Department of Electrical and Computer Engineering

# Indoor Location Estimation for Clinical Applications

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## Introduction

Indoor positioning is a necessity for many indoor location based services and applications, and requires location information of the objects under study. This location information can be gathered from indoor location sensors. However, due to the imposed noise to the system, the location estimation provided by the off-the-shelf location sensors lacks the required precision. Thus, we have used particle filters to post-process the location information gathered from the sensors and improved positioning.

## Particle Filters for Location Estimation

Having the motion and sensor models, particle filters can be used to probabilistically estimate the current location from the current sensor measurement. They use the *principle of importance sampling* to estimate the posterior discretely, by a set of particles drawn from an *importance function*, and their associated weights. The choice of this function can improve the performance of the particle filter, as this function approximates the posterior. Among the numerous choices, the *Prior*, and the *Optimal* importance functions have drawn more attention, since using them simplifies weight update. The Optimal Importance Function minimizes the variance of particle weights. This can be used to resolve *degeneracy*, which is a common problem with particle filters.

## Sensor Model

We have assumed an additive sensor noise at each iteration, i.e. $z_k = x_k + e_k$, where $e_k$ represents the sensor error at iteration $k$ and follows a Gaussian Mixture Model. Thus, assuming $e_k$ follows a GMM with $C$ clusters, the likelihood distribution can be written as:

$$P(z_k|x_k) = P(e_k = z_k - x_k) = \sum_{c=1}^{C} \mathrm{P}_c f(e_k; \mu_c, \sigma_c^2),$$

The histogram for error distribution in $x$ direction is shown in Figure 1.

