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# Multiple-Model Mobile Localization Based on Unscented Kalman Filter in Mixed Indoor

# Multiple-Model Mobile Localization Based on Unscented Kalman Filter in Mixed Indoor

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**Abstract.** In this paper, we present an Interactive multiple mode-Unscented Kalman filter (IMM-UKF) algorithm to achieve mobile node location under wireless sensor networks environments. In the IMM structure, UKF and Variational Bayesian Adaptive Method based on UKF are adapted in parallel, which can improve positioning accuracy in the process of line-of sight (LOS) and non-line-of-sight (NLOS) signal state switching. The estimated values by filtering are fused according to the weighting factors to get the estimated positions. Moreover, when NLOS measurement noise covariance change, we propose Variational Bayesian Adaptive Method based on UKF to improve robustness. Both Simulation and experiments illustrate that the propose algorithm performs can achieve competitive localization accuracy.

**Keywords.** Unscented Kalman filter; localization; mixed indoor; WSN.

## 1. Introduction

Wireless communication, digital electronics micro-electrical-mechanical systems (MENMS) and wireless sensor network (WSN) are booming recently for emergency and robot and so on [1]. For the WSN, Targets localization is one of the important applications, which consist of outdoor localization and indoor localization. GPS is effective means to deal with outdoor localization. However, it is not good choice for indoor localization due to the obstacle’s obstruction. WSN with hundreds of sensor nodes has been employed for indoor localization owing to its low-cost and low-power [2].

Unlike KALMAN filter (KF), it can only solve linear problems. The Unscented Kalman filter (UKF) can provide significant improvement in solving the problem of nonlinear positioning [3]. Therefore, we will discuss target localization problem under the UKF framework in this paper.

Another vital extension study has also been considered about the non-Gaussian distributed assumption. Here, measurements outliers and contaminated distribution can bring to modelling errors. Fortunately, there are many fruitful researches to deal with above problem, such as Gaussian mixture distributions (GMD) filter, variational Bayesian filter, M-estimation filter.

Undoubtedly, NLOS measurement error can be considered the dominant source of error in positioning. In most cases, we should consider its influence on the positioning accuracy. Hence, scholars carry out a research on the identification and elimination of NLOS. In [4], Researchers adopt a binary hypothesis test and Likelihood ratio test method to identify NLOS propagation channel [5-6]. Authors propose RSS localization approach for NLOS. This method introduces the selective residual test to identify the NLOS state, and then subtracting the mean of NLOS errors to correct the NLOS measurements error. However, this process is too tedious. In [7], Bayesian sequential test is proposed to identify measurement condition. After smoothing measurement range, modified Kalman filter is applied to localization. In [8], improved KF based on Gaussian mixture distributions is proposed to reduce the impact of the NLOS error.

In most of the ways, the prior conditions are needed known, but this is not possible in many cases.

Main motivation this article of is to design a modified UKF based on the IMM framework under the condition that the NLOS error is non-Gaussian distributed. The Proposed approaches do not need to accurately know the sight state.

The rest of paper is organized as follows: First, target localization system model is given and introduce Variational Bayesian Adaptive Method. Then derivation in the IMM framework is used modified UKF to solve nonlinear problems. Simulation Experimental result and analysis are state. Finally, the conclusion is present.

## 2. System Model

We consider a localization scenario in a 2-D space with K anchor nodes (ANs) and one moving target (MT), as shown in figure 1. Suppose the MT moves in office and corridor, and sight condition between MN and ANs might be LOS or NLOS.

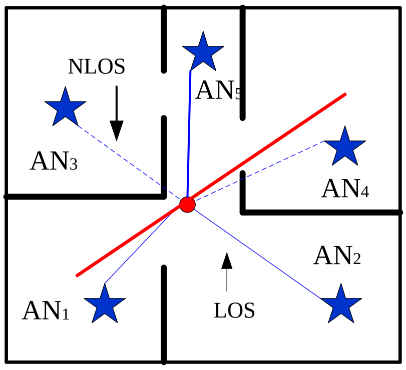


**Figure 1.** Localization scenario.

Although it is very difficult to get accurate motion model from MT, a reasonable motion model can be built according to constant velocity model and model error. At sampling instant *t*, MT is denoted by a state vector $X^t = [x, y, \dot{x}, \dot{y}]^T$, where$(x, y)$ denotes MT's position, $(\dot{x}, \dot{y})$ denotes MT's velocity. The state space model of localization system is defined as follows:

