A Mobile Beacon Based Localization Approach for Wireless Sensor Network Applications

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***Abstract*—In this paper, a novel localization approach based on the use of a mobile beacon is proposed for wireless sensor networks. The localization system consists of a mobile beacon and beacon receiving modules on each sensor node for measuring distance. The localization is based on the application of multidimensional scaling technique and a local map registration approach. The approach is designed to operate without requiring path planning for the mobile beacon. It estimates the relative coordinates of the sensor nodes, and does not require the location information of the mobile beacon, making them attractive for applications where access to GPS signals is not available. Finally, computer simulations are used to evaluate the localization performance of the proposed approaches under different scenarios.**

***Index Terms*—wireless sensor network, sensor localization, mobile beacon, multilateration, MDS, map registration, path planning, GPS, least squares**

I. INTRODUCTION

Sensor node localization is a highly desirable capability for wireless sensor network applications. Localization refers to the process of estimating the coordinates of the sensor nodes in a network based on various types of measurements and with the aid of a number of beacon or anchor nodes that know their locations. A beacon node broadcasts beacon signals with limited information content. Anchors are required for sensor localization in a global coordinate system. The location information of an anchor or beacon node can be hard-coded or acquired by using localization systems such as a Global Positioning System (GPS) receiver. There are a number of reasons why sensor localization is important. For example, sensor location information can be used for tagging sensory data, which is important for environmental monitoring and military surveillance applications. The operation of a sensor network relies on sensor location information for uncovering and healing coverage holes in the network. Sensor location information can also be used to perform efficient spatial querying or tasking, *e.g.*, scoping the query or task propagation to sensor nodes in specific locations or geographic regions without the need to flood the whole network, significantly reducing the network overhead and minimize consumption of energy and resources in the network.

Recently, many sensor localization techniques have been developed for wireless sensor network applications [1][2]. In this paper, we focus on mobile beacon-based sensor localization approaches. Localization using mobile beacons has many advantages over those that use static beacons. The use of mobile beacons pushes the hardware complexity and power consumption requirement on the mobile beacon, which is less resource constrained and has access to the required power for repetitive message transmission to sensor nodes to be localized. In addition, the use of mobile beacons can significantly reduce the cost of sensor deployment. A mobile beacon transmitting at different locations can be considered equivalent of multiple static beacon deployment. Mobile beacons can move and easily avoid environmental obstructions. Using mobile beacons can also avoid the problem of interference and collision of beacon signals due to uncoordinated beacon transmissions of static beacons. In [3], Sichitiu *et al.* proposed a mobile beacon based localization method, in which the received signal strength indicator (RSSI) was used for ranging. A mobile beacon traverses the deployment area while broadcasting beacon signals. Sensor nodes that receive beacon signals infer proximity constraints to the mobile beacon, and their positions are estimated using a Bayesian approach. In [4], a solution called the Walking GPS was proposed. In this approach, a mote equipped with a GPS receiver (mobile beacon) is carried by a sensor deployment person and periodically broadcasts its location. A sensor node being deployed infers its position from the location broadcast by the GPS mote. This approach is simple and cost effective. Its disadvantage is also obvious: the localization results are directly determined by GPS accuracy. Galstyan *et al.* [5] proposed a distributed online localization algorithm based on a moving beacon, in which sensor nodes use geometric constraints induced by both radio connectivity and sensing to reduce the uncertainty of their positions. The authors then generalized the approach to use a moving target with *a priori* unknown coordinates. In [6], a refined approach is proposed, which uses mobile anchor scenarios for anchor information distribution. Statistical techniques are adopted for localization with inaccurate range data. In [7], a walking beacon-assisted localization is discussed and two distributed localization methods are proposed where sensor nodes compute their position estimates based on the range-free technique. The first method uses the arrival and departure information of a walking beacon and the second method exploits the variance of the RSS measurements from the beacon.

