Mobile Tracking in Unknown Non-line-of-sight Conditions

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***Abstract*—This paper studies the mobile tracking problem in mixed line-of-sight (LOS) and non-line-of-sight (NLOS) conditions, where the statistics of NLOS error are assumed unknown. Three different models are used to describe the NLOS errors. A Rao-Blackwellized particle filtering with parameter learning (RBPF-PL) is presented, in which the posterior of sight conditions is estimated by particle filtering while the mobile state and NLOS parameters are analytically computed. Simulation results are provided to evaluate the performance of RBPF-PL variants in different situations. Simulation show that unless it is known that NLOS noise has the same bias and variance in all the observations, the more complicated models should be employed as they work correctly even in NLOS model mismatch, with only slightly more computational complexity.**

***Index Terms*—mobile tracking, non-line-of-sight, particle filtering, Rao-Blackwellized, parameter learning**

I. Introduction

Precise positioning in non-line-of-sight (NLOS) conditions is a challenge for many wireless positioning systems. In typical NLOS circumstances, such as dense urban areas, the direct path between the transmitter and receiver is blocked and the electromagnetic wave undergoes reflection, refraction and scattering before arriving to the receiver. Because of signal path lengthening, localization errors will be introduced.

In the literature, a number of methods have been proposed to mitigate NLOS errors in mobile tracking, including two-step Kalman filtering techniques for smoothing range measurements [1], a Kalman based interacting multiple model (IMM) smoother [2], grid based Bayesian estimation [3], particle filtering (PF) [4], a modified extended Kalman filter (EKF) bank [5], the improved Rao-Blackwellized particle filtering (RBPF) [6], joint particle filter and unscented Kalman filtering (UKF) method [7], etc. A posterior Cramér-Rao lower bound is further investigated in [8].

In contrast to the above-listed studies, which assumes a complete knowledge of statistics of NLOS errors, the study in [9] only assumes that the NLOS error is Gaussian while its mean and variance are fixed (static) but unknown. This assumption seems more plausible in practical situations, where the exact error statistics are unknown. In [9], the NLOS signals observed from different base stations (BSs) are assumed to all come from the same biased Gaussian distribution. In practical mobile tracking scenarios, however, these signals may travel through different environments. In this work, we therefore consider the problem of mobile tracking with unknown NLOS errors that can be different in different channels. Three models are used to describe the NLOS errors: a common mean and common variance parameter for each channel; different mean and common variance; different mean and different variance. Conventional particle filtering methods are ineffective for computing the resulting high-dimensional problem. A Rao-Blackwellized particle filtering method with parameter learning (RBPF-PL) is presented to track mobile station (MS) in the different NLOS conditions. Simulation results are provided to evaluate the performance of RBPF-PL variants in different situations.

The paper is organized as follows: Section II presents the system model and formulates the problem of mobile tracking in unknown NLOS conditions. Section III presents the RBPF-PL method in detail. Numerical results and performance comparison are presented and discussed in Section IV. Section V draws some conclusions.

II. System models

The mobile state at time t_k is defined as the length-4 vector $\mathbf{x}_k$, location $[x_k, y_k]^T$ and velocity $[\dot{x}_k, \dot{y}_k]^T$. The mobile state with random acceleration can be modeled as [10]:

$$\mathbf{x}_{k+1} = \mathbf{\Phi}_k \mathbf{x}_k + \mathbf{w}_k, \tag{1}$$

where the transition matrix Φ_k models the state kinematics. The random process $\mathbf{w}_k$ is a white zero mean Gaussian noise, with covariance matrix $\mathbf{Q}$.

