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Mobility-assisted Position Estimation in Wireless Sensor Networks

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Abstract-Wireless sensor networks (WSNs) have been proposed for a multitude of location-dependent applications. To stamp the collected data and facilitate communication protocols, it is necessary to identify the location of each sensor. In this paper, we discuss the performance of a novel received signal strength indicator (RSSI) positioning scheme, which uses a generalized geometrical location algorithm to achieve an accurate estimation based on mean received signal strength measurements. In order to improve the network performance and address limitations of static WSNs position estimation, mobile sensors are utilized effectively and an attractive movement strategy with mobile elements is designed. The effectiveness of our approach is validated and compared with the traditional RSSI method by extensive simulations.

Index Terms —RSSI, Geometrical location, Wireless sensor networks.

I. INTRODUCTION

Recent advances in wireless communications and micro electro-mechanical system (MEMS) technologies have enabled the development of low-cost, low-power and small size wireless sensor nodes [1]. Wireless sensor networks (WSNs) have become the current hot spot of networking area and have been used for various applications, such as habitant monitoring, environment monitoring, and target tracking. For all these applications, it is essential to know the locations of the data [2].

Many approaches to obtain this per-node location knowledge have been explored. Based on the type of knowledge used in localization, we can divide these localization protocols into two categories: range-based and range-free [3]. Range-based protocols estimate absolute point-to-point distance to calculate the location between neighboring sensors. The second class of methods, named range-free approach, employs connectivity to find the distances from the non-anchor nodes to the anchor nodes [4]. Range-based algorithms are typically based-on angle-of-arrival (AOA), RSSI [5] [25], time-of-arrival (TOA) or time-difference-of-arrival (TDOA) measurements [8]. A promising technology is the ultra wideband (UWB) technology where precise ranging can be embedded into data communication. The typical range-free localization algorithms include DV-Hop [6], Centroid algorithm [12], APIT [4] and Amorphous [7]. However, the performance of range-free algorithms is not high. When the sensor network is anisotropic or has complex topology, the performance of these methods also tends to deteriorate. Because the location accuracy of range-based approach is relatively higher than that of range-free algorithms, we focus on the study of range-based solutions and their applications in WSNs in this paper. Received signal strength is comparatively much easier and less costly to obtain from the time series recordings at each sensor. It is our opinion that radio localization can play an active role in several WSN applications provided that the accuracy requirement in terms of spatial resolution is not too strict. As such, we propose a novel received signal strength indicator (RSSI) localization algorithm and evaluate it when applied to mobility-assisted sensor networks. Unlike the static sensors, which are tightly constrained by the energy supplies, mobile sensor's batteries are rechargeable. Efficient collaboration between mobile and static nodes can also effectively change anchor densities on demand, potentially reducing the number of anchors needed comparing to all-static network deployments. Furthermore, mobile sensors can cooperate with the static sensors to fix the limitation of node localization in the static sensor networks. In this paper, mobile anchor node roams through the network and broadcasts beacon messages with its position to nodes periodically at various locations. Based on the active movement of mobile sensor, location performance is improved significantly.

This paper makes the following three main contributions. First, we present an effective localization scheme with minimum mobile element (ME), thus improving system scalability and usage as well as reducing hardware costs. Second, a new localization algorithm based on the volume is developed to allow any number of ME beacon points, which was inspired by the volume method utilized in [23]. Third, an attractive movement strategy for ME is proposed to reduce the total moving distance and improve moving efficiency of ME while satisfying the expected location performance, which can efficiently extend lifetime of the ME and optimizes the anchor distribution.

The rest of this paper is organized as follows. Section II introduces the related works. Section III provides the derivation of the proposed localization algorithm. In Section IV, simulation results are shown, some considerations about the impact of (additive white gauss noise) AWGN and

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Rayleigh fading are discussed. In Section V, the results of a real experiment are discussed. Finally, we present our conclusions in Section VI.

II. RELATED WORKS

Recent work demonstrated that the sensing performance of WSNs can be improved by using mobility capability node. Xing *et al.* [18] study target detection for mobility-assisted WSNs. They exploited reactive mobility to improve the target detection performance of WSNs. In their approach, mobile sensors collaborate with static sensors and move reactively to achieve the required detection performance. Wang *et al.* [19] used Voronoi diagrams to detect the coverage holes and devised three movement-assisted sensor deployment protocols based on the principle of moving sensors from densely deployed areas to sparsely deployed areas. Wang *et al.* [20] presented a mobility-assisted network for field coverage which can be remarkably improved by integrating a small set of mobile sensors. They offered an optimal algorithm to calculate the coverage contributions, which explores the potentials of the mobile sensors and extends the network lifetime.