$$X^t = \psi X^{t-1} + G\varsigma^t \tag{1}$$

$$Z_k^t = HX^t + \varphi_L^t + \varphi_N^t \tag{2}$$

where $X^t$ is MT's state and $Z_k^t$ is *k*th AN's measurement at sampling instant *t*. $\psi$ represents the state-transition matrix, $H$ is measure matrix. $\varsigma^t$ is the process noise with zero mean and covariance $Q^t$.$\varphi_L^t$ is the senor measurement noise in LOS sight, which is modelled as a white Gaussian with $N = (0, \sigma_L^2)$ .Whereas, sensor measurement noise $\varphi_N$ which caused by NLOS propagation channel is unknown for us. It might obey Uniform, Exponential or Gaussian distribution with non-zero mean.
$HX^t = ((x^t - x_k)^2 + (y^t - y_k)^2)^{1/2}$ is the actual distance between *k*th AS and MS.

## 3. A VB-UKF Based IMM Localization

The propagation state is continual change between LOS and NLOS in the complex indoor environment. Here, we employ the two-state Markov process to describe this switching state. The transition probabilities are defined as follows:

$$\begin{cases} p_{11} = p\left(\theta_i^t = 1 \middle| \theta_i^{t-1} = 1\right) \\ p_{12} = p\left(\theta_i^t = 2 \middle| \theta_i^{t-1} = 1\right) \\ p_{21} = p\left(\theta_i^t = 1 \middle| \theta_i^{t-1} = 2\right) \\ p_{22} = p\left(\theta_i^t = 2 \middle| \theta_i^{t-1} = 2\right) \end{cases} \tag{3}$$

As mentioned above, single measurement model is inappropriate to apply in both LOS and NLOS situations. So, we introduce IMM structure to deal with the problem of localization for the LOS/NLOS environment. Under circumstance of the unknown measurement noise, we adopt VB-AUKF method for the MS localization [9-11].

*3.1. Input Interaction*

We assume that all the transition probabilities are known, and the mixing probability $\beta_{ij}$ is defined as

$$\beta_{ij}^{(t-1|t-1)} = \frac{p_{ij}\beta_i^{t-1}}{\bar{\alpha}_j} \tag{4}$$

where $p_{ij}$ is transition probability, $\beta_i^{t-1}$ is the probability of the *i*th mode, $\bar{\alpha}_j$ is the normalization mode probability and is denoted as

$$\bar{\alpha}_j = \sum_{i=1}^{2} p_{ij}\beta_i^{t-1} \tag{5}$$

For the *j*th mode, the mixed prior state estimation $X_{0j}$ and covariance estimate $\hat{P}_{0j}$ is given by

$$X_{0j}^{(t-1|t-1)} = \sum_{i=1}^{2} X_i^{(t-1|t-1)} \beta_{ij}^{(t-1|t-1)} \tag{6}$$

$$\hat{P}_{0j}^{(t-1|t-1)} = \sum_{i=1}^{2} \beta_{ij}^{(t-1|t-1)} \{P_i^{(t-1|t-1)} + [X_i^{(t-1|t-1)} - X_{0j}^{(t-1|t-1)}] \times \left[X_i^{(t-1|t-1)} - X_{0j}^{(t-1|t-1)}\right]^T\} \tag{7}$$

where $X_i^{(t-1|t-1)}$ is the state estimation, $P_i^{(t-1|t-1)}$ is covariance for the *i*th mode.

*3.2. VB-UKF Filter*

As mentioned above, the NLOS measurement noise is different from the LOS's. Hence, we design two different UKF in mixed LOS/NLOS environment. For LOS propagation channel, the measurement noise is known, and we can directly use UKF to localization. However, the measurement noise is unknown for NLOS propagation channel and VB-UKF is designed to deal with this problem.

