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Adaptive mobile tracking in unknown non-line-of-sight conditions with application to digital TV networks

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Abstract

This paper studies the problem of tracking a mobile device in mixed line-of-sight (LOS) and non-line-of-sight (NLOS) conditions. NLOS error is assumed to be Gaussian with unknown mean and variance. An adaptive Rao-Blackwellized particle filter (RBPF) is proposed for mobile tracking in such scenarios. An extended Kalman filter is used to approximately estimate the mobile state, and the particle filter is applied to estimate the posterior distribution of sight conditions and the unknown static parameters, the distribution of which is updated by sufficient statistics. To improve the efficiency of the particle filtering, we use the approximate optimal proposal distribution for particle inference. Algorithm performance is investigated in the scenario of mobile tracking using signals of opportunity from digital TV (DTV) network. Simulation results show that the adaptive RBPF method is effective to infer the unknown NLOS parameter and can achieve good tracking accuracy using a small number of particles.

Keywords: Parameter estimation; Bayesian inference; Signal of opportunity; Digital TV; Non-line-of-sight; Rao-Blackwellized particle filter; Wireless positioning; Mobility tracking

1 Introduction

Accurate and reliable positioning in non-line-of-sight (NLOS) conditions is a challenging task in many wireless positioning systems. In typical NLOS circumstances, e.g. indoors and urban canyons, the direct path from the transmitter is blocked by buildings and other obstacles and the propagation wave may actually travel excess path lengths due to reflection, refraction and scattering. In terms of range-based measurements such as time of arrival (TOA), time difference of arrival (TDOA) and received signal strength (RSS), these extra propagation distances impose positive biases on the true path and thereby cause large errors on the location estimations. The NLOS effect is very common, especially in dense urban scenarios. A field test in a Global System for Mobile Communications (GSM) positioning system has shown that the mean and standard deviation of NLOS range errors are on the order of 513 and 436 m, respectively [1].

Methods proposed to deal with NLOS can generally be divided into two categories: methods for static positioning and methods for mobile tracking. Reference [2] gives a thorough summary for NLOS detection and mitigation in static positioning. However, these methods are not effective for mobile tracking. Methods to mitigate NLOS errors in mobile tracking applications generally exploit the measurements in time series. The proposed methods include two-step Kalman filtering techniques for smoothing range measurements and mitigating NLOS errors [3], a Kalman filter-based interacting multiple model (IMM) smoother [4], grid-based Bayesian estimation [5], particle filter (PF) [6], a modified extended Kalman filter (EKF) bank [7], the improved Rao-Blackwellized particle filter (RBPF) [8], and the joint particle filtering and unscented Kalman filtering (UKF) method [9]. A posterior Cramér-Rao lower bound for this problem is further investigated in [10]. A limitation of these methods is their assumption of complete knowledge of the model parameters, especially the statistical parameters of the NLOS errors, which is not realistic in many practical situations because of the unpredictable characteristics of the wireless channels in harsh environments.

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By assuming all the measurement errors including the LOS and NLOS errors as unknown, reference [11] introduces the Dirichlet Process Mixtures (DPM), a hierarchical mixture model to describe the unknown density; a Bayesian nonparametric method is further applied for density estimation. Although it offers flexibility for modeling, effectively tuning the hyperparameters of a DPM model is difficult, and nonparametric Bayesian inference on the infinite dimensional Dirichlet process is obviously complicated.

In this study, we consider the mobile tracking problem under the mixed LOS/NLOS conditions with a plausible assumption that the statistical properties of the LOS errors are known while the statistics of NLOS error are unknown. In essence, as assumed in [3-9], the LOS errors are treated as measurement noise in the receiver with zero mean Gaussian distribution and known variance. By considering a long period of observation, the distribution of NLOS range errors can be modeled by a positively biased Gaussian noise, while to be more reasonable, its mean and variance are assumed (static) unknown because the statistical parameters of the NLOS errors are highly dependent on the surroundings, and therefore can not be known beforehand [12].

Mobile tracking under such mixed LOS/NLOS conditions comes down to the problem of sequential state estimation with the inference of unknown static parameters. To tackle this kind of problem, Liu and West assumed an artificial dynamic evolution for the unknown parameter vector, which could be further included in the state vector [13]. In the literature of GPS (Global Positioning System), similar methods are applied in algorithms adapting the density estimation by mean jump [14] or variance jump [15] or both [16]. However, such treatment would enlarge the estimation (co)variance of the unknown parameter. Djurić et al. [17] suggested the use of density-assisted particle filters (DAPFs) as an alternative to jointly estimate the sequential state and the parameter without introducing an artificial dynamic model for the static parameters. However, in our situation, because of the Markov property of the sight condition, the derivation of the density update function for all the state variables, and the static parameter is not an easy task. Storvik [18] proposed to marginalize the static parameters out of the posterior distribution such that only the state vector needs to be considered. The method is applicable when the conditional posterior distribution of the parameters (given the observations and the states) can be compactly expressed in terms of a finite dimensional statistic that can be recursively updated. Because the analytical form of the marginal distribution is not available, we hereby perform an approximate (Monte Carlo) marginalization by sampling from the joint posterior distribution of the states and the parameters. An adaptive particle filtering method is therefore proposed, which uses an EKF to approximately estimate the mobile state and applies the particle filter to estimate the posterior density of sight conditions and the unknown static parameters, the distribution of which is updated by sufficient statistics.

The performance of the proposed algorithm is investigated by simulations of positioning with signals of opportunity from digital television (DTV) networks. Recently, research interest in positioning using DTV systems has grown rapidly after the DTV systems have been put into operation for massive use [19-28]. It has been recognized that, compared with GPS [29], the DTV signals have a range of potential advantages to achieve low cost and accurate positioning: a higher transmission power [30], larger signal transmission bandwidth [31], less Doppler effects and ionosphere disturbance [32], lower carrier frequency with better diffraction and better receiving quality for urban and indoor propagation [19], wide coverage of DTV transmitting stations to provide a substantially superior geometry [25] and the economic benefit of making use of existing facilities [27]. Rosum Company has shown that the location accuracy could reach meter-scale with the Advanced Television Systems Committee (ATSC) DTV signals [19]. However, ATSC DTV is a single-carrier modulation system, which is vulnerable to multipath fading. In order to mitigate the effect of multipath fading for making the technique suitable for mobile application [31], digital broadcasting signals based on orthogonal frequency division multiplex (OFDM) modulation have been investigated and tested. As the standards based on OFDM modulation, e.g. DVB-T/H/T2, T-DMB, etc, have been widely adopted in most countries, wireless position systems based on the multi-carrier OFDM may have a massive number of potential users in the future. Therefore, in this paper, we will focus on mobile tracking in the multi-carrier OFDM DTV networks.

The paper is organized as follows: Section 2 presents the system model of mobile tracking in the mixed LOS/NLOS conditions; Section 3 formulates the problem within the Bayesian framework; in Section 4, the RBPF based adaptive mobile tracking method is described in detail; numerical results and performance comparison are presented and discussed in Section 5; and Section 6 draws some conclusions.