Several studies exploited the effect of mobile nodes on node localization for WSNs. In these methods, a small number of mobile devices referred to as MEs roam about sensing fields and assist to improve localization performance. Luo *et al.* [9] proposed a TDOA localization algorithm for movement-assisted sensor networks. A mobile beacon is used to measure the mobility-differentiated TOA in [9], which will increase mobile beacon's communication cost. Based on the RF-based technology, [11] presented three algorithms for tracking transceiver-free moving objects in an indoor WSN.

RSSI has been widely used as a distance measure in the context of static WSNs because of its simplicity. The impact of a number of parameters, such as the operating frequency, the transmitter–receiver distance, the variation of transceivers, the antenna orientation, and the environment, on (received signal strength) RSS measurements were investigated using Tmote Sky nodes in real outdoor environments [12]. The results in [13] describe a thorough empirical study of the RSS in Mica2 sensor node for indoor environments with considering parameters such as operating frequency, antenna orientation, battery voltage, temporal and spatial properties of environment, and the environmental dynamics. Lymberopoulos *et al.* [14] investigated the RSS variability in 3-D indoor environment. In their experiments, all the sensor nodes are equipped with Chipcon CC2420 radio with monopole antennas. Their study is mainly focusing on the impact of the antenna orientation over the RSS.

Complementary to the above studies that deal with the node localization based on RSS measurements, we focus on improving target localization performance by utilizing the mobility of sensors. Different with the former work, our method takes advantage of mobility-assisted WSNs can efficiently detect the obstacle in the communication range and decrease the effect of (non-line of sight) NLOS through the active movement of ME. Since the ME is often resource rich node attached with better processing ability and longer transmission range comparing to the static sensor node, a series of beacon messages with its position will be broadcasted by the ME in our localization scheme, which will reduce the communication cost of static sensors. Thus, the unknown-position nodes will actively capture RSS measurements and initiate localization algorithm after receiving the incoming data from the MEs. The positions of MEs are known since they are usually equipped with GPS receivers or RFID tags [18], which will be acted as mobile anchor nodes in our localization system. If obstacles exist in between a sensor and certain anchors, static node might not obtain enough and accurate RSS measurements to estimate its position. By including a ME to replace multiple static anchors, we avoid the above disadvantage of static WSNs. However, several challenges must be fixed in order to make best use of the mobility of WSNs in target estimation. First, considering the higher design complexity and manufacturing cost, the number of mobile elements available in a network is often limited. Therefore, MEs must effectively cooperate with static sensors to obtain the maximum utility. Second, the moving trace of MEs must be optimized since MEs are only capable of low-speed and short-distance mobility in real environment due to the high power consumption of locomotion. The optimum moving scheme for MEs can further increase location accuracy for target estimation since the distribution of anchors can affect location performance in the static WSNs.

III. ALGORITHM DEVELOPMENT

In mobility-assisted WSNs, depending on some emergent applications there may be a need to rapidly respond to sensor input. For instance, in a fire application, actions should be performed on the event area as soon as possible. Moreover, the collected and delivered sensor data must still be valid at the time of acting. Different with former work on node localization for WSNs, the ME movement and coordination play an important role to provide accurate and timely localization to sensors. We will devise an attractive movement strategy for MEs to address this problem later.

The network proposed in this paper consists of static sensor nodes, which are located randomly, and MEs, which have a *priori* knowledge of their own positions with respect to a global coordinate system.

When an electromagnetic signal propagates, it may be diffracted, reflected and scattered. Due to the unique characteristics of each environment, most radio propagation models use a combination of analytical and empirical methods. One of the most common radio propagation models is the lognormal shadowing path loss model, which will be adopted in our system [15] [16] [25]. This model can be used for large and small coverage systems, furthermore, empirical studies have shown the lognormal shadowing model provides more accurate multi-path channel modeling than that of Nakagami and Rayleigh for indoor environments. The model is given by:

$$PL(d) = PL(d_0) - 10n\lg(d / d_0) - X_\sigma \tag{1}$$

where d is the transmitter-receiver separation distance, d_0 a reference distance, n the path loss exponent (rate at which signal decays), and X_σ a zero-mean Gaussian random vector (in dB) with standard deviation ó (multi-path effects). The $PL(d_0)$ is the signal power at reference distance d_0 and $PL(d)$ is the signal power at distance d. The value of $PL(d_0)$ can either be derived empirically or obtained from the WSN hardware specifications.