According to the reference [12], if ψ in equation (8) is linear, then the prediction state estimation and covariance prediction estimation of *j* model can be directly obtained by the following formula at step *t*-1:

$$X_j^{(t|t-1)} = \psi X_{0j}^{(t-1|t-1)} \tag{8}$$

$$P_j^{(t|t-1)} = \psi P_{0j}^{(t-1|t-1)} \psi^T + GQG^T \tag{9}$$

The points generated by sampling are as follows:

$$\begin{cases} \eta^{(0),(t|t-1)} = X_j^{(t|t-1)} \\ \eta^{(i),(t|t-1)} = X_j^{(t|t-1)} + \sqrt{n+\lambda}\left(\sqrt{P_j^{(t|t-1)}}\right)_i \\ i = 1, \dots, n \\ \eta^{(i),(t|t-1)} = X_j^{(t|t-1)} - \sqrt{n+\lambda}\left(\sqrt{P_j^{(t|t-1)}}\right)_i \\ i = n+1, \dots, 2n \end{cases} \tag{10}$$

where $n$ is the dimension of the state estimation $X^{(t-1|t-1)}$.

The weights of the sigma points are computed as follows:

$$\begin{cases} \omega_m^{(0)} = \frac{\lambda}{n+\lambda} \\ \omega_c^{(i)} = \frac{\lambda}{n+\lambda} + (1 - a^2 + b) \\ i = 1, \dots, n \\ \omega_m^{(i)} = \omega_c^{(i)} = \frac{\lambda}{2(n+\lambda)} \\ i = n+1, \dots, 2n \end{cases} \tag{11}$$

where λ is the scaling factor with $\lambda = an - n$. The selection of α controls the distribution state of the sampling points. Here, $b \geq 0$ is a nonnegative weight coefficient, which can incorporate the higher order components of distribution. It can be obtained that the optimal value $b = 2$, $a = 0.01$ through a large number of experimental analysis.

Prediction:

State prediction estimation of sigma points is given by the state update function:

The observation sigma points are yielded by the measurement function H.

$$Z^{k,i,(t|t-1)} = H\eta^{(i),(t|t-1)} \tag{12}$$

$$i = 0, \dots, 2n$$

$$k = 1, \dots, K$$

And measurement mean is calculated by observation sigma points and corresponding weights

$$\hat{Z}^{k,(t|t-1)} = \sum_{i=0}^{2n} \omega_m^{(i)} Z^{k,i,(t|t-1)} \tag{13}$$

The covariance, cross covariance and Kalman gain of the observed sigma point in LOS environment are as follows:

$$P_{Z_j} = \sum_{i=0}^{2n} \omega_c^{(i)} \left(Z^{i,(t|t-1)} - \hat{Z}^{(t|t-1)}\right)\left(Z^{i,(t|t-1)} - \hat{Z}^{(t|t-1)}\right)^T + R^t \tag{14}$$

$$P_{x_j Z_j} = \sum_{i=0}^{2n} \omega_c^{(i)} \left(\eta^{(i),(t|t-1)} - X_j^{(t|t-1)}\right)\left(Z^{i,(t|t-1)} - \hat{Z}^{(t|t-1)}\right)^T \tag{15}$$

$$K_j = P_{x_j Z_j} P_{Z_j}^{-1} \tag{16}$$

where

$$Z^{i,(t|t-1)} = [Z^{i,1,(t|t-1)}, \cdots Z^{i,K,(t|t-1)}]^T \tag{17}$$

$$\hat{Z}^{(t|t-1)} = [\hat{Z}^{1,(t|t-1)}, \cdots \hat{Z}^{K,(t|t-1)}]^T \tag{18}$$

The state and covariance are given by

$$X_j^{(t|t)} = P_j^{(t|t-1)} + K_j\left(Z^t - \hat{Z}^{(t|t-1)}\right) \tag{19}$$

$$P_j^{(t|t)} = P_j^{(t|t-1)} - K_j P_{Z_j} K_j^T \tag{20}$$

The noise parameters measured in LOS propagation model are known, but unknown in NLOS propagation model, so UKF can't be used directly to estimate the state. Here, VB-UKF algorithm is used to estimate the state of unknown nodes.

