Research Article

Indoor Mobile Localization in Mixed Environment with RSS Measurements

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Received 3 June 2014; Revised 24 September 2014; Accepted 29 September 2014

Academic Editor: Shigeng Zhang

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Mobile localization is a significant issue for wireless sensor networks (WSNs). However, it is a problem for the indoor localization using received signal strength (RSS) measurements that the signal is contaminated by the anisotropy fading and interference due to walls and furniture. Standard schemes such as Kalman filter are inadequate as the random transition of line-of-sight (LOS)/non-line-of-sight (NLOS) conditions occurs frequently. This paper proposes an indoor mobile localization scheme with RSS measurements in a mixed LOS and NLOS environment. First, a new efficient composite measurement model is induced and validated, which approximates the complex effects of LOS and NLOS channels. Second, a greedy anchor sensor selection strategy is adopted to break through the constraint of hardware consistency and the multipath interference. Third, for the Markov transition between LOS and NLOS conditions, an effective unscented Kalman filter (UKF) based interactive multiple model (IMM) is proposed to estimate not only the posterior model probabilities but also a weighted-sum position estimation with the aid of likelihood function. To evaluate the proposed algorithm, a complete hardware and software platform for mobile localization has been constructed. The numerical study, relying on the actual experiments, illustrates that the proposed UKF based IMM achieves a substantial gain in precision and robustness, compared with other works.

1. Introduction

Mobile location estimation has already been a popular research topic for decades. Different solutions based on angle of arrival (AOA), time difference of arrival (TDOA), time of arrival (TOA), and received signal strength (RSS) have been reported in literature [1, 2]. Applications of these techniques arise, such as in emergency services, location-based billing, smart home, fleet management, and intelligent transportation systems (ITS) [2]. Here, we concentrate on mobile terminal tracking based on RSS measurements in wireless sensor networks (WSNs).

Accurate position estimation would be feasible using an efficient filtering, if a direct physical connection between the mobile terminal (MT) and the anchor sensor (AS) exists; that is, the channel can be considered as line-of-sight (LOS). However, in certain environments, especially in indoor areas, reflection and diffraction occur often between the MT and AS. The worsened propagation decay, corresponding to non-line-of-sight (NLOS), leads to a misestimated range. The erroneous position estimations would occur when using normal strategies. Meanwhile, the frequent transition between LOS and NLOS will cause a serious measurement error for the range estimation because the estimated covariance of the measurement noise is not adaptively matched to the true covariance in the LOS and NLOS cases. So the estimators which are robust against a mixed LOS/NLOS environment are required.

This burning question has been of considerable interest for many years [3–14]. These localization algorithms can be grouped into two categories: detection-based approach and estimation-based approach. The detection-based localization algorithms rely on either the residual or the prior information of the NLOS error in the detection hypotheses on the basis of statistical decision theory [15–17]. One limitation of these algorithms is that it requires at least 3 measurements. Locating a MT in NLOS environments is also considered in [18, 19] to improve accuracy by smoothing the measurements or overweighting the LOS ASs. Another method based on modified probability data association (MPDA) is
proposed in [14]. This method constructs different subgroups of measurements. Then intermediate results of the LOS subgroups are combined to reach the final estimated position of the moving target. However, in severe NLOS conditions, it is very likely that no subgroup is detected as LOS at many time instances. As a result, no new measurement is available to update the filtering.

While the estimation-based approaches utilize the statistical properties of the LOS and NLOS noises and reconstruct posterior estimated position [3–5, 19], they are robust in many NLOS conditions but are not efficient as the high computational cost and incomplete measurement models. As for frequent LOS/NLOS transition in a mixed environment, some good progress with interactive multiple model (IMM) has been made in this category. It [20–22] has been demonstrated as one of the most effective schemes for position estimation in a hybrid dynamic system under uncertain environments. Yang et al. [23] present a location estimation algorithm using fuzzy-based IMM estimator. In [24], IMM is adopted for the MT location estimation as well. However, the indoor environment is quite different from the urban structure in [24]. The system model and estimator seems to be an oversimplification for an indoor application, since it fails to consider the signal attenuated by walls or furniture.

Most existing research works on a localization algorithm under the assumption of different probability distribution functions of the LOS and NLOS noise. However, some other significant distinctions exist between LOS and NLOS propagation, resulting in various new measurement models.

In this paper, we present an efficient MT positioning algorithm using UKF based IMM with individual RSS measurements in a mixed LOS/NLOS indoor environment. In addition, the proposed framework has been evaluated on a practical platform in a real application situation. The main works are as follows.

