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NLOS環境に適した低複雑度TOA位置推定アルゴリズム

藤田 隆弘† 大槻 知明†† 金子 敏信†††

† 東京理科大学大学院 理工学研究科 電気工学専攻 〒278-8510 千葉県野田市山崎2641
†† 慶応義塾大学 理工学部 情報工学科 〒223-8522 神奈川県横浜市港北区日吉3-14-1
††† 東京理科大学大学院 理工学研究科 電気工学専攻 〒278-8510 千葉県野田市山崎2641
E-mail: ††ohtsuki@ics.keio.ac.jp

あらまし センサネットワークにおける位置推定法の一つに到来時刻 (TOA: Time of Arrival) に基づく方法がある．TOA に基づく方法は，比較的高い位置推定推定精度を持つが，見通し外 (NLOS: Non Line of Sight) 環境では，到来波の伝搬遅延により距離推定精度が劣化し，そのため位置推定精度も劣化する．従来，NLOS 環境にあるノード（NLOS ノード）の信号を識別し，位置推定から除外する IMR (Iterative Minimum Residual) 法が提案されている．IMR 法は，位置推定精度を大きく改善するが，NLOS ノードの識別に多くの演算が必要であり，消費電力が増加してしまう．本稿では，低演算量の NLOS 判定を用いた TOA に基づく位置推定法を提案する．計算機シミュレーションにより，提案法は従来法に比べ，低演算量でありながら，従来法に迫る位置推定精度が得られることを示す．

キーワード ワイヤレスセンサネットワーク，到来時刻，見通し外，位置推定

Low Complexity TOA Localization Algorithm for NLOS Environments

Takahiro FUJITA†, Tomoaki OHTSUKI††, and Toshinobu KANEKO†††

† Graduate School of Science and Technology, Tokyo University of Science
2641 Yamazaki, Noda, Chiba, 278–8510 Japan
†† Faculty School of Science and Technology, Keio University
3-14-1 Hiyosi, Kohoku, Yokohama, Kanagawa, 223-8522 Japan
††† Graduate School of Science and Technology, Tokyo University of Science
2641 Yamazaki, Noda, Chiba, 278–8510 Japan
E-mail: ††ohtsuki@ics.keio.ac.jp

Abstract The location estimation in sensor networks is of great current interest. A general approach to location estimation is to gather Time-of-Arrival (TOA) measurements from a number of nodes and to estimate a target location. The two major sources of range measurement errors in geolocation techniques are measurement error and Non-Line-of-Sight (NLOS) error. NLOS errors caused by blocking of direct paths have been considered as a serious issue in the location estimation. Therefore, Iterative Minimum Residual (IMR) method, which identifies NLOS nodes and removes them from the data set used for localization, has been proposed. IMR improves location estimation precision in comparison with the technique that does not identify and remove NLOS nodes. However, IMR needs a lot of calculation to identify NLOS nodes. In this report, we propose a new location estimation method with low complexity NLOS node identification. We show that the proposed method achieves almost the same root mean square error (RMSE) as the conventional method with lower complexity.

Key words Wireless Sensor Networks, Time-of-Arrival (TOA), Non-Line-of-Sight (NLOS), Localization

1. Introduction

Location estimation is attracting considerable attention in recent years. The most widely employed location technology is radio location system. Radio location system can be based on signal strength, angle of arrival (AOA), time of arrival (TOA), or time difference of arrival (TDOA) [1]. One of the main problems for accurate localization in wireless communication systems is non-line-of-sight (NLOS) propagation caused by blocking of the direct path of radio signals by obstacles. Range measurements derived from TOA by multiplying the velocity of light, c, are corrupted by measurement noise and NLOS errors. The additive NLOS error is the excess path length traveled by the signal due to reflection or diffraction. Traditional positioning algorithm, Minimum Mean Square Error (MMSE) Estimator, is designed to provide accurate location in LOS environments with relatively small measurement noise. The NLOS error is relatively large and adversely affects the location accuracy. This has led to the development of several algorithms that focus on identifying and mitigating the NLOS error [2]–[6].

IMR algorithm is presented in [6], which is the method of NLOS identification. The IMR algorithm can significantly improve the location estimation performance in NLOS environments. However, the IMR algorithm needs a lot of calculation for NLOS identification.

In this report we propose a new low complexity TOA localization algorithm, which has considerably lower computational complexity than the IMR algorithm. The proposed algorithm can effectively remove the measurements with large errors and select the subsets of the measurement data to perform localization. Through various simulation results, it is demonstrated that the proposed algorithm achieves almost the same RMSE as the conventional method with lower complexity.