2 System description

2.1 Motion model

Assume the mobile device of interest moves in a plane. The state at time instant t_k is defined as the vector $\mathbf{x}_k = \left[x_k, y_k, \dot{x}_k, \dot{y}_k\right]^T$, where $\left[x_k, y_k\right]^T$ are the east and north coordinates of the mobile position; $\left[\dot{x}_k, \dot{y}_k\right]^T$ are the corresponding velocities. The mobile state with random acceleration can be modeled as:

$$\mathbf{x}_{k+1} = \Phi_k \mathbf{x}_k + \mathbf{w}_k, \quad (1)$$

where the transition matrix $\Phi_k = \begin{pmatrix} \mathbf{I}_2 & \Delta t_k \mathbf{I}_2 \\ 0 & \mathbf{I}_2 \end{pmatrix}$ models the state kinematics with $\mathbf{I}_2$ the 2×2 matrix and $\Delta t_k = t_{k+1} - t_k$. The random process $\mathbf{w}_k$ is a white zero mean Gaussian noise with covariance matrix $\mathbf{Q}_k = \begin{pmatrix} \frac{\Delta t_k^4}{4}\mathbf{Q} & \frac{\Delta t_k^3}{2}\mathbf{Q} \\ \frac{\Delta t_k^3}{2}\mathbf{Q} & \Delta t_k^2 \mathbf{Q} \end{pmatrix}$, where $\mathbf{Q} = \begin{pmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_y^2 \end{pmatrix}$. For a derivation of this motion model see [33].

2.2 Measurement model

In DVB-T/H networks, different emitters are coordinated to GPS time and transmit the same DTV signals at the same time with the same frequency, which is called the single frequency network (SFN) transmission [31]. The feature of network synchrony makes the pseudorange measurements available in practice for mobile tracking. Moreover, the DTV signals are transmitted continuously, which allows the receiver to track the arrival of the signals in order to improve the measurement accuracy.

For the purpose of communications, the DTV receivers are required to extract the timing measurements and recover the frequency offset from the received signals, which result in a synchronization problem. For reliable communications, the OFDM systems have stringent requirements on the timing and frequency synchronization. However, for the purpose of high accuracy positioning and navigation, an even finer synchronization is required. To achieve a finer time delay estimation, methods to determine the time of arrival (TOA) of the OFDM DTV signals include the coarse timing acquisition with a sliding correlator, which detects the start of an OFDM symbol by using the property of OFDM cyclic prefix (CP) [34], and the fine timing tracking with a delay-locked loop (DLL) [29], which achieves the accuracy within fractional portion of chip duration.

Scatter pilots inserted in the OFDM symbols [22,23] or full transmitted OFDM symbols [27] can be used for DLL tracking, which are the variants to the process inside conventional Global Navigation Satellite System (GNSS) receivers. Time delay can also be obtained using the time-domain synchronous OFDM signals [25] or the transmitter signature waveforms [26]. In DVB-T/H systems, the nominal signal bandwidth is designed as 6 to 8 MHz, which leads to a much higher chip/code rate than that in GPS L1 systems, thereby improving the precision of timing.

Based on the above discussion, we consider the pseudorange measurements for mobile tracking from different DTV emitters. The pseudorange is the product of the estimated time delay with the speed of the light. Under possible NLOS propagation condition between the transceivers, the distance measured at time t_k is

$$z_{i,k} = d_{i,k} + \nu(s_{i,k}), \quad (2)$$

where $d_{i,k} \triangleq h_{i,k}(\mathbf{x}_k) = \sqrt{(x_k - x_{\mathrm{bs}_i})^2 + (y_k - y_{\mathrm{bs}_i})^2}$ represents the true distance between the receiver's position $\left[x_k, y_k\right]^T$ and the location of the ith DTV transmitter $\left[x_{\mathrm{Tx}_i}, y_{\mathrm{Tx}_i}\right]^T, i \in \{1, 2, \ldots, M\}$, and M is the number of DTV transmitters. The Boolean variable $s_{i,k} \in \{0, 1\}$ represents LOS/NLOS condition between the receiver and Tx_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 further modeled as a time-homogeneous first-order Markov chain $s_{i,k} \sim \mathrm{MC}(\pi_i, \mathbf{A}_i)$ with initial probability vector π_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 $p_1 = \mathrm{P}(s_{i,k} = 1 | s_{i,k-1} = 1)$.

Assume that the measurement noise in the LOS condition has a zero mean Gaussian distribution $\mathrm{N}(0, \sigma_n^2)$, while the NLOS error is modeled as a biased Gaussian distribution $\mathrm{N}(\mu_{\mathrm{NLOS}}, \sigma_{\mathrm{NLOS}}^2)$ [3,4,7]. Thus, $\nu(s_{i,k}) \sim \mathrm{N}(m(s_{i,k}), \mathbf{R}(s_{i,k}))$ and

$$\begin{aligned} m(s_{i,k}) &= s_{i,k} \mu_{\mathrm{NLOS}} \\ \mathbf{R}(s_{i,k}) &= \sigma_n^2 + s_{i,k} \sigma_{\mathrm{NLOS}}^2. \end{aligned} \quad (3)$$

In this work, we assume that σ_n is known, while $\{\mu_{\mathrm{NLOS}}, \sigma_{\mathrm{NLOS}}^2\}$ are static but unknown.

To sum up, the overall dynamic model of the mobile tracking can be represented as follows:

$$\begin{cases} \mathbf{x}_k = \Phi_{k-1} \mathbf{x}_{k-1} + \mathbf{w}_{k-1} \\ s_{i,k} \sim \mathrm{MC}(\pi_i, \mathbf{A}_i) \\ \mathbf{z}_k = \mathbf{h}_k(\mathbf{x}_k) + \mathbf{v}_k(\mathbf{s}_k) \end{cases}, \quad (4)$$

where $s_{i,k}$ is the ith component of vector $\mathbf{s}_k$, $i \in \{1, 2, \ldots, M\}$, $k \in \mathbb{N}$.

3 Bayesian inference and sequential Monte Carlo method

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 $\eta \triangleq \sigma_n^2 + \sigma_{\mathrm{NLOS}}^2$ and $\boldsymbol{\theta} = \{\mu_{\mathrm{NLOS}}, \eta\}$. The problem of mobile tracking in unknown NLOS conditions is to infer the current mobile state $\mathbf{x}_k$ from the observation sequence $\mathbf{z}_{1:k}$. Within the framework of Bayesian inference, the problem corresponds to computing the marginal posterior probability density function (pdf) $p(\mathbf{x}_t|\mathbf{z}_{1:k})$. The marginal posterior is the mixture

$$\begin{aligned} p(\mathbf{x}_k|\mathbf{z}_{1:k}) &= \sum_{\mathbf{s}_k} \int_{\boldsymbol{\theta}} p(\mathbf{x}_k, \mathbf{s}_k, \boldsymbol{\theta}|\mathbf{z}_{1:k}) \mathrm{d}\boldsymbol{\theta} \quad \text{[marginalization]} \\ &\propto \sum_{\mathbf{s}_k} \int_{\boldsymbol{\theta}} p(\mathbf{z}_k|\mathbf{x}_k, \mathbf{s}_k, \boldsymbol{\theta}) p(\mathbf{x}_k, \mathbf{s}_k, \boldsymbol{\theta}|\mathbf{z}_{1:k-1}) \mathrm{d}\boldsymbol{\theta} \\ &\quad \text{[Bayes' law]} \end{aligned} \tag{5}$$