Let $h_i(\mathbf{x}_k)$ denotes the true range between the mobile position $[x_k, y_k]^T$ and the location of the ith BS $[x_{\text{bs}_i}, y_{\text{bs}_i}]^T$, where $i \in \{1, 2, \cdots, M\}$ and M is the number of BSs. Then the range measurement equations are

$$z_{i,k} = h_i(\mathbf{x}_k) + v(s_{i,k}), \tag{2}$$

The Boolean variable $s_{i,k} \in \{0, 1\}$ is introduced to represent LOS/NLOS condition between the MS and BS$_i$, with $s_{i,k} = 0$ for LOS and $s_{i,k} = 1$ for NLOS. In mobile tracking, the sight conditions undergo dynamical transitions, which can be modeled as a time-homogeneous first-order Markov chain $s_{i,k} \sim \mathrm{MC}(\boldsymbol{\pi}_i, \mathbf{A}_i)$ with initial probability vector $\boldsymbol{\pi}_i$ and the transition probability matrix

$$\mathbf{A}_i = \begin{bmatrix} p_0 & 1-p_0 \\ 1-p_1 & p_1 \end{bmatrix},$$

where $p_0 = \mathrm{P}(s_{i,k} = 0|s_{i,k-1} = 0)$ and $p_1 = \mathrm{P}(s_{i,k} = 1|s_{i,k-1} = 1)$.

The LOS error (usually treated as the measurement noise) conforms to zero mean Gaussian distribution: $n_{\text{LOS}} \sim \mathrm{N}(0, \sigma_n^2)$, while the NLOS errors from different BSs are modeled as a biased Gaussian distribution: $n_{i,\text{NLOS}} \sim \mathrm{N}(\mu_{i,\text{NLOS}}, \sigma^2_{i,\text{NLOS}})$.

In this work, three different models are assumed for $\{\mu_{i,\text{NLOS}}, \sigma_{i,\text{NLOS}}\}$:

- Model 1: all BSs have the same mean and the same variance
- Model 2: *different* mean for every BS but all BS have the same variance
- Model 3: *different* mean and *different* variance for every BS

Thus, the overall model of mobile tracking in the mixed LOS/NLOS conditions can be represented as

$$\begin{cases} \mathbf{x}_k = \Phi_{k-1}\mathbf{x}_{k-1} + \mathbf{w}_{k-1} \\ \mathbf{z}_k = \mathbf{h}(\mathbf{x}_k) + \mathbf{v}_k(\mathbf{s}_k) \\ s_{i,k} \sim \mathrm{MC}(\boldsymbol{\pi}_i, \mathbf{A}_i) \end{cases}, \tag{3}$$

where $\mathbf{v}(\mathbf{s}_k) = [v(s_{i,k}), \cdots, v(s_{M,k})]^T \sim \mathrm{N}(\mathbf{m}(\mathbf{s}_k), \mathbf{R}(\mathbf{s}_k))$. The values of $\{\mathbf{m}(\mathbf{s}_k), \mathbf{R}(\mathbf{s}_k)\}$ depend on the different NLOS error model, which can be explicitly expressed as:

- Model 1:

$$\begin{aligned} \mathbf{m}(\mathbf{s}_k) &= \mu_{\text{NLOS}}\mathbf{s}_k \\ \mathbf{R}(\mathbf{s}_k) &= \sigma_n^2\mathbf{I}_M + \sigma^2_{\text{NLOS}}\mathrm{diag}(\mathbf{s}_k). \end{aligned} \tag{4}$$

- Model 2

$$\begin{aligned} \mathbf{m}(\mathbf{s}_k) &= \mathrm{diag}(\mathbf{s}_k)\boldsymbol{\mu}_{\text{NLOS}} \\ \mathbf{R}(\mathbf{s}_k) &= \sigma_n^2\mathbf{I}_M + \sigma^2_{\text{NLOS}}\mathrm{diag}(\mathbf{s}_k). \end{aligned} \tag{5}$$

- Model 3

$$\begin{aligned} \mathbf{m}(\mathbf{s}_k) &= \mathrm{diag}(\mathbf{s}_k)\boldsymbol{\mu}_{\text{NLOS}} \\ \mathbf{R}(\mathbf{s}_k) &= \sigma_n^2\mathbf{I}_M + \boldsymbol{\Sigma}_{\text{NLOS}}\mathrm{diag}(\mathbf{s}_k) \\ \boldsymbol{\Sigma}_{\text{NLOS}} &= \mathrm{diag}(\boldsymbol{\sigma}^2_{\text{NLOS}}). \end{aligned} \tag{6}$$

In this work, it is assumed that σ_n is known, while NLOS parameters $\{\mu_{\text{NLOS}}, \sigma^2_{\text{NLOS}}\}$ or $\{\boldsymbol{\mu}_{\text{NLOS}}, \boldsymbol{\Sigma}_{\text{NLOS}}\}$ are all static but unknown.

