Mobile Element Assisted Cooperative Localization for Wireless Sensor Networks with Obstacles

Hongyang Chen, Qingjiang Shi, Rui Tan, H. Vincent Poor, *Fellow, IEEE,* and Kaoru Sezaki

***Abstract*—In this paper, a cooperative localization algorithm is proposed that considers the existence of obstacles in mobility-assisted wireless sensor networks (WSNs). An optimal movement scheduling method with mobile elements (MEs) is proposed to address limitations of static WSNs in node localization. In this scheme, a mobile anchor node cooperates with static sensor nodes and moves actively to refine location performance. It takes advantage of cooperation between MEs and static sensors while, at the same time, taking into account the relay node availability to make the best use of beacon signals. For achieving high localization accuracy and coverage, a novel convex position estimation algorithm is proposed, which can effectively solve the problem when infeasible points occur because of the effects of radio irregularity and obstacles. This method is the only range-free based convex method to solve the localization problem when the feasible set of localization inequalities is empty. Simulation results demonstrate the effectiveness of this algorithm.**

***Index Terms*—Mobility-assisted wireless sensor networks, mobile elements, convex localization algorithm, optimal movement scheduling.**

I. Introduction

LOCALIZATION algorithms for wireless sensor networks (WSNs) have been designed to find per-node location information, which is a key requirement in many applications of WSNs. Generally speaking, based on the type of information required for positioning, protocols can be divided into two categories: (i) range-based and (ii) range-free protocols. Due to the hardware limitations and power constraints of sensors, solutions of range-free localization are often preferable and can be considered as cost-effective options when compared with more expensive and energy-consuming range-based schemes [1]. In this paper, we focus on the investigation of range-free localization algorithms for mobility-assisted WSNs.

Some previous works have focused on exploiting sensor mobility for node localization in WSNs. Luo *et al.* [2] proposed a localization algorithm based on time difference of arrival (TDOA) for sensor networks with mobile sensors. Similarly, two localization algorithms that are based on radio frequency (RF) and receiver signal strength indication (RSSI) were presented in [3] and [4], respectively. Priyantha *et al.* [5] presented a range-based mobile-assisted localization (MAL) approach, in which mobile nodes measure distances and construct a *globally rigid* structure to achieve a unique localization. Vivekanandan *et al.* [6] proposed a concentric anchor beacon (CAB) localization algorithm for WSNs. Ssu *et al.* [7] proposed a range-free localization scheme using mobile anchor points. Semidefinite programming (SDP) [8] has also been introduced and applied to sensor network localization. However, most of the proposed methods deal with the range-based sensor network localization problem [9].

An obstacle can be dynamically formed due to unbalanced deployment, failure or power exhaustion of sensor nodes, animus interference, or physical obstacles such as mountains or buildings. In this paper, we consider only physical obstacles. Most previous algorithms cannot work well in anisotropic networks, where obstacles appear among sensor nodes.

In this work, we propose a multi-power-level mobile anchor assisted range-free algorithm for WSNs with obstacles, in which the node localization problem is formulated as a convex optimization problem. By using a relay node, our scheme can effectively reduce the effects of obstacles on node localization. Furthermore, our scheme can calculate the positions of infeasible points caused by a complex radio transmission environment, which is recognized as a problem when the feasible set for localization inequalities is empty. Based on the derived localization error bound, an optimal movement scheduling method is proposed to reduce the total moving distance of the mobile element (ME) while assuring high localization performance, which can efficiently extend the lifetime of the ME.

The rest of the paper is organized as follows. Section II describes the cooperative localization scheme, including its derivation. Section III derives the localization error bound. In Section IV, simulation results are reported and a comparative study of the localization performance is conducted. Section V gives concluding remarks.

II. Collaborative Localization using Mobile Element

In this section, we propose a collaborative node localization approach using an ME. We first introduce the technical preliminaries of our algorithm in subsection A and then formulate the localization problem as an optimization problem in subsection B. We propose an algorithm for decreasing the impact of obstacles in subsection C and the movement scheduling algorithm for the MEs in subsection D.

A. Background

In WSNs, a node can determine whether it is in the transmission radius of an anchor node according to a beacon signal received from the one-hop anchor. The anchor node can adjust its transmission radius by tuning its transmission

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power. For example, the TelosB mote is equipped with an IEEE 802.15.4 compliant Chipcon CC2420 radio, which has 31 transmission power levels between -25 and 0 dBm.

We assume an anchor node has M levels of transmission power, and the corresponding transmission radii are R_i, $i = 1, 2, \ldots, M$. Normally, the ME is assumed to have a global positioning system (GPS) receiver and knows its position [10] [11]. During the moving period, the ME transmits beacon signals at varying power levels consecutively including its ID, current position, transmission power and transmission radius. After receiving these beacon signals, an unknown-position sensor can construct an effective constraint on its position.