In this paper, we propose a novel localization approach, referred to as the MAP approach, based on the use of a mobile beacon for wireless sensor network applications. The localization hardware includes a mobile beacon and a beacon

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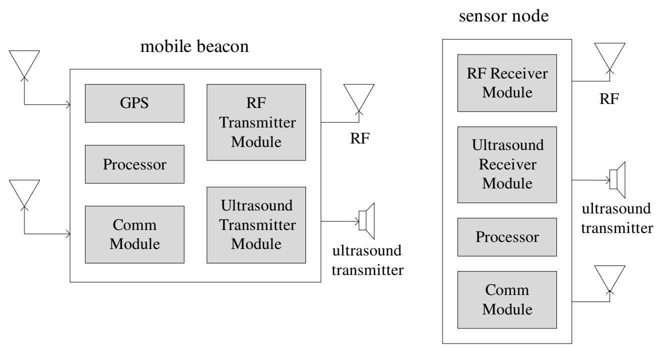

Fig. 1. Block diagram of the mobile beacon and sensor node.

receiving module on each sensor node. The mobile beacon moves in the sensor deployment area while broadcasting beacon signals to the network of sensor nodes. When a sensor node receives a beacon signal, it can estimate its distance to the mobile beacon at the time of beacon transmission. In the proposed approach, the user carries the mobile beacon and deploys sensor nodes. When a sensor node is deployed, the user turns on its power and set the mobile beacon to transmit a set of beacon signals. Any previously deployed nodes that are within the transmission range of the mobile beacon will receive the beacon signals and estimate their distances to the sensor node being placed. The inter-node distance measurements are obtained by using the mobile beacon, and the mobile beacon does not need a pre-planned path. All sensor nodes then pass the data back to a central node for localization using a map registration algorithm developed by Zhou *et al.* [10][11]. The rest of the paper is organized as follows. In Section II, the mobile beacon system is discussed with a detailed description of the hardware systems on both the mobile beacon and the sensor nodes. The ranging mechanism of the mobile beacon is also discussed. The proposed MAP localization approach is also presented in Section III. In Section IV, computer simulations are used to demonstrate and compare the performance of the proposed mobile beacon based localization approaches. Finally, the simulation results are analyzed and conclusions are presented.

II. System Hardware and Ranging

Fig. 1 is the the block diagram for the mobile beacon and sensor node. The mobile beacon consists of a GPS receiver and an RF/ultrasound transmitter in addition to a processor and a communication module. All sensor nodes in the network are equipped with an RF/ultrasound receiver module. Note that the GPS receiver is required for the mobile beacon when global coordinates of sensor nodes are required. A beacon signal contains an RF message followed by an ultrasound pulse that is synchronized in time. The RF message contains the beacon sequence number, time stamp and the current location of the mobile beacon (optional and obtained through the onboard GPS receiver).

When a sensor node receives a beacon signal, it can estimate its distance to the mobile location at the time of beacon transmission based on the TDOA between the RF signal and the ultrasound pulses. There are different ranging techniques including those based on time-of-flight (TOF), TDOA, and RSSI *etc.* [2]. They typically use either RF, acoustic or optical signals. The extreme fast propagation speed of RF signals makes them impractical for TOF ranging due to the tight time synchronization requirements for sensor nodes that often operate at a low clock frequency. The relatively inexpensive and simple RSSI based ranging tends to be highly susceptible to environmental interference and is known to be unpredictable for distance estimation. The ranging approach used in this study is similar to the one used by the Cricket system [12]. The underlying principle of RF/ultrasound ranging is to use their different propagation speeds in the air. The fact that ultrasound waves propagate at a much slower speed than RF in the air makes it possible for low cost implementation of accurate ranging. The TOA of the RF signal is used as a reference assuming that it is negligible. Then, the TDOA between the RF and the ultrasound represents the TOF of the ultrasound signal traveling from the mobile becon to the sensor node. Ranging based on RF and ultrasound signals can achieve an accuracy of a few centimeters over a short distance [12][13]. It is also able to eliminate the requirement for tight time synchronization between the mobile beacon and deployed nodes. However, it should be noted that since the speed of ultrasound in air varies with ambient temperature, humidity and atmospheric pressure, the impact of these factors on the speed of ultrasound should be accounted for in practice. This is typically done by installing temperature and humidity sensors on the sensor nodes.

