Optimizing Event-Driven Localization

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***Abstract*—Sensor node localization is a challenging task because of severe constraints on cost, energy, and effective range of sensor devices. To overcome limitations in existing solutions, this paper formally describes, designs, implements, and evaluates a Convex Optimization-based Method for Event-Driven Localization, i.e., COMEDL, in large-scale wireless sensor networks. The key idea behind COMEDL is to estimate the two-dimensional location coordinates of sensor nodes by processing multiple one-dimensional node sequences that can be easily obtained via loosely guided localization event distributions. The proposed design is evaluated through theoretical analysis, extensive simulations, and physical experiments (an indoor test-bed with 44 MICAz sensor nodes). Evaluation results demonstrate that COMEDL can effectively localize nodes with improved accuracy and flexibility.**

***Keywords*-Sensor Node Localization; Convex Optimization; Linear Programming**

I. Introduction

Wireless sensor network (WSN) has important military and civil applications such as remote environmental monitoring and target tracking. The location information of each sensor node is critical for many applications because users need to know not only what happened but also where interested events happened. Besides, some routing protocols and target tracking methods are based on the geographic parameters of sensor nodes. However, sensor node localization remains one of the challenging problems due to requirements for low cost, tiny size and high energy efficiency at the sensor node side.

Over the years, many methods have been proposed for dealing with node localization in sensor networks. Indeed, most of the previous works on the sensor network node localization problem fall into two categories: (i) range-based localization [1]–[7], and (ii) range-free localization [8]–[11]. Range-based localization approaches are built on top of distance or angle measurements among sensor nodes. These approaches can provide good accuracy performance, however, generally require costly hardware and have limited effective range due to energy constraints. The requirement of low cost and power prohibits many range-based methods for sensor node localization, especially for large-scale deployments. On the contrary, range-free approaches localize a node based only on simple sensing results such as network connectivity (proximity) information to the anchor nodes. However, methods in this category normally have low accuracy, highly depending on the density and distribution of anchor nodes. Moreover, since wireless connectivity is highly influenced by environments and hardware calibration, existing solutions require substantial environment survey and calibration on a case-by-case basis.

To overcome the problems of traditional range-free methods, event-driven localization methods provide novel solutions to sensor node localization using the external events, such as straight-line scans and sound wave propagation, which propagate across the area where sensor networks are deployed [12]–[14]. Since sensor nodes only need to detect the events and report the time of arrival (TOA), event-driven localization methods can apply an asymmetric system architecture which significantly reduces the cost and energy consumption at the resource constrained sensor node side. In this paper, we present a Convex Optimization-based Event-Driven Localization (COMEDL) method to estimate each sensor nodes' locations by processing multiple one-dimensional node sequences. As a range-free approach, this design applies node sequences instead of direct distance or TOA measurements for localization, and brings in the following two advantages: (i) node sequences features better robustness to the measurement noise; (ii) node sequences significantly alleviates the accuracy requirement of network-level time synchronization.

Compared with earlier works on node localization in sensor networks (e.g. MSP [15], [16]), the primary contribution of this article is providing an effective and optimal approach to solve the event-driven localization problem for sensor networks. The proposed COMEDL system formulates the sensor node localization as an convex optimization problem of finding a feasible solution to a system of multiple linear inequalities, which is produced by multiple node sequences. Then, linear programming (LP) can be applied to reliably and efficiently deal with the convex optimization problem, even in large-scale sensor networks. The proposed design is evaluated with both test-bed experiments and extensive simulations. Evaluation results show that the proposed COMEDL system can provide improved node localization accuracy.

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II. System Overview

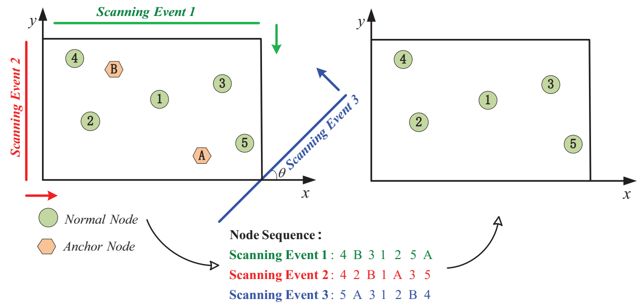

Figure 1. The COMEDL system overview

For the sake of clarity, straight-line scan is used in the following sections as the example localization event. hexagons to denote anchor nodes with known locations. Fig. 1 shows a layout of a sensor network with anchor nodes and target nodes. We use numbered circles to denote target nodes to be localized and numbered hexagons to denote anchor nodes with known locations An example event-driven localization system uses a straight-line light beam to scan the area along different directions, and each scan is treated as a localization event. Briefly, such an event-driven localization system works as follows. As an event propagates, sensor nodes detect the event sequentially at different time instances that naturally gives an ordering of related nodes, called a node sequence. For instance, in Fig. 1, a top-down scan (i.e. Event 1) generates node sequence (4 B 3 1 2 5 A); for Event 2, the node sequence (4 2 B 1 A 3 5) is obtained after a left-right scan; Event 3 generates node sequence (5 A 3 1 2 B 4) as shown outside the right boundary of the area in Fig. 1. Relative position information along the event propagation direction is embedded within the node sequence. By collecting all sensing results, locations of target nodes can be estimated by processing those node sequences [12].