Since the NLOS measurement noise is unknown, the covariance of the observed sigma points in the NLOS environment will be transformed as follows:

$$\tilde{P}_{Z_j} = \sum_{i=0}^{2n} \omega_c^{(i)} \left(Z^{i,(t|t-1)} - \hat{Z}^{(t|t-1)}\right)\left(Z^{i,(t|t-1)} - \hat{Z}^{(t|t-1)}\right)^T \tag{21}$$

According to reference [13], NLOS measurement noise can be approximately written as:

$$\hat{R}^t = (V^t - n - 1)^{-1}\, W^t \tag{22}$$

Iteration $i$ = 1: $n$ step, the covariance matrix and gain of the observation point can be rewritten as follows:

$$P_{Z_j}^{i+1} = \tilde{P}_{Z_j} + (V^t - n - 1)^{-1}\, W^t \tag{23}$$

$$K_j^{i+1} = P_{x_j Z_j} / P_{Z_j}^{i+1} \tag{24}$$

where, $V^t = 1 + \, V^{(t|t-1)}$, $V^{(t|t-1)} = \rho(V^{t-1} - n - 1) + n + 1$, $n$ is the number of state variables; $\rho$ is a constant around 0 to 1. $\lambda$ is a matrix with $\lambda = \sqrt{\rho I}$. The renewal equations of state and covariance are as follows:

$$X_j^{i+1,(t|t)} = X_j^{(t|t-1)} + K_j^{i+1}(Z^t - \hat{Z}^{(t|t-1)}) \tag{25}$$

$$P_j^{i+1,(t|t)} = P_j^{(t|t-1)} - \; K_j^{i+1,t} P_{Z_j}^{i+1} (K_j^{i+1})^T \tag{26}$$

$$W^{i+1,t} = W^{(t|t-1)} + \sum_{j=0}^{2n} \omega_m^{(j)} \left( Z^t - Z^{i,j,(t|t-1)} \right) ( Z^t - Z^{i,j,(t|t-1)} )^{T\cdot} \tag{27}$$

Iteration steps until $W^t = W^{N,t}$, $P_j = P_j^N$， $X_j = X_j^N$, where, $Z^t = [Z^{1,t}, \cdots, Z^{K,t}]^T$.

### *3.3. Model Probability Update*

We have got the state estimation of model *j*, then the probability of the model needs to be updated to complete the output combination. $\Lambda_j^t$ is the likelihood function of model ta*j*, which is a zero mean. covariance is $S_j^t$, and residual $e_j^t$ is the Gaussian density function. The definition is as follows:

$$\Lambda_j^t = N\left(e_i^t \middle| 0, S_i^t\right) \tag{28}$$

where

$$S_i^t = H^t P_i^{(t|t-1)} \tag{29}$$

$$e_j^t = \frac{1}{K} \sum_k^{k=K} (Z^{k,t} - \hat{Z}^{k,(t|t-1)}) \tag{30}$$

The probability of model *j* will be updated in the following form:

$$\beta_i^{(t|t)} = \frac{\Lambda_j^t \bar{\alpha}_j}{\alpha} \tag{31}$$

where

$$\alpha = \sum_{j=1}^{2} \Lambda_j^t \bar{\alpha}_j$$

### *3.4. Combination Output*

Based on the previous derivation, combined total state estimation and covariance of two models are expressed as:

$$X^{(t|t)} = \sum_{j=1}^{2} X_i^{(t|t)} \beta_j^t \tag{32}$$

$$P^{(t|t)} = \sum_{j=1}^{2} \beta_j^t \, \{ P_j^{(t|t)} + \left[ X_i^{(t|t)} - X^{(t|t)} \right] \left[ X_i^{(t|t)} - X^{(t|t)} \right]^T \} \tag{33}$$

## 4. Experimental Result and Analysis

In this section, we will compare proposed algorithm with other algorithm to evaluate the algorithm performance by simulation experiment. The position of AS's and obstacles are stochastic deployment. The experimental environment and deployment are shown in figure 1. We assume that all the ASs have same the communication range and structure, and the upper limit of the communication range of the node is 120m. The Markov transition probability matrix is defined as:

$$pp = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} = \begin{bmatrix} 0.9 & 0.1 \\ 0.1 & 0.9 \end{bmatrix} \tag{34}$$