III. Mobile Beacon Based Localization

The proposed localization approach starts from the stage of sensor node deployment. After the sensor deployment planning process, the user that carries the mobile beacon starts to deploy sensor nodes. When a sensor node is placed, the user turns its power on, and sets the mobile beacon to transmit a set of beacon signals. Any previously deployed nodes that are within the transmission range of the mobile beacon will receive the beacon signals and estimate their distances to the current mobile beacon location (or the location of the sensor node under deployment). The user then moves to deploy the rest of the sensor nodes and repeats the same procedures until all sensor nodes are deployed. After all sensor nodes are deployed, each sensor node will have a set of distance measurements to its neighbors, which are then passed to a central node for localization using the MAP localization algorithm.

The MAP localization algorithm is proposed to overcome the problem of mismatching of the shortest distances in the MDS method. The MDS localization method requires that the full Euclidean matrix be known. In practice, due to power constraint, the mobile beacon may have a limited transmission range. When two nodes are out of the transmission range of the mobile beacon, the distance measurement between them becomes unavailable and needs to be estimated or approximated

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[8]. A common approach is to replace the unavailable inter-node distances by their shortest path distances. In a network of regular topology, a shortest path distance is found to match its corresponding Euclidean distance well. However, in a sparse network or a network of irregular topology, a shortest path distance may not match its Euclidean distance, and the use of the approximated distance matrix will result in localization errors [10][8]. In MAP, the network is divided into many small sub-groups of nodes, where adjacent groups share common sensor nodes. A commonly used approach is to form a sub-group for each sensor node, which involves the node and its neighbors with a given number of hops (*e.g.*, one or two hops). One hop is determined by the transmission range of the mobile beacon rather than the radio range of the sensor nodes. A local map is built for each sub-group of sensor nodes using the MDS method [8]. The local maps are then merged into a global map based on the common sensor nodes shared by different groups. In [8], an incremental greedy algorithm was proposed for merging the local maps in a sequential manner. One local map is randomly selected as the core map, which is grown by merging the local maps one by one. During the merging process, an optimal rigid transformation is determined, which minimizes the conformation difference between the locations of the common nodes in the core map and those of the local map subject to the rigid transformation. The incremental greedy algorithm is seen to be locally optimal since it only explores the commonalities of the shared sensor nodes in two maps. In practice, the common sensor nodes are often shared by more than two local maps. The sequential merging process can also lead to error propagation and perhaps unacceptable errors as the network grows. In [10], the MAP approach was introduced to counter the problems of the incremental greedy approach. In MAP, instead of using a sequential pairwise approach for merging local maps, the construction of the global map is considered at a global level. An affine transformation is defined for each local map. The set of optimal affine transformations are obtained simultaneously by considering all available nodes that are shared by various local maps. The set of optimal affine transformations are found, which minimize the location discrepancies of sensor nodes subject to their corresponding affine transforms in the global map. The discrepancy is represented by the sum of the squared distances of all nodes to their respective geometric centers in the global map. The resulting coordinates of the sensor nodes in the global map are relative coordinates. If desired, they can be transformed into their global coordinates based on the use of a few selected beacon nodes.