For example, we assume that the current position for the ME is a and its transmission radius is R. If the unknown-position sensor, at position x, receives the beacon signal, we can conclude that the distance between the two nodes satisfies $||x - a|| \le R$. Otherwise, $||x - a|| > R$. Using the multiple transmission radius of the ME by tuning the transmission power at each position, the unknown-position sensor can obtain a set of inequalities on x:

$$r_i < ||x - a_i|| \le R_i, \ i = 1, 2, ..., n \tag{1}$$

where a_i is the position of the ME at the time i, r_i (it might be zero) and R_i are *valid radii* for that time. Herein, the valid constraint radii denote the corresponding lower and upper bounds, for the tightest constraint among all of the constraints that are constructed by all of the transmission powers for the mobile anchor node at position a_i.

Hence, the localization problem based on an ME with multiple transmission radius can be converted into the problem of solving a set of quadratic inequalities (1). Some algorithms (e.g., [6] [16]) are also based on the solution of a set of quadratic inequalities. However, their methods all assume that the set of quadratic inequalities (1) must have solutions. But, because of the complex transmission environment, there are two different location scenarios: the set of quadratic inequalities has a solution (i.e., the feasible set is nonempty); and the set of quadratic inequalities have no solution (i.e., the feasible set is empty). For these two different scenarios, we propose a novel localization algorithm based on convex optimization to solve the problem whether the feasible set is empty or not. To the best of our knowledge, our proposed method is the only range-free algorithm using convex optimization to solve the problem when the feasible set is empty.

Note that the communications between wireless terminals are affected by several phenomena in practice, such as signal path loss, channel fading and shadowing [12]. The transmission radius and the location accuracy are affected by such phenomena. However, it is very difficult to quantify these effects as these practical factors are often unknown and complicated. Thus, in this paper, we assume deterministic transmission radii, i.e., two wireless terminals cannot communicate if they are farther apart than the transmission radius. We note that such a deterministic model has been widely adopted in previous work on localization in WSNs, e.g. [6] [7] [16], and it is a reasonable approximation to actual communication behavior. We can use a numerical example to illustrate the impact of these phenomena. We use the link model in [13] with the settings of the MICA2 mote to compute the packet reception ratio (PRR) between two sensors. The link model in [13] accounts for signal path loss and channel fading. Fig. 1 plots the PRR versus the distance between the two sensors under various transmission powers. Denote by P_{Tx} the transmission power of the ME. When $P_{Tx} = 0\,\text{dBm}$, we set the transmission radius to be $R_{0\,\text{dBm}} = 9\,\text{m}$. When $P_{Tx} = 15\,\text{dBm}$, we set the transmission radius to be $R_{15\,\text{dBm}} = 18\,\text{m}$. We note that the ME is more powerful than the deployed low-cost motes and hence the transmission power of the ME can be much larger than that of the low-cost motes. We now compute the probability that a mote located in the ring region from $R_{0\,\text{dBm}}$ to $R_{15\,\text{dBm}}$ centered at the ME is successfully localized in the ring region. We note that a mote is localized in the ring region if it *cannot* hear the beacon packet when $P_{Tx} = 0\,\text{dBm}$ and it *can* hear the beacon packet when P_{Tx} increases to $15\,\text{dBm}$. From Fig. 1, the average probabilities that a mote located in the ring region *cannot* and *can* hear beacon packets when $P_{Tx} = 0\,\text{dBm}$ and $P_{Tx} = 15\,\text{dBm}$ are 0.936 and 0.888, respectively. Therefore, the average probability that a mote located in the ring is successfully localized in the region is $0.936 \times 0.888 = 0.831$. We note that we can improve this success probability by adopting a larger transmission power interval, e.g., we can use 0 dBm and 20 dBm. However, doing so will introduce larger range estimation error, i.e., e given by (11) below. In practice, we can balance such a trade-off to meet different requirements on localization performance.

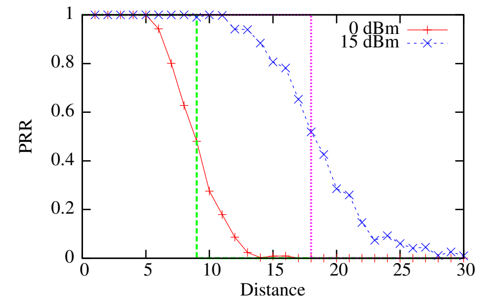


Fig. 1. The packet reception ratio (PRR) vs. the distance between two MICA2 motes under various transmission powers.

B. Localization Algorithm using Convex Optimization

In real environments, the actual transmission radius varies in different directions of radio propagation because of the non-isotropic properties of the propagation medium and the heterogeneous properties of devices, as noted above. According to the model of [1], to model this radio irregularity all nodes within half of the maximum transmission radius of anchors are guaranteed to hear from the anchor. If nodes are beyond the maximum transmission radius, they cannot hear from the anchor. If nodes are between the maximum transmission radius and half of that radius, three scenarios are possible: (1) symmetric communication, (2) unidirectional asymmetric communication, and (3) no communication. Therefore, it is possible that there is no communication between two nodes although their relative distance is smaller than their ideal transmission radius. In this case, the inequalities for the original optimization problem will have no solutions and an infeasible case would occur.

