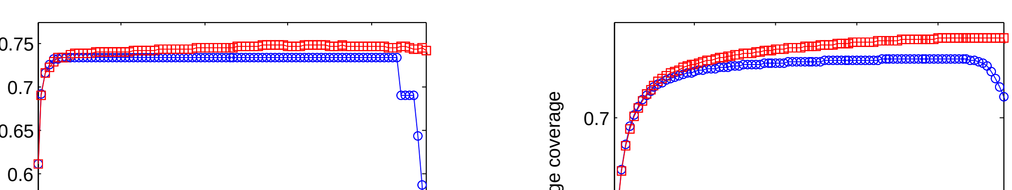
(a) (b)

Fig. 5: Residual energy of sensors under (a) the FPB algorithm, and (b) the LMFPB algorithm in a network of sensors with the same initial energy.



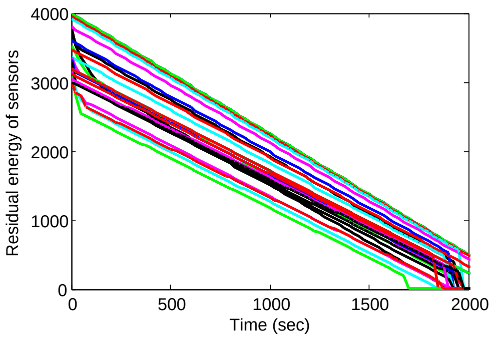
(a) (b)

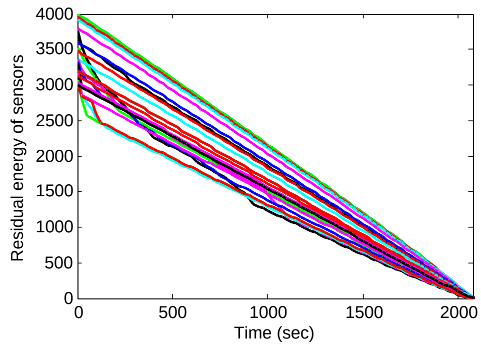
Fig. 6: Coverage performance under the FPB and LMFPB algorithms. The graphs demonstrate (a) the coverage factor, and (b) average coverage, both versus time.



(a) (b)

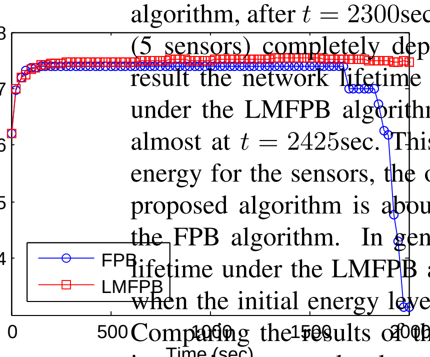
Fig. 7: Residual energy of sensors under (a) the FPB algorithm, and (b) the LMFPB algorithm in the second scenario.

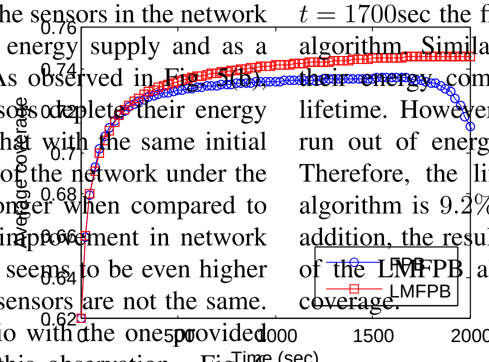




(a) (b)

Fig. 8: Coverage performance under the FPB and LMFPB algorithms. The graphs demonstrate (a) the coverage factor, and (b) average coverage, both versus time.





algorithm, after $t = 2300$sec 20% of the sensors in the network (5 sensors) completely deplete their energy supply and as a result the network lifetime is over. As observed in Fig. 5(b), under the LMFPB algorithm all sensors deplete their energy almost at $t = 2425$sec. This means that with the same initial energy for the sensors, the operation of the network under the proposed algorithm is about 5.4% longer when compared to the FPB algorithm. In general, the improvement in network lifetime under the LMFPB algorithm seems to be even higher when the initial energy levels of the sensors are not the same. Comparing the results of this scenario with the one provided in previous example also points to this observation. Fig. 6 shows the coverage factor and average coverage of the network versus time for the case when the sensors have the same initial energy. As observed, the LMFPB algorithm outperforms the FPB algorithm in both measures. where in the beginning of the FPB algorithm each sensor sets its sensing range based on its initial energy.

