Mobile Localization with NLOS Mitigation using Improved Rao-Blackwellized Particle Filtering Algorithm

Chen Liang $^{1,2}$, Wu Lenan $^1$

(1. School of Information Science and Engineering, Southeast University, 210096, China) (2. Department of Testing and Control, Jiangsu University, 210013, China) 

Cliang@seu.edu.cn, wuln@seu.edu.cn

Abstract

An improved Rao-Blackwellized Particle Filtering (RBPF) is proposed to track the mobility of mobile station (MS) in mixed line-of-sight (LOS) or non-line-of-sight (NLOS) conditions in cellular network. The algorithm first estimates the sight condition state using particle filtering method, in which particles are sampled by the optimal trial distribution and selected by one-step backward prediction. Then, by applying decentralized Extended Kalman Filter (EKF), the mobile state could then be analytically computed. Simulations show more accurate results can be achieved by the proposed method than by current methods.

Keywords: mobility localization, non-line-of-sight (NLOS), extended kalman filter (EKF), particle filter (PF)

1. Introduction

The NLOS propagation is generated in the condition that, the direct path from the mobile station (MS) to a base station (BS) is blocked by buildings and other obstacles, and electromagnetic wave is affected by reflection, refraction and scattering before it approaches to the MS.

NLOS effect can be utilized to achieve the diversity gain in wireless communications, while in mobile location systems, it causes large errors yet. In terms of range based measurements such as time of arrival (TOA), time difference of arrival (TDOA) or received signal strength (RSS), the extra distances affected by NLOS propagations impose positive biases on the true path that has important adverse impact on the precise positioning [1]. In dense urban scenarios, the non-line-of-sight (NLOS) condition is very common. A field test shows that the mean and standard deviation of NLOS range errors are on the order of 513 m and 436 m respectively [2].

Many methods have been proposed to deal with the NLOS problem. Reference [3] have summarized the methods for static position systems. By exploiting the redundant measurements in time series, several algorithms have been proposed to track the mobility more effectively. Reference [4] applies a two-step Kalman filtering techniques to smooth range measurements and mitigate NLOS errors. It is based on the reasonable assumption that the standard deviation of the range measurement in the case of NLOS is significantly larger than that of LOS case. But the false detection of LOS often takes place because the deviation threshold is difficult to set manually when the communication channel between the corresponding BS and MS is often changed. Ref. [5] introduces a Markov process with two interactive modes to describe the LOS and NLOS dynamic transition, and a Kalman based interacting multiple model (IMM) smoother is further proposed to estimate the range between corresponding BS and MS. It can track the true range distance more accurately than the rough LOS/NLOS smoother in Ref. [4], especially in the transitional intervals. In our previous work, a method is proposed, which firstly uses modified EKF banks to jointly estimate both mobile state (position and velocity) and the hidden sight state based on the measurements from single BS. Then Bayesian data fusion algorithm is further applied to achieve a high estimation accuracy [6]. Simulation results show that the location errors of the method are all significantly smaller than that of the FCC requirement in different LOS/NLOS conditions. In addition, the method is more robust in the parameter mismodeling test than the methods in Ref.[4][5]. Complexity experiments suggest that it is promising for real-time application. Moreover, this algorithm is flexible to incorporate different types of measurement methods and asynchronous or synchronous observations data, which is especially suitable for the future cooperative location systems.

In this study, we continue to investigate the mobile positioning problem in mixed LOS/NLOS conditions. An improved Rao-Blackwellized Particle Filtering (RBPF) method is proposed for mobility tracking. Different from the method in Ref. [6], the method firstly estimates the sight condition state using particle filtering, then applies decentralized EKF method to analytically compute the mobile state.

The paper is organized as follows: Section 2 presents the dynamic system models and formulates the problem of mobility tracking in the mixed LOS/NLOS conditions. Section 3 describes the proposed method. Numerical results and performance comparison are presented and discussed in Section 4. Section 5 draws some conclusions.
2. System Model

The mobile state at time $k$ is defined as $X_k = (x_k, y_k, \dot{x}_k, \dot{y}_k)^T$, with location $(x_k, y_k)$ and velocity $(\dot{x}_k, \dot{y}_k)$. We consider a dynamic white noise acceleration model for MS moving on a 2-D Cartesian coordinate plane [7]:

$$X_k = FX_{k-1} + \Gamma W_k$$

(1)

where $F$, $\Gamma$ models the state kinematics, $W_k$ is a white Gaussian noise, with covariance matrix $Q$.