Specifically, as shown in Figure 2, the node sequence (2 C 1 B A) can be obtained by time of arrival (TOA) information of the event. Moreover, the TOA sequence $t_2 < t_C < t_1 < t_B < t_A$ is determined by the distance sequence $d_2 < d_C < d_1 < d_B < d_A$ from each node to the scanning starting-line l. Therefore, we state the following problem:

Problem 1: Assume that the location of sensor nodes are known, the node sequence can be obtained by the distances from nodes to the starting line.

Event-driven localization can be considered as an inverse problem of Problem 1, and described as:

Problem 2: Assume that multiple node sequences obtained by the multiple event are known, estimate the location of nodes.

In practice, solving the inverse problem is extremely difficult. In prior research, MSP estimated the location of nodes roughly by using a geometric method with heavy computation. While in this paper, we carefully formulate Problem 2 as a convex optimization issue and propose an efficient solution which can provide the optimal localization results without significant overhead. To the best of our knowledge, this is the first work to leverage convex optimization for solving event-driven localization problems in sensor networks.

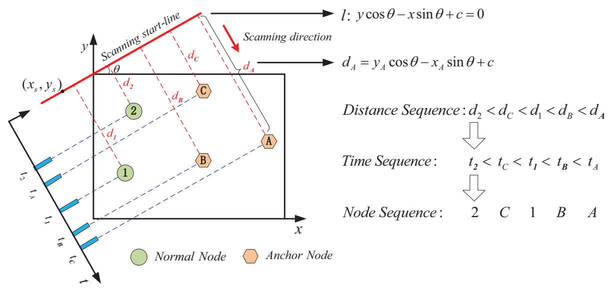

Figure 2. Relationship between distances and node sequences.

III. Design

This section provides the design of the proposed COMEDL localization method. A basic COMEDL is provided in the subsection A. After that, we consider the design of COMEDL with uncontrolled events in the subsection B.

A. Basic COMEDL

Considering a sensor network in the 2D space with N nodes, the set of all nodes is $S = \{node_1, \cdots, node_i, \cdots, node_N\}$, where any node $node_i$ has its location coordinates denoted as $[x_i, y_i]$. The first M nodes make up the set A of anchors, the remaining $N - M$ nodes make up the set T of target nodes, and $S = A \cup T$.

As showed in in Figure 2, given an external event occurred at $X_s = [x_s, y_s]$, with the scanning angle θ, the scanning start-line l can be defined as

$$y\cos\theta - x\sin\theta + c = 0 \tag{1}$$

where c is a constant related to X_s and θ.

In the Cartesian coordinate systems, the distance d_i from $node_i$ to the scanning start-line l is given by

$$d_i = y_i\cos\theta - x_i\sin\theta + c \tag{2}$$

The node sequence is determined by the distances from nodes to the scanning start-line. Given the following node sequence $NodeSeq(\cdots, i, j, \cdots)$, $d_i < d_j$ can be inferred. According to (2), we have the following inequality:

$$y_i\cos\theta - x_i\sin\theta < y_j\cos\theta - x_j\sin\theta; \;\; i,j \in S \tag{3}$$

Given multiple node sequences from T scans with different scanning angles, we can get $T(N-1)$ linear constraints if only the relation of two adjacent nodes is considered. The locations of nodes can be computed by solving the following linear feasibility problem:

$$y_i\cos\theta - x_i\sin\theta + \varepsilon \le y_j\cos\theta - x_j\sin\theta; \;\; i,j \in S \tag{4}$$

where $\varepsilon > 0$. The problem of finding a feasible solution to a system of linear inequalities is a linear programming problem in which the objective function is the zero [17]. We can find a solution to this feasibility program only if there is an embedding satisfying all of the constraints. Describing the problem of sensor node localization in the standard form of linear programming as

$$\hat{X} = \min c^T X \tag{5}$$

$$\begin{aligned} s.t.\ A_{IEQU} X &\leq b_{IEQU} \\ A_{EQU} X &= b_{EQU} \\ 0 \leq X &\leq G_{\max} \end{aligned}$$

where c is zero vector. We use the location information of anchor node to get the equality constraint, and utilize the nodes sequences to set the inequality constraint. The bound constraint in the linear programming problem is set based on the size of the network deployment area.

