# Adaptive Filtering for Indoor Localization using Wireless Sensor Network

Yubin Zhao
Institute of Computer Science, Freie Universität Berlin
Email: zhaoyubin@inf.fu-berlin.de

***Abstract*—The estimation accuracy of localization using wireless sensor networks is an essential problem in the indoor environment. The non-line-of-sight (NLOS) effect and high dynamic wireless channel influence the quality of sensor measurement and degrade the estimation. Particle filter is proved to have accurate estimations in many cases. However, the estimation error is still high in the indoor localization. In this paper, we analyze the instantaneous noise effect for the particle filter and illustrate how it influences the location estimation. Based on our analysis, we propose a likelihood adaptation method and integrate it into the particle filter. The experimental results indicate that the performance of our algorithm for indoor localization is effectively improved and the estimation error is only half of the particle filter without our adaptation method.**

## I. Introduction

Wireless sensor networks collect range or angle measurements to estimate the target in the indoor environment. The measurements are easily influenced by the dynamic wireless channel and non-line-of-sight (NLOS) effect[1]. Although particle filter has a promising estimation performance for the location estimation, the estimation accuracy is still need to improve. In this paper, we analyze the likelihood function in particle filter and find that if we consider the instantaneous measurement noise, the likelihood function is biased from the actual value and the estimation is influenced accordingly.

Based on our analysis, we propose a likelihood adaptation method to reduce the instantaneous measurement noise effect. We employ the prior measurement, which is a prediction measurement value, and a belief factor $\theta$ to collaborative estimate the actual measurement with the noisy measurement. We derive the optimal $\theta$ to achieve the optimal performance. Then, we integrate our adaptation method into the particle filter. An indoor target tracking experiment is constructed and our algorithm is implemented. The results indicate that our algorithm has $50\%$ estimation errors than the original particle filter.

## II. Problem Statement

We consider $N$ sensor nodes deployed in a 2D plane to form a network. The sensor node with known position, $a_j = (a_j^x, a_j^y)$ where $j = [1, ..., N]$, is denoted as anchor and the mobile device with unknown position, $x_t = (p_t^x, p_t^y)$, is denoted as the target.

The estimated distribution of the target state in particle filter 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[2]:

$$p(z_t|x_t^i) = \pi_v(z_t - h_t(x_t^i)). \tag{1}$$

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

In (1), $z_t$ 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. However, if we extend the imprecise $z_t$ with error $v_t$ in the real case, (1) is expressed as:

$$p_E(z_t|x_t^i) = \pi_v(h_t(x_t) + v_t - h_t(x_t^i)). \tag{2}$$

in which, $z_t = h_t(x_t) + v_t$ and $v_t$ is an instantaneous value at time $t$. If $v_t$ is small, the difference between the real measurement likelihood and noise measurement is not big. But if $v_t$ is large, the measurement likelihood function is biased significantly.

## III. Adaptive Particle Filter

### A. Prior Measurement and $\theta$

Prior measurement is a prediction for measurement. It is derived based on the prediction state and is the reference for the real measurement. The calculation steps are as follows: $\hat{x}_t$ denotes the prediction value of $x_t$:

$$\hat{x}_t = f_t(x_{t-1}) \tag{3}$$

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

$$\hat{x}_t = x_t + q_t \tag{4}$$

where $q_t$ is assumed to be the additive noise and follows normal distribution $q_t \sim \mathcal{N}(0, Q_t)$; $Q_t$ is the covariance at time $t$. Then we obtain a prior measurement for sensors:

$$\hat{z}_t = h_t(\hat{x}_t) = h_t(x_t + q_t) \tag{5}$$

in which $\hat{z}_t$ indicates the prediction of measurement derived from $\hat{x}_t$. The prior measurement $\hat{z}_t$ is not the actual measurement but is used as the reference for measurement likelihood adaptation.