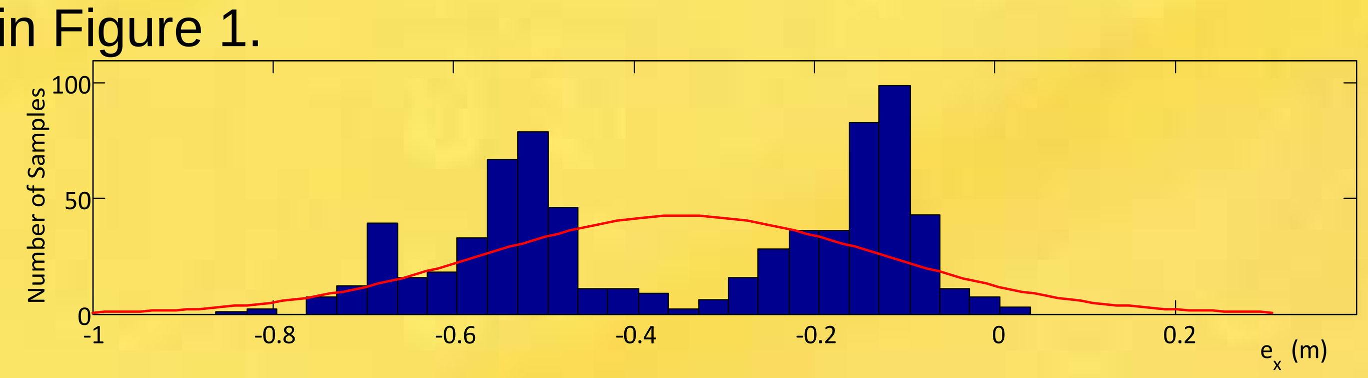


Figure 1 : Histogram of sensor error in x and y directions

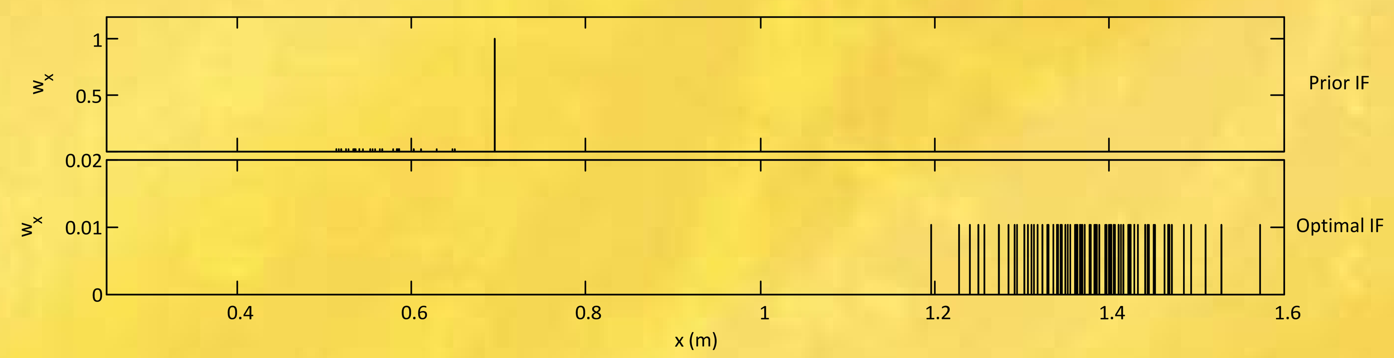


Figure 3 : Particles before resampling at iteration 8 in x direction

## Motion Model

For the motion model we have used a random walk velocity model: at iteration $k$, we have $v_k = v_{k-1} + n_k$, where $v_k$ represents the current velocity and $n_k$s are iid Gaussian random variables. Using the fact that the noise vectors are uncorrelated and independent, we could evaluate the prior density:

$$P(x_k|x_{k-1}) = f\left(x_k; \mu_{k|k-1}, \sigma_{k|k-1}^2\right)$$

## Optimal Importance Function

Using the above mentioned motion and sensor models, we could evaluate the Optimal Importance Function:

$$P\left(x_k|x_{k-1}^i, z_k\right) = \sum_{c=1}^{C} \frac{\rho_c}{\sum_{j=1}^{C} \rho_j} f\left(x_k; \alpha_c, \beta_c^2\right)$$

This importance function is a GMM with the same number of clusters as the sensor model and its parameters can be evaluated as follows:

$$\frac{1}{\beta_c^2} = \frac{1}{\sigma_c^2} + \frac{1}{\sigma_{k|k-1}^2};\ \alpha_c = \beta_c^2\left(\frac{z_k - \mu_c}{\sigma_c^2} + \frac{\mu_{k|k-1}}{\sigma_{k|k-1}^2}\right)$$

$$\rho_c = \frac{P_c}{\sqrt{2\pi\left(\sigma_c^2 + \sigma_{k|k-1}^2\right)}} exp\left(-\frac{\left(z_k - \mu_c - \mu_{k|k-1}\right)^2}{2\left(\sigma_c^2 + \sigma_{k|k-1}^2\right)}\right)$$

## Simulation Results

The data for our simulation is gathered using ultra-wideband sensors. The system consists of four stationary sensors, four stationary tags and one moving tag in a

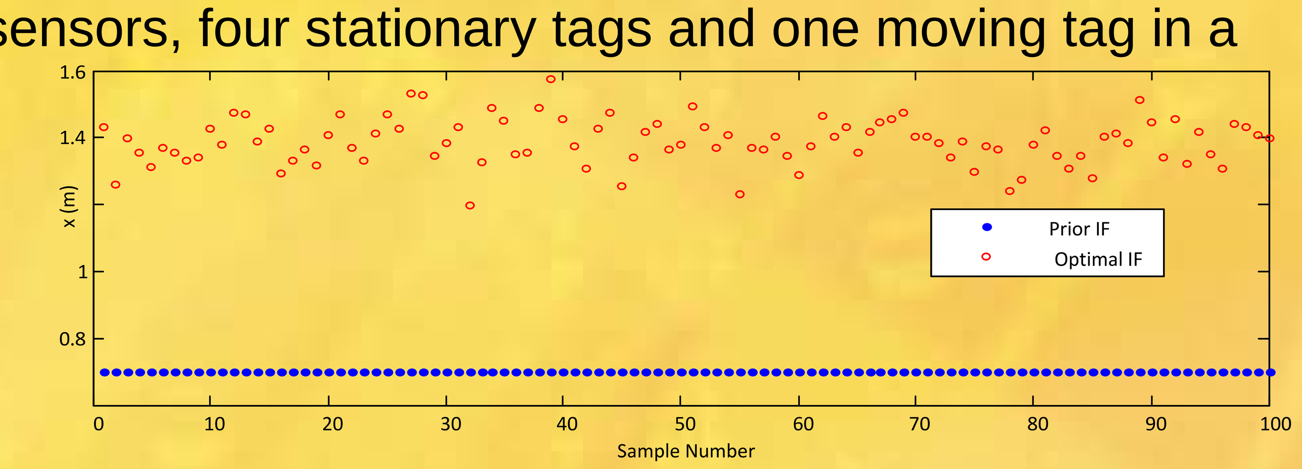


Figure 4 : Particles after resampling at iteration 8 in x direction

room with the area of $5.5 \times 8\, m^2$. To improve the location estimation of the sensors, we have applied Kalman and particle filters and compared the results.