(i) An effective measurement model is derived to describe the influence of fading caused by the indoor environment and defined as a superposition RIM and Gaussian noise. Furthermore, the model has been verified in an actual indoor building containing the LOS and NLOS channel conditions.

(ii) A greedy AS selection strategy is introduced to choose the AS with the largest RSS measurement in each time instant. The proposed strategy is much easier to implement in the practical application, to reduce the communication traffic and lower the requirement of the hardware.

(iii) The unscented Kalman filter (UKF) is employed to treat the estimator. The point of sampling conquers the severe nonlinear of the mapping of RSS to range. By integrating the filter into IMM, the model probabilities are updated according to the likelihoods of errors. A combination of the weighted respective estimations is achieved as the output result.

(iv) A complete mobile localization platform, which works on STM32F107VCT and AT86RF231, is established by applying the algorithm into a real indoor scenario. The experiments illustrate that the proposed estimator outperforms some other localization methods [14, 24, 25].

The rest of this paper is organized as follows. Section 2 briefly states the problem of mobile localization in a time-variant environment. Section 3 derives a composite measurement model and validates it in a real application scenario. Section 4 presents the proposed UKF based IMM scheme, with both theoretical analysis and formula derivation. A numerical study relying on the practical experiment data is presented in Section 5 to illustrate the merits of the proposed algorithm and some deep analysis compared with other works. Finally, conclusions are drawn in Section 6.

2. Problem Statement

A synchronous network of $N$ anchor sensors (AS) fixed at the known positions is assumed. Their positions are denoted by a set of $m$-dimensional vectors $A = [A_1, A_2, \ldots, A_n]$, respectively. $m = 2$ is considered in this paper although $m = 3$ is also possible for a stereoscopic situation. Thus, for $i \in \{1, 2, \ldots, N\}$, the $i$th AS is fixed at $A_i = [x_i, y_i]$.

In order to state the problem, a corridor situation in our lab building is illustrated in Figure 1. The solid triangles represent the ASs; the dashed line represents the trace of a MT. All the ASs are located in the rooms along the corridor. Due to the doors, some ASs can be exposed to the MT at some certain locations.

The MT moves along the corridor. The unknown positions of the MT at time instant $t$ are denoted by a $2m$-dimensional vector

$$X_t = [x_t, \dot{x}_t, y_t, \dot{y}_t],$$

(1)
However, the approximate description of the alternative estimation of the locations in the time-dependent fading channels. Multiple measurement models in a mixed environment and on the RSS values. Some other works [24, 25] demonstrate the channel, which makes it difficult to estimate the range based on the RSS values. On account of the complicated effects on the RSS measurement, the measurement model, a mathematical mapping of RSS to range, is hardly denoted by a single curve.

As a consequence, the measurement model RSS = H(d) is illustrated as the superimposed effects on the path loss between the MT and the AS. In addition, the measurement model is time variant, altering between LOS and NLOS fading channels, which makes it difficult to estimate the range based on the RSS values. Some other works [24, 25] demonstrate the multiple measurement models in a mixed environment and estimate the locations in the time-dependent fading channels. However, the approximate description of the alternative measurement model is not complete, lack of the irregularity of a radio pattern. And the estimator is not robust enough especially when the ASs are not deployed densely, which indicates that the nonlinear mapping enlarges the filter errors.

From the above, an appropriate measurement model is an urgent issue to approximate the mapping of RSS to range. More importantly, it is essential to propose an adaptive localization estimator in order to accommodate the time-variant fading channels.

3. A Composite Measurement Model

In order to approximate the time-variant measurement model, especially the irregular effect on wireless signal fading caused by the obstacles, the RIM model has been introduced [26]. Furthermore, as a measurement, the power measurement $P_i(t)$ corresponding to the RSS value between the AS $i$ and the MT at the time instant $t$ can be modeled as

$$P_i(t) = P_T - PL_0 - 10\eta\log_{10}\left(\frac{d_i}{d_0}\right)^{1+DOI} + \nu(t),$$

where $DOI$ is the degree of irregularity defined as the maximum path loss percentage variation per unit degree change in the direction of the radio propagation [26]. As shown in Figure 3, when the DOI is set to 0, there is no range variation, and the communication range is a perfect sphere. However, when the DOI value increases, the communication range becomes more and more irregular.