In order to deal with the case with an empty feasible set, we propose a novel convex position estimation algorithm, which

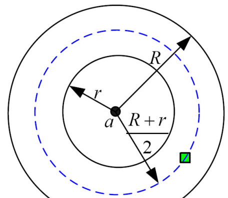


Fig. 2. The single constraint case.

can provide good position estimation accuracy in both the feasible case and the infeasible case.

As shown in Fig. 2, for the single constraint case ($r < ||x-a|| < R$), it is easy to see that an efficient position estimate lies on the circle with center a and radius $\frac{R+r}{2}$. In the figure, the square indicates the possible position for the optimal position estimate and the black dot denotes the anchor node with position a.

The position estimate can be found by minimizing the following expression:

$$(||x-a||-r)^2 + (||x-a||-R)^2.$$

Inspired by the single constraint case, for the inequalities under multiple constraints, we can seek an optimal position estimate by solving the following problem:

$$\min_x \sum_i \left[(||x-a_i||-r_i)^2 + (||x-a_i||-R_i)^2\right]. \tag{2}$$

Obviously, the problem (2) is nonconvex. Moreover, this problem cannot be directly approximated by using convex relaxation techniques like that of [9]. To approximately solve the problem via convex relaxation techniques, we note that it is equivalent to the following problem[1]:

$$\min_x \sqrt{\sum_i [(||x-a_i||^2 - r_i^2)^2 + (||x-a_i||^2 - R_i^2)^2]} \ . \tag{3}$$

Although, the problem (3) is still nonconvex, we can turn it into a convex problem by using a convex relaxation technique. Firstly, we write the problem as follows:

$$\begin{aligned} \min_{x,y} & \sqrt{\sum_i \begin{bmatrix} (y - 2a_i^T x + \|a_i\|^2 - r_i^2)^2 \\ +(y - 2a_i^T x + \|a_i\|^2 - R_i^2)^2 \end{bmatrix}} \\ s.t. \quad & y = \|x\|^2. \end{aligned} \tag{4}$$

Then by relaxing the equality constraint in (4) into an inequality constraint, we obtain the following convex problem:

$$\begin{aligned} \min_{x,y} & \sqrt{\sum_i \begin{bmatrix} (y - 2a_i^T x + \|a_i\|^2 - r_i^2)^2 \\ +(y - 2a_i^T x + \|a_i\|^2 - R_i^2)^2 \end{bmatrix}} \\ s.t. \quad & \|x\|^2 \le y. \end{aligned} \tag{5}$$

Using epigraph form[8], we can further transform it into a standard linear cone programming problem:

$$\begin{aligned} \min_{x,y,v,t} \quad & t \\ \text{s.t.} \ ||v|| & \le t \\ y - 2a_i^T x + \|a_i\|^2 - r_i^2 &= v_{i1} \\ y - 2a_i^T x + \|a_i\|^2 - R_i^2 &= v_{i2} \quad \forall i \\ \|x\|^2 &\le y \end{aligned} \tag{6}$$

where $v = \left[\ v_{11} \quad v_{12} \quad \cdots \quad v_{i1} \quad v_{i2} \quad \cdots \quad v_{n1} \quad v_{n2}\ \right]^T$. Herein, in order to write in the standard form, we introduce a dummy variable t. t is also introduced in the epigraph model of the problem; please refer to [8]. All vector variables in this paper are column vectors. The resulting problem can be solved by using efficient interior-point algorithms, e.g., the solver SeDuMi [26].

C. Algorithm for Decreasing the Impact of Obstacles

In this paper, we assume that boundary nodes around the obstacle have been discovered by some boundary recognition algorithms [14], so that each sensor node knows whether it is a boundary node or not. Only boundary nodes can participate in contention for relaying beacons from the ME because their rebroadcasts may cover some blind areas as shown in Fig. 3. Hearing a beacon from the ME, boundary nodes will compete to relay this location information through a distributed contention process. The probability that a candidate node wins the contention depends on the node's remaining energy and the number of neighboring sensors. The node with greater remaining energy and greater number of neighbors has higher priority to be the optimal relay node. The proposed selection scheme for the optimal relay node is concluded as follows: Receiving a beacon from the ME, a boundary node sets a backoff timer which defines the amount of time that the node must wait before rebroadcasting the location information. The backoff time δ is calculated as

$$\begin{aligned} \delta = (\alpha(used\_energy/initial\_energy) + \\ \beta/num\_neighbors) * max\_delay \end{aligned} \tag{7}$$

where α and β are the modification coefficients to provide different weights for different parameters. We can see that a greater remaining energy and a greater number of neighbors will lead to a shorter backoff time. If a candidate boundary node does not hear any beacon signal from other sensors during its backoff time, it will rebroadcast the beacon signal and other boundary nodes will cancel their contentions if they receive the rebroadcast of the beacon. As a result, the node with the highest priority will rebroadcast first and win the competition to serve as the relay for the ME's beacon signal. Note that this distributed relay node selection process is triggered by the reception of a beacon message from the ME. Therefore, we do not require an explicit time synchronization protocol among the candidate relays. They are implicitly synchronized by the beacon message. However, due to the existence of propagation delay and receive-to-transmit switch time, the relay selection may fail when one relay cannot hear the best relay's rebroadcast of the beacon message. This is the case when the backoff timer of a candidate relay expires before

[1]The possible case where there is only the lower bound r_i or the upper bound R_i is not considered in this formulation. However, such a case can still be handled by using the same convex relaxation technique.