III. RBPF-PL

Denote the total observation sequence up to time t_k as $\mathbf{z}_{1:k}$, where $\mathbf{z}_k \triangleq [z_{1,k}, z_{2,k}, \ldots, z_{M,k}]^T$. For brevity, let $\eta_i \triangleq \sigma_n^2 + \sigma^2_{i,\text{NLOS}}$, $\theta_i = \{\mu_{i,\text{NLOS}}, \eta_i\}$ and $\boldsymbol{\theta} = [\theta_1, \cdots, \theta_M]$. The problem of mobile tracking in the unknown NLOS conditions is to simultaneously infer the mobile state $\mathbf{x}_k$, the sight condition $\mathbf{s}_k$ and NLOS noise $\boldsymbol{\theta}$ from the observation sequence $\mathbf{z}_{1:k}$, which corresponds to computing the joint posterior $p(\mathbf{x}_k, \mathbf{s}_k, \boldsymbol{\theta}|\mathbf{z}_{1:k})$.

The solution requires high-dimensional integrals. Here, we resort to sequential Monte Carlo techniques [11]. To numerically compute the joint posterior $p(\mathbf{x}_k, \mathbf{s}_k, \boldsymbol{\theta}|\mathbf{z}_{1:k})$, standard particle filtering is not effective in such a high dimensional space constituted by $\{\mathbf{x}_k, \mathbf{s}_k, \boldsymbol{\theta}\}$. We present a RBPF-PL method. Basically, RBPF-PL method uses particle filtering to estimate the posterior of sight condition $\mathbf{s}_k$ while applying an analytical method to estimate the mobile state $\mathbf{x}_k$ and update the NLOS parameters $\boldsymbol{\theta}$. The method is described as follows.

Factorize $p(\mathbf{x}_k, \mathbf{s}_k, \boldsymbol{\theta}|\mathbf{z}_{1:k})$ according to:

$$p(\mathbf{x}_k, \mathbf{s}_k, \boldsymbol{\theta}|\mathbf{z}_{1:k}) = p(\mathbf{x}_k|\mathbf{s}_k, \boldsymbol{\theta}, \mathbf{z}_{1:k})p(\mathbf{s}_k, \boldsymbol{\theta}|\mathbf{z}_{1:k}). \tag{7}$$

If $p(\mathbf{s}_k, \boldsymbol{\theta}|\mathbf{z}_{1:k})$ is represented by a set of weighted samples $\{\mathbf{s}_k^j, \boldsymbol{\theta}^j, w_k^j\}_{j=1}^N$, then

$$p(\mathbf{x}_k|\mathbf{z}_{1:k}) \approx \sum_{j=1}^{N} w_k^j p(\mathbf{x}_k|\mathbf{s}_k^j, \boldsymbol{\theta}^j, \mathbf{z}_{1:k}) \tag{8}$$

where the component $p(\mathbf{x}_k|\mathbf{s}_k^j, \boldsymbol{\theta}^j, \mathbf{z}_{1:k})$ approximately conforms to Gaussian distribution $\mathrm{N}(\hat{\mathbf{x}}_k^j, \hat{\mathbf{P}}_k^j)$, which can be computed by standard extended Kalman filter (EKF):

- Prediction:

$$\begin{aligned} \hat{\mathbf{x}}^j_{k|k-1} &= \boldsymbol{\Phi}_{k-1}\hat{\mathbf{x}}^j_{k-1} \\ \hat{\mathbf{P}}^j_{k|k-1} &= \boldsymbol{\Phi}_{k-1}\hat{\mathbf{P}}^j_{k-1}\boldsymbol{\Phi}^T_{k-1} + \mathbf{Q} \end{aligned} \tag{9}$$