For different fading channels of LOS and NLOS, there are various DOI values, respectively, marked as $DOI_{LOS}$ and $DOI_{NLOS}$. To simplify model (4), a general expression for the LOS and NLOS channels is as follows:

$$P_i(t) = P_T - PL_0 - 10\eta_{LOS}\log_{10}\left(\frac{d_i}{d_0}\right)^{1+DOI_{LOS}} + \nu_{LOS}(t),$$

$$P_i(t) = P_T - PL_0 - 10\eta_{NLOS}\log_{10}\left(\frac{d_i}{d_0}\right)^{1+DOI_{NLOS}} + \nu_{NLOS}(t),$$

where $\nu_{LOS}$ and $\nu_{NLOS}$ are the RSS measurement noise modeled as a white Gaussian with $N(\mu_{LOS}, \sigma^2_{LOS})$ and $N(\mu_{NLOS}, \sigma^2_{NLOS})$. The parameters of $\eta$, $P_T$, $d_0$, and $P_0$ are channel attenuation coefficient, transmitting power of the RF model, reference distance between the MT and the AS, and the path loss at $d_0$. $d_i$ is the Euclidean distance between the MT $(x_i, y_i)$ and the $i$th AS $(x'_i, y'_i)$, which is defined as

$$d_i = \sqrt{(x_i - x'_i)^2 + (y_i - y'_i)^2}, \quad i = 1, 2, \ldots, N.$$
To determine the key parameters above, we make an experiment of RSS measurements collection using 8 ASs and 1 MT over a set of distances ranging from 1 m to 28 m with LOS and NLOS conditions. The whole experiment takes more than 6 hours, with a sampling period 1 s. Figure 4 shows the anchor node and the mobile node. The node is composed of a STM32F107VCT MCU running with an embedded system μCOSII and a ATRF231 RF model working at 2.4 GHz.

The experiment dataset contains about 380 sets of measurements, and each set corresponds to a certain MT’s...
For any pair of RSS measurement and the known distance, a constraint should be satisfied:

$$
\min_{\eta, \mu} \sum_{i,j} | \text{RSS}_i^j - \left[ P_T - PL_0 - 10\eta \log_{10} \left( \frac{d_i^j}{d_0} \right) + \mu \right] |
$$

$$
= \begin{bmatrix}
R \text{SS}_1^j - P_T + PL_0 \\
\vdots \\
R \text{SS}_N^j - P_T + PL_0
\end{bmatrix},
$$

(7)

where (9) is the matrix format of (8). For convenience, we define the left matrix of (9) as $A$ and the right matrix of (9) as $B$. Then the optimal solution is given below:

$$
[\mu \eta ] = (A^T A)^{-1} A^T B.
$$

In order to validate the efficiency of the optimal $\mu$ and $\eta$ for LOS or NLOS, we examine it in another experiment where 7 ASs and 1 MT are set at different positions. Figure 5 compares the fitting RSSs according to $\mu$ and $\eta$ above with the real RSS measurements at a series of sampling positions in LOS and NLOS conditions, respectively. Figure 6 illustrates the approximation result in the form of logarithmic ranges. It is clear that the fitting curve can approximate the fading trend of RSS measurements along with the increasing ranges in both propagation conditions. The proposed composite measurement model makes a more complete description of the complex fading model for LOS and NLOS propagation channels.

$Z_i(t)$ is the RSS measurement measured by the $i$th AS at time instant $t$, and $H(X_t, A_S)$ indicates the mathematical mapping of the RSS measurement and the MT’s state $X_t$. 
As a consequence, the composite measurement model of a LOS/NLOS mixed fading channel is defined as follows:

\[ Z_i(t) = H(X_i, AS_i) \]

\[ = \begin{cases} 
P_T - PL_0 - 10\eta_{LOS}\log_{10}\left(\frac{d_i}{d_0}\right) + \eta_{LOS}(t) & \text{for LOS} \\
P_T - PL_0 - 10\eta_{NLOS}\log_{10}\left(\frac{d_i}{d_0}\right) + \eta_{NLOS}(t) & \text{for NLOS},
\end{cases} \]

(11)

where \( \eta_{LOS} = 1.3063, \eta_{NLOS} = 1.9508, \eta_{LOS} = N(-0.591, 36.7567), \) and \( \eta_{NLOS} = N(5.7512, 44.7445) \). The definitions of \( P_T, PL_0, d_0, \) and \( d_i \) are identical to those in (5).

4. UKF Based IMM Localization Estimation

As mentioned above, since the signal propagation indoor is complicated, the fading condition alters between LOS and NLOS cases. The transmission channels between the AS and the MT are considered as a switching mode system. In other words, a LOS/NLOS transition occurs when the MT moves into an environment with the different properties of the propagation medium. A two-state Markov process in Figure 7 is employed to describe the switching system.