Table 1 : RMSE and Maximum Error for the three methods in x and y directions

| | x (m) | | y (m) | |
|---|---|---|---|---|
| | $E_{Max}$ | RMSE | $E_{Max}$ | RMSE |
| Kalman Filter | 1.888 | 1.339 | 1.423 | 1.191 |
| Particle-Optimal | 0.983 | 0.565 | 0.680 | 0.344 |
| Particle-Prior | 1.182 | 0.970 | 4.594 | 4.390 |

For particle filtering, we have run the simulation using the Prior and Optimal Importance Functions with 100 particles and sample size threshold of 50 for resampling. The resampling algorithm we used is the *systematic* or *deterministic* resampling method.

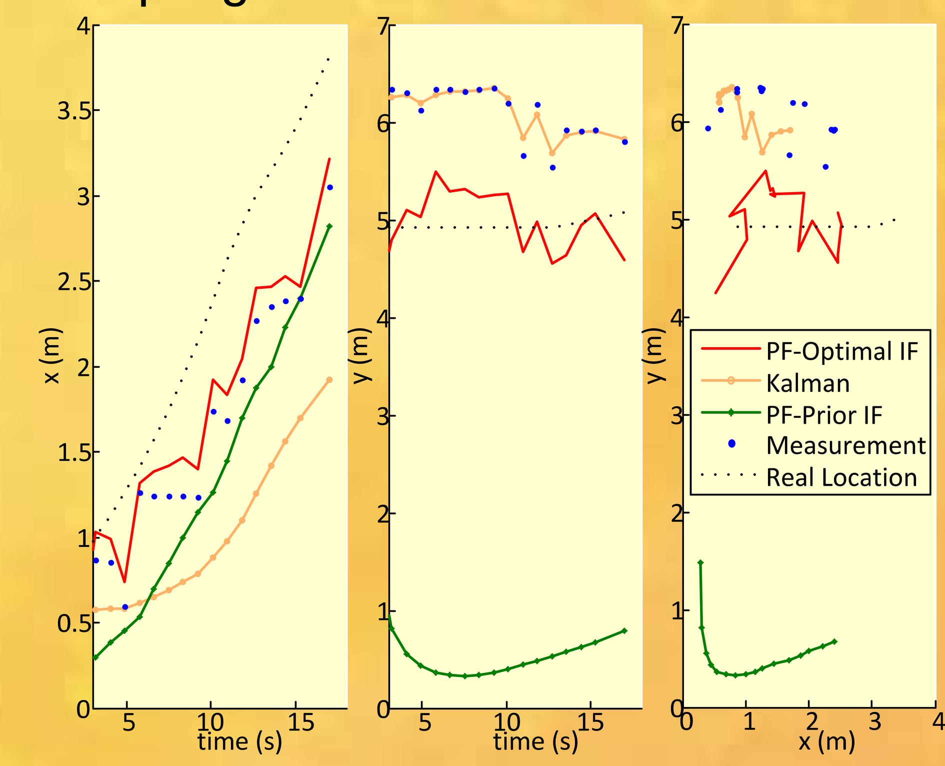


Figure 5 : Location estimation using the three methods

## Conclusion

Although location sensors provide information about the position of the objects, their precision is not acceptable, especially in indoor applications, where the approximations should be more exact. In this work we have used particle filters, but unlike the previous work, we have evaluated and applied the *Optimal Importance Function*. This importance function minimizes the variance of particle weights and hence resolves the degeneracy of particles. Simulation results support the validity of our models for motion and sensor error. Also we have compared the results from Kalman filter, particle filter with Prior Importance Function, and particle filter with Optimal Importance Function. These results show a great improvement for the particle filer with our Optimal Importance Function.

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