AN ADAPTIVE LIKELIHOOD FUSION METHOD USING DYNAMIC GAUSSIAN MODEL FOR INDOOR TARGET TRACKING

Yubin Zhao, Yuan Yang and Marcel Kyas

Institute of Computer Science, Freie Universität Berlin.
E-mail: ({yubin.zhao, yangyuancs, marcel.kyas}@fu-berlin.de)

ABSTRACT

It is hard to obtain a general error model for range-based wireless indoor target tracking system due to the complicated hybrid LOS/NLOS environment. In this paper, we employ a dynamic Gaussian model (DGM) to describe the indoor ranging error. A general Gaussian distribution is constructed firstly. The instantaneous LOS or NLOS error at a typical time is considered as the drift from this general distribution dynamically. Based on this modeling method, we propose an adaptive likelihood method of particle filter. Our method is adaptable for dynamic environment and achieves accurate estimation. The simulation and real indoor experiment demonstrate that the estimation accuracy of our algorithm is greatly improved without imposing computational complexity

***Index Terms*—** indoor target tracking, adaptive likelihood, particle filter, dynamic Gaussian model.

1. INTRODUCTION

One major challenge for indoor target tracking system is the ranging error. Due to the complicated infrastructure and hybrid line-of-sight/non-line-of-sight (NLOS/LOS) transmission channel, the measurement error is quite high and makes the estimation unreliable[1]. Some references model the noise as Exponential, Rayleigh, Weibull or Gamma distribution[2]. However, these model is suitable for some typical static position. The parameters and type of distributions can be quite different in different positions due to the complicated infrastructure of indoor environment.

In this paper, we propose a dynamic Gaussian modeling (DGM) method to describe the measurement error for real indoor environment. First, a general Gaussian distribution model is constructed to approximate the ranging error based on histogram. For a typical scenario, we consider the instantaneous ranging error from LOS or NLOS as the drift from the general Gaussian distribution. Based on DGM model, the hybrid LOS/NLOS indoor ranging error, can be modeled dynamically within a uniform framework.

Although it is not an accurate model, it is suitable and adaptable for non-linear filters with low complexity. The major contribution of this paper is that: we propose a new particle filter with adaptive likelihood fusion method according to DGM for indoor wireless target tracking system. The likelihood function is constructed not only based on the range measurement but also based on the predicted state and a tuning parameter θ. The optimal θ is derived using minimum Kullbeck-Leibler divergence (KLD). Then the particle filter can generate particles randomly without considering the previous weight. Thus, the complexity is reduced. Besides, our algorithm can achieve high estimation accuracy. The proposed method is evaluated in the indoor target tracking simulation and real experiment, which demonstrates the performance of our algorithm and DGM.

2. RANGE-BASED MEASUREMENT ERROR MODELING

2.1. Range based Wireless Positioning System

We consider N wireless nodes deployed in a 2D plane to form a network. The nodes with known positions are denoted as anchors and the mobile device with unknown position is denoted as the target. The anchor's positions are assigned as $a_j = (a_j^x, a_j^y)$ where $j \in [1, ..., N]$. The target position is denoted as $x_t = (p_t^x, p_t^y)$. According to the Bayesian estimation model, the state x_t is evolved with the previous state x_{t-1} according to the prediction equation:

$$x_t = f_t(x_{t-1}) + q_t \tag{1}$$

where $f_t()$ is the prediction function, x_{t-1} is the previous state and q_t is the additive prediction noise, which follows the normal distribution $q_t \sim \mathcal{N}(0, Q_t)$, implying the prediction error of x_t.