A single measurement model corresponding to one propagation condition cannot adjust to both LOS and NLOS situations. It is necessary to introduce a mixed and adaptive scheme against this challenge. Therefore, an UKF based IMM localization estimator is adopted for the LOS/NLOS environment.

4.1. General Concept. The flowchart of the UKF based IMM localization estimation is illustrated in Figure 8.

First, as the MT moves, it broadcasts a discovery signal. Based on greedy anchor sensor selection, the AS with the largest RSS measurement \( Z(t) \) is chosen from the candidates which have received the discovery signal. It should be noted that a larger RSS measurement indicates either a LOS propagation model or a shorter distance between the transmitter and receiver. It is instinctive and easy to implement.

Then, the state \( X(t | t) \) for the \( i \)th AS is simultaneously estimated by two parallel UKFs according to the LOS and NLOS models, respectively. The mode probabilities of the present measurement model can be calculated and updated by a likelihood function via the respective estimation error. Afterwards, the IMM structure combines the independent estimation results with their different mode probabilities. For the next time instant, the prior state transition probabilities rely on a constant Markov switching matrix and the previous mode probabilities.

4.2. Greedy Anchor Sensor Selection. As the MT broadcasts the discovery signal in a constant transmitting power, each AS receives this signal and obtains a different RSS measurement due to the different distance. After that, each AS enables a timer with an initial \( T_i, i \in \{1, 2, \ldots, N\} \):

\[ T_i = \frac{T_0}{Z_i(t)}, \]

(12)

where \( Z_i(t) \) is the RSS measured by the \( i \)th AS at time instant \( t \). \( T_0 \) is a constant to adjust each \( T_i \) to a practical value for the hardware clock. According to (12), a larger RSS measurement indicates a shorter \( T_i \). Therefore, the AS with the largest RSS times out firstly, then it replies to the MT a message including its own coordinates and the largest RSS \( Z_i(t) \). Once the MT received any reply, it broadcasts a stop-reply signal to all the ASs. The subsequent ASs abort their timers and return to the state of monitoring.

In this way, the largest RSS is collected to the MT. In (11), the RSS is related to \( P_T \). However, in [24, 25], \( P_T \) is assumed to be identical and time-invariant for all the ASs. It is usually unpractical for most of the applications. On this view, the proposed anchor sensor selection ensures all RSS measurements are based on one \( P_T \) which is emitted by the MT, rather than any AS, in each time instant.

Furthermore, in a practical system, it is hard to distinguish the ASs if a subtle difference between the first smallest \( T_i \) and the second smallest \( T_j \) happens. It is injudiciousness to enlarge \( T_0 \), because it leads to a more significant delay. From this view, an improved scheme is presented in Figure 9.

4.3. UKF-IMM Algorithm. The proposed algorithm consists of three major stages: interaction, filtering, and combination.

4.3.1. Interaction. \( i, j \in \{1, 2\}, 1 \) for the LOS estimator and 2 for the NLOS estimator.

We suppose that the current multiple-mode states depend on the previous modes, and all the transition probabilities are known. The mixing probability from mode \( i \) to mode \( j \) can be denoted as

\[ \mu_{ij}(t | t-1) = \frac{p_{ij} \mu_i(t-1 | t-1)}{\bar{c}_j}, \]

(13)

where \( p_{ij} \) is the Markov transition probability from mode \( i \) to mode \( j \), \( \mu_i(t-1 | t-1) \) is the probability of mode \( i \) at time instant \( t-1 \), and \( \bar{c}_j \) is a normalization factor for the prior mode and is expressed as

\[ c_j = \sum_i p_{ij} \mu_i(t-1 | t-1). \]

(14)
The mixed prior state $X_{0j}(t-1 | t-1)$ and covariance $P_{0j}(t-1 | t-1)$ for the $j$th mode-matched estimator at time instant $t-1$ can be obtained by

$$
X_{0j}(t-1 | t-1) = \sum_i X_i(t-1 | t-1) \mu_{i|j}(t-1 | t-1)
$$

$$
P_{0j}(t-1 | t-1) = \sum_i \left[ [X_i(t-1 | t-1) - X_{0i}(t-1 | t-1)] \times [X_i(t-1 | t-1) - X_{0i}(t-1 | t-1)]^T + P_i(t-1 | t-1) \right] \mu_{i|j}(t-1 | t-1),
$$

(15)

where $X_i(t-1 | t-1)$ and $P_i(t-1 | t-1)$ are the state estimation and covariance for the $i$th mode-matched estimator at time instant $t-1$, respectively. $X_i(t-1 | t-1)$ and $P_i(t-1 | t-1)$ are prepared by the previous mode-matched unscented Kalman filtering stage.