- Update:

$$\begin{aligned} \hat{\mathbf{z}}^j_{k|k-1} &= \mathbf{h}(\hat{\mathbf{x}}^j_{k|k-1}) + \mathbf{m}(\mathbf{s}^j_k) \\ \mathbf{K}^j_k &= \hat{\mathbf{P}}^j_{k|k-1}(\mathbf{H}^j_k)^T\left[\mathbf{H}^j_k\mathbf{P}^j_{k|k-1}(\mathbf{H}^j_k)^T + \mathbf{R}(\mathbf{s}^j_k)\right]^{-1} \\ \mathbf{H}^j_k &= \frac{\partial \mathbf{h}^T(\mathbf{x})}{\partial \mathbf{x}}|_{\mathbf{x}=\hat{\mathbf{x}}^j_{k|k-1}} \\ \hat{\mathbf{x}}^j_k &= \hat{\mathbf{x}}^j_{k|k-1} + \mathbf{K}^j_k(\mathbf{z}_k - \hat{\mathbf{z}}^j_{k|k-1}) \\ \hat{\mathbf{P}}^j_k &= (\mathbf{I} - \mathbf{K}^j_k\mathbf{H}^j_k)\hat{\mathbf{P}}^j_{k|k-1} \end{aligned} \tag{10}$$

Conditioned upon $\{\mathbf{s}^j_{k-1}, \mathbf{x}^j_{k-1}, \mathbf{z}_k\}$, to sample $\{\mathbf{s}^j_k, \boldsymbol{\theta}^j\}$, we choose the following trial distribution:

$$\begin{aligned} &q(\mathbf{s}_k, \boldsymbol{\theta}|\mathbf{s}^j_{k-1}, \mathbf{x}^j_{k-1}, \mathbf{z}_{1:k}) \\ &= \mathrm{P}(\mathbf{s}_k|\mathbf{s}^j_{k-1}, \mathbf{x}^j_{k-1}, \boldsymbol{\theta}, \mathbf{z}_k)p(\boldsymbol{\theta}|\mathbf{s}^j_{k-1}, \mathbf{x}^j_{k-1}, \mathbf{z}_{k-1}) \end{aligned} \tag{11}$$

The corresponding importance weight can be calculated as

$$w^j_k \propto w^j_{k-1}p(\mathbf{z}_k|\mathbf{s}^j_{k-1}, \mathbf{x}^j_{k-1}, \boldsymbol{\theta}) \tag{12}$$

The trial distribution for $\mathbf{s}_k$ in (11) can be expressed as

$$\mathrm{P}(\mathbf{s}_k|\mathbf{s}^j_{k-1}, \mathbf{x}^j_{k-1}, \boldsymbol{\theta}, \mathbf{z}_k) = \frac{p(\mathbf{z}_k|\mathbf{s}_k, \mathbf{x}^j_{k-1}, \boldsymbol{\theta})\mathrm{P}(\mathbf{s}_k|\mathbf{s}^j_{k-1})}{p(\mathbf{z}_k|\mathbf{s}^j_{k-1}, \mathbf{x}^j_{k-1}, \boldsymbol{\theta})} \tag{13}$$

where the likelihood

$$p(\mathbf{z}_k|\mathbf{s}_k, \mathbf{x}^j_{k-1}, \boldsymbol{\theta}) \approx \mathrm{N}(\hat{\mathbf{z}}^j_k, \hat{\boldsymbol{\Sigma}}^j_{k|k-1}), \tag{14}$$

and

$$\begin{aligned} \hat{\mathbf{z}}^j_k &= \mathbf{h}(\hat{\mathbf{x}}^j_{k|k-1}) + \mathbf{m}(\mathbf{s}_k) \\ \hat{\boldsymbol{\Sigma}}^j_{k|k-1} &= \mathbf{H}^j_k\hat{\mathbf{P}}^j_{k|k-1}(\mathbf{H}^j_k)^T + \mathbf{R}(\mathbf{s}_k). \end{aligned} \tag{15}$$