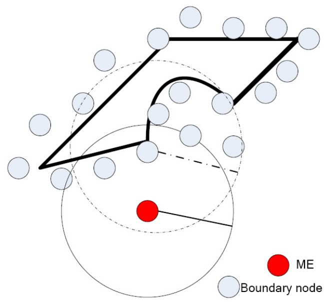


Fig. 3. A sensor network with an obstacle.

the rebroadcast of the best relay arrives at it. However, such a case is rare according to the analysis in [15]. For example, selecting $c/\lambda = 1/200$ will result in a collision probability less than 0.6% where c is the propagation delay and switching time and λ is the max delay in equation (9). Typically $c = 5\mu s$; this means the max delay can be 1 ms, which implies the best relay will be selected within 1 ms. In this way, we can deliver the ME's location information to some areas that cannot receive the ME's direct communication. Similarly to (3), the unknown-position sensor in these special areas can obtain a set of inequality constraints on x :

$$|R_i - R_{relay}| \leqslant \|x - a_i\| \leqslant R_i + R_{relay}, \quad i = 1, 2, \ldots, n \quad (8)$$

where R_{relay} is the current transmission radius for the relay node and $|\cdot|$ represents the absolute value operator. We can also use the proposed convex localization algorithm to solve the problem (8). Based on this scheme, we can efficiently decrease the impact of the obstacle on node localization and improve the location accuracy.

Note that the beacon signal transmission is affected by several affecting phenomena such as signal path loss and channel fading. It is difficult to solve this problem well in WSNs due to hardware constraints. The sensors that cannot be covered directly by the ME due to physical obstacles will have larger localization errors than the requirement since (10) gives a looser bound than (3). Due to fading and shadowing of wireless channels, it is possible that the relay node cannot successfully relay the beacon signal to the unknown-position sensor within the area that cannot receive the ME's direct communication. However, the ME will transmit beacon signals at varying power levels consecutively when it is stationary. With different beacon signals at a given position of the ME, the selected relay node will differ. Thus it will increase the probability of covering the unknown-position sensor within the area that cannot receive the ME's direct communication. In the worst case, if the relay node still cannot cover a node, we will consider it to be a blind node that cannot be localized.

D. Movement Scheduling for Mobile Elements

Several types of MEs capable of free movement are currently available, e.g., Packbot [17] and Robomote [21]. In practice, the ME cannot visit some positions due to physical obstacles. We assume that the regions that the ME cannot visit are known. We only consider the minimal set of hexagons that cover the visitable region. Due to power constraints, the ME is capable of only low-speed and short-distance movement in practical deployments. For instance, the normal speed of several mobile sensor platforms (e.g., Packbot and XYZ) is only $0.5 \sim 2m/s$. An XYZ mobile sensor node that is powered by two AA batteries can move only about 165 meters before exhausting its power. Therefore, the movement trace of the ME must be efficiently planned in order to maximize the number of localized unknown-position sensors with the required localization accuracy.

The optimal movement schedule for MEs in our algorithm needs to achieve the shortest path length so that the ME covers the entire area with the shortest time and consumes the minimum energy. Based on the derived localization error bound (which will be derived in Section III), we propose an optimal movement schedule for MEs as follows:

When the ME has no prior information about sensors' positions, in order to guarantee that each sensor is localized with error ϵ, the entire geographical region should be covered by disks with radii r_d centered at the beacon points of the ME. The most efficient coverage is the hexagonal tiling of the entire region, in which the edge length of each hexagon is r_d and each beacon point is at the center of each hexagon. In the optimal movement schedule of the ME, the center of a hexagon is visited by the ME once. Obviously, the shortest length of a path that crosses a hexagon is $\sqrt{3}r_d$. In the line-by-line scan as shown in Fig. 4, the shortest path length is achieved. Therefore, the line-by-line scan is an optimal movement schedule of the ME.

When each sensor has coarse prior information about its position, the ME does not need to cover the entire region. Suppose there are N sensors and sensor i is in region A_i with high probability. Let $\{H_i\}$ denote the minimal set of hexagons that covers the united regions $\bigcup_{i=1}^{N} A_i$, where H_i is one of the hexagons in the hexagonal tilings of the entire geographical region. Note that $\{H_i\}$ can be found by checking whether each hexagon has intersection with $\bigcup_{i=1}^{N} A_i$, and hence in polynomial time. Construct a undirectional graph $G = (V, E)$, where V is the set of centers of $\{H_i\}$ and E is the set of Euclidean distances between any two points in V. The movement schedule of the ME can be formulated as the shortest Hamiltonian path problem. Specifically, given a starting point that is a vertex in V, find the shortest path that visits each vertex in V exactly once. We note that the problem of finding a Hamiltonian path is NP-complete and therefore the problem of finding the shortest Hamiltonian path is also NP-complete [18].