A theoretically accurate model for RSSI is logarithmic attenuation over distance. The specifications from our radio [17] indicate that the output voltage V_{RSSI} on the RSSI pin is proportional to the received power as

$$RSSI = -51.3V_{RSSI} - 49.2(dBm) \tag{2}$$

The ChipCon CC1000 radio generates an analog signal that serves as an indication to the strength of the received signal [22]. This is the RSSI signal that has a dedicated ADC channel (channel 0), and its range varies from 0 to 1.2*V*. The RSSI voltage is calculated as:

$$V_{RSSI} = (V_{batt} \times ADC\_Counts)/1024 \tag{3}$$

where V_{batt} is the reference voltage of the A/D converter and ADC_Counts is the ADC counts.

In our localization mechanism, the distance between target node and ME is observable using the forward link RSSI of the receiver. The procedure for our scheme to obtain RSSI measurements works as follows: the ME periodically transmit a RF beacon signal to sensor nodes in range. During this period, sensor node will constantly sample the received signal strength from each ME beacon point orderly and store them for later use.

The triangulation estimation method does not perform well using RSSI. Wan *et al.* [23] proposed a localization algorithm for mobile system based on a linear relationship between the rectangular and the volume coordinates. However, only four (base station) BSs can be utilized in [23]. Inspired by the volume method utilized in [23], we develop a new volume based localization approach which allows any number of ME beacon points. In our localization system, we will not adopt traditional RSSI algorithm based on the triangulation but propose to use the generalized geometrical location algorithm which is inspired by [23]. The proposed generalized geometrical location algorithm is based on the volume of the tetrahedron which is formed by the target senor node and ME.

A. Mathematical Procedure for Geometrical Localization

In this section, we generalize the volume based localization approach in [23] with any number of anchor nodes. The linear relationship between the rectangular and the volume coordinates can be found in [23]. The detailed derivation procedure for our generalized volume based localization method will be described in this subsection.

Lemma 1: Assume that the rectangular coordinate of the vertex A_i of the tetrahedron is (x_i, y_i, z_i) $(i = 1,2,3,4)$. Then its signed volume can be expressed in the form of determinant as follows:

$$V = \frac{1}{6}\begin{vmatrix} 1 & 1 & 1 & 1 \\ x_1 & x_2 & x_3 & x_4 \\ y_1 & y_2 & y_3 & y_4 \\ z_1 & z_2 & z_3 & z_4 \end{vmatrix} = \frac{1}{6}\begin{vmatrix} x_2 - x_1 & y_2 - y_1 & z_2 - z_1 \\ x_3 - x_2 & y_3 - y_2 & z_3 - z_2 \\ x_4 - x_3 & y_4 - y_3 & z_4 - z_3 \end{vmatrix} \tag{4}$$

Lemma 2: The volume of the general tetrahedron is also given by the determinant

$$V^2 = \frac{1}{288}\begin{vmatrix} 0 & 1 & 1 & 1 & 1 \\ 1 & 0 & r_{12}^2 & r_{13}^2 & r_{14}^2 \\ 1 & r_{12}^2 & 0 & r_{23}^2 & r_{24}^2 \\ 1 & r_{13}^2 & r_{23}^2 & 0 & r_{34}^2 \\ 1 & r_{14}^2 & r_{24}^2 & r_{34}^2 & 0 \end{vmatrix} \tag{5}$$

where r_{ij} is the range between vertexes A_i and A_j.

Let $A = \begin{bmatrix} 1 & 1 & 1 & 1 \\ X_1 & X_2 & X_3 & X_4 \\ Y_1 & Y_2 & Y_3 & Y_4 \\ Z_1 & Z_2 & Z_3 & Z_4 \end{bmatrix}$.

Let $P(x_0, y_0, z_0)$ be the random unknown-position node location and (X_i, Y_i, Z_i) be the known location of the *i*th ME beacon point. The four ME beacon points A_1, A_2, A_3, A_4 will be used to calculate the position of target node. The ME beacon points A_1, A_2, A_3, A_4 can form a tetrahedron. Then using Lemma 1 we can get the volume coordinates of the unknown node $P(v_{1i}, v_{2i}, v_{3i}, v_{4i})$.

As shown in Eqs. (1)-(3) of [23] , only four ME beacon points in range can be used for unknown-position sensor nodes positioning. In order to use any number of beacon points in range, we generalize their scheme as follows.