where the prior pdf $p(\mathbf{x}_k, \mathbf{s}_k, \boldsymbol{\theta}|\mathbf{z}_{1:k-1})$ can be obtained via the Chapman-Kolmogorov equation:

$$\begin{aligned} p(\mathbf{x}_k, \mathbf{s}_k, \boldsymbol{\theta}|\mathbf{z}_{1:k-1}) &= \sum_{\mathbf{s}_{k-1}} \int_{\mathbf{x}_{k-1}} p(\mathbf{x}_k, \mathbf{s}_k, \boldsymbol{\theta}|\mathbf{x}_{k-1}, \mathbf{s}_{k-1}, \mathbf{z}_{1:k-1}) \\ &\quad \times p(\mathbf{x}_{k-1}, \mathbf{s}_{k-1}|\mathbf{z}_{1:k-1}) \mathrm{d}\mathbf{x}_{k-1} \\ &= \sum_{\mathbf{s}_{k-1}} \int_{\mathbf{x}_{k-1}} p(\mathbf{x}_k|\mathbf{x}_{k-1}) \mathrm{P}(\mathbf{s}_k|\mathbf{s}_{k-1}) p(\boldsymbol{\theta}|\mathbf{x}_{k-1}, \mathbf{s}_{k-1}, \mathbf{z}_{1:k-1}) \\ &\quad \times p(\mathbf{x}_{k-1}, \mathbf{s}_{k-1}|\mathbf{z}_{1:k-1}) \mathrm{d}\mathbf{x}_{k-1} \end{aligned} \tag{6}$$

In (5) and (6), the number of mixture components grows exponentially with time. Thus, the analytical solution to the posterior $p(\mathbf{x}_k|\mathbf{z}_{1:k})$ requires very high-dimensional integrals, which is prohibitive to compute in practice. The sequential Monte Carlo (SMC) method (also called particle filtering) has proven to be successful in tracking applications with nonlinear and non-Gaussian models [35]. Here, we resort to this kind of sample-based numerical approximate method.

Denote $\mathbf{y}_k = \{\mathbf{x}_k, \mathbf{s}_k\}$, and suppose a set of N weighted samples $\{\mathbf{y}^j_{k-1}, \boldsymbol{\theta}^j, w^j_{k-1}\}_{j=1}^N$ is used to approximate the posterior $p(\mathbf{y}_{k-1}, \boldsymbol{\theta}|\mathbf{z}_{1:k-1})$ at time t_{k-1} with the following point-distribution:

$$p(\mathbf{y}_{k-1}, \boldsymbol{\theta}|\mathbf{z}_{1:k-1}) \approx \sum_{j=1}^N w^j_{k-1} \delta(\mathbf{y}_{k-1} - \mathbf{y}^j_{k-1}) \delta(\boldsymbol{\theta} - \boldsymbol{\theta}^j)$$

where $\delta(\cdot)$ is the Dirac delta measure, and the multiplication of Dirac deltas is the product measure of the one-dimensional Delta functions in each variable separately [36].

With the new reception of measurement $\mathbf{z}_k$, the new samples at time t_k are generated from a suitably designed proposal distribution:

$$q(\mathbf{y}_k, \boldsymbol{\theta}|\mathbf{y}^j_{k-1}, \mathbf{z}_{1:k}) = q_2(\boldsymbol{\theta}|\mathbf{y}^j_{k-1}, \mathbf{z}_{1:k}) q_1(\mathbf{y}_k|\mathbf{y}^j_{k-1}, \mathbf{z}_{1:k})$$

Accordingly, importance weights are updated as

$$w^j_k \propto \frac{p(\mathbf{z}_k|\mathbf{y}^j_k, \boldsymbol{\theta}^j) p(\mathbf{y}^j_k|\mathbf{y}^j_{k-1}) p(\boldsymbol{\theta}^j|\mathbf{y}^j_{k-1}, \mathbf{z}_{1:k-1})}{q_2(\boldsymbol{\theta}|\mathbf{y}^j_{k-1}, \mathbf{z}_{1:k}) q_1(\mathbf{y}_k|\mathbf{y}^j_{k-1}, \mathbf{z}_{1:k})} w^j_{k-1} \tag{7}$$

In standard particle filtering (SPF), transition priors are used as the proposal distribution:

$$\begin{aligned} q(\mathbf{y}_k, \boldsymbol{\theta}|\mathbf{y}^j_{k-1}, \mathbf{z}_{1:k}) &= p(\mathbf{x}_k|\mathbf{x}^j_{k-1}) p(\mathbf{s}_k|\mathbf{s}^j_{k-1}) \\ &\quad \times p(\boldsymbol{\theta}^j|\mathbf{y}^j_{k-1}, \mathbf{z}_{1:k-1}). \end{aligned}$$

Thus, the weight update equation (7) can be simplified as:

$$w^j_k \propto w^j_{k-1} p(\mathbf{z}_k|\mathbf{y}^j_k, \boldsymbol{\theta}^j).$$

In SPF, since $\{\mathbf{x}_k, \mathbf{s}_k, \boldsymbol{\theta}\}$ constitutes a high-dimensional state estimation space, a large number of particles should be used to achieve good estimation results, which is computationally expensive. Additionally, using the transition prior as the proposal, which fails to consider the information of current measurements, would easily suffer from the 'particle impoverishment' problem. In order to overcome these two limitations, we re-formulate the inference problem using a RBPF.

4 Adaptive RBPF algorithm for mobile tracking

Factorize the posterior density of the hidden state $p(\mathbf{x}_k, \mathbf{s}_k, \boldsymbol{\theta}|\mathbf{z}_{1:k})$ according to the chain rule:

$$p(\mathbf{x}_k, \mathbf{s}_k, \boldsymbol{\theta}|\mathbf{z}_{1:k}) = p(\mathbf{x}_k|\mathbf{s}_k, \boldsymbol{\theta}, \mathbf{z}_{1:k}) p(\mathbf{s}_k, \boldsymbol{\theta}|\mathbf{z}_{1:k}). \tag{8}$$

If the marginal posterior density $p(\mathbf{s}_k, \boldsymbol{\theta}|\mathbf{z}_{1:k})$ is represented by a set of weighted samples $\{\mathbf{s}^j_k, \boldsymbol{\theta}^j, w^j_k\}_{j=1}^N$, i.e.,

$$p(\mathbf{s}_k, \boldsymbol{\theta}|\mathbf{z}_{1:k}) \approx \sum_{j=1}^N w^j_k \delta(\mathbf{s}_k - \mathbf{s}^j_k) \delta(\boldsymbol{\theta} - \boldsymbol{\theta}^j), \tag{9}$$

then the marginal density $p(\mathbf{x}_k|\mathbf{z}_{1:k})$ can be approximately expressed by a mixture of densities:

$$p(\mathbf{x}_k|\mathbf{z}_{1:k}) \approx \sum_{j=1}^N w^j_k p(\mathbf{x}_k|\mathbf{s}^j_k, \boldsymbol{\theta}^j, \mathbf{z}_{1:k}). \tag{10}$$

Based on the system model in (4), the mixture component $p(\mathbf{x}_k|\mathbf{s}^j_k, \boldsymbol{\theta}^j, \mathbf{z}_{1:k})$ can be calculated by an EKF.