4.3.2. Filtering. Based on the prior knowledge that the measurement models are quite different between LOS and NLOS conditions, two unscented Kalman filters are designed for these two measurement models.

Initializing. For either estimator, the initial state $X_i(0)$ and $P_i(0)$ are obtained from the system initialization.

Sampling. A set of sigma points $S_j = \{X_j, W_j\}$ is generated so that the mean and the covariance of the samples are

$$
X_j^0(t-1 | t-1) = X_i(t-1 | t-1)
$$

$$
X_j^i(t-1 | t-1) = X_i(t-1 | t-1) + \left( \sqrt{(n+\kappa) P_i(t-1 | t-1)} \right)_j
$$

$$
, \quad j = 1, \ldots, n
$$

Figure 9: The scheme of greedy anchor sensor selection.

MT broadcasts a discovery signal

ASs measure RSSs and set $T_j$'s

MT receives the anchor info and RSS with the smallest $T_j$

A subtle difference between $T_j$ and $T_i$ happens

MT chooses the AS which is nearest to $FX(t | t-1)$

MT broadcasts a stop-reply signal

Yes

No

$X_i(t-1 | t-1)$ and $P_i(t-1 | t-1)$. The samples are not drawn randomly but according to a specific, deterministic algorithm, as follows:
\[ x_i(t-1 | t-1) = X_i(t-1 | t-1) - \left( \sqrt{(n+\kappa)P_i(t-1 | t-1)} \right)_j, \]
\[ j = n+1, \ldots, 2n, \]
\[ \begin{align*}
W_0^m &= \frac{\kappa}{n + \kappa} \\
W_0^m &= \frac{\kappa}{n + \kappa} \\
W_j^m &= W_j^c = \frac{\kappa}{2(n + \kappa)},
\end{align*} \]  
(17)

where \( n \) is the dimension of the state estimation \( X_i(t-1 | t-1) \) and \( \kappa \) is the scaling factor which determines the approximating precision. When the state estimation \( X_i(t-1 | t-1) \) is assumed Gaussian, an useful heuristic is to select \( n + \kappa = 3 \) [27].

The weights \( W_j^m, W_j^c \) should also meet some constraint principles. Here, \( \alpha \) determines the "size" of the sigma point distribution. It is recommended to be a small value to avoid sampling nonlocal effects when the system is nonlinear strongly. \( \beta \) in (17) is a nonnegative weighting term to incorporate knowledge of the higher order components of the distribution. For a Gaussian assumption, the optimal \( \beta \) is 2. This parameter can also control the deviation in the kurtosis which affects the "heaviness" of the tails of the posterior state distribution [28].

**Time Update.** Instantiate each point in (16) by the state update function and the measurement function to yield the set of transformed sigma points:

\[ x_i^j(t | t-1) = F x_i^j(t-1 | t-1), \quad j = 0, 1, \ldots, 2n, \]
\[ \psi_i^j(t | t-1) = H \left( x_i^j(t | t-1) \right), \quad j = 0, 1, \ldots, 2n. \]  
(18)

The mean is given by the weighted sum of the transformed points. And the covariance is the weighted outer product of the transformed sigma points:

\[ \begin{align*}
\overline{X}_i(t | t-1) &= \sum_{j=0}^{2n} W_j^m x_i^j(t | t-1) \\
\overline{Z}_i(t | t-1) &= \sum_{j=0}^{2n} W_j^m \psi_i^j(t | t-1) \\
P_i(t | t-1) &= \sum_{j=0}^{2n} W_j^m \left[ x_i^j(t | t-1) - \overline{X}_i(t | t-1) \right] \\
&\quad \times \left[ \psi_i^j(t | t-1) - \overline{Z}_i(t | t-1) \right]^T + Q,
\end{align*} \]  
(19)

where \( Q \) is the covariance of Gaussian process noise as mentioned in (2).

**Measurement Update.** With the chosen RSS measurement \( Z_i(t) \), a measurement update is computed:

\[ \begin{align*}
P_{Z,Z_i} &= \sum_{j=0}^{2n} W_j^m \left[ \psi_i^j(t | t-1) - \overline{Z}_i(t | t-1) \right] \\
&\quad \times \left[ \psi_i^j(t | t-1) - \overline{Z}_i(t | t-1) \right]^T + R \\
P_{X,Z_i} &= \sum_{j=0}^{2n} W_j^m \left[ x_i^j(t | t-1) - \overline{X}_i(t | t-1) \right] \\
&\quad \times \left[ \psi_i^j(t | t-1) - \overline{Z}_i(t | t-1) \right]^T \\
K_i &= P_{X,Z_i} P_{Z,Z_i}^{-1},
\end{align*} \]  
(20)