We apply the root of mean square errors (RMSEs) to assess the effectiveness of the proposed algorithm. And compare it with the UKF-LOS EKF-NLOS and ML. The RMSE is formed as follows:

$$\text{ALE} = \frac{1}{C \cdot T} \sum_{i=1}^{C} \sum_{t=1}^{T} \sqrt{(x^t - \hat{x}_i^{(t|t)})^2 + (y^t - \hat{y}_i^{(t|t)})^2} \tag{35}$$

where $(x(t), y(t))$ is the true position coordinate of MS; $(\hat{x}_i^{(t|t)}, \hat{y}_i^{(t|t)})$ is the estimated position coordinate for the *i*th trial; *T* is total sampling times. *C* is the number of Monte Carlo trial. We use table 1 to illustrate the experimental default parameters.

**Table 1.** Parameters of simulation.

| Parameters | Default value |
|---|---|
| Number of ANs ($K$) | 5 |
| Sampling number | 100 |
| Sampling time $T$ | 1s |
| speed | 1m/s |
| $\rho$ | 1-exp(3) |

The ALE of the four algorithms fluctuates with the change of sampling time is shown in figure 2, but the change range is different. The fluctuation amplitude of the proposed algorithm with sampling time is relatively small, ALE is not more than 2. ML algorithm amplitude fluctuation is relatively large and there are many spikes. UKF algorithm and EKF algorithm fluctuation amplitude are also more than the proposed algorithm.

Next, we will discuss the NLOS error performance of the proposed algorithm. It is assumed that the NLOS error obeys a Gaussian distribution $\varphi_N \sim N(\mu, \sigma_N^2)$. Figure 3 describes the relationship between ALE of the four algorithms and the mean $\mu$ of NLOS measurement error. The ALE of the proposed algorithm is 43.1%, 52% and 76.1% higher than that of UKF, EKF and ML, respectively. So, we know that the ALE of the proposed algorithm is the smallest and the degradation degree of positioning accuracy is the smallest, which can suppress NLOS error to a certain extent. In addition, degradation degree of the ML positioning accuracy is the largest. For the other two algorithms, when the parameter $\mu$ is small, the positioning accuracy of UKF and EKF are close, but with the increase of $\mu$, the degradation degree of EKF positioning accuracy is greater than UKF.

When NLOS measurement error $\sigma_N$ is very small, we can observe that the ALE of UKF and EKF are very small as the standard deviation of NLOS measurement, as shown in figure 4. When $\sigma_N = 2$, the ALE of the proposed algorithm is 52.9% and 57.7% higher than UKF and EKF respectively, while 78% higher than ML. The ALE of the proposed algorithm is the smallest with $\sigma_N = 7$, less than 2m. The ALE of UKF and EKF algorithm is close to 3m, but the ALE of ML algorithm is more than 7m. It shows that the performance of the proposed algorithm has least affected by the change of parameter $\sigma_N$.

It is assumed that the NLOS error parameter follows an exponential distribution, i.e., $\varphi_{\text{N}} \sim E(1/\lambda)$.

We can see from the figure 5 when λ=1, the ALE of the proposed algorithm, EKF and UKF algorithm are relatively close. With the increase of parameters, the ALE of the four algorithms will increase.

Compared with ML algorithm, the ALE of ML algorithm will increase greatly and is sensitive to the change of parameters. However, the performance of the proposed algorithm is insensitive to the change of parameters. And ALE increases more smoothly and the positioning accuracy is higher.