Using [23], we obtain

$$v_{1i} = \frac{1}{6}\begin{vmatrix} 1 & 1 & 1 & 1 \\ x_0 & X_2 & X_3 & X_i \\ y_0 & Y_2 & Y_3 & Y_i \\ z_0 & Z_2 & Z_3 & Z_i \end{vmatrix} \tag{6}$$

$$v_{2i} = \frac{1}{6}\begin{vmatrix} 1 & 1 & 1 & 1 \\ X_1 & x_0 & X_3 & X_i \\ Y_1 & y_0 & Y_3 & Y_i \\ Z_1 & z_0 & Z_3 & Z_i \end{vmatrix} \tag{7}$$

$$v_{3i} = \frac{1}{6}\begin{vmatrix} 1 & 1 & 1 & 1 \\ X_1 & X_2 & x_0 & X_i \\ Y_1 & Y_2 & y_0 & Y_i \\ Z_1 & Z_2 & z_0 & Z_i \end{vmatrix} \tag{8}$$

$$v_{4i} = \frac{1}{6}\begin{vmatrix} 1 & 1 & 1 & 1 \\ X_1 & X_2 & X_3 & x_0 \\ Y_1 & Y_2 & Y_3 & y_0 \\ Z_1 & Z_2 & Z_3 & z_0 \end{vmatrix} \tag{9}$$

where $i \geq 4$.

Let $A_i = \begin{bmatrix} 1 & 1 & 1 & 1 \\ X_1 & X_2 & X_3 & X_i \\ Y_1 & Y_2 & Y_3 & Y_i \\ Z_1 & Z_2 & Z_3 & Z_i \end{bmatrix}, V_i = \frac{1}{6}\begin{vmatrix} 1 & 1 & 1 & 1 \\ X_1 & X_2 & X_3 & X_i \\ Y_1 & Y_2 & Y_3 & Y_i \\ Z_1 & Z_2 & Z_3 & Z_i \end{vmatrix}$

$i \geq 4$. From (6)-(9), we get

$$\begin{bmatrix} v_{14} \\ v_{24} \\ v_{34} \\ v_{44} \end{bmatrix} = \frac{1}{6}A_4^* \begin{bmatrix} 1 \\ x_0 \\ y_0 \\ z_0 \end{bmatrix}; \begin{bmatrix} v_{15} \\ v_{25} \\ v_{35} \\ v_{45} \end{bmatrix} = \frac{1}{6}A_5^* \begin{bmatrix} 1 \\ x_0 \\ y_0 \\ z_0 \end{bmatrix} \text{ and}$$

$$\begin{bmatrix} v_{1i} \\ v_{2i} \\ v_{3i} \\ v_{4i} \end{bmatrix} = \frac{1}{6}A_i^* \begin{bmatrix} 1 \\ x_0 \\ y_0 \\ z_0 \end{bmatrix} \tag{10}$$

where A_i^* is the adjugate matrix of the matrix A_i.

Let $T = \begin{bmatrix} 1 \\ x_0 \\ y_0 \\ z_0 \end{bmatrix}$. Using (10), we have

$$\begin{bmatrix} v_{14} & v_{15} & \cdots & v_{1i} \\ v_{24} & v_{25} & \cdots & v_{2i} \\ v_{34} & v_{35} & \cdots & v_{3i} \\ v_{44} & v_{45} & \cdots & v_{4i} \end{bmatrix} = \frac{1}{6}\begin{bmatrix} \mathrm{A}_4^* & \mathrm{A}_5^* & \cdots & \mathrm{A}_i^* \end{bmatrix} \begin{bmatrix} T \\ T \\ \vdots \\ T \end{bmatrix} \tag{11}$$

Then (11) can be converted into

$$h_c = G_c Z_c \tag{12}$$

where $Z_c = [T \ \ T \ \ \cdots \ \ T]^T$

$$h_c = \begin{bmatrix} v_{14} & v_{15} & \cdots & v_{1i} \\ v_{24} & v_{25} & \cdots & v_{2i} \\ v_{34} & v_{35} & \cdots & v_{3i} \\ v_{44} & v_{45} & \cdots & v_{4i} \end{bmatrix}$$

$$G_c = \frac{1}{6}\begin{bmatrix} \mathrm{A}_4^* & \mathrm{A}_5^* & \cdots & \mathrm{A}_i^* \end{bmatrix}.$$

Using weighted least square (WLS) algorithm [26], we can get

$$Z_c = (G_c^T \psi_2^{-1} G_c)^{-1} G_c^T \psi_2^{-1} h_c \tag{13}$$

where $\psi_2 = BQB$

$$B = diag\left\{\frac{2}{n}r_1^{2-n}, \frac{2}{n}r_2^{2-n}, \frac{2}{n}r_3^{2-n}, \cdots, \frac{2}{n}r_i^{2-n}\right\}$$

$Q = diag(\sigma_1^2, \sigma_2^2, \sigma_3^2, \cdots, \sigma_i^2)$. r_i is the distance between the ith ME beacon point and target unknown node, which can be calculated using (1).