We now propose a heuristic algorithm to solve the movement scheduling problem formulated above by using any solver of the travelling salesman problem (TSP). Note that the optimal solution to the TSP is the shortest Hamiltonian cycle for the given graph G. Our basic idea is as follows. We first connect a vertex v and the starting point with an edge of large negative cost, and then apply the TSP solver to the modified graph. Heuristically, this added edge will be included in the TSP solution and the shortest Hamiltonian path that ends at v_i can be found by removing the added edge from the TSP solution. By iterating $v \in V$, we can find the shortest Hamiltonian path. Algorithm 1 shows the pesudo code of the heuristic algorithm. In the pesudo code, `INT_MAX` represents the maximum integer of the programming language, and $|P \backslash e|$ represents the cumulative cost of the path $P \backslash e$.

Algorithm 1 Find the shortest Hamiltonian path

Input: $G = (V, E)$, starting point v_0
Output: The shortest Hamiltonian path in G
$cost$ = INT_MAX
for $v \in V \backslash v_0$ **do**
  creat edge e that connects v_0 and v with cost of -INT_MAX
  $E' = E \bigcup e$, $G' = (V, E')$
  P = TSPsolver(G')
  if $|P \backslash e| < cost$ **then**
    $hpath = P \backslash e$
    $cost = |P \backslash e|$
  end if
end for
return $hpath$

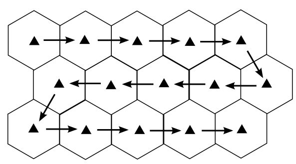


Fig. 4. The optimal movement schedule of the mobile anchor when no information about sensors' positions is available. The triangles represent the way points of the mobile anchor. The edge length of each hexagon is r_d.

III. Performance Analysis

A. Localization Error Bounds

Wang *et al.* [19] investigated the network coverage for range-based target localization applications. We compare our method with their method implemented in the ideal environment without obstacles. As the simulation results described in subsection IV.C show, our algorithm outperforms their method. Hence, based on their analytical localization error bound, it is feasible to extend their analysis to the scenario of range-free localization using an ME and thereby to derive a loose localization error bound for our localization algorithm. In [19], Wang *et al.* proved a sufficient condition for achieving a target localization error of $\frac{4\sqrt{3}e}{3}$, where e is the maximal range estimation error. The major limitation of their result is that they consider only a specific value of localization error. In this section, we will extend their result to the scenario of range-free localization using ME with *any* required localization error.

We first derive the maximal range estimation error, *i.e.*, e, under the scenario of range-free localization.

Let R_i denote the transmission radius when the ME broadcast beacon using the i^{th} transmission power level. We assume $R_i < R_j$ if $i < j$. The ME can determine the distance from a sensor, denoted by d, which satisfies $R_i \leq d \leq R_{i+1}$. The optimal estimate of the sensor position lies on the circle centered at the ME and with radius $\frac{R_i+R_{i+1}}{2}$. Hence, the distance estimate made by the ME is $\frac{R_i+R_{i+1}}{2}$ and the maximal range estimation error is given by

$$e = \max_i \left\{ \frac{R_{i+1} - R_i}{2} \right\}. \quad (9)$$

In [19], the network resolution is defined to facilitate derivation of the localization error bound. We now extend this definition to the scenario of range-free localization using an ME.

Definition 1: Two points t and t' are *distinguishable* if the ME can always distinguish whether a sensor is at point t or t' through the measurements provided by the ME at different

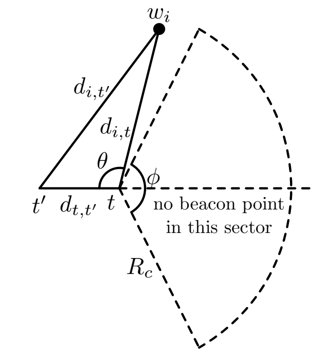


Fig. 5. The ME cannot distinguish two points t and t'.

locations. The *network resolution* is the minimal distance l, such that the ME can distinguish any pair of points when the distance between them is larger than l.

The following lemma gives the relationship between network resolution and the localization error bound, which has been proved in [19]. We refer interested readers to [19] for the details of the proof. We note that it also holds for the scenario of range-free localization using ME.

Lemma 1 ([19]): If the network resolution is better than $\sqrt{3}\epsilon$, the localization error is upper bounded by ϵ.

The following theorem gives a sufficient condition for achieving a localization error of ϵ, which enables us to schedule the movement of ME to satisfy the required localization error.

Theorem 1: The localization error is upper bounded by ϵ if there is at least one ME beacon point in any arbitrary sector of radius R_c and angle ϕ, where R_c is the maximal transmission radius of the ME, ϕ is given by

$$\phi = 2 \arccos \left(\frac{2e}{\sqrt{3}\epsilon} \right), \quad (10)$$

and $\epsilon > \frac{2}{\sqrt{3}}e$. Note that e is the maximal distance estimation error of the ME when the sensor is within R_c meters from the ME, which is given by (9).