Since the proposed local map registration algorithm minimizes the overall discrepancies of the locations of all sensor nodes, it is able to counter the problems associated with approaches based on pairwise map merging, and achieve the global optimal performance. The problem of finding the optimal rigid transformation for two maps based on common nodes has closed-form solutions [14]. The approach by Arun *et al.* [15] is shown to have provable optimality and the advantage of computational efficiency over other methods. Arun's approach minimizes the squares error between two sets of matched points under rotation and translation, and the optimal transformation is obtained using a singular value decomposition (SVD). The problem of finding a set of optimal transforms for multiple local maps, however, is not trivial, and analytic solutions do not exist due to the highly nonlinear optimization criterion involved. In this study, a gradient projection algorithm is developed for finding the optimal transforms for transforming local maps to a global map [10]. The algorithm is developed based on the general idea by Jennrich in [16][17] and is suitable to the constrained optimization problem of coordinate transformation. In spite of the iterative nature of the algorithm, it has faster convergence and is computationally more efficient than many general numerical optimization techniques [19][18] for nonlinear programming.

The proposed localization approach does not rely on the knowledge of the mobile beacon locations, which is important for applications where access to GPS satellites is not available. However, it is necessary to point out that the localization results from MAP are relative sensor locations, *i.e.*, the estimated sensor locations are given in an arbitrary coordinate system. In many applications, relative location information is sufficient. For example, in applications such as detecting and tracking an intruder, the user is concerned about the location of a target relative to the network rather than its global coordinates. Relative locations of the sensor nodes will suffice for wireless network functions such as routing for communications and tasking. If global coordinates of the sensor nodes are desired, then, a number of anchors are needed to determine a rigid transformation of the relative coordinates into global coordinates.

IV. Computer Simulations and Performance Analysis

In this section, we use computer simulations to demonstrate the performance of the proposed mobile beacon based localization techniques. Four types of network shapes and sensor deployment scenarios are used in the simulation: rectangular random network, rectangular grid network, C-shape random network, and C-shape grid network. A C-shape area is defined as a rectangle that contains a concave on one side. In this study, the concave is located at the center of the rectangle's bottom line.

The mobile beacon is simulated to have a transmission range of 25 meters. The user moves at a speed of 0.694 meters per second and spends 4 seconds to place a sensor node. When in periodic broadcasting mode, the mobile beacon broadcasts beacons to the network regularly every 10 seconds. For a grid network, the deploying person starts from the left-most column of the sensors, and places the sensor nodes from bottom to top. The next column of sensor nodes are placed from top to bottom along the y-axis. This process continues until all sensor nodes are placed. For a random network, the sensor deployment area is divided into multiple segment of equal length on the x-axis. In the first (left-most) segment, sensor nodes are placed from bottom to top along the y-axis. In the

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next segment, the sensor nodes are placed from top to bottom along the negative direction of the y-axis. This process repeats itself until all sensor nodes are placed.

The distance estimates computed by a sensor node from receiving the mobile beacon signals is assumed to contain additive errors, which are modeled as a random variable that follows a uniform distribution with boundaries (both positively and negatively) proportional to the actual distance. For an actual distance d between the mobile beacon and sensor node, the distance estimate error is uniformly distributed in the interval $[-\kappa d, \kappa d]$, where κ is the proportionality constant. The mobile beacon is assumed to carry a GPS receiver to acquire its own coordinates (this information is only needed for multilateration based approaches). The mobile beacon location errors are simulated to be additive Gaussian distributed with zero mean in both x and y coordinates. The errors in x and y coordinates are assumed to be statistically independent and have a same standard deviation of $1/\sqrt{2}$ meters. For each scenario, we vary the constant of proportionality κ and use Monte-Carlo simulations to compute the root mean squares errors (RMSE) of the sensor location estimates. In the simulation, κ varies from 0 to 0.1 with a step size of 0.01. For each value of κ, 100 tests are repeated to obtain the RMSEs of the location estimate of each sensor node. An averaged RMSE is then computed by averaging the RMSEs of all nodes.