Thus, the decomposition (8) leads to developing a more efficient algorithm, with only the posterior density $p(\mathbf{s}_k, \boldsymbol{\theta}|\mathbf{z}_{1:k})$ approximately calculated through a sampling method, while the mobile state $p(\mathbf{x}_k|\mathbf{s}_k, \boldsymbol{\theta}_{1:k})$ is analytically computed. This method, motivated by the decomposition (8), is known as RBPF. In what follows, the method is illustrated in detail.

4.1 Inference for the mobile state

Let a set of weighted samples $\{\mathbf{s}^j_k, \boldsymbol{\theta}^j, w^j_k\}_{j=1}^N$ represent the marginal posterior density of $p(\mathbf{s}_k, \boldsymbol{\theta}|\mathbf{z}_{1:k})$. The sampling method and parameter update will be described in Sections 4.2 and 4.3. Then, the marginal posterior $p(\mathbf{x}_k|\mathbf{z}_{1:k})$ in (10) is approximated by a mixture of Gaussians, with the component $p(\mathbf{x}_k|\mathbf{s}_k^j, \boldsymbol{\theta}^j, \mathbf{z}_{1:k})$ approximately conforming to Gaussian distribution $\mathrm{N}(\hat{\mathbf{x}}_k^j, \hat{\mathbf{P}}_k^j)$, where

$$\hat{\mathbf{x}}_k^j = \hat{\mathbf{x}}_{k|k-1}^j + \sum_{j=1}^{M} \mathbf{K}_{i,k}^j (z_{i,k} - \hat{z}_{i,k|k-1}^j) \tag{11}$$

$$\hat{\mathbf{P}}_k^j = \left[(\hat{\mathbf{P}}_{k|k-1}^j)^{-1} + \sum_{i=1}^{M} (\mathbf{H}_{i,k}^j)^T \mathbf{R}(s_{i,k}^j)^{-1} \mathbf{H}_{i,k}^j \right]^{-1} \tag{12}$$

$\hat{\mathbf{x}}_{k|k-1}^j$ is the predicted mean of $\mathbf{x}_{k-1}^j$:

$$\hat{\mathbf{x}}_{k|k-1}^j = \Phi \hat{\mathbf{x}}_{k-1}^j \tag{13}$$

and $\hat{\mathbf{P}}_{k|k-1}^j$ is the corresponding predicted covariance:

$$\hat{\mathbf{P}}_{k|k-1}^j = \Phi_{k-1} \hat{\mathbf{P}}_{k-1}^j \Phi_{k-1}^T + \mathbf{Q} \tag{14}$$

The predicted mean of measurement $\hat{z}_{i,k|k-1}^j$ is

$$\hat{z}_{i,k|k-1}^j = h_i(\hat{\mathbf{x}}_{k|k-1}^j) + m(s_{i,k}^j) \tag{15}$$

The Kalman gain is

$$\mathbf{K}_{i,k}^j = \hat{\mathbf{P}}_{i,k}^j (\mathbf{H}_{i,k}^j)^T \mathbf{R}(s_{i,k}^j)^{-1} \tag{16}$$

and $\mathbf{H}_{i,k}^j = \frac{\partial h_i}{\partial \mathbf{x}}|_{\mathbf{x}=\hat{\mathbf{x}}_{k|k-1}^j}$. In LOS conditions, $m(s_{i,k}^j) = 0$ and $\mathbf{R}(s_{i,k}^j) = \sigma_n^2$, while in NLOS, $m(s_{i,k}^j) = \mu_{\mathrm{NLOS}}^j$ and $\mathbf{R}(s_{i,k}^j) = \eta^j$.

4.2 Particle sampling and weights updating

The proposal trial distribution is said to be optimal if it minimizes the variance of the important weights [37]. To sample $\{\mathbf{s}_k^j, \boldsymbol{\theta}^j\}$, conditioned upon $\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \boldsymbol{\theta}^j$, and $\mathbf{z}_{1:k}$, the optimal proposal distribution is:

$$\begin{aligned} q(\boldsymbol{\theta}|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \mathbf{z}_{1:k})_{\mathrm{opt}} &= p(\boldsymbol{\theta}|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \mathbf{z}_{1:k}) \\ &= \frac{p(\mathbf{z}_k|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \boldsymbol{\theta}) p(\boldsymbol{\theta}|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \mathbf{z}_{1:k-1})}{p(\mathbf{z}_k|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j)} \\ &\propto \sum_{\mathbf{s}_k} \mathrm{P}(\mathbf{s}_k|\mathbf{s}_{k-1}^j) \int_{\mathbf{x}_k} p(\mathbf{z}_k|\mathbf{s}_k, \mathbf{x}_k, \boldsymbol{\theta}) p(\mathbf{x}_k|\mathbf{x}_{k-1}^j) \\ &\quad \times p(\boldsymbol{\theta}|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \mathbf{z}_{1:k-1}) d\mathbf{x}_k \end{aligned} \tag{17a}$$

$$\begin{aligned} q(\mathbf{s}_k|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \boldsymbol{\theta}, \mathbf{z}_{1:k})_{\mathrm{opt}} &= p(\mathbf{s}_k|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \boldsymbol{\theta}, \mathbf{z}_{1:k}) \\ &= \frac{p(\mathbf{z}_k|\mathbf{s}_k, \mathbf{x}_{k-1}^j, \boldsymbol{\theta}) \mathrm{P}(\mathbf{s}_k|\mathbf{s}_{k-1}^j)}{p(\mathbf{z}_k|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \boldsymbol{\theta})} \\ &\propto \mathrm{P}(\mathbf{s}_k|\mathbf{s}_{k-1}^j) \int_{\mathbf{x}_k} p(\mathbf{z}_k|\mathbf{s}_k, \mathbf{x}_k, \boldsymbol{\theta}) p(\mathbf{x}_k|\mathbf{x}_{k-1}^j) \mathrm{d}\mathbf{x}_k \end{aligned} \tag{17b}$$