Proof: From Lemma 1, a sufficient condition for the localization error of ϵ is that the network resolution provided by the ME is $\sqrt{3}\epsilon$. We prove this theorem by contradiction. Suppose the network resolution is worse than $\sqrt{3}\epsilon$, i.e., we can find at least one pair of points t and t' which are apart by more than $\sqrt{3}\epsilon$, and the ME cannot distinguish them. Now we will prove that if the conditions for this theorem are satisfied, such a network resolution cannot be true and hence the localization error of ϵ is guaranteed.

Suppose two points, t and t', cannot be distinguished by the ME and the distance between them is $d_{t,t'} \geq \sqrt{3}\epsilon$. We denote the sector of radius R_c and angle ϕ by (R_c, ϕ). As we assumed that there is at least one ME beacon point in any sector of (R_c, ϕ), there must be at least one beacon point within R_c meters from t. Suppose this beacon point is w_i as shown in Fig. 5. A necessary condition for t and t' to be indistinguishable is $|d_{i,t} - d_{i,t'}| \leq 2e$; otherwise, t and t' can be distinguished by the ME at beacon point w_i. Moreover, t' must be within R_c meters from w_i, as otherwise t and t' can be distinguished by the ME. Without loss of generality, we assume $d_{i,t} \leq d_{i,t'}$ and therefore $d_{i,t'} \leq d_{i,t} + 2e$ according to the above necessary condition. As shown in Fig. 5, according to the law of cosines, we have

$$\cos\theta = \frac{d_{i,t}^2 + d_{t,t'}^2 - d_{i,t'}^2}{2d_{i,t}d_{t,t'}} \geq \frac{d_{i,t}^2 + d_{t,t'}^2 - (d_{i,t}+2e)^2}{2d_{i,t}d_{t,t'}} = \frac{d_{t,t'}^2 - 4e^2 - 4d_{i,t}e}{2d_{i,t}d_{t,t'}}.$$

As $d_{t,t'} \geq \sqrt{3}\epsilon > 2e$, we have $d_{t,t'}^2 - 4e^2 > 0$. Therefore, $\cos\theta > -\frac{2e}{d_{t,t'}} \geq -\frac{2e}{\sqrt{3}\epsilon}$. Accordingly, $0 \leq \theta < \arccos\left(-\frac{2e}{\sqrt{3}\epsilon}\right) = \pi - \arccos\left(\frac{2e}{\sqrt{3}\epsilon}\right)$ and $\phi < 2(\pi-\theta) \leq 2\pi$. There is no beacon point within the sector of $(R_c, 2(\pi-\theta))$ centered at t and bisected by ray $t't$, otherwise, t and t' can be distinguished. However, as $2(\pi-\theta) > \phi$, this result is a contradiction to the assumption that there is at least one beacon point in any sector (R_c, ϕ). ■

From Theorem 1, when $\epsilon \in \left(\frac{2}{\sqrt{3}}e, \infty\right)$, $\phi \in (0, \pi)$. Theorem 1 can be extended to the disk coverage model as follows.

Corollary 1: The localization error is upper bounded by ϵ if disks of radius $\frac{\sin\frac{\phi}{2}}{1+\sin\frac{\phi}{2}}R_c$ centered at the ME's beacon points cover the entire field, where R_c is the maximal transmission radius of the ME and ϕ is given by (10).

Proof: A sector of (R, ϕ) contains an inscribed circle of radius $r_d = \frac{\sin\frac{\phi}{2}}{1+\sin\frac{\phi}{2}}R_c$. Therefore, if the disks of radius r_d centered at the ME's beacon points cover the entire field, there will be no sector (R_c, ϕ) that contains no sensor and hence the location estimation error bound is guaranteed according to Theorem 1. ■

We note that the disc coverage model has several advantages over the sector coverage model. First, the disc coverage problem has been extensively studied in the previous literature [20]. The previous results and algorithms can be applied to schedule the movement of the ME. Second, the disc model is easier than the sector model in the geometric treatment due to its simplicity. Therefore, we adopt the disc coverage model to schedule the movement of the ME.

B. Communication Cost and Power Consumption

The number of messages that a sensor node needs to transmit is used to gauge the communication cost in our localization algorithm. In our localization process, the MEs will perform the broadcasting operation at every time slot. Thus the communication cost is related to the number of beacon signals, which can be calculated as follows:

For the communication cost in the line-by-line case, on letting l be the width of the deployment area, the number of hexagonal tilings in a row can be calculated as $l/\sqrt{3}r_d$. In the same way, on letting h be the height of the deployment area, the number of rows is $h/\sqrt{3}r_d$. For each hexagonal tiling, we assume the ME will beacon twice. Therefore, the total number of beacons is $2hl/3r_d^2$. For the communication cost in the TSP case, the number of beacon points is $2\{H_i\}$, i.e., two times the size of the set $\{H_i\}$. Thus, it is upper bounded by the communication cost of the line-by-line case. The ME broadcasts to unknown-position sensors a hello message with its ID, location and some recognize-bits which amounts to only several bytes. For low beacon point density, this would require roughly hundreds of bytes.