To infer the parameter θ_i, we first specify the Gaussian inverse chi-square prior [12]. Suppose at time t_{k-1},

$$\begin{aligned} &p(\theta_i|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \mathbf{z}_{1:k-1}) = p(\theta_i|s_{i,k-1}^j, \mathbf{x}_{k-1}^j, \mathbf{z}_{1:k-1}) \\ &= \mathrm{N-Inv}-\chi^2(\breve{\mu}_{i,k-1}^j, \breve{\kappa}_{i,k-1}^j, \breve{\nu}_{i,k-1}^j, \breve{\eta}_{i,k-1}^j) \end{aligned} \tag{16}$$

at the end of t_k, the sampling density for θ_i is updated as:

$$\begin{aligned} p(\theta_i|\mathbf{x}_k^j, \mathbf{s}_k^j, \mathbf{z}_{1:k}) &\propto p(z_{i,k}|\theta_i, \mathbf{x}_k^j, s_{i,k}^j) p(\theta_i|s_{i,k-1}^j, \mathbf{x}_{k-1}^j, \mathbf{z}_{1:k-1}) \\ &= \mathrm{N-Inv}-\chi^2(\breve{\mu}_{i,k}^j, \breve{\kappa}_{i,k}^j, \breve{\nu}_{i,k}^j, \breve{\eta}_{i,k}^j) \end{aligned} \tag{17}$$

where$\{\breve{\mu}_{i,k}^j, \breve{\kappa}_{i,k}^j, \breve{\nu}_{i,k}^j, \breve{\eta}_{i,k}^j\}$ can be explicitly derived in terms of the prior parameters and the sufficient statistics of the data:

$$\begin{aligned} \breve{\mu}_{i,k}^j &= \frac{\breve{\kappa}_{i,k-1}^j}{\breve{\kappa}_{i,k-1}^j + n_{i,k}^j} \breve{\mu}_{i,k-1}^j + \frac{1}{\breve{\kappa}_{i,k-1}^j + n_{i,k}^j} \varphi_{i,k}^j \\ \breve{\kappa}_{i,k}^j &= \breve{\kappa}_{i,k-1}^j + n_{i,k}^j \\ \breve{\nu}_{i,k}^j &= \breve{\nu}_{i,k-1}^j + l_{i,k}^j \\ \breve{\eta}_{i,k}^j &= \frac{1}{\breve{\nu}_{i,k}^j} \left[\breve{\nu}_{i,k-1}^j \breve{\eta}_{i,k-1}^j + \phi_{i,k}^j \right] \end{aligned} \tag{18}$$

The computation of $\{n_{i,k}^j, l_{i,k}^j, \varphi_{i,k}^j, \phi_{i,k}^j\}$ depends on different NLOS error models:

- Model 1 (the same mean and the same variance):

$$\begin{aligned} &n_{i,k}^j = l_{i,k}^j = \sum_{i=1}^M \delta(s_{i,k}^j - 1) \\ &\epsilon_{i,k}^j = z_{i,k} - h_i(\mathbf{x}_k^j), \quad \varphi_{i,k}^j = \sum_{i=1}^M \epsilon_{i,k}^j \cdot \delta(s_{i,k}^j - 1) \\ &\bar{\epsilon}_{i,k}^j = \frac{1}{n_{i,k}^j} \epsilon_{i,k}^j, \ (n_{i,k}^j \neq 0) \quad \text{or} \quad \bar{\epsilon}_{i,k}^j = 0, \ (n_{i,k}^j = 0) \\ &\phi_{i,k}^j = \sum_{i=1}^M (\epsilon_{i,k}^j - \bar{\epsilon}_{i,k}^j)^2 \cdot \delta(s_{i,k}^j - 1) + \\ &\qquad \frac{\breve{\kappa}_{k-1}^j n_{i,k}^j}{\breve{\kappa}_{k-1}^j + n_{i,k}^j} (\bar{\epsilon}_{i,k}^j - \breve{\mu}_{i,k-1}^j)^2 \end{aligned}$$