The paper is organized as follows. The problem formulation is given in section II. Section III describes IMR algorithms proposed in [6]. Section IV describes the proposed NLOS identification algorithms. The performance of the proposed method is evaluated in Section V. Final conclusion is drawn in Section VI.

2. Problem Formulation

We focus on the case of grid and two-dimensional (2-D) location. A target node is located at unknown location (x, y) and N reference nodes are deployed at known locations (x_k, y_k), $k = 1, \ldots, N$. The unknown location of the targets need to be estimated based on the measured distances between the target and nodes. The distance between two nodes can be measured by estimating TOA.

The LOS range estimates $d_{k_{\mathrm{LOS}}}$ are modeled as unbiased Gaussian estimates of the true measurements:

$$d_{k_{\mathrm{LOS}}} = \sqrt{(x - x_k)^2 + (y - y_k)^2} + n_k \qquad (1)$$

where $\sqrt{(x - x_k)^2 + (y - y_k)^2}$ are the true distances between the target and the kth node, and n_k are independently and identically distributed (i.i.d.) zero mean Gaussian random variables denoting measurement error, $n_k \sim \mathcal{N}(0, \sigma_k^2)$. The NLOS range estimates $d_{k_{\mathrm{NLOS}}}$ are assumed to be positively biased Gaussian estimates of the true measurements:

$$d_{k_{\mathrm{NLOS}}} = \sqrt{(x - x_k)^2 + (y - y_k)^2} + n_k + b_k \qquad (2)$$

where $n_k \sim \mathcal{N}(0, \sigma_k^2)$ and b_k are the NLOS errors. We assume that the NLOS errors are uniformly distributed, $b_k \sim \mathcal{U}(0, B_{\mathrm{MAX}})$, where B_{MAX} represents the maximum possible bias. Equivalently, we can formulae (1) into the following vector form,

$$\mathbf{d} = \mathbf{g}(\boldsymbol{\theta}) + \mathbf{n} + \mathbf{b} \qquad (3)$$

where

$$\begin{aligned} \mathbf{d} &= [d_1 \ldots d_N]^T \\ \boldsymbol{\theta} &= [x, y]^T \\ \mathbf{g}(\boldsymbol{\theta}) &= [g_1(\boldsymbol{\theta}) \ldots g_N(\boldsymbol{\theta})]^T \\ g_i(\boldsymbol{\theta}) &= \sqrt{(x - x_i)^2 + (y - y_i)^2} \\ \mathbf{n} &= [n_1 \ldots n_N]^T \\ \mathbf{b} &= [b_1 \ldots b_N]^T \end{aligned} \qquad (4)$$

When the distributions of ranging errors and NLOS errors are unknown, conventional Minimum Mean Square Error (MMSE) algorithm can be employed to solve this location estimation problem. The MMSE estimator $\hat{\boldsymbol{\theta}}$ for the problem defined in (3) can be obtained by minimizing the MSE,

$$\hat{\boldsymbol{\theta}} = \arg\min_{\hat{\boldsymbol{\theta}}} \varepsilon(\hat{\boldsymbol{\theta}})$$

where $\varepsilon(\hat{\boldsymbol{\theta}})$ is MSE and described as follows,

$$\varepsilon(\hat{\boldsymbol{\theta}}) = \arg\min_{\hat{\boldsymbol{\theta}}} [\mathbf{d} - \mathbf{g}(\hat{\boldsymbol{\theta}})]^T [\mathbf{d} - \mathbf{g}(\hat{\boldsymbol{\theta}})]. \qquad (5)$$

If the distribution of observation data is unspecified, the statistical performance of the MMSE is unknown. The MMSE is optimal only in the sense of minimum MSE for the given set of observation data. However, the MMSE derived using all observation data is not necessarily the best estimator possible.

In the next section, Iterative Minimum Residual (IMR) algorithm proposed in [6] is explained. When more than three distance measurements are available, IMR can identify and remove the measurements with NLOS errors and utilize only accurate measurements in the MMSE.

3. Iterative Minimum Residual (IMR) Algorithm [6]

In this section, we explain the IMR algorithm for NLOS identification.

(1) Initialization:

$n = N$, $\mathbf{D}_{\min} = \{d_k, 1 \le k \le n\}$. N is the number of sensor nodes and $\mathbf{D}_{\min}$ is the measurement set of nodes.