Then the position of target node $P(x_0, y_0, z_0)$ is expressed as

$x_0 = Z_c(2)$, $y_0 = Z_c(3)$, and $z_0 = Z_c(4)$.

B. Movement Strategy for Mobile Elements

Due to the power constraint, ME is only capable of low-speed and short-distance movement in real deployments. For instance, the normal speed of several mobile sensor platforms (e.g., Packbot and XYZ) is only 0.5 ~ 2 m/s. A XYZ mobile sensor node can only move about 165 meters before exhausting its power, which is supported by two AA batteries [18]. Therefore, the movement trace of ME must be efficiently planned in order to maximize the amount of target positions that can be obtained with satisfied localization accuracy within a short moving distance. Moreover, scheduling an optimal path for ME improves the system reliability and network lifetime [21].

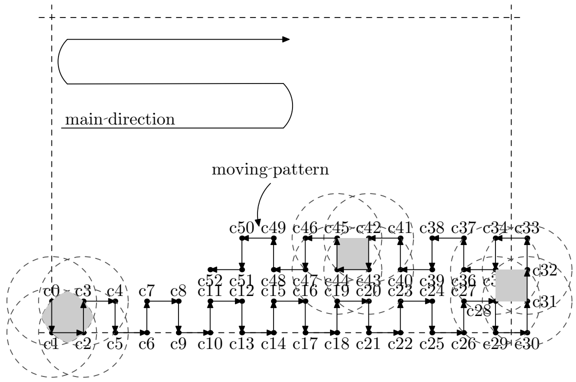

Fig.1. Movement strategy

To address the above constraints, we propose an efficient moving trace for MEs. We use a 'S' type as macro moving trace for ME illustrated in Fig.1. The target area can be divided into small circulars developed by ME's different positions. The radius of the circular is dependent on radio range of ME. In practical environment, the radio pattern is not a theoretical circular model because of degree of irregularity for radio signal. Here, we use circular model only for simple presentation. As shown in Fig.1, for micro-moving pattern, the ME starts to move from c0 and intermittenly stops at c1 after moving $R/\sqrt{2}$, where R is the radio range of ME. When ME stops at c1, it will broadcast a beacon message including its position to other sensor nodes in its radio range. After a short stop, ME continues to move as the same way. Note that although we can utilize any number of ME beacon points as proposed the previous subsection, we only use four optimal beacon points in a cell coverage area to reduce the cost for ME. Based on this attractive moving strategy, unnecessary movement of ME is avoided, ME can effectively decrease total moving distance and number of broadcast to extend its lifetime and improve the system reliability. Another merit for this moving strategy, the unknown nodes can receive four uniformly distributed beacon messages in one little square area, which can increase location accuracy.

Effective side for the cell coverage area

We regard those little rectangles as the effective coverage areas. In order to make the best use of ME, we need to assure all of the unknown-position nodes can receive the beacon messages from ME. Thus, we let $c_0c_2 = R$. Let the side of little rectangles a and b, respectively. In order to maximum the use of ME, we need to find a rectangle which has the maximize area but the minimum perimeter. We define λ to be the ratio between the area and perimeter for the little rectangle. Thus, we get:

$$\lambda = \frac{ab}{2(a+b)} = \frac{1}{2(1/b+1/a)} \le \frac{1}{4(ab)^{-1/2}} \tag{14}$$

Consequently, we obtain the maximum value of λ, $\lambda_{\max} = \frac{\sqrt{2}R}{8}$, when $a = b = R/\sqrt{2}$. Thus, the optimal cell coverage area for our localization scheme is square.