where \( K \) is the Kalman gain and \( R \) is the measurement noise. For a LOS model, \( R = \sigma^2_{LOS} I \), for a NLOS model, \( R = \sigma^2_{NLOS} I \). \( \psi_i(t) \), \( P_i(t | t) \), and \( X_i(t | t) \) should be substituted to the process of combination to derive the mode probabilities and the weighted estimation result:

\[ \begin{align*}
\nu_i(t) &= Z_i(t) - \overline{Z}_i(t | t-1), \\
P_i(t | t) &= P_i(t | t-1) - K_i P_{Z,Z_i} K_i^T, \\
X_i(t | t) &= X_i(t | t-1) + K_i \nu_i(t).
\end{align*} \]  
(21)

**4.3.3. Combination.** When the estimated states are obtained by both estimators, respectively, the model likelihoods and probabilities are required to be calculated in the combination module.

Firstly, the model likelihood \( \Lambda_i(t) \) is measured by a Gaussian density function of residual error \( \nu_i(t) \) in (21), with zero mean and covariance \( S_i(t) = P_{Z,Z_i} \) in (20). The updated \( \mu_i(t | t) \) is a normalized weighted sum of the model likelihoods and the previous prior mode probabilities in (14):

\[ \begin{align*}
\Lambda_i(t) &= N \left( \nu_i(t) ; 0, S_i(t) \right), \\
\mu_i(t | t) &= \frac{\Lambda_i(t) \overline{c}_i}{c}, \\
c &= \sum_i \Lambda_i(t) c_i.
\end{align*} \]  
(23)

According to the posterior mode probability \( \mu_i(t | t) \), the combined estimation can be derived as

\[ \begin{align*}
X(t | t) &= \sum_i X_i(t | t) \mu_i(t | t), \\
i &= 1, 2 \text{ respectively for LOS and NLOS model.}
\end{align*} \]  
(24)

Here, the combined result is exported in the form of \( X(t | t) = (\overline{x}_i, \overline{y}_i) \). For each estimator, the estimated \( X_i(t | t) \) and \( P_i(t | t) \) return to the interaction process at the next time instant.
the LOS propagation channel, has the ability to obtain the RSS of the MT’s signal. For the monitoring region have the same structure. Each AS field as shown in Figure 1. The total monitoring time is 88s, and the sampling period $T$ is 1s. All the ASs within the monitoring region have the same structure. Each AS has the ability to obtain the RSS of the MT’s signal. For the LOS propagation channel, $\eta_{\text{LOS}}$ is set to 1.3063 and the Gaussian noise $\eta_{\text{LOS}}$ is set to $N(0.01, 36.7567)$; for the NLOS propagation channel, $\eta_{\text{NLOS}}$ is set to 1.9508 and the Gaussian noise $\eta_{\text{NLOS}}$ is set to $N(5.7512, 44.7445)$. The MT broadcasts its discovery signal at a power output of 3dBm, and the $PL_0$ is 46dBm. All the parameters are acquired from the experiment in Section 3. In both cases, the process noise $\omega$, $\alpha$, $P_r$, and $PL_0$ are illustrated in Table 1.

In order to describe the actual experiment, we set the initial states as follows. A MT starts to move along the corridor at $t = 0$ with an initial position and velocity $[0.226, 0.6, 12, 0]^T$. Then the MT makes a turn at the corner of the corridor and continues to move.

### 5. Numerical Study

In this section, we use the experiment platform, which is mentioned in Section 3, to evaluate the performance of the proposed localization algorithm. Firstly, we describe our experiment environment and parameters. Then we define the performance metrics to compare the proposed algorithm with other works.

#### 5.1. Experiment Environment

We set up an indoor wireless sensor network with $N$ ASs to monitor a $50 \times 50$ m arch field as shown in Figure 1. The total monitoring time is 88s, and the sampling period $T$ is 1s. All the ASs within the monitoring region have the same structure. Each AS has the ability to obtain the RSS of the MT’s signal. For the LOS propagation channel, $\eta_{\text{LOS}}$ is set to 1.3063 and the Gaussian noise $\eta_{\text{LOS}}$ is set to $N(0.01, 36.7567)$; for the NLOS propagation channel, $\eta_{\text{NLOS}}$ is set to 1.9508 and the Gaussian noise $\eta_{\text{NLOS}}$ is set to $N(5.7512, 44.7445)$. The MT broadcasts its discovery signal at a power output of 3dBm, and the $PL_0$ is 46dBm. All the parameters are acquired from the experiment in Section 3. In both cases, the process noise $\omega$, $\alpha$, $P_r$, and $PL_0$ are illustrated in Table 1.