Accordingly, the weight is updated as:

$$\begin{aligned} w_k^j &\propto \frac{p(\mathbf{s}_{1:k}^j, \boldsymbol{\theta}|\mathbf{x}_{1:k-1}^j, \mathbf{z}_{1:k})}{q(\mathbf{s}_{1:k}^j, \boldsymbol{\theta}|\mathbf{x}_{1:k-1}^j, \mathbf{z}_{1:k})} \\ &= w_{k-1}^j \frac{p(\mathbf{z}_k|\mathbf{s}_k^j, \mathbf{x}_{k-1}^j, \boldsymbol{\theta}^j) p(\mathbf{s}_k^j|\mathbf{s}_{k-1}^j) p(\boldsymbol{\theta}^j|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \mathbf{z}_{1:k-1})}{q(\mathbf{s}_k^j|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \boldsymbol{\theta}^j, \mathbf{z}_{1:k})_{\mathrm{opt}} q(\boldsymbol{\theta}^j|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \mathbf{z}_{1:k})_{\mathrm{opt}}} \\ &= w_{k-1}^j p(\mathbf{z}_k|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j) \\ &= w_{k-1}^j \sum_{\mathbf{s}_k} \mathrm{P}(\mathbf{s}_k|\mathbf{s}_{k-1}^j) \int_{\boldsymbol{\theta}} \int_{\mathbf{x}_k} p(\mathbf{z}_k|\mathbf{s}_k, \mathbf{x}_k, \boldsymbol{\theta}) p(\mathbf{x}_k|\mathbf{x}_{k-1}^j) \\ &\quad \times p(\boldsymbol{\theta}|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \mathbf{z}_{1:k-1}) d\mathbf{x}_k d\boldsymbol{\theta} \end{aligned} \tag{18}$$

Obviously, the importance weight update equation in (18) involves a high-dimension integral and it is difficult to get the closed-form solution. To approximate the integral in (18), we use the mean-value point approximation

$$\begin{aligned} &\int_{\boldsymbol{\theta}} \int_{\mathbf{x}_k} p(\mathbf{z}_k|\mathbf{s}_k, \mathbf{x}_k, \boldsymbol{\theta}) p(\mathbf{x}_k|\mathbf{x}_{k-1}^j) p(\boldsymbol{\theta}|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \mathbf{z}_{1:k-1}) d\mathbf{x}_k d\boldsymbol{\theta} \\ &\approx \int_{\boldsymbol{\theta}} \int_{\mathbf{x}_k} p(\mathbf{z}_k|\mathbf{s}_k, \mathbf{x}_k, \boldsymbol{\theta}) \delta(\mathbf{x}_k - \hat{\mathbf{x}}_{k|k-1}^j) \delta(\boldsymbol{\theta} - \hat{\boldsymbol{\theta}}^j) d\mathbf{x}_k d\boldsymbol{\theta} \\ &= p(\mathbf{z}_k|\mathbf{s}_k, \hat{\mathbf{x}}_{k|k-1}^j, \hat{\boldsymbol{\theta}}^j) \end{aligned} \tag{19}$$

where

$$\hat{\mathbf{x}}_{k|k-1}^j = \mathbf{E}(\mathbf{x}_k|\mathbf{x}_{k-1}^j) \tag{20a}$$

$$\hat{\boldsymbol{\theta}}^j = \mathbf{E}(\boldsymbol{\theta}|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \mathbf{z}_{1:k-1}) \tag{20b}$$

where $\mathbf{E}(\cdot)$ is the expectation operator.

Then, substituting (19) and (20) into (18), the importance weight update is approximated by:

$$w_k^j \approx w_{k-1}^j \sum_{\mathbf{s}_k} p(\mathbf{z}_k|\hat{\mathbf{x}}_{k|k-1}^j, \mathbf{s}_k, \hat{\boldsymbol{\theta}}^j) \mathrm{P}(\mathbf{s}_k|\mathbf{s}_{k-1}^j) \tag{21}$$

Applying the same mean-point approximation (20) into (17), the optimal proposal distribution can be approximated as

$$\begin{aligned} q(\boldsymbol{\theta}|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \mathbf{z}_{1:k})_{\mathrm{opt}} &\propto \sum_{\mathbf{s}_k} p(\mathbf{z}_k|\mathbf{s}_k, \hat{\mathbf{x}}_{k|k-1}^j, \boldsymbol{\theta}) \mathrm{P}(\mathbf{s}_k|\mathbf{s}_{k-1}^j) \\ &\quad \times p(\boldsymbol{\theta}|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \mathbf{z}_{1:k-1}) \end{aligned} \tag{22a}$$

$$q(\mathbf{s}_k|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \boldsymbol{\theta}, \mathbf{z}_{1:k})_{\mathrm{opt}} \propto p(\mathbf{z}_k|\mathbf{s}_k, \hat{\mathbf{x}}_{k|k-1}^j, \boldsymbol{\theta}) \mathrm{P}(\mathbf{s}_k|\mathbf{s}_{k-1}^j) \tag{22b}$$

4.3 Update of the static parameters

In this work, the NLOS error is modeled as a Gaussian random variable with positive mean. To infer the statistical parameter $\boldsymbol{\theta}$, we specify on them the Gaussian inverse chi-square prior, which is conjugate prior distribution and has computational convenience in Bayesian inference [38].

Suppose at time t_{k-1},

$$p(\boldsymbol{\theta}|\mathbf{s}_{k-1}^j, \mathbf{x}_{k-1}^j, \mathbf{z}_{1:k-1}) = \text{N-inv-}\chi^2(\breve{\mu}_{k-1}^j, \breve{\kappa}_{k-1}^j, \breve{\nu}_{k-1}^j, \breve{\eta}_{k-1}^j)$$

that is,

$$\begin{aligned} p(\mu_{\text{NLOS}}|\eta, \mathbf{s}^j_{k-1}, \mathbf{x}^j_{k-1}, \mathbf{z}_{1:k-1}) &= \text{N}(\breve{\mu}^j_{k-1}, \eta/\breve{\kappa}^j_{k-1}) \\ p(\eta|\mathbf{s}^j_{k-1}, \mathbf{x}^j_{k-1}, \mathbf{z}_{1:k-1}) &= \chi^{-2}(\breve{\nu}^j_{k-1}, \breve{\eta}^j_{k-1}) \end{aligned} \quad (23)$$

where the four hyperparameters $\{\breve{\mu}^j_{k-1}, \breve{\kappa}^j_{k-1}, \breve{\nu}^j_{k-1}, \breve{\eta}^j_{k-1}\}$ can be identified as the location and scale of μ_{NLOS} and the degrees of freedom and scale of η.

At time t_k, the sampling density for $\boldsymbol{\theta}$ is updated according to

$$\begin{aligned} p(\boldsymbol{\theta}|\mathbf{x}^j_{k|k-1}, \mathbf{s}^j_k, \mathbf{z}_{1:k}) &\propto p(\mathbf{z}_k|\boldsymbol{\theta}, \mathbf{x}^j_{k|k-1}, \mathbf{s}^j_k) \\ &\quad \times p(\boldsymbol{\theta}|\mathbf{x}^j_{k-1}, \mathbf{s}^j_{k-1}, \mathbf{z}_{1:k-1}) \\ &= \text{N-inv-}\chi^2(\breve{\mu}^j_k, \breve{\kappa}^j_k, \breve{\nu}^j_k, \breve{\eta}^j_k) \end{aligned} \quad (24)$$