Belief factor $\theta$ is the tuning parameter for the prior measurement and it is used to adapt the measurement $z_t$ to approach the actual measurement $h_t(x_t)$. Therefore, the adaptive measurement is formulated as:

$$\bar{z}_t = \theta\hat{z}_t + (1-\theta)z_t \tag{6}$$

### B. Optimal $\theta$

We construct the objective function to derive the optimal $\theta$ with the minimum distance between the adaptive measurement and actual measurement:

$$\theta = \arg\min \, ||h_t(x_t) - [\theta \hat{z}_t + (1-\theta) z_t]||^2 \tag{7}$$

where $h_t(x_t)$ is the actual measurement. Since $\hat{z}_t$ is the non-linear function of $q_t$, it is difficult to obtain an analytical result. Thus, we use first order Taylor series expansion at $x_t$ to linearize (7):

$$\hat{z}_t \approx h_t(x_t) + \frac{\partial h_t(x_t)}{\partial x_t} q_t \tag{8}$$

where $\partial h_t(x_t)/\partial x_t$ is the partial differential of $h_t(x_t)$ with respect to $x_t$. Then, substitute (8) into (7), we obtain:

$$\theta \approx \arg\min \, ||\theta \frac{\partial h_t(x_t)}{\partial x_t} q_t + (1-\theta) v_t||^2 \tag{9}$$

which is a least-squares approximation problem. The unique $\theta$ is derived:

$$\theta = \frac{R_t}{\frac{\partial h_t(x_t)}{\partial x_t} Q_t [\frac{\partial h_t(x_t)}{\partial x_t}]^T + R_t} \tag{10}$$

To integrated our adaptation method into particle filter, the algorithm is illustrated as 1.

**Algorithm 1** Adaptive Particle Filter

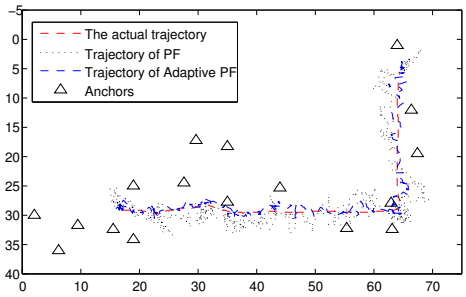
Prediction: $\hat{x}_t = f_t(x_{t-1})$;
Prior Measurement: $\hat{z}_t = h_t(\hat{x}_t)$;
//Importance Sampling
Draw: $\{x_t^i\} \sim p(x_t^i | x_{t-1}^i)$;
//Measurement Adaptation
**for** particle $i = 1 : N_s$ **do**
  Likelihood: $p_{AL}(z_t | x_t^i) = \pi_v(\theta \hat{z}_t + (1-\theta) z_t - h_t(x_t^i))$;
  Weight: $w_t^i = w_{t-1}^i p_{AL}(z_t | x_t^i)$;
**end for**
Normalizing: $w_t^i = \frac{w_t^i}{\sum_{i=1}^{N_s} w_t^i}$;
Resampling: $\{x_t^i, w_t^i\}_{i=1}^{N_s}$;

## IV. Experiment

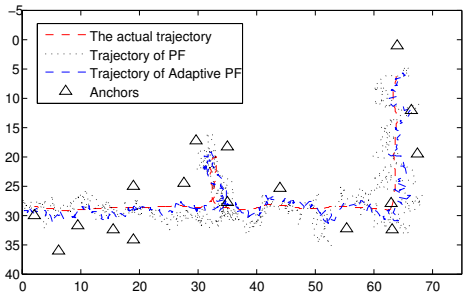
We employ a reference system for indoor localization test-beds to examine our proposed algorithms. 17 anchors are deployed either along the corridor or in the offices of our research building. A robot carrying a sensor node as target moved along the corridor of the building with constant speed 0.5 m/s while recording its own positions[3]. The estimated trajectories and error comparisons are listed in Fig. 1 and Table I and II.

## V. Conclusion

The experiment results show that the RMSE of our algorithm is nearly half or the original particle filter. And the maximum error, which indicates the worst case of estimation, is also much lower than the original particle filter. Thus, our algorithm is feasible for the indoor localization.




(a) Trajectory I




(b) Trajectory II

Fig. 1. Trajectories for Indoor Target Tracking.

TABLE I
Trajectory I: Performance comparison

| Algorithm | RMSE(m) | min error(m) | max error(m) |
|---|---|---|---|
| PF | 2.3624 | 0.1373 | 6.8348 |
| Adaptive PF | 1.2966 | 0.0579 | 3.7989 |

TABLE II
Trajectory II: Performance comparison

| Algorithm | RMSE(m) | min error(m) | max error(m) |
|---|---|---|---|
| PF | 2.3738 | 0.1216 | 6.8775 |
| Adaptive PF | 1.3971 | 0.0808 | 3.3884 |

## References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