Table 1: The set of the experiment parameters.

| Experiment parameters | Values                      |
|-----------------------|-----------------------------|
| Monitoring region     | $50 \times 50$ m            |
| Monitoring time       | 88 s                        |
| Number of ASs $N$     | 14                          |
| AS deployment error   | 0.1 m                       |
| Sampling period $T$   | 1 s                         |
| $\eta$                | 1.3063 for LOS; 1.9508 for NLOS |
| Measurement noise $\eta$ | $N(0.01, 36.7567)$ for LOS, $N(5.7512, 44.7445)$ for NLOS |
| Process noise $\omega$ | $\begin{bmatrix} 0.01^2 & 0 \\ 0 & 0.01^2 \end{bmatrix}$ |
| Transmitting power $P_r$ | 3 dBm                       |
| Path loss at $d_0$ $PL_0$ | 46 dBm                      |

#### 5.2. Performance Metrics

To evaluate the performance of the proposed algorithm and other frameworks, we calculate the root of mean square errors (RMSEs) of localization estimations at each time instant. The RMSE metric [14] is defined as follows:

$$\text{RMSE}(t) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2}. \quad (25)$$

$(\hat{x}_i, \hat{y}_i)$ is the estimated coordinate of MT at $t$ time instant, while $(x_i, y_i)$ is the true position at that time instant. A time series of RMSEs of positions and velocities will be given in the following subsection.

#### 5.3. Results and Analysis

##### 5.3.1. Performance of Localization

In order to validate the performance of localization accuracy, a comparison with an EKF based LOS model, an EKF based on NLOS model, IMM-EKF [24, 25], and MPDA [14] is carried out below. In Figure 10, the tracking trajectory obtained by the proposed algorithm is shown. Compared with the real trace, which is denoted by the solid line, the trajectory generated by the UKF based IMM algorithm is quite close and follows the moving trend although a maneuver turn happens at 48s.

It is clear that the whole trajectory can be divided into two parts: one is from the starting position to the sudden turning point and the other is from the turning point to the end point. The trajectory estimated by UKF based IMM scheme has larger errors in the second part than in the first part. It is noticed that the parameters of the measurement model are obtained in a similar scenario to the first part. It is appreciable that the prior knowledge about the fading conditions fits the first part of the trace more precisely. On the other hand, the proposed algorithm is able to offset the errors produced by a biased measurement model in some degree.

As shown in Figure 11, the performance of UKF based IMM is obviously superior to other works. During the first 20s, the fading channel is mainly LOS condition with a slight propagation variation. Then the channel condition changes to NLOS. The proposed algorithm remains a smaller RMSE during the next 20s. In the rest of the monitoring time, the fading channel switchovers several times. The EKF based
Table 2: The time-averaging localization RMSEs of the proposed algorithm and other works.

| RMSE           | IMM-UKF | IMM-EKF | EKF based on LOS | EKF based on NLOS | MPDA |
|----------------|---------|---------|------------------|-------------------|------|
| $v_x$ [m/s]    | 0.013   | 0.038   | 0.1656           | 0.0334            | 0.0868|
| $v_y$ [m/s]    | 0.0148  | 0.0199  | 0.1066           | 0.0417            | 0.0409|
| $\sqrt{x^2 + y^2}$ [m] | 0.84539 | 1.4254  | 10.0769          | 2.1763            | 5.1728|

Figure 11: RMSEs of positions estimated by UKF based IMM and other works.

Figure 12: The comparison of the velocities of $X$ and $Y$ directions is summarized. Table 2 lists the time-averaging localization RMSEs of the proposed algorithm and other works. Considering the maximum velocity in $X$ or $Y$ direction during the maneuvering is about 0.6 m/s, the velocity errors estimated by MPDA and EKF based on LOS are sizable. It is obvious that the proposed UKF based IMM algorithm remains much smaller errors in velocities. At 47 s in Figure 12, the RMSEs of our algorithm undergoes a estimator transition, while some other works encounter the breaking points.