To summarize, the basic COMEDL is presented in Algorithm 1. The input is multiple node sequences $NodeSeqs$, the scanning angles, and anchor locations; the output is the locations of target nodes. Step 1 sets the objective function of the optimization problem. Step 2 uses the anchor information to get the equality constraint. Each node sequence is processed at step 3 to get the inequality constraint. For each sequence, two adjacent nodes are used to construct an inequality constraint. After processing all sequences, Step 4 solves the LP problem to get the location of target nodes.

Algorithm 1 Basic COMEDL

Input: Multiple node sequences $NodeSeqs$
Scanning angles
Anchor locations
Output: Location of target nodes
1: Objective function : setting c = **0;**
2: Equality constraint: setting A_{IEQU} and b_{IEQU} according to the location of anchor nodes;
3: Inequality constraint: setting A_{EQU} and b_{EQU} according to the node sequence;
4: **repeat**
5: GetOneUnprocessedSeqence();
6: **repeat**
7: i = GetOneNodeFromSequenceInOrder();
8: j = GetNextNodeFromSequenceInOrder();
9: According to inequality (4) to get inequality constraint;
10: **until** All the nodes in the sequence are processed ;
11: **until** All the node sequences are processed;
12: Solve LP problem to get the location of target nodes;

B. COMEDL with Uncontrolled Events

Basic COMEDL method get the accurate localization with the given angle of each scanning event. In practical systems, the scanning angle of event could be costly to control. Localization using uncontrolled events allows the use of much simplified event generation mechanisms or even natural events, which makes the system flexible and convenient to work with. In this Section, we consider the design of COMEDL with uncontrolled events. The basic idea is to estimate the generation parameters of uncontrolled events with a small number of anchor nodes in the field, and then estimate the possible location area of each normal node according to its ranking in node sequences obtained from the event detections.

1) Scanning Angles Estimation: By utilizing the ordered anchors in the node sequence, event generation parameters, i.e., the scanning angle can be estimated. Rewrite the inequality constraint (3) as

$$(y_i - y_j)\cos\theta - (x_i - x_j)\sin\theta < 0;\ i, j \in A \tag{6}$$

We use the inequality constraint to find a feasible solution to the scanning angle estimation. the scanning angle is in the range of $(-\pi/2, \pi/2)$, and $tan\theta$ is set as the variable α. The scanning angle estimation is formulated as the following convex optimization problem with linear constraint

$$\begin{aligned} &\min_{\alpha}\ 0 \\ &s.t.\ (y_i - y_j) - (x_i - x_j)\alpha < 0;\ i, j \in A \end{aligned} \tag{7}$$

Algorithm 2 depicts the computing architecture of scanning angles estimation. The input is multiple node sequence NodeSeqs and anchor locations, the output is the scanning angles of events. Step 1 sets the objective function of the optimization problem. Step 2 uses the anchors information to get the inequality constraint. Step 3 solves the LP problem and the scanning angles of events is estimated in Step 4.

Algorithm 2 Scanning angle estimation

Input: Multiple node sequences: $NodeSeqs$
Anchor locations
Output: Estimated scanning angles
1: **repeat**
2: GetOneUnprocessedSeqence();
3: Set objective function: $c = 0$;
4: Construct the inequality constraint;
5: **repeat**
6: i = GetAnchorNodeFromSequence();
7: j = GetNextAnchorNodeFromSequence();
8: Set A_{IEQU} and b_{IEQU} by inequality (6);
9: **until** All the nodes in the sequence are processed;
10: Solve the optimization problem to get α ;
11: Estimate the scanning angle: $\hat{\theta} = \arctan(\alpha)$;
12: **until** All the node sequences are processed;

2) Node Localization : With estimated scanning angles given by Algorithm 2, cooperating with the COMEDL method proposed in Algorithm 1, this section provides a general computation architecture for uncontrolled event based sensor node localization.

Algorithm 3 depicts overall system design of COMEDL with uncontrolled events. The input is the node sequences obtained from uncontrolled events detections, and the output is the estimated location coordinates of target nodes. Firstly, Algorithm 2 is adopted to estimate event generation parameter; then utilize Algorithm 1 to determine the location of each target node.

Algorithm 3 COMEDL with uncontrolled events

Input: Multiple node sequences: $NodeSeqs$

Output: Estimated location of target nodes

1: Estimate scanning angles using the anchors sequence and anchor locations:

$\hat{\theta}$ =**Algorithm 2** ($NodeSeqs$, $Anchor$);

2: Compute the location of each node with the estimated scanning angles:

S = **Algorithm 1** ($NodeSeqs$, $\hat{\theta}$, $Anchor$);

IV. DISCUSSION ON PRACTICAL ISSUES

For the sake of presentation, until now we have described COMEDL in an ideal case where a complete and perfect node sequence can be obtained. In this section, we describe how to make COMEDL work well under more realistic conditions firstly. Then, the computational complexity analysis of COMEDL is given.