Five other localization approaches, referred to as MLE, LLS, MDS PATH-MLE and PATH-LLS, respectively, are included for comparisons. MLE and LLS are based on the use of multilateration. The user carries the mobile beacon and deploys sensor nodes. The mobile beacon broadcasts beacon signals periodically. If a sensor node receives beacon signals from more than three locations, it can apply multilateration to find its coordinates. The only difference between MLE and LLS is that MLE uses a nonlinear least squares formulation of multilateration while LLS is formulated as a linear solution. MDS uses the same deployment strategy as the proposed MAP approach. PATH-MLE and PATH-LLS are the nonlinear and linear least squares solutions of multilateration, respectively. They differ from MLE and LLS in that the mobile beacon moves along a planned path around or in the sensor deployment area. In this study, simple paths are used in evaluating PATH-MLE and PATH-LLS, which are along the perimeter of the sensor deployment area.

A. Rectangular random network

30 sensor nodes are deployed in a rectangular area of 100 meters by 20 meters. The mobile beacon moves on a Z-shape path in the deployment area. Four anchor nodes are selected. The anchor nodes are required by MAP and MDS to transform the resulting relative coordinates of the sensor nodes into global coordinates for comparison. For PATH-MLE and PATH-LLS, the mobile beacon moves on a Z-shape path in the deployment area.

Fig. 2 shows the RMSEs of the location estimates versus κ. Among all the approaches, the MDS approach performs the worst in terms of RMSEs for all κ. Even when $\kappa = 0$,

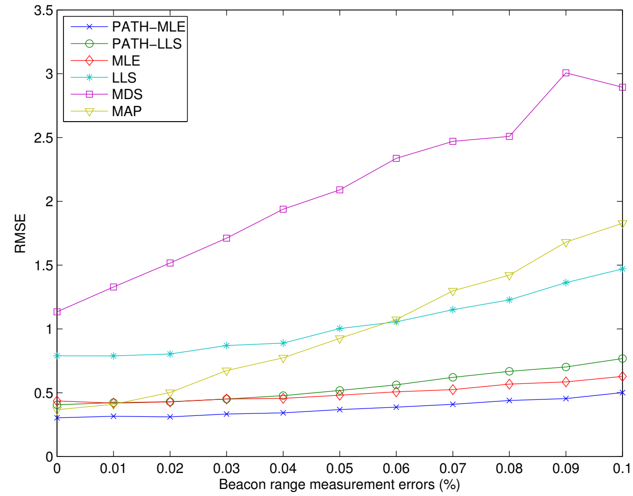

Fig. 2. RMSEs of location estimates via κ: rectangular random network.

i.e., there are no ranging errors at all, MDS still shows an RMSE of 1 meter. This phenomenon is due to the use of approximated distances in the Euclidean matrix in MDS. As discussed before, due to the limited transmission of the mobile beacon, all inter-node distance estimates are not available. For node pairs that have separation distances greater than the mobile beacon transmission range, the distance estimates will be approximated by their shortest path distances. As the number of unavailable distance estimates increases, the localization performance deteriorates. We use connectivity level to characterize the availability of inter-node distances, which is defined as the averaged number of nodes that a node can receive mobile beacon signals from. Note that this connectivity is defined based on the mobile beacon transmission range instead of the radio range of the sensor nodes. In Fig. 2, the connectivity level is computed as 11.2, which means that each node can directly measure its distances to about 11 nodes instead of the 29 nodes in the ideal case. In general, the connectivity level increases with node density of a network and the mobile beacon transmission range. PATH-MLE, Path-LLS and MLE outperform the others. The LLS approach outperforms MAP only for low values of κ ($\kappa < 0.06$). It is interesting to note that, for relatively small κ ($\kappa < 0.06$), the RMSEs for PATH-MLE, PATH-LLS, MLE, LLS, and MAP, are all smaller than 1 meter, which is the simulated RMSE for GPS location errors. This indicates that these approaches are able to suppress errors in the mobile beacon locations, and provide better localization performance than by using GPS alone.