where the hyperparameters are updated as

$$\begin{aligned} \breve{\mu}^j_k &= \frac{\breve{\kappa}^j_{k-1}}{\breve{\kappa}^j_{k-1} + n^j_k}\breve{\mu}^j_{k-1} + \frac{n^j_k}{\breve{\kappa}^j_{k-1} + n^j_k}\bar{\epsilon}^j_k \\ \breve{\kappa}^j_k &= \breve{\kappa}^j_{k-1} + n^j_k \\ \breve{\nu}^j_k &= \breve{\nu}^j_{k-1} + n^j_k \\ \breve{\nu}^j_k\breve{\eta}^j_k &= \breve{\nu}^j_{k-1}\breve{\eta}^j_{k-1} + \sum_{i=1}^{M}(\epsilon^j_{i,k} - \bar{\epsilon}^j_k)^2 \cdot \delta(s^j_{i,k} - 1) \\ &\quad + \frac{\breve{\kappa}^j_{k-1}n^j_k}{\breve{\kappa}^j_{k-1} + n^j_k}(\bar{\epsilon}^j_k - \breve{\mu}^j_{k-1})^2 \end{aligned} \quad (25)$$

where $\{n^j_k, \epsilon^j_k, \bar{\epsilon}^j_k\}$ are computed as

$$\begin{aligned} n^j_k &= \sum_{i=1}^{M}\delta(s^j_{i,k} - 1) \\ \epsilon^j_{i,k} &= z_{i,k} - h_i(\mathbf{x}^j_{k|k-1}) \\ \bar{\epsilon}^j_k &= \begin{cases} \frac{1}{n^j_k}\sum_{i=1}^{M}\epsilon^j_{i,k} \cdot \delta(s^j_{i,k} - 1) & \text{if } n^j_k \neq 0 \\ 0 & \text{if } n^j_k = 0 \end{cases} \end{aligned} \quad (26)$$

The n^j_k is the total number of NLOS conditions in $\mathbf{s}^j_k$, and $\bar{\epsilon}^j_k$ is the mean of the innovation in NLOS conditions. Intuitively, the updated hyperparameters in (25) combine the prior information and the information contained in $\{n^j_k, \bar{\epsilon}^j_k\}$. Obviously, for $n^j_k = 0$, which means there is no NLOS condition inferred in $\mathbf{s}^j_k$, the hyperparameters remain unchanged from time t_{k-1} to t_k because there is no innovation to update. Thus, $\{n^j_k, \bar{\epsilon}^j_k\}$ derived from $\{\mathbf{s}^j_k, \mathbf{x}^j_k, \mathbf{z}_k\}$ are the sufficient statistics to infer the parameter $\boldsymbol{\theta}$.

To get the samples $\boldsymbol{\theta}^j$ from the proposal distribution (22a), first sample $\mathbf{s}^j_k \sim \text{P}(\mathbf{s}_k|\mathbf{s}^j_{k-1})$. Then update the hyperparameters according to (25-26), and generate the particles $\boldsymbol{\theta}^j$ from the Gaussian-Inverse-chi-square, which corresponds to $\eta^j \sim \chi^{-2}(\breve{\nu}^j_k, \breve{\eta}^j_k)$ and $\mu^j_{\text{NLOS}} \sim \text{N}(\breve{\mu}^j_k, \eta^j/\breve{\kappa}^j_k)$. To get the weights at each time epoch in (21), the mean of $\boldsymbol{\theta}^j$ is computed as:

$$\mathbf{E}(\mu_{\text{NLOS}}|\mathbf{x}^j_k, \mathbf{s}^j_k, \mathbf{z}_{1:k}) = \breve{\mu}^j_k \quad (27a)$$

$$\mathbf{E}(\eta|\mathbf{x}^j_k, \mathbf{s}^j_k, \mathbf{z}_{1:k}) = \frac{\breve{\nu}^j_k}{\breve{\nu}^j_k - 2}\breve{\eta}^j_k \quad (27b)$$

4.4 Algorithm description

The importance weight w^j_k in (18) only depends on the current measurement $\mathbf{z}_k$ and the particles of t_{k-1}, i.e. $\{\hat{\mathbf{x}}^j_{k-1}, \mathbf{s}^j_{k-1}\}_{j=1}^N$, while $\{\mathbf{x}_k, \mathbf{s}_k, \boldsymbol{\theta}\}$ are all marginalized out. Thus, to improve the sample effectiveness, the particles of t_{k-1} could be first selected (resampled) based on the current measurement $\mathbf{z}_k$, and the fittest particles could be allowed to propagate. Then, $\{\boldsymbol{\theta}^j, \mathbf{s}^j_k\}_{j=1}^N$ is sampled from the (approximately) optimal distribution, with an EKF attached to every particle to further update the mobile state $\mathbf{x}^j_k$. Thus, the whole algorithm infers the sight conditions, the mobile state and adaptively learns the unknown statistical parameters of the biased NLOS errors. The proposed method is summarized in Algorithm 1.

Algorithm 1 RBPF-based adaptive mobile tracking algorithm

Input $\left[\left\{w^j_{k-1}, \mathbf{s}^j_{k-1}, \hat{\mathbf{x}}^j_{k-1}, \hat{\mathbf{P}}^j_{k-1}, \breve{\mu}^j_{k-1}, \breve{\kappa}^j_{k-1}, \breve{\nu}^j_{k-1}, \breve{\eta}^j_{k-1}\right\}_{j=1}^N\right]$
Output $\left[\left\{w^j_k, \mathbf{s}^j_k, \hat{\mathbf{x}}^j_k, \hat{\mathbf{P}}^j_k, \breve{\mu}^j_k, \breve{\kappa}^j_k, \breve{\nu}^j_k, \breve{\eta}^j_k\right\}_{j=1}^N\right]$
for $k = 1, 2, \ldots$ **do**
  for $j = 1, 2, \ldots, N$ **do**
1. Predict mean $\hat{\mathbf{x}}^j_{k|k-1}$ and covariance $\hat{\mathbf{P}}^j_{k|k-1}$ according to (13) and (14)
2. Predict measurement mean $\hat{\mathbf{z}}^j_{k|k-1} = \mathbf{h}(\hat{\mathbf{x}}^j_{k|k-1})$ and the linearized matrix $\mathbf{H}^j_k$
3. Calculate the predict prior mean $\hat{\boldsymbol{\theta}}^j$ according to (27)
4. Compute the new weight w^j_k using (21)

  end for
  Resample particles $\left\{w^j_k, \mathbf{s}^j_{k-1}, \hat{\mathbf{x}}^j_{k|k-1}, \hat{\mathbf{P}}^j_{k|k-1}, \breve{\mu}^j_{k-1}, \breve{\kappa}^j_{k-1}, \breve{\nu}^j_{k-1}, \breve{\eta}^j_{k-1}\right\}_{j=1}^N$ using new weights w^j_k to obtain $\left\{w^l_k, \mathbf{s}^l_{k-1}, \hat{\mathbf{x}}^l_{k|k-1}, \hat{\mathbf{P}}^l_{k|k-1}, \breve{\mu}^l_{k-1}, \breve{\kappa}^l_{k-1}, \breve{\nu}^l_{k-1}, \breve{\eta}^l_{k-1}\right\}_{l=1}^N$, where $w^l_k = \frac{1}{N}$.
  for $l = 1, 2, \ldots, N$ **do**
1. Update $\left\{\breve{\mu}^l_k, \breve{\kappa}^l_k, \breve{\nu}^l_k, \breve{\eta}^l_k\right\}_{l=1}^N$ according to (25) and (26)
2. Sample $\boldsymbol{\theta}^l$ according to (22a)
3. Sample $\mathbf{s}^l_k$ according to (22b)
4. Update $\{\hat{\mathbf{x}}^l_k, \hat{\mathbf{P}}^l_k\}_{l=1}^N$ according to (11) to (16)

  end for
end for

5 Simulation results

Computer simulations are performed in a DVB-T-based positioning system to evaluate the proposed adaptive mobile tracking algorithm in the mixed LOS/NLOS conditions.