A. COMEDL with Error Tolerance

In the practical application, if two nodes are located too close to each other along the direction of event propagation, they detect the scan almost simultaneously. In this case, the node ordering in the sequence may occur flip. For instance, the true sequence is $NodeSeq(\cdots, i, j, \cdots)$, but the detected sequence is $NodeSeq(\cdots, j, i, \cdots)$. Algorithm 1 can find a solution to this feasibility program only if there is an embedding satisfying all of the constraints. However, it is impossible to find a feasible solution that satisfies all of the constraints when sequence flip occurs. In this section, we propose the solution to address the problem of sequence flip using convex relaxation techniques.

We thus introduce a slack variable ξ_{ij} for each inequality constraint to allow for inequality violations. As a result, event-driven localization in sensor networks can be formulated as a convex optimization problem with linear inequalities constraints as follows:

$$\min_{x_i, y_i} \sum_{(i,j)\in X} \xi_{ij}; \ \xi_{ij} \geq 0 \tag{8}$$

$$s.t. \ -\sin\theta x_i + \cos\theta y_i + \sin\theta x_j - \cos\theta y_j - \xi_{ij} \leq -\varepsilon$$

where the objective function of optimization problem is the total amount of all slacks.

B. COMEDL for Wave Propagation Event

So far, the COMEDL method is described only in the context of straight-line scanning event. In fact, our proposed methods in this article are conceptually independent of specific type of events, as long as node sequences can be obtained. This section gives a brief explanation for wave propagation based events (e.g., sound propagation). Without losing generality, the assumption is made that wave propagates uniformly in all directions and thus it has a circle frontier surface, as shown in Fig. 3.

The distance between each node and the event source determines the rank of the node in the corresponding node sequence. For instance, given a node sequence $NodeSeq(\cdots, i, j, \cdots)$, we can get $d_{i,s} < d_{j,s}$ as

$$(x_i - x_s)^2 + (y_i - y_s)^2 + \varepsilon \leq (x_j - x_s)^2 + (y_j - y_s)^2 \tag{9}$$

We apply this constraint to formulate localization with circular wave-front events in the framework of the COMEDL design.

1) Event Source Localization: when the event parameter (e.g., location of event source) is unknown, we can utilize the inequality constraint (9) to estimate the event source location coordinates. Rewrite (9) as

$$2(x_j - x_i)x_s + 2(y_j - y_i)y_s \leq -x_i^2 - y_i^2 + x_j^2 + y_j^2 - \varepsilon \tag{10}$$

Then, we can use the inequality constraint (10) to set A_{IEQU} and b_{IEQU} in Algorithm 2 to estimate the location of event source.

2) Node Localization: once the event parameter (e.g., the source location) is estimated, the location of each node is estimated by using multiple inequality constraint (9). Finding a feasible solution to the system is a nonconvex quadratically constrained programming problem. In this section, we utilize semi-definite programming method to deal with the optimization problem.

Let $K = SS^T$, we relax product terms to an element $k_{i,j}$ of matrix K . Define $\tilde{K} = [\ 1 \quad S^T; \quad S \quad K\ ]$, rewrite the quadratic inequality constraint (9) as

$$x_i^2 + y_i^2 - 2x_s x_i - 2y_s y_i - x_j^2 - y_j^2 + 2x_s x_j + 2y_s y_j \leq -\varepsilon \tag{11}$$

The quadratic constraint can be presented in the form of $Trace(A\tilde{K}) \leq 0$. Then, COMEDL for wave propagation

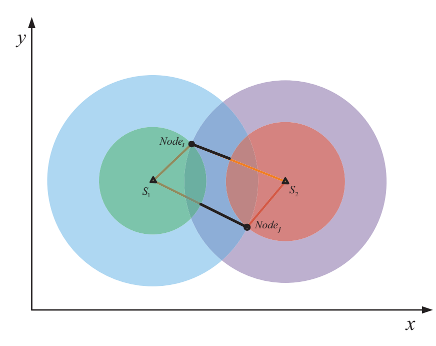

Figure 3. COMEDL for wave propagation

can be written in the following semi-definite programming form:

$$\min_{\tilde{D}} \sum \xi_{ij} + \lambda Trace(\tilde{K}); \quad \xi_{ij} \geq 0, \qquad \tilde{K} \geq 0$$
$$s.t. \quad x_i^2 + y_i^2 - 2x_{s1}x_i - 2y_{s1}y_i + \varepsilon - \xi_{ij} \leq x_j^2 + y_j^2 - 2x_{s1}x_j - 2y_{s1}y_j \tag{12}$$

C. Complexity Analysis

This section provides the complexity analysis for the proposed COMEDL design. It needs to be emphasized that COMEDL itself adopts an asymmetric design in which sensor nodes need only to detect and report the events. Therefore, we only analyze the computational cost on the node sequence processing side, where resources are plentiful.