Effective beacon messages

As proved above, we need to utilize those square areas as the effective coverage area to take best advantage of MEs. Since $c_0c_2 = R$, we have $2c^2 = R^2$, where c represents the side of little squares. As a result, $c = R/\sqrt{2}$. Note that $c_2c_3c_4c_5$ can be constructed by $c_0c_1c_2c_3$ and $c_4c_5c_6c_7$. Thus, let l be the width of deployment area, the number of useful little squares in a row can be calculated as $l/2c = l/\sqrt{2}R$. In the same way, let h be the height of deployment area, the number of rows is $h/2c = h/\sqrt{2}R$. For each useful little square, ME will beacon four times. Therefore, the total number of beacons is $4(hl)/(2R^2) = 2hl/R^2$.

C. Obstacle Detection and Evasion

The main problem of RSSI algorithm is that of NLOS scenarios in real-world WSN localization systems. In these conditions communication is maintained via multi-paths. However multi-paths will have a different trajectory and path length to the line-of-sight (LOS) path, which will cause errors in the final location accuracy. These errors will be spatially correlated, potentially over large distances, and often biased in nature. Based on the real-time physical link measurements and the physical layer characteristics of a mobile multi-path fading environment and the radio in use, an obstacle detection procedure is proposed which can be utilized to evade obstacle and enhance location performance.

Obstacles which are on the direct line between sensor and ME are a further cause for signal attenuation. Of course, this attenuation effect, also known as shadowing, depends on the object's size, the material it is made of, as well as the radio technology and the utilized frequency.

Normally, the unknown-position node can periodically receive beacon message from ME. One way, if the unknown-position node cannot receive a beacon message abruptly after a period of time, the unknown-position node thinks that link between ME and sensor has been destroyed by obstacle. Then the unknown-position node will send a message to ME to require it resend a new beacon message. Another way, when the average RSS, which is calculated using a sliding window of N samples by the unknown-position sensor node, and link quality indicator go below their thresholds, RSS_{th} and LQI_{th} after receiving the related beacon message, the unknown-position node thinks that the current link between ME and sensor has been destroyed by obstacle. However, this scheme may also make inaccurate decision since the undetermined statistical distribution of NLOS error. Thus, we further propose to use the following obstacle detection scheme based on hypothesis test.

Here, we would like to use a binary hypothesis test to identify the channel state as follows [24]:

$$H = H_0 \qquad \text{(LOS condition)}$$

$$H = H_1 \qquad \text{(NLOS condition)}$$

In Eq. (1), X_σ is a zero-mean Gaussian random vector with standard deviation ó. The density function of X_σ can be written as [24]

$$f_X = \begin{cases} (2\pi\sigma_{los}^2)^{-1/2}\exp(-\dfrac{x^2}{2\sigma_{los}^2}), H = H_0 \\ (2\pi\sigma_{nlos}^2)^{-1/2}\exp(-\dfrac{x^2}{2\sigma_{nlos}^2}), H = H_1 \end{cases} \tag{15}$$

Thus, the conditional density functions of $PL(d)$ for different scenarios can be described by

$$f_{PL(d)} = \begin{cases} (2\pi\sigma_{los}^2)^{-1/2}\exp(-\dfrac{(PL(d_0)-PL(d)-10n\lg(d/d_0))^2}{2\sigma_{los}^2}), \\ H = H_0 \\ (2\pi\sigma_{nlos}^2)^{-1/2}\exp(-\dfrac{(PL(d_0)-PL(d)-10n\lg(d/d_0))^2}{2\sigma_{nlos}^2}), \\ H = H_1 \end{cases} \tag{16}$$

The probability that the RSS measurement was captured with obstacle effect is higher than the LOS probability. Based on this decision metric, we can further estimate the channel state whether it is affected by the obstacle or not.

After receiving the request message from the unknown-position node, the ME will construct a new link between ME and sensor node and broadcast a new beacon message after moving a short distance from the former beacon point. The former RSS contaminated by NLOS effect will be discarded by the unknown-position node for position estimation. The simulation and in-depth analysis of this obstacle detection and evasion mechanism will be presented in the future work.

IV. SIMULATION RESULTS AND PERFORMANCE ANALYSIS

In this section, simulation results are presented and analyzed. We deploy 100 sensor nodes randomly in a three-dimensional space. The radio range of sensor nodes (R) is set to 50 meters first. We simulated a single general node with four different positions of ME beacons in a cell coverage area, and explored single point estimation through sets of 1,000 independent simulations. Each run generated a given number of different positions of ME beacon points randomly. The parameters of propagation model adopted for our simulation scenario are n=2.3, $PL(d_0) = -56.6519$, ó=3.92 [16]. We use a sliding window of 10 samples to compute the mean signal strength on a continuous basis, which will be adopted in our proposed algorithm. This window size can be varied with the density of the nodes. Firstly, we study the performance of our algorithm based on Gaussian noise environment. The RSS measurement error caused by target node and all network devices is assumed to be Gaussian distributed with mean 0 and variance $1*i$ dB (where $i = 1,2,\cdots,5$). Secondly, we will simulate our algorithm based on AWGN and Rayleigh channels respectively. The simulation results are presented in the following figures:

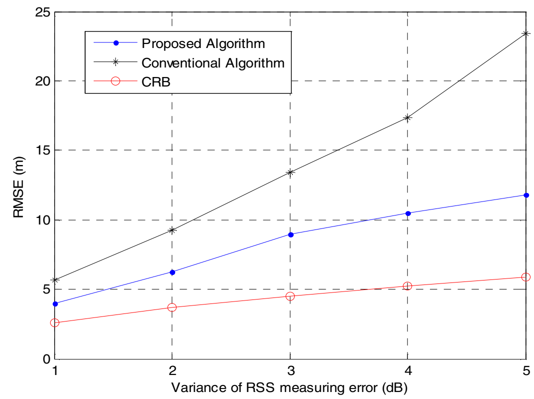

Fig.2 Position errors of algorithm in LOS environment

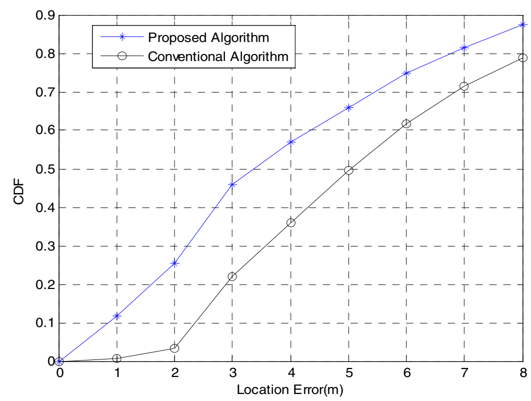

Fig.3 Cumulative distribution functions of estimation error

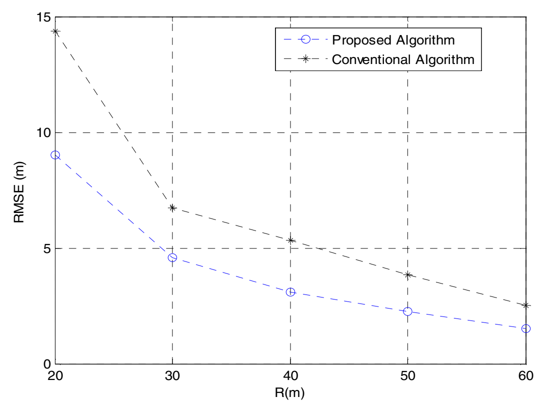

Fig.4 Position errors of algorithm in AWGN Channels

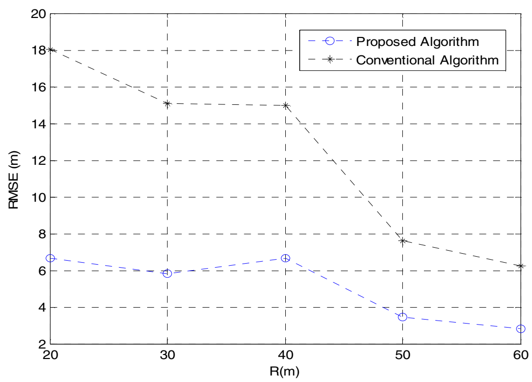

Fig.5 Position errors of algorithm in Rayleigh Channels

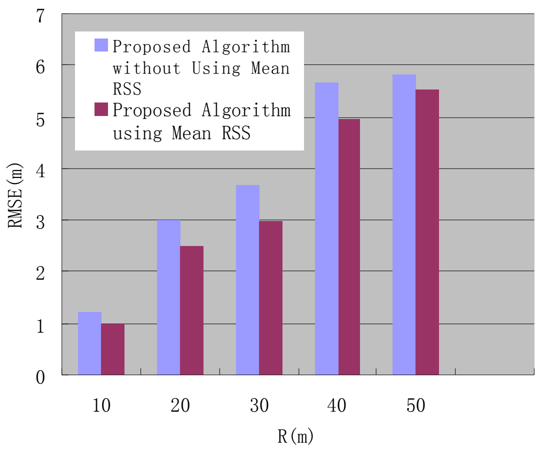

Fig.6 Analysis localization errors in LOS environment

As can be seen from the simulation results of Fig.2, our proposed algorithm achieves better performance than the conventional RSSI algorithm in LOS environment. The root mean square error (RMSE) increases as the measurement error variance increases. From Fig.2, we can also see that the RMSE of our scheme is closer to CRLB than that of the conventional RSSI algorithm. Fig. 3 is the cumulative density function of position error. Over 81% of the nodes have less than 7m error in our proposed algorithm, but it decrease to 72% for the conventional RSSI algorithm. For the same variance, position error is smaller when our scheme is applied in LOS environment than in AWGN or Rayleigh channels as shown in Figs.4-5. In AWGN and Rayleigh channels, our proposed algorithm also behaves better than the conventional RSSI algorithm in this scenario. From Fig.6, we improve the location accuracy of our proposed algorithm by using a sliding window of 10 samples to compute the mean signal strength on LOS environment. The performance of our scheme exceeds the conventional RSSI location algorithm from our simulation results.

V. TESTBED EXPERIMENTATION

We have implemented our novel localization scheme to verify its computational efficiency and estimation accuracy in a real environment. We now describe this implementation and report on preliminary experimental results.

A. GANIS Sensor Node Platform

Fig.7 GAINS Sensor Node

GAINS sensor node, shown in Fig.7, is our testbed and run the GOS event-driven operating system. The GAINS sensors deployed in our experiment use the CC1000 radio from ChipCon, which provides an analog RSSI measurement that can be connected to an analog to digital converter (ADC) to produce digital signals. These RSSI measurements can be used for localization. A laptop computer attached with sensor node is acted as a ME in our experiment.

B. Experimental Results for Wireless Channel Model

In the first experiment, we estimate the path loss in WSNs using measured signal strengths of received frames and their known transmission power levels.

Table I contains the numerical values of the model parameters for the three anchor nodes considered separately and when taken together. We do this experiment in a large meeting room with a size of 10 m x 10 m. We vary the distance between an anchor node and target node while the position of anchor node is fixed. After obtaining a number of RSSI measurements with different distances, we calculate the statistical feature for these measurements and the parameters of wireless channel model.