It is assumed that at every epoch, the signals can be received from five transmitters. By considering the SFN coverage in 4K mode of DVB-T/H, which supports the application of the mobile reception [31], the DTV transmitters are set at [−2 km, −1 km], [−2 km, 6 km], [5 km, −1 km], [6 km, 5 km] and [1 km, −2 km], respectively. The receiver's trajectories are generated according to the motion model described in Section 2.1, in which the initial position is set to [−1.5 km, 1.5 km], and the initial velocity is set at [10 m/s, 0 m/s]. The random acceleration variances σ_x^2, σ_y^2 are both chosen to 0.5 $(\mathrm{m/s}^2)^2$. The simulated trajectory has $L = 1{,}000$ time steps, and the time step size is $\Delta t = 0.2$ s. The measurement data are generated by adding the measurement noise and the NLOS noise to the true distance from receiver to each transmitter. The measurement noise is assumed to be a white Gaussian random variable with zero mean and standard deviation $\sigma_n = 15$ m, which is in agreement with the theoretical analysis of the 4K mode in the DVB-T system in [23] and the simulation results in [27]. The NLOS measurement errors are usually much larger than LOS errors [1]. Thus, the parameters of the positive Gaussian distribution of the NLOS errors are assumed with mean $\mu_{\mathrm{NLOS}} = 50$ m and standard deviation $\sigma_{\mathrm{NLOS}} = 40$ m. The mode transition probability is chosen to be $p_0 = p_1 = 0.8$. The LOS or NLOS mode is generated by making a Markov chain transition every 10 steps, which simulates a highly dynamic environment during the tracking process.

In the algorithms, the initial estimation of sight condition is set to $\mathrm{P}(s_{i,0} = 0) = \mathrm{P}(s_{i,0} = 1) = 0.5$, where $i = 1, \cdots, 5$. The initial position is calculated by Chan's algorithm [39] using the first five range measurements. For the lack of definitive prior information on the mobile state, the initial velocity is set as [0 m/s, 0 m/s] and the covariance matrix $\mathbf{C}_{t0} = \begin{bmatrix} 15^2 \cdot \mathbf{I}_2 & \mathbf{0} \\ \mathbf{0} & 10^2 \cdot \mathbf{I}_2 \end{bmatrix}$ corresponding to a standard deviation of 15 m for the position and 10 m/s (36 km/h) for the velocity of each coordinate. For vague prior information on NLOS parameter θ, the initial values of the hyperparameters are set as $\{\breve{\mu}_0 = 1{,}000, \breve{\kappa}_0 = 1, \breve{\nu}_0 = 1, \breve{\eta}_0 = (5\sigma_n)^2\}$ in the algorithm. The simulation results are obtained based on $n_{\mathrm{MC}} = 20$ Monte Carlo realizations with the same parameters.

We compare the performance of the adaptive RBPF method with the following three reference methods. The first is the RBPF method [8], where the NLOS parameters $\boldsymbol{\theta}$ is assumed known and only the mobile state $\mathbf{x}_k$ and the sight condition $\mathbf{s}_k$ have to be inferred. The second reference method assumes the sight conditions known for the whole trajectory and the adaptive RBPF is modified only to infer the mobile state $\mathbf{x}_k$ and the static parameters $\boldsymbol{\theta}$ (adaptive RBPF with $\mathbf{s}_k$ known). The aim of the comparisons with these two methods is to show how the different parameters affect the final inference for the mobile tracking. In addition, to show the superiority of the RBPF method over the SPF method mentioned in Section 3, we also compare the results obtained by the SPF, which uses the transition prior as the proposal to sample the high dimensional state space $\{\mathbf{x}_k, \mathbf{s}_k, \boldsymbol{\theta}\}$, and applies the same parameter update method for $\boldsymbol{\theta}$ in Section 4.3. In what follows, the third reference method is called adaptive SPF.

The accuracies are compared in terms of root square error (RSE), position root-mean-square error (RMSE) and average RMSE. RSE is defined as $\mathrm{RSE} \triangleq \sqrt{(\hat{x}_k - x_k)^2 + (\hat{y}_k - y_k)^2}$ and the position RMSE at time t_k as: $\mathrm{RMSE}_k \triangleq \sqrt{\frac{1}{n_{\mathrm{mc}}} \sum_{m=1}^{n_{\mathrm{mc}}} [\, (\hat{x}_{k,m} - x_k)^2 + (\hat{y}_{k,m} - y_k)^2]}$, while average $\mathrm{RMSE} \triangleq \frac{1}{L} \sum_{k=1}^{L} \mathrm{RMSE}_k$.

5.1 Tracking accuracy of the proposed algorithm

In the algorithms of RBPF, adaptive RBPF with $\mathbf{s}_k$ known and adaptive RBPF, the number of the particles is set to 10. To achieve a comparable accuracy, 1,000 particles are used in the adaptive SPF. Figure 1 shows comparison of the CDF of RSE, in which the positioning accuracy of 66.7% and 99% errors are also marked and the comparison of the position RMSE versus time is in Figure 2. Figures 3 and 4 show one realization of updating the static parameters μ_{NLOS} and $\sqrt{\eta}$; 3-σ confidence intervals are also shown. In all these figures, the numbers in the brackets denote the number of particles used.

From Figures 1 and 2, the adaptive RBPF with $\mathbf{s}_k$ known achieves the smallest positioning errors with the 67% error 6.0 m and 95% error 10.0 m, while RBPF and adaptive RBPF has approximately the same accuracy. Although using 1000 particles, the adaptive SPF still has the largest error statistics. In Figures 3 and 4, the true values of the static parameters are within the 3-σ confidence interval, which suggests a good inference of the unknown parameters of all three algorithms. By further comparisons, the sequential estimations by the adaptive RBPF with $\mathbf{s}_k$ known are slightly better than the adaptive RBPF. Both of the above two algorithms achieve better estimations than the adaptive SPF method, which is obvious in Figure 3.