The number of linear constraints is $T(N-1)$ in COMEDL, where N is the number of nodes, and T is scanning event times. The complexity of low dimensional linear programming with L constraints is $O(L)$ [18]. Thus, the overall computation complexity of COMEDL can be written as $O(T \cdot N)$.

V. EVALUATION

COMEDL is evaluated with both extensive simulation and test-bed experiments with 44 MICAz motes using straight-line light scan as localization events. We have also compared its performance with that of MSP [12].

A. System Evaluation

In this section, we report system implementation of our design on a physical test-bed called Mirage, a large indoor test-bed that can support up to 360 nodes. The whole test-bed is composed of six 4-feet by 8-feet boards. Figure 1 shows a snapshot of an optical straight-line scanning event generated by projectors of our Mirage test-bed. We use three high-end HITACHI CP-X1250 projectors, connected through a MATROX Triplehead2go graphics expansion box, to create an ultra-wide integrated display on six boards. In our evaluation, totally 44 MICAz motes were mounted on the test-bed. We have generated straight-line scan at scanning line speed of 4.3 feet/s on Mirage test-bed. The localization performance is evaluated by root mean square error (RMSE) in feet.

Impact of number of anchors: we randomly selected 24 nodes to be target nodes. The number of anchor nodes varies from 3 to 21 in steps of 2 with 10 scans. In Fig. 4, with the increasing number of anchors, localization error drops significantly. With 3 anchors we can achieve accuracy as low as 0.6 feet, which is nearly a 40% improvement than MSP.

Impact of number of target nodes: Fig. 5 show that the root mean square error of our method With 5 anchors and 10 scans. The number of target nodes varies from 10 to 40

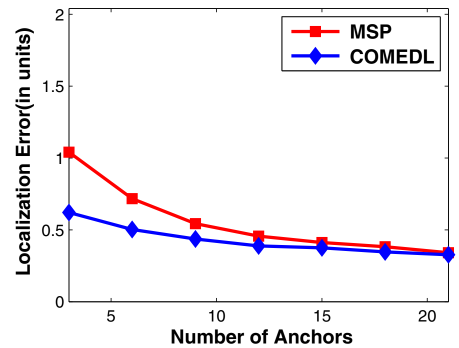

Figure 4. Average error vs. Number of anchors

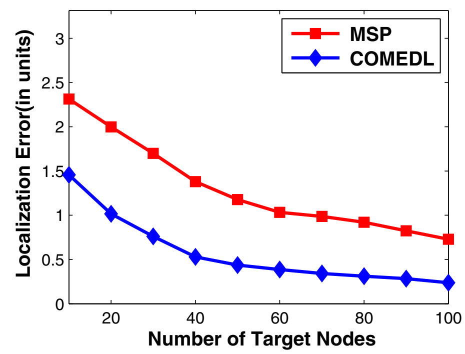

Figure 5. Average error vs. Number of target nodes

in steps of 5. With the increasing number of target node, localization error drops slightly. We can achieve accuracy as low as 0.62 feet With 40 target nodes, which is nearly a 60% improvement.

Impact of number of events: we selected 40 nodes to be target nodes. The number of event varies from 5 to 10 with 4 anchors. Similarly, with increasing number of scans, localization error drops significantly as well for COMEDL and MSP. We can observe that the proposed COMEDL method can obtain about a 60% performance gain when we increase the number of scans from 5 to 10 in Fig. 6. With 5 scans we can achieve accuracy as low as 1.64 feet, which is nearly a 45% improvement than MSP.

Impact of error tolerance: In this experiment, we show the effects of protection band on the localization accuracy. The protection band of 0.35 feet MSP. Fig. 7 shows clearly that our method achieves better performance: with 5 anchors, our method achieves 0.32 feet accuracy that is nearly 33% more accurate than MSP.

System performance with known scanning angle: Fig. 8 and Fig. 9 depict the results of node localization with 3 anchors and 30 target nodes. The number of scanning events is 10, and the scanning angle is known. In MSP, the whole area is modeled as a 240∗80 grid map since the test-bed has a size of 24 feet by 8 feet. In the figures, red squares stand for anchor nodes, and blue circles are the target nodes. An arrow origins from the real position of each target node and