Anchors measure the ranging values and forward the measurements to the fusion center. At time t, the fusion center formulates a noisy measurement vector z_t with the available ranging value. The relationship between x_t and z_t follows the measurement equation of Bayesian estimation model:

$$z_t = h_t(x_t) + v_t \tag{2}$$

where $h_t()$ is the measurement function, and v_t is the measurement noise at time t. The range measurement obtained

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from TOA, TOF or RSS for anchor j is formulated as:

$$z_t^j = d(x_t, a_j) - b_j + v_t \tag{3}$$

where $d(x_t, a_j)$ is the distance between the target and anchor j:

$$d(x_t, a_j) = \sqrt{(p_t^x - a_j^x)^2 + (p_t^y - a_j^y)^2} \tag{4}$$

and b_j is the offset which is caused by the asynchronous clock of anchors and target.

2.2. Dynamic Gaussian Model

Since it is not easy to obtain an accurate distribution model for indoor ranging measurement error, we attempt to use a dynamic Gaussian model (DGM) to approximate such error. Firstly, we obtain a general Gaussian distribution to describe the ranging error. The Gaussian distribution function is a symmetrical function, however, the TOA ranging error is always positive and not symmetrical. Thus, we can not use a real Gaussian distribution function to represent the error distribution. Our general Gaussian model is to use the part of the shape of the Gaussian distribution function to represent the distribution. The negative values of the Gaussian distribution is discarded. The expectation of the constructed Gaussian distribution is the maximum probability point of the error distribution, and the standard deviation indicates the shape of the error distribution. Unlike Gaussian distribution fitting method, which uses the mean and standard deviation of the errors to construct a Gaussian distribution, our method does not attempt to construct a real distribution but rather a function to approximate the error.

The general Gaussian model fitting is illustrated in Fig. 1. The mean value for the general Gaussian model represents the maximum probability of the distribution function. The standard deviation attempts to tune the shape of Gaussian function to fit the error distribution. The negative values are discarded. For the histogram, which is fitting with any typical distribution in Fig. 1(f), the general Gaussian model attempts to cover all the error values with a proper shape of Gaussian function.

The parameters of Gaussian distribution are obtained from the histograms of extensive ranging experiments in the indoor environment. As illustrated in Fig. 2, the general Gaussian distribution is derived from the general histograms. No additional information is required and the histograms are not restrict to LOS or NLOS. Then the distribution based on the instantaneous error at this time is considered as the drift from the generic Gaussian distribution accordingly. As illustrated in Fig. 2, The dash curve represents the generic Gaussian model for ranging error. The star marks an instantaneous error at a typical time. Then, the expectation of the error distribution moves to the position of star from the general Gaussian model with the same standard deviation, just as the solid curve depicted. Thus, when the instantaneous measurement is available, the error distribution is biased by

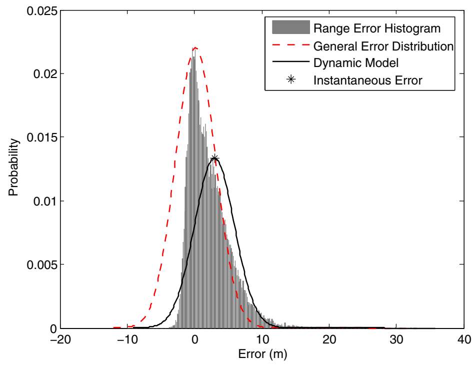


Fig. 2. Dynamic Gaussian Modeling for Indoor Ranging Error.

the instantaneous error. In this case, the error distribution is dynamically modeled based on the Gaussian distribution.

DGM indicates that the instantaneous error is still within the Gaussian distribution framework, no matter what actual distribution is. Therefore, non-linear filters is implemented easily without considering an accurate error model. Besides, DGM illustrates how the error influences the estimation. Take particle filters for example: the estimated distribution of the target state is based on the measurement likelihood. When the measurement z_t and particle samples $\{x_t^i\}_{i=1}^{N_s}$ are available, the measurement likelihood for each particle is calculated as[3]:

$$p(z_t|x_t^i) = \pi_v(z_t - h_t(x_t^i)). \tag{5}$$

where $\pi_v()$ is the probability density function (PDF) of measurement noise v_t.