We can evaluate the corresponding energy consumption of our approach. We account for the energy consumed in locomotion of the ME, wireless communication, and idle state at local sensors. We assume that the ME is a wheeled robot such as the Robomote [21]. The energy consumed in locomotion by a wheeled robot, denoted by $E_M(d)$, can be approximated by $E_M(d) = k \cdot d$ [22], where d is the moving distance and $k = 2$ J/m if the ME moves at optimal speed. For typical low-power transceivers such as CC2420, the energy consumed in wireless communication, denoted by $E_C(d)$, can be modeled as $E_C(d) = m \cdot (a + b \cdot d^2)$ [23], where d is the transmission distance, m is the number of bits transmitted, and a and b are constants. a and b can be set to be 0.6×10^{-7} J/bit and 4×10^{-10} J/m$^2 \cdot$ bit according to the experiments in [23]. The power consumption of an idle node is set to be 21 mW, which is consistent with that of the TelosB mote [24]. We assume that a node stays asleep when it is outside of the communication range of the ME during the localization phase. Moreover, we ignore the power consumption of a sleeping node, as it is much less than the idle state power consumption. For instance, a TelosB mote consumes 1 μW in sleep mode [24].

In our line-by-line case, the energy consumed in wireless communication by the ME is $E_c(R_i) = m\cdot(a+b\cdot R_i^2)\cdot\frac{2hl}{3r_d^2}(J)$, the energy consumed in locomotion by the ME is $E_m(d) = 2\left(\frac{hl}{\sqrt{3}r_d} - \sqrt{3}r_d\right)(J)$, and the average power consumption of sensors in the ME radio coverage area is $E_s = 21 \cdot N_s(mW)$, where N_s is the average number of sensors in the ME radio coverage. Therefore, $N_s = \rho \cdot \pi R_i^2 = \frac{N\pi R_i^2}{A}$, where N is the total number of sensors and A is the total area of the network.

For the method of [16], if it adopts the dense-straight-line (DSL) movement pattern and the broadcasting interval of the beacon is 0.25 meters, the energy consumed in wireless communication of their method is $E_c = m\cdot(a+b\cdot R_i^2)(\frac{hl}{4R_i^2} + \frac{h}{2R_i})\cdot 4(J)$, the energy consumed in locomotion by the mobile beacon is $E_m = 2\left[(l+2R_i)\cdot(\frac{h}{2R_i}+1)+h\right](J)$, and the power consumption of sensors in the ME radio coverage area is $E_s = 21 \cdot N_s(mW)$.

By setting $\phi = \frac{2\pi}{3}$ and $R_i = 45\ m$, we have the following conclusion. The energy consumed in wireless communication by the ME in our approach is slightly smaller than that of the method in [16]. However, the energy consumed in locomotion of the ME in our method is significantly smaller than that of the method in [16]. The power consumption of idle sensors is almost the same for both methods.

IV. Numerical Results

In this section, simulation results are presented and analyzed. We consider a 2-dimensional region with a size of 100 m x 100 m. We assume the ME has two level transmission power with the transmission radii r and $R = 2r$, respectively. First, we deploy 100 sensor nodes randomly and the transmission radius r is set to 15 meters. All simulation results are averaged over 100 network scenarios. The average localization error is used to evaluate the performance for our localization algorithm. The average localization error is defined as follows:

$$error = \frac{1}{N}\sum_{i=1}^{N}\|x_i - \hat{x}_i\| \times \frac{1}{r},$$

where x_i is the actual position for node i, N is the number of unknown-position sensor nodes and $\hat{x}_i$ is the estimated position of node i.

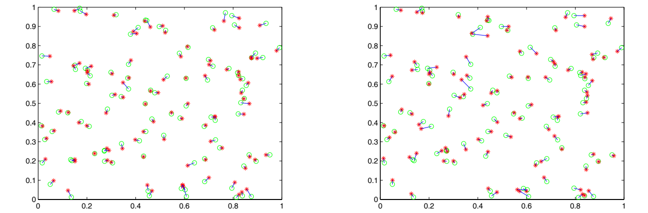
A. Performance in the Ideal Environment

In this subsection, we give the simulation results for different algorithms in the ideal situation, namely, there is no obstacle in the sensing area. We use the degree of irregularity (DOI) to indicate the radio irregularity characteristic. Its value denotes the maximum range variation per unit degree change in the direction of radio propagation. Similarly to [16], we formally define the DOI model as follows: $DOI\ Adjusted\ Path\ Loss = Path\ Loss * (1 \pm Rand \times DOI)$. Fig. 6(a) and 6(b) show the simulation results in this ideal situation, where the true nodes are denoted by circles, the position estimates are denoted by asterisks, and the lines that link the true nodes and the estimates represent the estimation errors. It is clear from Fig. 6(a) and 6(b) that our algorithm works better than the algorithm of [16] in terms of the average localization error.