Scenario 2: In this scenario it is assumed that the initial energy of every sensor is a random number between 3000J and 4000J and in the beginning of the deployment each sensor selects its sensing range based on its initial energy. Fig. 7 shows the residual energy of all sensors versus time for both algorithms. It can be noticed from Fig. 7(a) that after $t = 1700$sec the first sensor runs out of energy under the FBP algorithm. Similarly, after $t = 1900$sec five sensors deplete their energy completely, signifying the end of the network lifetime. However, under the proposed algorithm all sensors run out of energy almost at $t = 2075$sec (see Fig. 7(b)). Therefore, the lifetime of the network under the LMFPB algorithm is 9.2% longer compared to the FPB algorithm. In addition, the results depicted in Fig. 8 confirm the superiority of the LMFPB algorithm in terms of coverage and average coverage.

V. CONCLUSIONS

An autonomous sensor deployment algorithm is proposed to improve field coverage in a mobile sensor network while increasing the lifetime of the network. The proposed strategy monitors the residual energy of every sensor, and adjusts the sensing radii of all sensors accordingly, while relocating them. The multiplicatively weighted Voronoi (MW-Voronoi) diagram is used to plan for relocation of the sensors. Every sensor moves iteratively to improve coverage within its MW-Voronoi regions, which is guaranteed to increase the coverage of the entire network. Simulations demonstrate the advantages of the proposed algorithm.

APPENDIX

Consider a flat surface, and a set of n distinct weighted nodes on it, denoted by $(S_1, w_1), (S_2, w_2), \ldots,\ (S_n, w_n)$, where $w_i > 0$ is the weighting factor associated with the node S_i, for any $i \in \mathbf{n} := \{1, 2, \ldots, n\}$. Define the weighted distance between a point Q and a node (S_i, w_i), $i \in \mathbf{n}$ as:

$$d_w(Q, S_i) = \frac{d(Q, S_i)}{w_i}$$

where $d(Q, S_i)$ denotes the Euclidean distance between the node S_i and the point Q in the plane. The *multiplicatively weighted Voronoi* (MW-Voronoi) diagram partitions the plane into a set of n regions, referred to as the MW-Voronoi regions, such that: (i) Each region contains only one node, called the *generating node* of that region, and (ii) the nearest node to any point inside a region, in the sense of weighted distance, is the generating node of that region [40].

Definition 4. A pair of nodes whose MW-Voronoi regions share a boundary curve are referred to as *neighbors*. The set of all neighbors of S_i is denoted by $\mathbf{N}_i$.

Definition 5. The *Apollonian circle* of the segment AB is the geometric location of all points C such that $\frac{AC}{BC} = k$ [41]. This circle will be denoted by $\Omega_{AB,k}$.

To construct the MW-Voronoi diagram, the Apollonian circle $\Omega_{S_iS_j,\frac{w_i}{w_j}}$ is obtained for every $i \in \mathbf{n}$ and $S_j \in \mathbf{N}_i$. The smallest region generated by these circles which contains node i is, in fact, the MW-Voronoi region of that node. Fig. 9 illustrates the above procedure for a group of five nodes.

Consider a group of n weighted sensors in a flat field, and let the position of each sensor be represented as a node with a weight equal to the sensor's sensing radius. Then, construct the MW-Voronoi region for every sensor to obtain a diagram that covers the whole sensing field. It is noted from the formulation of the MW-Voronoi diagram that each sensor needs to only check its own MW-Voronoi region in order to identify the points that cannot be covered by the sensors. The set of points in a region which are not covered are called *coverage holes*. Note also that if a sensor cannot cover a point in its region, other sensors cannot cover it either.

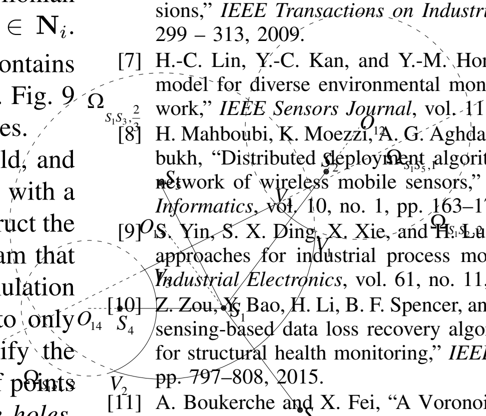


Fig. 9: The MW-Voronoi region for a node S_1 with four neighbors $S_2, \ldots, S_5$ [37].

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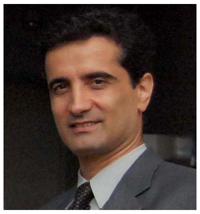

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