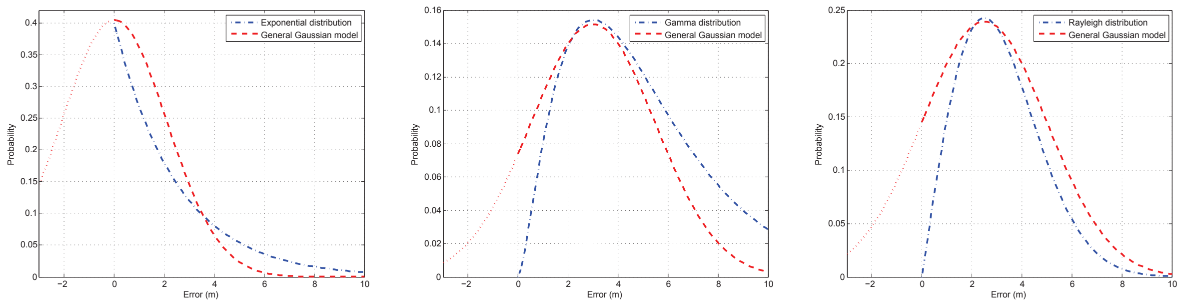
In (5), z_t is a beacon, and the likelihood for particle x_t^i dependents on the difference between z_t and $h_t(x_t^i)$. In this case, z_t is assumed to be a reliable measurement without any noise, which is indicated as the dash curve in Fig. 2. However, if we extend the imprecise z_t with error v_t in the real case, (5) is expressed as:

$$p_E(z_t|x_t^i) = \pi_v(h_t(x_t) + v_t - h_t(x_t^i)). \tag{6}$$

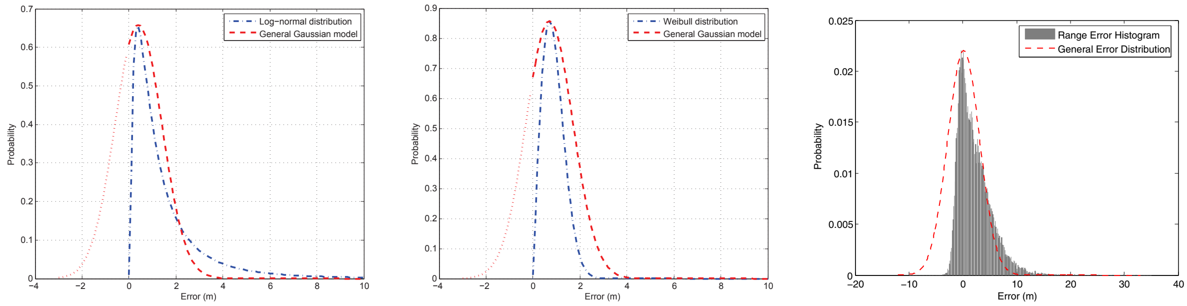
in which, $p_E()$ denotes the probability containing errors, $z_t = h_t(x_t) + v_t$ and v_t is an instantaneous value at time t. Thus $p_E()$ contains an unpredictable value v_t. Thus, the likelihood based on (6) is denoted as the solid curve in Fig. 2. If v_t is small, the difference between the real measurement likelihood and noise measurement is not big. But if v_t is large in the most of time, the measurement likelihood function is biased significantly just as Fig. 2 shows.

3. LIKELIHOOD ADAPTATION

Likelihood adaptation attempts to construct the likelihood function based on DGM. We employ the predicted measurement and belief factor θ to adjust the instantaneous error back to the general Gaussian model.



(a) Exponential distribution (b) Gamma distribution (c) Rayleigh distribution



(d) Log-normal distribution (e) Weibull distribution (f) Error histogram

Fig. 1. General Gaussian model fitting for different indoor ranging error distributions. The negative values of Gaussian function is discarded.