B. Rectangular grid network

In this scenario, 30 sensor nodes are placed on a rectangular grid with 20% placement errors. The unit length of the grid is $r = 8$ meters. The placement errors are simulated as additive and uniformly distributed in the interval $[-0.2r, 0.2r]$ in both the x and y coordinates of the node's original grid position. For PATH-MLE and PATH-LLS, the mobile beacon moves on

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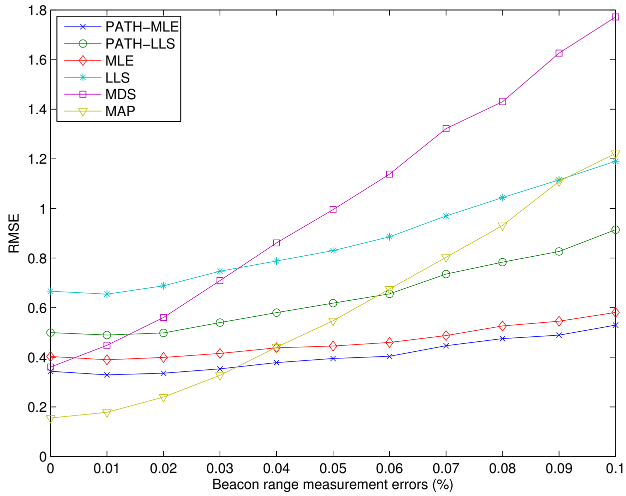

Fig. 3. RMSEs of location estimates via κ: rectangular grid network.

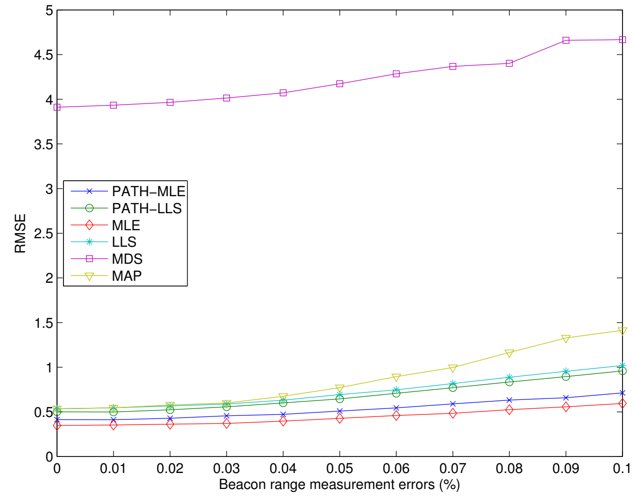

Fig. 4. RMSEs of location estimates via κ: C-shape random network.

a Z-shape path in the deployment area. Four anchor nodes are selected.

Fig. 3 shows the RMSEs of the location estimates versus the beacon ranging errors (κ). The MAP approach performs better than PATH-LLS and LLS when $\kappa < 0.06$. The performance of MDS lags behind the other approaches. All the approaches have better localization performance in the rectangular grid network than in the rectangular random network. In particular, MDS sees significant improvement in the rectangular grid network, which may partially be attributed to the increased connectivity level of the grid network and its relatively uniform node density. The simulated grid network has a connectivity level of 14.1. For a rectangular grid network, the shortest path between a pair of nodes corresponds well with their Euclidean distance.

C. *C-shape random network*

The C-shape random network is simulated by randomly placing 45 sensor nodes in a C-shape area. The rectangle size is 100 meters by 40 meters, and the concave size is 60 meters by 20 meters. The placement of the sensor nodes follows a uniform distribution. Five anchor nodes are selected. For PATH-MLE and PATH-LLS, the mobile beacon moves along the perimeter of the C-shape area.

Fig. 4 shows the RMSEs of location estimates versus κ. PATH-MLE and MLE have similar performance and perform best among all approaches for all κ. PATH-LLS and LLS are close in their RMSEs for all κ, and they are slightly outperformed by PATH-MLE and MLE. The MAP approach performs reasonably well and has RMSE values that are less than 1 meter when $\kappa < 0.07$. On the other hand, the MDS performs poorly and fails to provide satisfactory localization performance. The RMSE values for MDS are larger than 3.5 meters for all κ. The failure may be due to the irregular shape of the C-shape network as well as the low connectivity level of the network. As discussed in [10], for a sensor network of irregular shape, the shortest paths between pairs of sensor nodes usually do not correlate well with their Euclidean distances. The simulated C-shape random network has a connectivity level of 13.5.