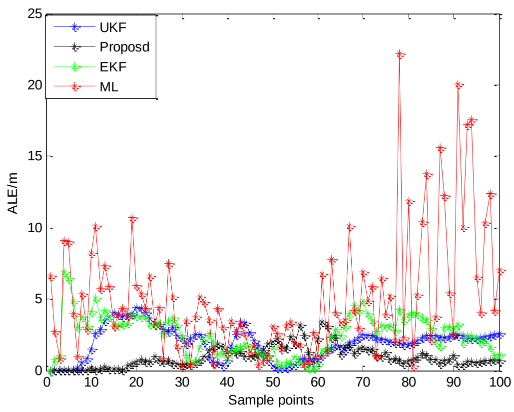


**Figure 2.** The ALE of the algorithm at the sampling time.

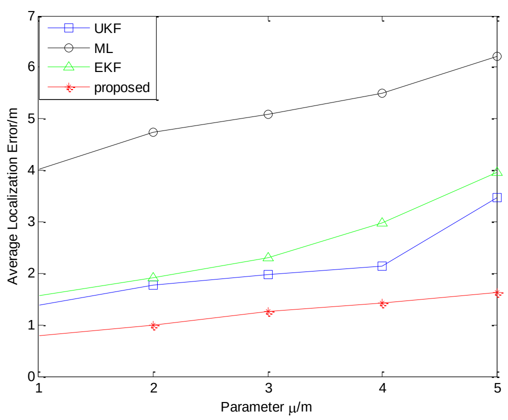


**Figure 3.** ALE vs. the mean of NLOS measurement error $\mu$.

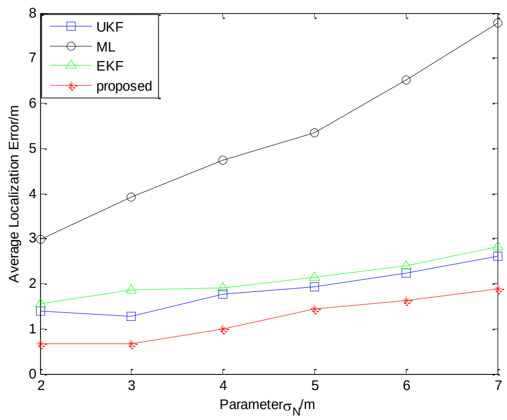


**Figure 4.** ALE vs. standard deviation of NLOS measurement error $\sigma_N$.

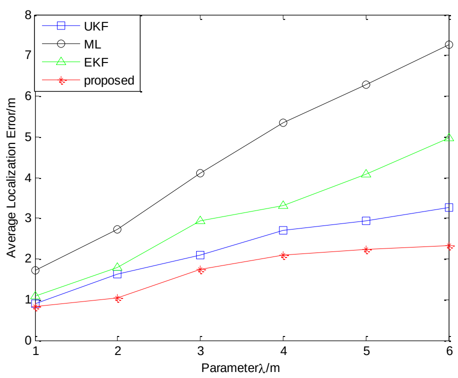


**Figure 5.** ALE vs. the parameter λ.

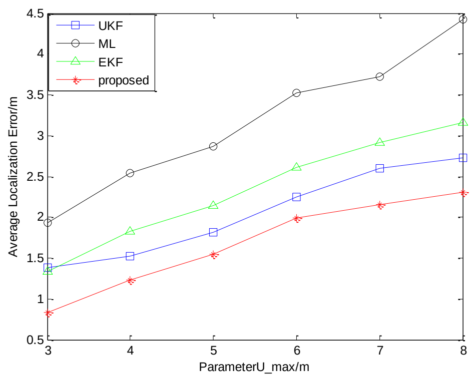


**Figure 6.** ALE vs. the parameter $U_{max}$.

It is assumed that the NLOS error parameter $U_{max}$ is uniformly distributed, i.e, $\varphi_N \sim U(0, U_{max})$. From figure 6, we can see the performance of four algorithms change with the parameter $U_{max}$. In the whole process of parameter change, the ALE of the proposed algorithm is 17.9% higher than that of

UKF, 27.8% higher than EKF and 46.9% higher than ML. It can be seen that the proposed algorithm has the highest positioning accuracy and the best superiority.

## 5. Conclusion

In order to improve the positioning accuracy of MT in the LOS/NLOS indoor environment, we propose IMM-UKF filter algorithm. For LOS and NLOS measurements, UKF and VB-UKF filters in IMM algorithm are used for filtering to get the estimated value. The position estimation can be obtained by weighting the filtering results. The above analysis show that positioning accuracy of the proposed algorithm is higher than that of EKF, UKF and ML model algorithm in LOS/NLOS environment.

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