3.1. Predicted Measurement

Predicted measurement is calculated as follows: $\hat{x}_t$ denotes the prediction value of x_t according to (1):

$$\hat{x}_t = f_t(x_{t-1}) \tag{7}$$

where x_{t-1} is the estimation at previous time $t-1$. When considering the predicted noise q_t, we denote $\hat{x}_t$ as:

$$\hat{x}_t = x_t + q_t \tag{8}$$

Then we obtain a predicted measurement for sensors:

$$\hat{z}_t = h_t(\hat{x}_t) = h_t(x_t + q_t) \tag{9}$$

3.2. Belief Factor θ

The adaptive likelihood function is constructed as:

$$p_{AL}(z_t|x_t^i) = \pi_v(\theta\hat{z}_t + (1-\theta)z_t - z_t^i) \tag{10}$$

where $p_{AL}()$ indicates the adaptive likelihood.

We employ Kullback-Leibler divergence (KLD) as a metric to find optimal θ which minimizes the distance between the general Gaussian model and $p_{AL}(z_t|x_t)$. Then, the KLD function is constructed as:

$$D_{KL}(p_A||p_{AL}) = \int p_A(z_t|x_t)\log\frac{p_A(z_t|x_t)}{p_{AL}(z_t|x_t)}dz_t^i \tag{11}$$

The optimal θ is attainted with minimum $D_{KL}(p_A||p_{AL})$:

$$\theta = \arg\min D_{KL}(p_A||p_{AL}) \tag{12}$$

If $p_A()$ and $p_{AL}()$ are based on the same Gaussian distribution function, (11) is expressed as[4]:

$$D_{KL}(p_A||p_{AL}) = \frac{||h_t(x_t) - [\theta\hat{z}_t + (1-\theta)z_t]||^2}{2R_t} \tag{13}$$

Since R_t is independent on θ, we simplify the objective function as:

$$\theta = \arg\min ||h_t(x_t) - [\theta\hat{z}_t + (1-\theta)z_t]||^2 \tag{14}$$

Here, we use first order Taylor series expansion at x_t to linearize (9) :

$$\hat{z}_t \approx h_t(x_t) + \frac{\partial h_t(x_t)}{\partial x_t}q_t \tag{15}$$

where $\partial h_t(x_t)/\partial x_t$ is the partial differential of $h_t(x_t)$ with respect to x_t. And substitute (15) and $z_t = h_t(x_t) + v_t$ into (14), we obtain:

$$||h_t(x_t) - [\theta\hat{z}_t + (1-\theta)z_t]||^2 \approx ||\theta\frac{\partial h_t(x_t)}{\partial x_t}q_t + (1-\theta)v_t||^2 \tag{16}$$

Therefore, the problem is solvable analytically by expressing the objective as the convex quadratic function[5]:

$$F_t(\theta) = \theta\frac{\partial h_t(x_t)}{\partial x_t}Q_t[\frac{\partial h_t(x_t)}{\partial x_t}]^T\theta^T + (1-\theta)R_t(1-\theta)^T \tag{17}$$

where Q_t is the covariance of q_t and R_t is the covariance of v_t using the general Gaussian model. Then, the optimal θ can be obtained if and only if:

$$\frac{\partial F_t(\theta)}{\partial \theta} = 2\theta \frac{\partial h_t(x_t)}{\partial x_t} Q_t [\frac{\partial h_t(x_t)}{\partial x_t}]^T - 2R_t + 2\theta R_t = 0 \quad (18)$$

And the unique θ is derived:

$$\theta = \frac{R_t}{\frac{\partial h_t(x_t)}{\partial x_t} Q_t [\frac{\partial h_t(x_t)}{\partial x_t}]^T + R_t} \quad (19)$$

Particle filter is designed as follows: the particles $\{x_t^i\}_{i=1}^{N_s}$ are generated randomly using the predicted state; then, the weight w_t^i for each particle is prone to the adaptive likelihood function (10); finally, re-sample the particles with significant weight and attain the estimation using $\bar{x} = \sum_{i=1}^{N_s} w_t^i x_t^i$.