Table 3: Average localization RMSEs for different numbers of ASs.

| Algorithms [m] | 14 | 12 | 10 | 8  | 6  |
|----------------|----|----|----|----|----|
| UKF based IMM  | 0.85| 0.91| 0.89| 1.05| 1.19|
| IMM-EKF        | 1.43| 1.41| 1.72| 1.80| 2.00|
| EKF based on LOS | 10.08| 10.74| 9.20| 11.0| 10.61|
| EKF based on NLOS | 2.18| 2.09| 2.23| 2.48| 3.04|
| MPDA           | 5.18| 6.9 | 8.40| 11.27| 15.94|

5.3.2. Performance of Robustness. For the referenced works in [22, 24, 25], localization estimators using IMM and EKF with TOA or RSS measurements in a mixed propagation model were presented. The employed EKF achieves an acceptable performance in those cases. However, according to the fading channels and deployment environment, the quotative estimator encounters a performance degradation, especially when the distance between the MT and the AS increases. Table 3 also shows that as the numbers of AS decrease, the average RMSEs of other works increase obviously or remain as a larger level. Some discussion in detail comes below.

An UKF recommended by the proposed algorithm performs better than an EKF. It is proved that the approximation precision is closely 3rd-order of Taylor expansion at least, while an EKF depends on 1st-order of Taylor expansion. Besides that, UKF’s computation complexity of $n^3$ is much easier to implement in a practical application, due to no explicit calculation of a Jacobians or Hessians like an EKF does. In Figure 14, each marker point represents an average localization RMSE during the monitoring time for a certain number of anchors. As the numbers of anchors decrease, the distance between the MT and any specific anchor increases. Then the referenced IMM-EKF decays rapidly, whereas the proposed UKF based IMM is hardly affected by the sparsity of anchors.
Through [29], let $X^m$ be a random variable with mean $\bar{X}$ and covariance $P_{XX}$. $Z$ is related to $X^m$ through the nonlinear transformation, namely, the measurement model (5),

$$Z(X^m) = H(X^m, AS_i).$$

The EKF used refers to the Taylor series expansion of this equation. Let $X^m = \bar{X} + \delta X^m$, where $\delta X^m$ is a zero mean random variable with covariance $P_{XX}$. Expanding $H(\cdot)$ about $\bar{X}$,

$$H(X^m, AS_i) = H(\bar{X}, AS_i) + \nabla H\delta X^m + \frac{1}{2}\nabla^2 H\delta^2 X^m + \cdots$$

$$= H(\bar{X}, AS_i) + \nabla H\delta X^m + \frac{1}{2}\nabla^2 H P_{XX} + \cdots,$$

(27)

where the 1st-order term in the multidimensional is

$$\nabla H = \begin{bmatrix} \nabla H_X \\ \nabla H_Y \end{bmatrix}$$

$$= \begin{bmatrix} c \cdot \frac{x^m - x'}{(x^m - x')^2 + (y^m - y')^2} \\ c \cdot \frac{y^m - y'}{(x^m - x')^2 + (y^m - y')^2} \end{bmatrix}. \quad (28)$$

Here $X_m = (x^m, y^m)$, and $(x', y')$ is the coordinate of the specific AS. $c$ is a constant. Considering in (27), as the numbers of anchors decrease, the measurement range becomes larger, which leads to a nonignorable term. In consequence, an EKF estimator fails to approximate the higher order term in (27).

It is crucial for an UKF that it approximates an arbitrary nonlinear system with the weighted sigma points. These points are deterministically chosen so that certain properties match those of the prior distribution. With this set of points,
an UKF guarantees the same performance as the truncated 3rd-order filter.

6. Conclusion

In this paper, we address the problem of robust positioning of a mobile terminal, using RSS measurements in a mixed LOS/NLOS environment. The original measurement models have been reformulated as nonlinear ones, which indicates the anisotropy caused by the indoor obstacles in a NLOS case. We construct the measurement models, which completely describe the differences between LOS and NLOS channel conditions for an indoor application, and validate our composite measurement model in a real scenario. In particular, the UKF based IMM localization estimator is proposed for mobile location estimation in a practical rough wireless environments. An UKF works better than an EKF, due to its superior ability to approximate the nonlinear system in a higher order. With the aid of the likelihood function to determine the mode probabilities in LOS and NLOS, the proposed UKF based IMM could accurately estimate range distance between the MT and the AS even with the channels switching randomly between LOS and NLOS conditions.

The real experiment results illustrate that the performance of our proposed algorithm achieves high accuracy even in a complex environment where the LOS and NLOS channel conditions switch frequently with obviously different fading. Furthermore, the UKF based IMM scheme manifests robustness against the sparse deployment of ASs. It makes it more practical to utilize a localization system widely.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

This work is supported in part by the Strategic Priority Research Program of the Chinese Academy of Sciences (CAS) under Grant no. XDA06020300 and the IoT National Standards System Research and Industrial Application and Demonstration based on Information Perception and Identification Technology of Shanghai Science and Technology Commission (SSTC) research projects under Grant no. 12DZ0500100.

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