A two-state variant $s_{ik} \in \mathbb{R}_+ \triangleq [0, 1]$ can be used to model the sight condition between MS and the BS, at the time instant $k$, with $s_{ik} = 0$ for LOS and $s_{ik} = 1$ for NLOS. The transitions between the two states can be further assumed as a first-order Markov chain with initial probability vector $\pi$, and transition probability matrix $A$ [5][6]. The $M$ sight conditions are assumed as i.i.d. first-order Markov chains for the independence of the BSs.

Suppose $d_{ik}$ represents the true range between mobile’s position $(x_k, y_k)$ and the location of BS $(x_i, y_i)$, then the range measurement equations are:

$$\text{LOS: } z_{ik} = d_{ik} + n_{ik}$$

(2)

$$\text{NLOS: } z_{ik} = d_{ik} + n_{ik} + b_{ik}$$

(3)

where, $n_{ik}$ is the white Gaussian noise $N(0, \sigma_n^2)$ measured and $b_{ik}$ is the NLOS error with the positively biased Gaussian noise $N(m_{NLOS} \cdot \sigma_n^2)$ measured and $b_{ik}$ is the NLOS error with the positively biased Gaussian noise $N(m_{NLOS} \cdot \sigma_n^2)$ measured and $b_{ik}$ is the NLOS error with the positively biased Gaussian noise $N(m_{NLOS} \cdot \sigma_n^2)$ measured.

Equations (2) and (3) can be further transferred to:

$$z_{ik} = d_{ik} + m(s_{ik}) \cdot v_{ik}, \quad s_{ik} \in \mathbb{R}^+$$

(4)

where, $v_{ik}$ is the normalized i.i.d. zero mean white Gaussian noise and

$$m(s_{ik}) = \begin{cases} 0, & \text{if } s_{ik} = 0 \\ m_{NLOS}, & \text{if } s_{ik} = 1 \end{cases}$$

(5)

$$R(s_{ik}) = \begin{cases} \sigma_w, & \text{if } s_{ik} = 0 \\ \sqrt{\sigma_w^2 + \sigma_{NLOS}^2}, & \text{if } s_{ik} = 1 \end{cases}$$

(6)

To sum up, the overall dynamic model of the mobility tracking in the mixed LOS/NLOS conditions can be represented as follows:

$$\begin{align*}
X_k &= FX_{k-1} + \Gamma W_k \\
z_{ik} &= d_{ik} + m(s_{ik}) \cdot v_{ik} + R(s_{ik}) w_{ik} \\
s_{ik} &= MC(\pi, A)
\end{align*}$$

(7)

where $i \in {1, 2, \ldots M}$.

3. New Tracking Method based on Improved RBPF

Denote the total observation sequence up to time $k$ as $Z_{ik} \triangleq [Z_i, Z_{i+1}, \ldots, Z_k]$, where $Z_i \triangleq [z_{ik}, z_{i+1,k}, \ldots, z_{M,k}]^T$ the corresponding discrete sight condition sequence $S_{ik} \triangleq [s_i, s_{i+1}, \ldots, s_k]$ , where $S_i \triangleq [s_{ik}, s_{i+1,k}, \ldots, s_{M,k}]^T$ and the continuous state sequence $X_{ik} \triangleq [X_i, X_{i+1}, \ldots, X_k]$. Then, our problem is to compute the marginal posterior $p(X_{ik} / Z_{ik})$, which can be derived from $p(X_{ik}, S_{ik}/Z_{ik})$ by standard marginalization. The exact analytical expression is hard to compute in practice, while a sample-based numerical approximation could be applied.

In this study, we propose a RBPF method, which uses particle filtering method to estimate the posterior probability of sight conditions, and then applies the analytical method to estimate the mobile state. When estimating the posterior probability of sight conditions, the particles are sampled by the optimal trial distribution and selected by one-step backward prediction. The sampling method is different from the standard particle filtering, in which the transition prior is used as proposal distribution, and the likelihood function is applied to update the important weights. So, the proposed method is called as improved RBPF. It is described in detail as follows.

Factorize the posterior $p(X_{ik}, S_{ik}/Z_{ik})$ according to Bayes rule:

$$p(X_{ik}, S_{ik}/Z_{ik}) = p(X_{ik}, S_{ik} / Z_{ik}) p(S_{ik} / Z_{ik})$$

(8)

The method in this work is to represent the marginal posterior density of $p(S_{ik} / Z_{ik})$ by a set of weighted samples $\{S_{ik}^{(j)}, w_{ik}^{(j)}\}_{j=1}^{N}$, and then, using decentralized EKF method to analytically compute the distribution of $p(X_{ik} / Z_{ik}, S_{ik}^{(j)})$.