We note that the values for the path loss exponent (n) and the reference signal strength ($PL(d_0)$) for all three anchor nodes are similar despite their different physical locations and surroundings. This result is encouraging since it indicates that the parameter values are not tied to the specific location of the anchor nodes. The values of $PL(d_0)$ are higher than those published by the manufacturer (for d_0 = 1 meter) because our real experimental environment does not account for multi-path propagation but only in LOS scenario. The values of the path loss exponent are also smaller than those reported in previous work on radio propagation modeling. However, they are consistent with our expectations since we do not consider multi-path (which can boost the signal strength at a given location). These data reinforce the observation that log-normal shadowing path loss model fits the measured data well.

TABLE I. PARAMETER ESTIMATES IN REAL EXPERIMENTAL ENVIRONMENT

	ANCHOR NODE1	ANCHOR NODE2	ANCHOR NODE3
PL(d0)	-58.0095	-62.2229	-54.6847
n	2.3728	2.3776	2.5946
ó	3.5804	2.8637	3.3632
Voltage	3.91	3.88	3.83

TABLE II. RSSI RANGE

READER	MAX (DBM)	MIN(DBM)	VOLTAGE (V)
Anchor Node1	-54.1878	-106.4651	3.91
Anchor Node2	-56.3386	-108.0481	3.88
Anchor Node3	-53.0931	-104.8931	3.82

In the second experiment we identify the validity range of the data acquisition in terms of minimum and maximum receiving power. Results are given in Table II where our experiments well match with the constructor claims. We do this experiment in a large LOS outdoor square.

VI. CONCLUSIONS AND FUTURE WORK

In the paper, we have proposed a scheme for node localization which uses the generalized weighted geometrical location algorithm to achieve more accurate estimation in mobility-assisted wireless sensor networks. Our positioning scheme does not require sensor nodes to make radio transmission constantly but listen to ME beacon signals passively. This efficiently reduces sensor energy cost and also improves the usage ratio of RF channels. An effective moving trace for ME is devised to make best use of ME while achieving the localization requirement. To reduce the effect of obstacle on node localization, a method for obstacle detection and evasion has also been studied. As shown in the simulation results, it is found that the proposed approach is effective and has good location accuracy than the conventional RSSI algorithm. Now that we have validated our ideas through simulation, implementation and experiment, it can be stated that the approach is effective and has good application foreground in some special mobility-assisted sensor networks areas.

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