(2) MMSEs for all the nodes:

Find the temporal estimate of target location $\hat{\boldsymbol{\theta}}$ using the observation data $\mathbf{D}_{\min}$ and determine the normalized MSE of the estimator $\bar{\varepsilon}(\hat{\boldsymbol{\theta}}_{\min})$.

$$\begin{aligned} \hat{\boldsymbol{\theta}}_{\min} &= \hat{\boldsymbol{\theta}} \\ \bar{\varepsilon}(\hat{\boldsymbol{\theta}}_{\min}) &= \varepsilon(\hat{\boldsymbol{\theta}}_{\min})/n \end{aligned} \qquad (6)$$

(3) Iteration:

Make $\binom{n}{n-1}$ combinations, $(\mathbf{D}_m : 1 \leqq m \leqq n)$.

$\mathbf{D}_m$ have $(n-1)$ measurements. Find the $\hat{\theta}^{(m)}$ and the normalized residual error $\bar{\varepsilon}(\hat{\theta}^{(m)})$ for each set.

$$
\begin{aligned}
\hat{\theta}'_{\min} &= \hat{\theta}^{(\arg\min_m \varepsilon(\hat{\theta}^{(m)}))} \\
\bar{\varepsilon}(\hat{\theta}'_{\min}) &= \varepsilon(\hat{\theta}'_{\min})/(n-1). \qquad (7)
\end{aligned}
$$

If $|\bar{\varepsilon}(\hat{\theta}_{\min}) - \bar{\varepsilon}(\hat{\theta}'_{\min}) > \delta|$, then $\hat{\theta}_{\min} = \hat{\theta}'_{\min}$; else return $\hat{\theta}_{\min}$.

If $n > 4$, then $n = n-1$, $\mathbf{D}_{\min} = \mathbf{D}'_{\min}$, $\bar{\varepsilon}(\hat{\theta}_{\min}) = \bar{\varepsilon}(\hat{\theta}'_{\min})$, repeat (3); else return $\hat{\theta}_{\min}$.

In 3), we must calculate temporal estimate of target location using MMSE to all the coordinates in the field for each set. Therefore, the calculation quantity becomes enormous.

4. Propose Method

In this section we explain our proposed low complexity TOA localization algorithm for NLOS environment. Firstly we explain Lines of Positions (LOP) that is a calculation method of the temporal estimate of target location and explain the proposed algorithm next.

4.1 Lines of Positions (LOP)

We explain LOP that is a calculation method of the temporal estimate of target location. We calculate an intersection point of LOP like Fig. 1. A calculation method of an intersection point is as follows,

$$
\begin{aligned}
x_s &= \frac{(y_2-y_1)C_3 - (y_3-y_2)C_1}{[(x_3-x_2)(y_2-y_1)-(x_2-x_1)(y_3-y_2)]} \\
y_s &= \frac{(x_2-x_1)C_3 - (x_3-x_2)C_1}{[(y_3-y_2)(x_2-x_1)-(y_2-y_1)(x_3-x_2)]} \\
C_1 &= \frac{1}{2}[x_2^2+y_2^2-(x_1^2+y_1^2)+d_1^2-d_2^2] \\
C_3 &= \frac{1}{2}[x_3^2+y_3^2-(x_2^2+y_2^2)+d_2^2-d_3^2] \qquad (8)
\end{aligned}
$$

where $\Theta(x_s, y_s)$ is an intersection point of LOP, $(x_i, y_i), d_i, i = 1, \ldots, 3$ are coordinates and measurements of each node. In addition, it is assumed that three nodes do not form a line on a straight line. MSE for Θ is as follows.

$$
\varepsilon(\Theta) = \sum_{i=1}^{3}\left(d_i - \sqrt{(x_s-x_i)^2+(y_s-y_i)^2}\right)^2 \qquad (9)
$$

4.2 Proposed Algorithm

When we calculate a temporal estimate of target location, the proposed method does not search for all coordinates. Therefore, the proposed method can reduce the amount of calculation. The proposed method can be described as follows.

(1) Initialization

$n = N$, $\mathbf{D}_{\min} = \{d_k, 1 \leqq k \leqq n\}$. $\mathbf{D}_{\min}$ is the measurement set of nodes.

(2) LOP:

Make $\binom{n}{3}$, $(\mathbf{E}_s \ : \ s = 1, ..., \binom{n}{3})$ combinations. Compute $\Theta^{(s)}$, $\varepsilon(\Theta^{(s)})$ for each set, and decide $\hat{\theta}_{\min}$ and, $\bar{\varepsilon}(\hat{\theta}_{\min})$ using RWGH [7]