It is shown that, when sampling $S_{ik}^{(j)}$ from $p(S_{ik} / Z_{ik})$, the optimal trial distribution is $p(S_{ik} | S_{i,k-1}^{(j)}, Z_{ik})$, which can achieve the minimum conditional variance of the importance weights [8]. This distribution satisfies Bayes rule:

$$p(S_{ik}^{(j)} | S_{i,k-1}^{(j)}, Z_{ik}) = \frac{p(Z_i | Z_{i-1}, S_{i,k}^{(j)}) p(S_{i,k}^{(j)} | Z_{i,k-1}, S_{i,k}^{(j)}, S_{i,k}^{(j)})}{p(Z_i | Z_{i-1}, S_{i,k}^{(j)})}$$

(9)

The corresponding important weight can be calculated as:

$$w_{ik}^{(j)} = \frac{p(S_{ik}^{(j)} | Z_{ik})}{q(S_{ik}^{(j)} | Z_{ik})} \frac{q(S_{i,k-1}^{(j)} | Z_{i,k-1}) p(S_{i,k}^{(j)} | Z_{i,k-1}, S_{i,k}^{(j)})}{q(S_{i,k}^{(j)} | Z_{i,k-1})}$$

(10)

Substitute Eq. (9) into Eq. (10), we get
Recursive: time instant $k = 1, 2, \ldots$.

\textbf{I.} Predict the mean and covariance of mobile state
\[ \tilde{X}_{k|k-1} = F \tilde{X}_{k-1|k-1} ; \]
\[ \hat{P}_{k|k-1} = F \hat{P}_{k-1|k-1} F^T + \Gamma Q \Gamma^T . \]

\textbf{II.} for particle $j = 1, \ldots, N$,

1) For $j = 1, M$, and $s_{j|k} = 0$ and 1
\[ z_{k|k-1}^{(j)} = h(\tilde{X}_{k|k-1}) + m(s_{j|k}^{(0)}) ; \]
\[ \hat{P}_{k|k} = H_{k|k} \hat{P}_{k|k-1} H_{k|k}^T + R(s_{j|k}^{(0)}) . \]

2) Evaluate important weights using Equ. (11)
\[ p(z_{k|k} | X_{k|k-1}^{(j)}, \hat{X}_{k|k-1}^{(j)}, s_{j|k-1}^{(0)}, S_{k|k-1}^{(0)}) \]
\[ = \sum_{j=1}^{2^k} \prod_{i=1}^{M} p(z_{k|k} | X_{k|k-1}^{(j)}, s_{j|k}^{(0)}) p(S_{k|k} | S_{k|k-1}^{(0)}) \]
\[ = \sum_{j=1}^{2^k} p(Z_{k} | Z_{k-1}, S_{k-1}^{(0)}, S_{k} | S_{k-1}^{(0)}) \]
\[ = \sum_{j=1}^{2^k} \prod_{i=1}^{M} p(z_{k|k} | X_{k|k-1}^{(j)}, s_{j|k}^{(0)}) p(S_{k|k} | S_{k|k-1}^{(0)}) \]
\[ \text{The derivation in Equ.(11) considers the } M \text{ sight conditions are independent. And the likelihood } p(z_{k|k} | X_{k|k-1}^{(j)}, s_{j|k}^{(0)}) \text{ conforms to a Gaussian distribution with mean } \tilde{z}_{k|k-1}^{(j)} = h(\tilde{X}_{k|k-1}^{(j)}) + m(s_{j|k}^{(0)}) \text{ and covariance: } \hat{P}_{k|k} = H_{k|k} \hat{P}_{k|k-1} H_{k|k}^T + R(s_{j|k}^{(0)}) \]
\[ p(s_{j|k} | S_{k} | S_{k-1}^{(0)}) \]

3) Multiply/Discard particles $\{ X_{k|k-1}^{(j)}, \hat{X}_{k|k-1}^{(j)}, S_{k}^{(0)} \}_{j=1}^{N}$ with respect to high/low importance weights $w_{j|k}^{(i)}$ to obtain $N$ sight condition particles $\{ X_{k|k-1}^{(j)}, \hat{X}_{k|k-1}^{(j)}, S_{k}^{(0)} \}_{j=1}^{N}$.

4) EKF prediction: for $s_{j|k}^{(i)} = 1 \ldots 2^M$
\[ z_{k|k}^{(i)} = h(\tilde{X}_{k|k}^{(i)}) + m(s_{j|k}^{(0)}) ; \]
\[ \hat{P}_{k|k} = H_{k|k} \hat{P}_{k|k-1} H_{k|k}^T + R(s_{j|k}^{(0)}) \]

5) For $s_{j|k}^{(i)} = 1 \ldots 2^M$ compute
\[ p(S_{k} | S_{k-1}^{(0)}, X_{k|k-1}^{(i)}, Z_{k}) \approx \prod_{i=1}^{N} N(z_{k|k}^{(i)}, \hat{P}_{k|k}^{(i)}, S_{k}^{(i)}) \]