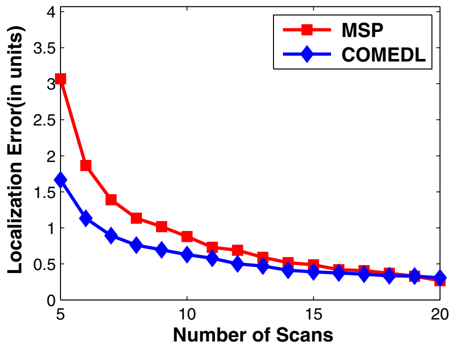

Figure 6. Average error vs. Scanning times

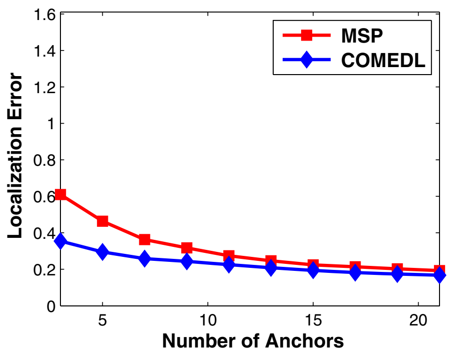

Figure 7. COMEDL vs. MSP with error tolerance

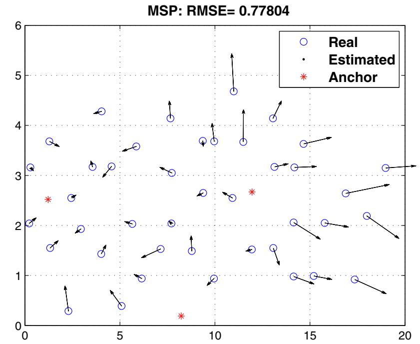

Figure 8. Test-bed localization result of MSP

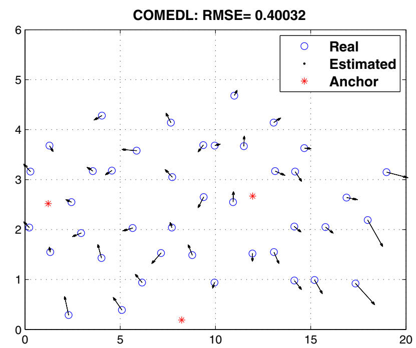

Figure 9. Test-bed localization result of the proposed COMEDL

points to its estimated location. From Fig. 8 and Fig. 9, we can see that our method successfully accomplished sensor node localization with less location error.

System performance with uncontrolled events: In this experiment, we show the performance using 10 uncontrolled events. The number of anchors and target nodes is 10 and 34 respectively. From Fig. 10 and Fig. 11, we can see that our method successfully accomplished sensor node localization with less location error than MSP.

Summary: The system evaluation in this subsections shows that our method can achieve sensor node localization with controlled/uncontrolled localization events.

B. Simulation Evaluation

In order to evaluate the performance of COMEDL in scale, extensive simulations have been carried out. In the simulation, all anchor nodes and target nodes are deployed randomly with uniform distribution. All the simulations are based on the straight-line scan example and every event is generated with angles rotating uniformly from -90 degree to 90 degree. Table 1 illustrates the default simulation setup parameters. We intend to illustrate the impact of the number of anchors, the number of scans, and the target nodes density(the number of target nodes in a fixed-size region) on the localization error.

1) Performance of the basic COMEDL Method: **Impact of the number of anchors:** In this experiment, we use different number of anchors from 3 to 21 in steps of 3. As shown in Fig. 12, the RMSE of our method is much smaller than that of MSP, especially when there is a limited number of anchors in the system. For example, for 3 anchors, the errors were almost halved by using COMEDL. As the number of anchor nodes increases, the performance gap between our method and MSP lessens.

Impact of the number of target nodes: In this experiment, we compare our method with MSP under different number of scans from 10 to 100 in steps of 10. Fig. 13 demonstrates that the RMSE of our method is smaller than

Table I
DEFAULT CONFIGURATION PARAMETER

Parameter	Description
Field Area	100×100
Number of Anchors	3 (Default)
Number of Target Nodes	50 (Default)
Scanning Times	6 (Default)
Scanning Type	Regular (Default)
Monte Carlo Simulation	50 times
Error Statistics	RMSE