- Model 2 (different mean and the same variance):

$$\begin{aligned} &n_{i,k}^j = \delta(s_{i,k}^j - 1), \quad l_{i,k}^j = \sum_{i=1}^M \delta(s_{i,k}^j - 1) \\ &\varphi_{i,k}^j = (z_{i,k} - h_i(\mathbf{x}_k^j)) \cdot \delta(s_{i,k}^j - 1) \\ &\phi_{i,k}^j = \sum_{i=1}^M \frac{\breve{\kappa}_{k-1}^j n_{i,k}^j}{\breve{\kappa}_{k-1}^j + n_{i,k}^j} (\varphi_{i,k}^j - \breve{\mu}_{i,k-1}^j)^2 \end{aligned}$$

- Model 3 (different mean and different variance):

$$\begin{aligned} &n_{i,k}^j = l_{i,k}^j = \delta(s_{i,k}^j - 1) \\ &\varphi_{i,k}^j = (z_{i,k} - h_i(\mathbf{x}_k^j)) \cdot \delta(s_{i,k}^j - 1) \\ &\phi_{i,k}^j = \frac{\breve{\kappa}_{k-1}^j n_{i,k}^j}{\breve{\kappa}_{k-1}^j + n_{i,k}^j} (\varphi_{i,k}^j - \breve{\mu}_{i,k-1}^j)^2 \end{aligned}$$

IV. Simulation results

We simulate 1600 epoch trajectories of mobile station (MS) using random acceleration motion model. At each epoch there are range measurements from 5 BSs with $\sigma_n^2 = 150^2\mathrm{m}^2$. The three different models described in Section II are used to simulate NLOS data. In each of the models the transition probabilities between LOS and NLOS modes are set for each of the signals $p_0 = p_1 = 0.8$, with initial modes having equal probability of LOS or NLOS. However, the simulated transitions can occur only at every 10th epoch.

Our three test scenarios correspond to the Models 1, 2 and 3 described in II. The NLOS biases are randomly sampled from uniform distribution Uni$[0, 1000](\mathrm{m})$ and the standard deviation of NLOS is sampled from Uni$[10, 600](\mathrm{m})$.

We simulate $n_{\mathrm{MC}} = 100$ tracks and sets of measurements in each of the scenarios. We do cross-testing of the different models of Section II applied to the scenarios defined above. The initial values for the hyperparameters are chosen as $\{\breve{\mu}_{0,i} = 1000, \breve{\kappa}_{0,i} = 1, \breve{\nu}_{0,i} = 1, \breve{\mu}_{0,i} = 750^2\}$, which are chosen to represent vague a priori information about the NLOS parameter $\boldsymbol{\theta}$. The RBPF-PL filters based on the three different models are denoted RBPF1, RBPF2 and RBPF3 corresponding to different models and they use 10 particles.

We use root square error $\mathrm{RSE}_k \triangleq \sqrt{(\hat{x}_k - x_k)^2 + (\hat{y}_k + y_k)^2}$ to compare the performance. The results are reported in Figures $1-3$ using empirical cumulative distribution functions. In the first scenario, the performance of the method based on the simplest model performs the best but only by a very small margin. The degraded performance of the more complicated models is due to estimation of higher number of parameters from the same amount of data, so the data is not used as efficiently as with the simpler model.

In the second scenario where different observations can have different biases, the methods that have modeled this perform the same as in the first scenario, but the method based on a common bias in all of the observations has its performance degraded clearly.

In the third test scenario, the observations are affected by biases with their individual mean and variance. As expected, the method based on the correct model has very similar performance as in the simpler cases. The simplest model performs similarly as in the Scenario 2, implying that the estimation of individual biases has a larger influence on the performance than estimation of variances. This notion is backed up by the fact that the method estimating individual biases but single variance has its performance degraded but not by much.