6) Sampling step:
\[ S_{k}^{(i)} \sim p(S_{k} | S_{k-1}^{(0)}, X_{k|k-1}^{(i)}, Z_{k}) \]

7) Updating step using decentralized EKF method according to Equ. (15)-(17)

The performance gain of the proposed method is achieved by:
1) using the optimal trial distribution to achieve the minimum weight conditional variance of importance weights.
2) In Equ.(11), by marginalization, the important weights $w_{j|k}^{(i)}$ do not based on $S_{k}$. Thus, the particles $S_{k}^{(i)}$ could be selected based on current measurement $Z_{k}$. Therefore, using this kind of one-step backward prediction, the fittest particles $S_{k}^{(i)}$ could be survival to propagate, which improve the particle effectiveness.

### 4. Performance Evaluation

We assume that the MS can receive the signals from only three BSs all the time. The coordinates of BSs are [-3000m, -1000m], [-3000m, 5000m], [5000m, -1000m]. The mobile trajectories are generated according to the mobility model described in Section 2, in which the initial position of the MS is set to [-1500m, 1500m], and the initial velocity is [10m/s, 0m/s]. The random acceleration $\sigma^2_a, \sigma^2_r$ are both chosen to 1m/s$^2$. The simulated trajectory has $L=1600$ time samples, and the sample interval $\Delta t=0.2$. The simulation measurement data are generated by adding the measurement noise and the NLOS noise to the true distance from MS to each BS. The measurement noise is assumed to be a white random variable with zero mean and standard deviation $\sigma_n=150$m, whereas the NLOS measurement noise is also assumed to be a white random variable but with positive mean $\sigma_{\text{NLOS}}=513$m, and standard deviation $\sigma_{\text{NLOS}}=409$m [4][5][6]. The LOS or NLOS mode between the MS with each BS is generated by sampling the transition probability $P_{\text{LOS}}=0.5$ for $i=1, 2, 3$. In Ref. [5][6], the prior mode transition probability is chosen as...
This choice depends on the assumption that the transition probability of the sight condition can be correctly estimated, thus the prior mode transition probability is set to be equal to the true transition probability that generates the LOS/NLOS conditions. In this work, we relax the assumption, and set the prior probability \( p_0 = p_1 = 0.85 \), which has some difference with the true transition probability.

In the proposed improved RBPF method, only 10 particles are used. We compare the performance of the rough LOS/NLOS smoother [4], the IMM-KF smoother [5], and the proposed method. All the simulation results are obtained based on \( M = 20 \) Monte Carlo realizations with the same parameters.

Fig 1 shows position root mean square error (RMSE) results. (RMSE = \( \frac{1}{M} \sum_{m=1}^{MC} \sqrt{(\hat{x}_{k,m} - x_k)^2 + (\hat{y}_{k,m} - y_k)^2} \). \( MC \) is Monte Carlo runs). It is clear that, the proposed method achieves the smallest RMSE, thus tracks more closely to the mobile trajectory than the other methods.

Table 2 gives the performance comparison in terms of RSE (RSE = \( \sqrt{(\hat{x}_k - x_k)^2 + (\hat{y}_k - y_k)^2} \)). The mobile location error is calculated with the elimination of the first 100 samples so as to ignore the large location error caused by the initial conditions. Table 2 demonstrates that, from the statistical point of view, the proposed method also outperforms the other two.

Table 2 RSE comparison within three algorithms

<table>
<thead>
<tr>
<th>RSE Error (m)</th>
<th>67% error</th>
<th>95% error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rough Smoother [4]</td>
<td>96.26</td>
<td>213.38</td>
</tr>
<tr>
<td>IMM Smoother [5]</td>
<td>82.23</td>
<td>161.20</td>
</tr>
<tr>
<td>The proposed method</td>
<td>56.26</td>
<td>109.26</td>
</tr>
</tbody>
</table>

Therefore, according to the simulation results, it is clear that, even using a very few particles, the method proposed gives more accurate results than the existing method [4][5].

Thus, it can be concluded that, sampled by the optimal trial distribution and selected by one-step backward prediction, the posterior distribution of the sight conditions can be effectively estimated. And based on this relatively accurate estimation of the sight conditions, the mobile state can be further estimated by the decentralized EKF method, which achieves performance gain than the method in ref.[4][5].

5. Conclusion

An improved RBPF method has been developed to track mobility in unknown LOS or NLOS conditions. The algorithm estimates the sight condition state using particle filtering method, in which particles are sampled by the optimal trial distribution and selected by one-step backward prediction. Then, by applying decentralized Extended Kalman Filter (EKF), the mobile state could then be analytically computed. Simulation results show that the proposed method outperforms the existing mobility estimation schemes.

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7. Reference