From Figures 1, 2, 3 and 4, among all the algorithms, the adaptive RBPF with $\mathbf{s}_k$ known achieves the best accuracy. The reason is that, in the proposed algorithm, the sufficient statistics for updating $\boldsymbol{\theta}$ and the mobile state inference for $\mathbf{x}_k$ are largely dependent on the density estimation of $\mathbf{s}_k$. When the sight conditions are known during

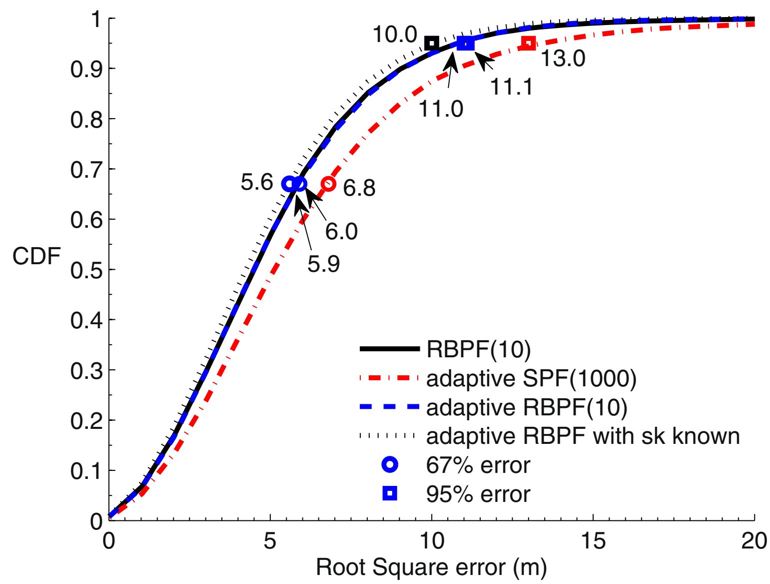

Figure 1 CDF of RSE.

the whole trajectory, the algorithm could have more accurate estimation on NLOS parameter θ, which further improves the estimation for the mobile state. Therefore, to improve the estimation accuracy, the accurate inference on the sight condition has the most importance. RBPF achieves slightly better performance over adaptive RBPF, which is reasonable, since in RBPF, the NLOS parameter is known and the parameter updating is not included. But the improvement is slight, as shown in Figures 1 and 2. Combined with the results of Figures 3 and 4, it is clear that the proposed adaptive RBPF can effectively estimate the unknown mean and variance. Even with 100 times more particles and having the most computation complexity, the adaptive PF still has the worst accuracy among all the algorithms, which suggests that using the prior transition as the proposal distribution is not effective to get the fittest particles in mobile tracking and the unknown parameter inference.

5.2 Complexity comparison

Table 1 compares the relative complexity and accuracy of the algorithms. It is clear that with the increase of the particle numbers, the computing time of the adaptive RBPF increases proportionally. Accordingly, the accuracy also increases. But the improvement is slight when the number is larger than 50. Also, the accuracy improvement can be omitted when considering the large increase of complexity between 100 and 1,000 particles. Thus, the adaptive RBPF (10) achieves a good tradeoff between complexity and accuracy.

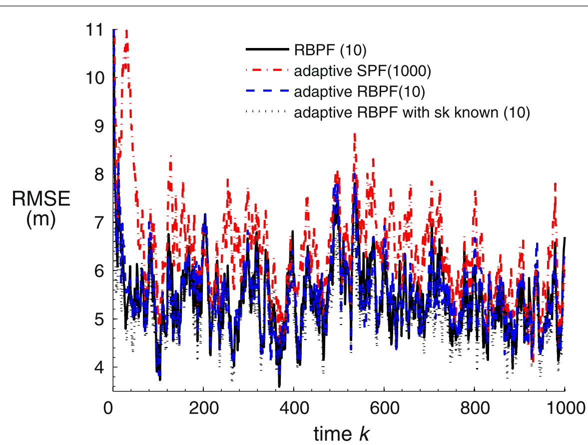

Figure 2 Position RMSE vs. time.

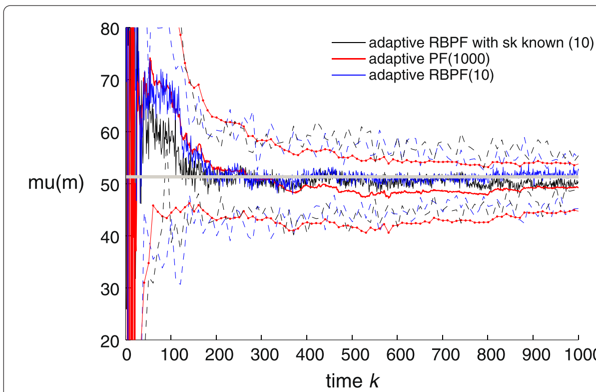

Figure 3 One realization of updating μ_{NLOS} with 3-σ confidence interval.

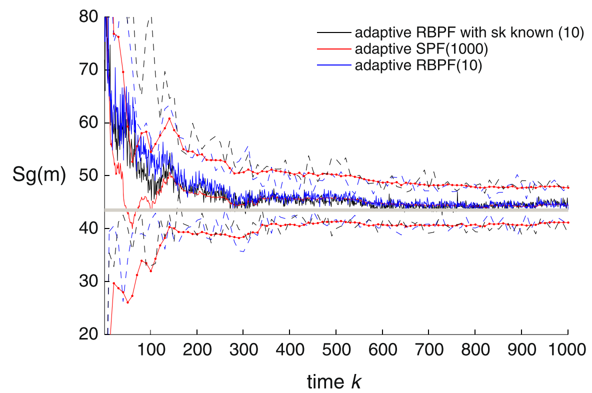

Figure 4 One realization of updating $\sqrt{\eta}$ with 3-σ confidence interval.

In this section, we compared the performance of adaptive RBPF with the other three algorithms, i.e. the adaptive RBPF with $\mathbf{s}_k$ known, the RBPF which assumes the static parameters are known and the adaptive SPF method. Simulation results show that the accurate estimation of sight condition has an important effect on the ultimate accuracy of mobile tracking and parameter estimation. By applying the approximate optimal proposal distribution to sample the posterior distribution of the sight conditions, the adaptive RBPF method is effective to infer the unknown NLOS parameter and achieves a good tracking accuracy with small number of particles.

6 Conclusions

We have considered the problem of mobile tracking in the mixed LOS/NLOS conditions, where the statistical parameter of NLOS error is unknown. Under the sequential Monte Carlo Bayesian framework, an adaptive RBPF method is developed, which uses an analytical method to estimate the mobile state while applying the particle filter to estimate the posterior density of sight conditions and the unknown static parameters. The distribution of the static parameters is updated by sufficient statistics from the mobile state, the sight condition and the measurements at current step. To improve the efficiency of the particle filtering, the approximate optimal proposal distribution is used for particle inference.

Table 1 Complexity vs. accuracy

	Adaptive RBPF				
	1	**10**	**50**	**100**	**1,000**
Complexity	1	7.5	35.2	70.7	749.8
Accuracy	1	1.8	2.1	2.3	2.5

Complexity is based on the CPU running time of the algorithms and the value is proportion to that of adaptive RBPF with 1 particle. The accuracy is the reciprocal of the average RMSE that each algorithm achieves, and also the accuracy of adaptive RBPF (1) is normalized.

Simulation tests of positioning with signals from DTV networks show that the adaptive RBPF method is effective to infer the mobile state and the unknown NLOS parameters simultaneously. With only 10 particles, the adaptive RBPF achieves a good accuracy of the mobile tracking while the complexity has not been increased much.

To achieve more accurate and robust mobile tracking, future work will investigate the impact of NLOS in the case of non-Gaussian distribution. We will also compare the unscented Kalman filter or the cubature Kalman filter with the current EKF method in the adaptive particle filter scheme.

Competing interests
The authors declare that they have no competing interests.

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