V. Conclusions

A RBPF method with parameter learning is proposed to track MS in the mixed LOS/NLOS conditions, where the NLOS condition induces noise with unknown mean and variance. Three variations were studied which were based on the knowledge of the type of the observation and the surroundings. In the most versatile case, all the signals observed can be

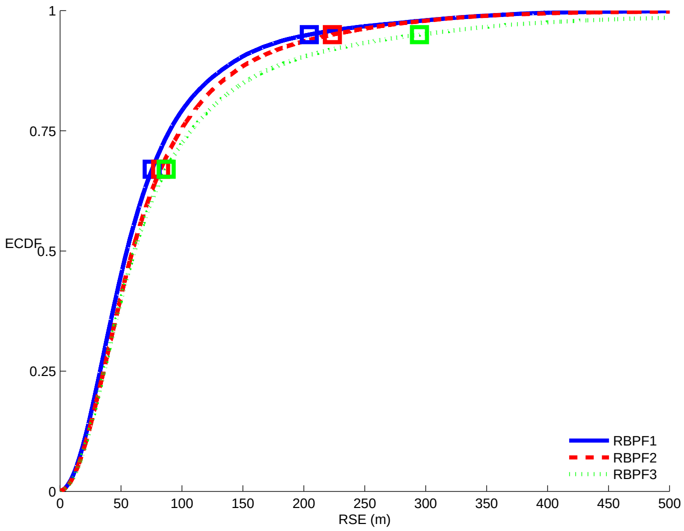

Fig. 1. Scenario 1.

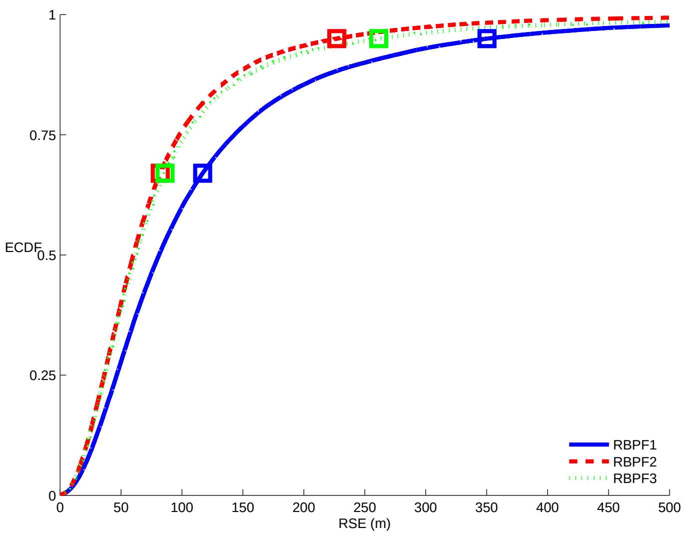

Fig. 2. Scenario 2.

from different type of BSs and travel through different environments. In this case we model all the NLOS noises to have their individual mean and variance. The tests show that unless being certain that NLOS noise is of the same type in all the observations, more complicated models should be employed as they work as supposed in all the different scenarios, with only little more computational complexity.

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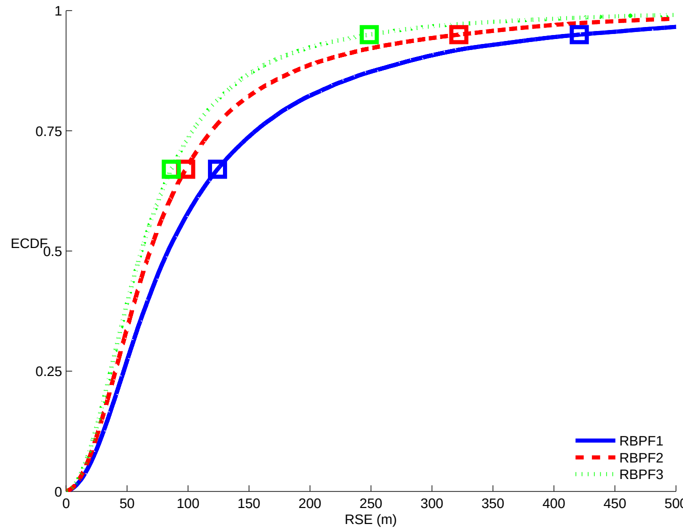

Fig. 3. Scenario 3.

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