D. *C-shape grid network*

In the simulation of the C-shape grid network, 38 sensor nodes are placed on a C-shape grid with 20% placement errors. The gird has 10 sensor nodes in the x direction and 5 sensor nodes in the y direction. The concave contains 4 and 2 sensor nodes in the x and y directions, respectively. The unit length of the grid is 8 meters. Five anchor nodes are selected. The anchor nodes are selected by dividing the sensor deployment area into five sub-areas and randomly selecting one sensor node from each area. The mobile beacon moves along the perimeter of the C-shape area.

Fig. 5 shows the RMSEs of location estimates versus κ. The RMSE curves for the C-shape grid network are similar to those for the C-shape random network. The RMSEs for all six approaches increase as κ increases. PATH-MLE and MLE perform best and have close RMSE for all κ. PATH-LLS and LLS are slightly outperformed by PATH-MLE and MLE, but have close RMSE values for all κ. The MAP approach outperforms PATH-LLS and LLS for $\kappa < 0.4$. The MDS approach fails to produce satisfactory results with RMSE values larger than 3 meters for all κ. Note that MDS has slightly smaller RMSE values than in the C-shape random network. As the simulated C-shape grid network has a connectivity level of 16, which is larger than the connectivity level for the C-shape random network, this may explain the improved RMSEs of the sensor location estimates for the MDS approach.

V. CONCLUSIONS

In this paper, the MAP localization approach based on the use of a mobile beacon has been presented for wireless sensor network applications. The use of a mobile beacon has the advantage of flexibility and can greatly simplify the process of sensor localization. In addition, it is able to overcome many of

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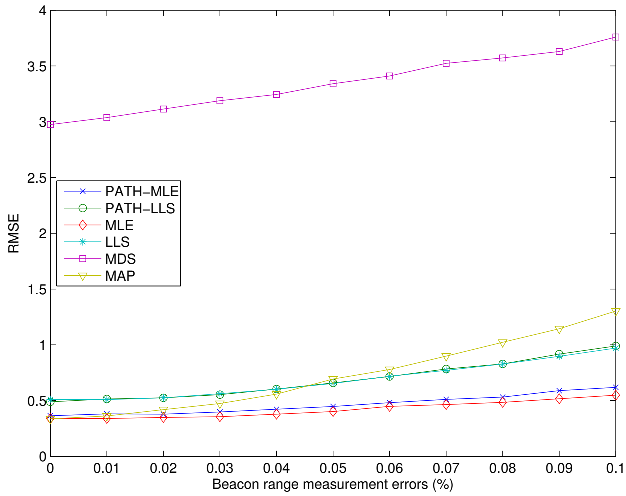

Fig. 5. The RMSE of location estimates versus κ: C-shape grid network.

the difficulties that would be encountered by using static beacons or localization approaches based on inter-node ranging. The performance of the MAP approaches was evaluated using computer simulations and compared with other approaches that are also based on the use of mobile beacons. Four types of network topology and sensor node placement were simulated. The simulation results show that the MAP approach has significant improvement in terms of RMSEs of sensor location estimates in comparison with the MDS approach. It outperforms or performs as well as LLS for low κ values. In the case of rectangular grid network, MAP outperforms LLS for all κ. It is observed that MAP performs better for grid networks than for random networks partly due to the relatively large and more balanced connectivity levels of grid networks. In general, MAP is a practical sensor localization techniques that can provide satisfactory localization results. Although the simulation results showed that maximum likelihood based approaches (*e.g.*, MLE and PATH-MLE) are able to provide the best localization performance, they are not considered practical due to the nonlinear optimization procedures. MAP is a GPS-less approach, *i.e.*, it does not need to know its own location coordinates. However, if global coordinates of the sensor nodes are desired, then a sufficient number of anchor nodes with known global coordinates is required.

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