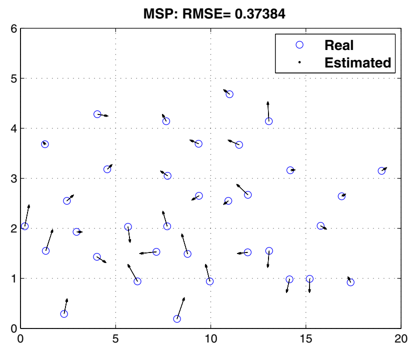

Figure 10. Localization result of MSP with uncontrolled events

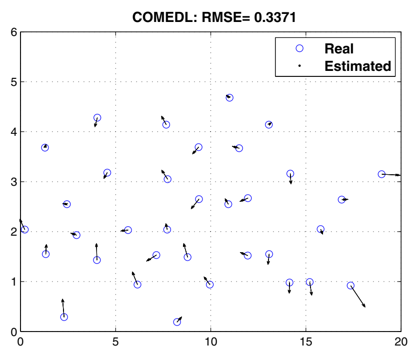

Figure 11. Localization result of COMEDL with uncontrolled events

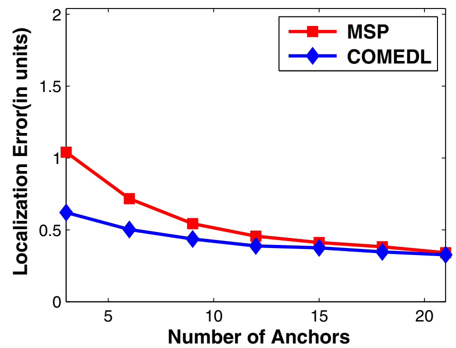

Figure 12. Average error vs. Number of anchors

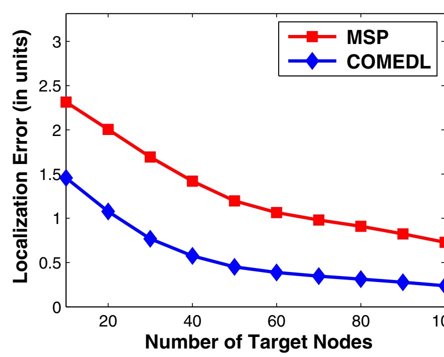

Figure 13. Average error vs. Number of target nodes

that of MSP. Since our method MSP makes use of the order information among target nodes in sequence, more nodes contributes to the overall system accuracy. As a result, with increasing number of target nodes, localization error decreases in our method.

Impact of the number of scans: In this experiment, we compare our method with MSP under different number of scans from 5 to 20 in steps of 1. Fig. 14 indicates significant performance improvement in our method over MSP across all scanning settings, especially when the number of scans is small. For example, when the number of scans is 6, errors in our method are only about 30% of that of MSP. Since our method makes use of the order information among target nodes in sequence, more scans contributes to the overall system accuracy. We conclude that our method performs extremely well when there are many scanning events.

Summary: From these experiments, we conclude that our optimization-based method can improve localization accuracy, especially when we have limited events or few anchor nodes.

2) Performance of COMEDL with Uncontrolled Events:

Impact of number of anchors: In this experiment, we evaluate the scanning angle estimation and localization error under a different number of anchors from 3 to 20. The number of scans is 6 and the number of target nodes is 50 by default. Firstly, according to Algorithm 2, only the anchor nodes contribute to the event generation parameter estimation. Thus, we expect that with more anchor nodes, more accurate estimation for the event generation parameter should be achieved. Fig. 15 shows the RMSE result of the scanning angle estimation in degrees. This means that with more anchors, more accurate scanning angle estimation can be achieved. Fig. 16 shows the result of the node localization. With more anchor nodes, localization error gets reduced significantly. Actually, more anchor nodes provide more inequality constraints, thus further benefits the localization accuracy.

Impact of number of target nodes: In this experiment, we investigated the impact of the number of events. The system is set up with 10 anchors and 6 scans respectively. Fig. 17 shows that with increasing number of target nodes, the location error of COMEML gets reduced with less location error than MSP.

Impact of number of events: In this experiment, we investigated the impact of number of events on the localization performance. The system is set up with 10 anchors and 50 target nodes respectively. With more events, each target node has more linear constraints, thus smaller location error is possible to be obtained. Fig. 18 confirms this analysis. With increasing the number of generated events, the system error

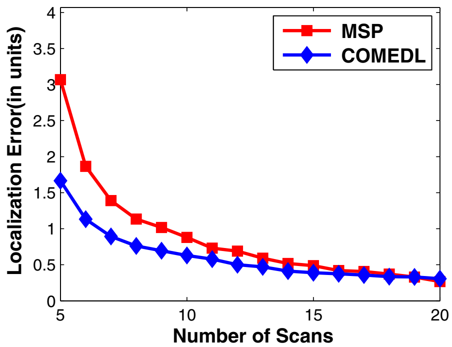

Figure 14. Average error vs. Number of scanning times

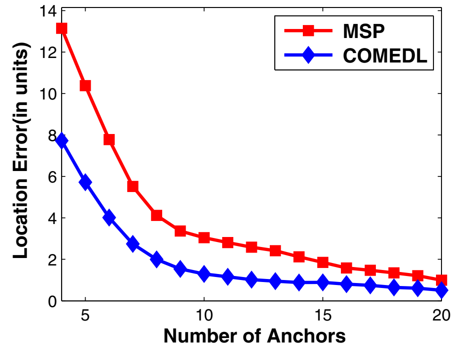

Figure 16. Location error vs. Number of anchors

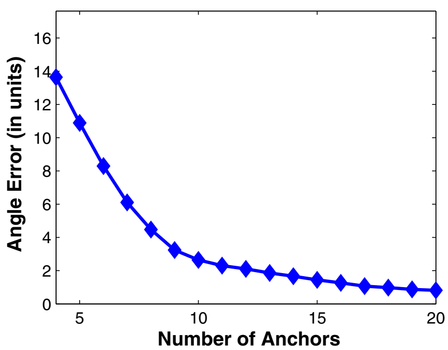

Figure 15. Angle error vs. Number of anchors

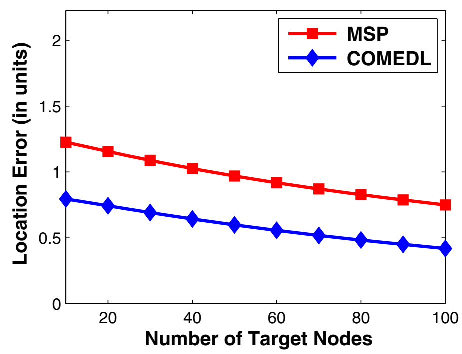

Figure 17. Location error vs. Number of target nodes

also gets reduced. We notice from this figure that both using more anchors and accumulating more localization events can improve the system localization performance.