In practical environments, the actual transmission radius varies in different directions of radio propagation because of the non-isotropic properties of the propagation medium and the heterogeneous properties of devices. In this experiment, we investigate the impact of irregular radio patterns on the precision of our proposed localization algorithm. Similarly to [16], we use a random value to denote the variance of path loss, and this random value follows a Weibull distribution. The parameter DOI determines the maximum variance. Using this DOI model, we not only obtain the property that the variance of path loss is distinct in every direction but also show that pass losses in the same direction may be varying due to the dynamic environment. As shown in Fig. 7(a), the localization accuracy of our algorithm decreases as the DOI increases. When the DOI is smaller than 0.1, the localization error varies slightly. Fig. 7(a) indicates that our method outperforms the method of [16] in terms of the average localization error with the various values of DOI. We evaluate the localization accuracy of our localization algorithm in both the proposed and random movement strategies for different values of DOI. Fig. 7(b) indicates that our localization algorithm using the proposed movement strategy outperforms that using the random movement strategy.

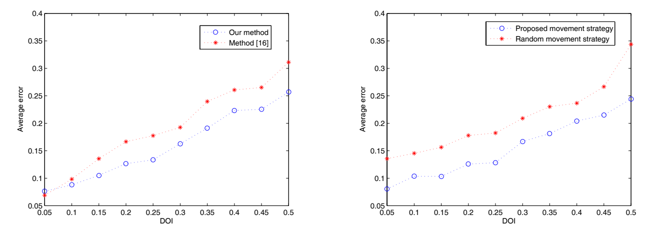
B. Performance in the Non-ideal Environment

For the next set of experiments, we use a channel fading model to indicate the effect of obstacles on localization accuracy. Herein, we use a fading coefficient *(f)* that represents the percentage of total mobile beacon points that cannot be heard by the sensor at any given time. This models obstacles encountered in the sensing area that limit the number of mobile beacon points that can be heard at any point. As Fig. 8(a) and 8(b) illustrate, our algorithm outperforms the algorithm of [16] in terms of the average localization error in this non-ideal environment.



(a) (b)

Fig. 6. Performance comparison: (a) Localization error of our method (DOI=0.2, error = 11.68%); (b) Localization error of method [16] (DOI=0.2, error = 13.7%).



(a) (b)

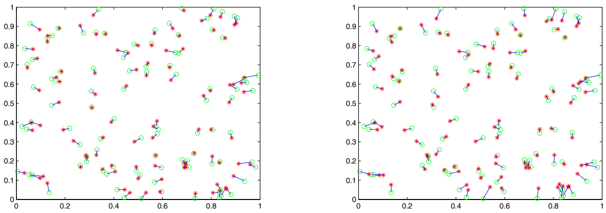
Fig. 7. Performance comparison: (a) The average localization error vs. DOI; (b) Impact of movement strategy.

C. Performance Comparison with a Range-based Method

In this section, we employ the range-based localization algorithm in [19] as the baseline. Fig. 9(a) and 9(b) show the localization results obtained by our method and the baseline algorithm, respectively, in the ideal environment without an obstacle. We can see from these two figures that our method outperforms the baseline algorithm in terms of average localization error. Specifically, the average localization errors are 12.03% and 18.68%, respectively. Note that the settings of our method can be configured to meet any required localization error as discussed in section III.A. However, the baseline algorithm can only achieve a specific localization error that depends on the range estimation error of the ME. Therefore, our method outperforms the baseline method.

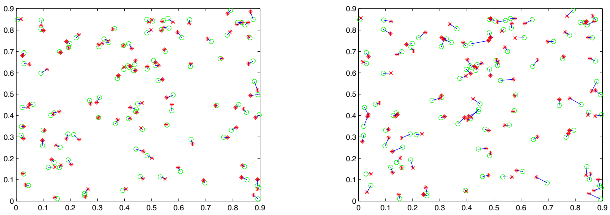
V. Conclusions

We have presented a new cooperative localization scheme that can achieve high localization accuracy in mobility-assisted wireless sensor networks when obstacles exist. Considering the complex localization scenario, namely, the feasible set is empty, a convex localization algorithm has been presented to address the effects of non-ideal transmission of radio signals. We have developed an optimal movement schedule for MEs that can achieve a shortest path under expected localization accuracy. It has been shown via the simulation results that the proposed cooperative localization scheme can achieve high localization accuracy by including a mobile element. In future



(a) (b)

Fig. 8. Performance comparison in the non-ideal environment: (a) Localization error of our method (DOI=0.25, f=0.1, error = 17.07%); (b) Localization error of method [16] (DOI=0.25, f=0.1, error = 19.34%).



(a) (b)

Fig. 9. Performance comparison with a range-based method: (a) Localization error of our method (DOI=0.25, error = 12.03%); (b) Localization error of method [19] (DOI=0.25, error = 18.68%).

work, we intend to verify and improve the proposed cooperative localization scheme using real sensors in a mobility-assisted wireless sensor network. We will extend our work to address other limited mobility models of MEs, such as the straight-line mobility model of the XYZ mobile sensor [25]. Using distributed space-time-codes [15] to reduce the impact of channel fading on the cooperative localization algorithm is also an important issue to be considered in the future.

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