4. EXPERIMENT

4.1. Simulation Results

Our scheme is evaluated in the simulation of target tracking. We randomly deploy 100 sensors in a two-dimensional square $100m \times 100m$ region. One target randomly walks with a constant speed $0.5m/s$. The sensors measure the ranging value based on time-of-flight (TOF). To simulate the indoor environment, the measurement noise follows Gamma distribution. We employ two algorithms: the first one is the bootstrap particle filter (PF); the second one is our proposed algorithm based on DGM. To improve the estimation accuracy, the likelihood calculation for PF is based on Gamma distribution function, with the same parameters of the simulation settings. Our algorithm, which is named A-PF, uses DGM for adaptive likelihood function. The results are averaged according to 1000 Monte-Carlo trials, which is shown in Fig. 3. The solid curve represents the mean square error (MSE) of PF, while the dash curve is the results of A-PF. It is clearly observed that the estimation error of PF converge to a higher value than A-PF. Therefore, A-PF is accurate and DGM is suitable for indoor noise modeling.

4.2. Real Indoor Target Tracking Results

We employ an indoor localization reference system to evaluate our proposed algorithms. In this system, we deployed 17 wireless sensor nodes either along the corridor or in the offices of our research building. A robot carrying a sensor node as the target moved along the corridor of the building with constant speed while recording its own positions[6]. The error of record positions is less than 15 cm, which can be seen as a the actual positions. We also implement PF and A-PF in this experiment.

The building layout is illustrated in Fig. 4. The triangles mark the anchor's positions. Various kinds of trajectories are tested within this reference system. The solid curve lists one of the actual trajectories. Others are the estimated trajectories. The root mean square error (RMSE) of bootstrap particle filter is about 2.37m while the RMSE of our method is 1.4m, as shown in Talbe 1. Thus, our method is better than PF and suitable for the real indoor environment.

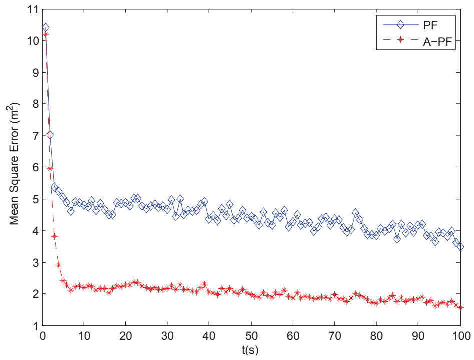


Fig. 3. Mean square error result for simulation.

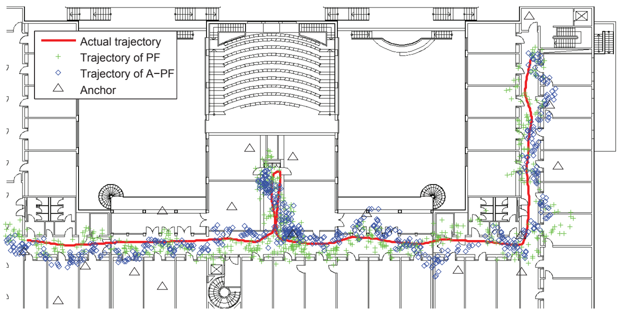


Fig. 4. Estimated trajectories for real indoor target tracking application.

Table 1. Performance comparison

Algorithm	RMSE(m)	min error(m)	max error(m)
PF	2.3722	0.0493	6.6393
A-PF	1.3950	0.0139	3.5162

5. CONCLUSION

We propose a new fusion method which constructs adaptive likelihood function for particle filters based on the dynamic Gaussian error model. Dynamic Gaussian model is suitable to describe the indoor ranging noise. The proposed particle filter does not need to consider the previous weight and is adaptable in the highly dynamic environment. Experimental and simulation results demonstrate that our method has a very accurate estimation for indoor target tracking.

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