Summary: The simulation in this subsections shows that the proposed COMEDL system can also achieve sensor node localization with uncontrolled localization events and bring in improved accuracy performance.

VI. RELATED WORK

Many methods have been proposed to localize sensor nodes in wireless sensor networks. Most of these can be classified into two categories: range-based localization and range-free localization. Range-based localization is based on fine-grained point-to-point distance or angle measurements among nodes in the network to identify per-node location [1]–[7]. Most works in this category can achieve good accuracy, but are costly for requiring per-node ranging hardware or careful in-field calibration and environment profiling. Limitations on the cost, energy and hardware footprint of individual sensor node make most of the range-based methods undesirable for massive deployment. In addition, ranging signals generated by sensor nodes have a very limited effective range because of energy and form factor concerns. Range-free methods don't need to estimate or meter accurate distances or angles [8]–[11]among nodes in the network. Instead, the coordinates of a node is determined by its proximity to anchor nodes whose location information are known. Range-free localization features low system cost but less accuracy, depending on the density and distribution of anchor nodes.

Realizing the impracticality of existing solutions for large-scale outdoor environment, event-driven sensor network localization methods have been proposed for wireless senor networks to address these limitations in current node localization approaches [12]–[14]. Lighthouse [12], SpotLight [13] and indoor experiments using laser events [14] provide us with examples for achieving good localization accuracy without any anchor using the spatio-temporal correlation of controlled events (i.e., inferring the location of a node based on its detection time of controlled events). Given event detection time at each sensor node, centralized localization engine could map the detection time to the position of the corresponding node. These solutions demonstrate that long range and highly accurate localization can be achieved simultaneously with little additional cost at sensor nodes. These benefits, however, come along with an implicit assumption that localization events can be precisely controlled and distributed to a specified location at a specified time. Although asymmetric system architecture shifts the resource cost from the sensor nodes to the event generation device, which significantly brings down the overall system cost, accurate control of localization event distribution could be

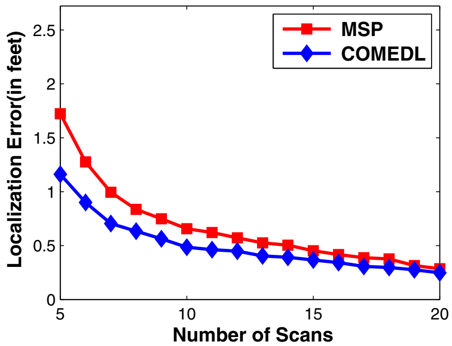

Figure 18. Location error vs. Number of scanning times

difficult, costly or time consuming to achieve for large area outdoor scenarios. In Spotlight system, the event distribution needs to be precise in both time and space domains. However, precise event distribution is difficult to achieve without careful calibration.

There exist some works for the localization problem in sensor networks using convex optimization. Biswas and Ye proposed semi-definite programming methods for the localization problem in sensor networks [19]. Specially, in order to handle larger-sized localization problems, the second-order cone programming (SOCP) relaxation was studied in [20], [21]. However, these methods based on convex optimization using distance or TDOA as the range measurements, are sensitive to the background noise. In this paper, we use convex optimization-based methods to deal with the event-driven localization problem. The purpose of using convex optimization is to compute an accurate solution of the localization problem. One approach closely related to ours is described in [22] wherein the proximity constraints between nodes which are within 'hearing distance' of each other are modeled as convex constraints, then a feasibility problem can be solved by efficient convex programming techniques. If the feasible region is bounded, an optimal basic feasible solution is also an optimal solution. To our knowledge, the proposed COMEDL method is the first time to estimate node location by node sequences within convex optimization framework.

VII. Conclusions

In this paper, we have proposed a convex optimization-based method for event-driven localization in wireless sensor networks. The proposed COMEDL design formulates the problem of event-driven localization as a linear programming task, and then the optimal solution can be obtained for node location estimation. COMEDL is verified and evaluated through analysis, extensive simulation as well as the test-bed experimentation. Our test results have shown that the proposed method can effectively estimate nodes' locations by making full use of the relative position information embedded in the node sequences. As the ongoing and future work, we plan to use column generation technology to deal with the adaptive event generation problem with the minimal number. Besides, further evaluating our design with different event modalities such as sound wave propagation in outdoor environments with noise is also an important project.

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