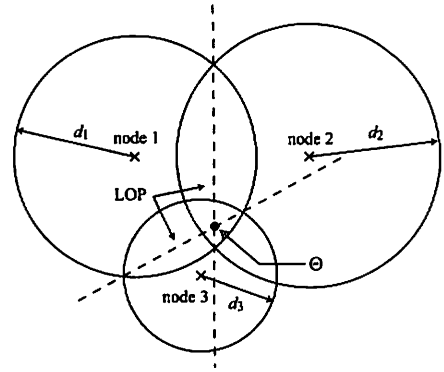

Fig. 1 An intersection point of LOP: $\Theta(x_s, y_s)$

$$
\begin{aligned}
\hat{\theta}_{\min} &= \frac{\sum_{s=1}^{{}_nC_3} \Theta^{(s)}/\varepsilon(\Theta^{(s)})}{\sum_{s=1}^{{}_nC_3} 1/\varepsilon(\Theta^{(s)})} \\
\bar{\varepsilon}(\hat{\theta}_{\min}) &= \varepsilon(\hat{\theta}_{\min})/n \qquad (10)
\end{aligned}
$$

(3) Iteration:

Make $\binom{n}{n-1} = n$, $(\mathbf{D}_m : m = 1, ..., n)$ combinations, and $\binom{n-1}{3}$, $(\mathbf{E}_s$: $s = 1, ..., \binom{n-1}{3})$ for each set. Compute $\hat{\theta}^{(m)}$, $\varepsilon(\hat{\theta}^{(m)})$ for each set using MMSE and decide $\hat{\theta}'_{\min}$, $\bar{\varepsilon}(\hat{\theta}'_{\min})$

$$
\begin{aligned}
\hat{\theta}'_{\min} &= \arg\min_m \varepsilon(\hat{\theta}^{(m)}) \\
\bar{\varepsilon}(\hat{\theta}'_{\min}) &= \varepsilon(\hat{\theta}'_{\min})/(n-1). \qquad (11)
\end{aligned}
$$

If $|\bar{\varepsilon}(\hat{\theta}_{\min}) - \bar{\varepsilon}(\hat{\theta}'_{\min}) > \tau|$, then $\hat{\theta}_{\min} = \hat{\theta}'_{\min}$; else return $\hat{\theta}$ where $\hat{\theta}$ can be described as follows

$$
\hat{\theta} = \arg\min_{(x,y)} \varepsilon(\theta) \qquad (12)
$$

where $\hat{\theta}$ is the estimated target location by MMSE using n nodes.

If $n > 4$, then $n = n-1$, $\mathbf{D}_{\min} = \mathbf{D}'_{\min}$, $\bar{\varepsilon}(\hat{\theta}_{\min}) = \bar{\varepsilon}(\hat{\theta}'_{\min})$, repeat (iii); else return $\hat{\theta}$ where $\hat{\theta}$ can be described as follows

$$
\hat{\theta} = \arg\min_{(x,y)} \varepsilon(\theta) \qquad (13)
$$

where $\hat{\theta}$ is the estimated target location by MMSE using three nodes in the minimum MSE set.

The proposed method searches for all the coordinates only once. Therefore, we can reduce the amount of calculation in comparison with the IMR method.

5. Simulation results

In this section, we present our computer simulation results to show the localization precision of IMR and the proposed method. Firstly, we compare the amount of calculation of the proposed

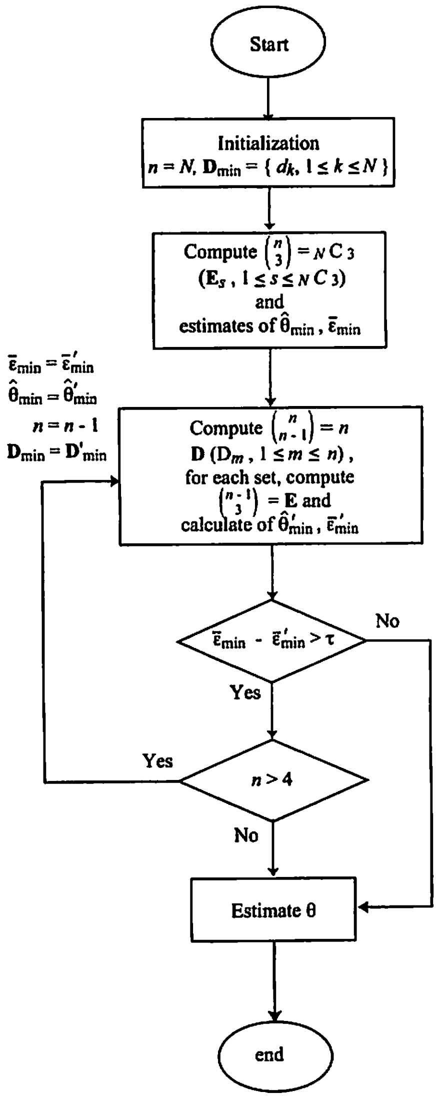

Fig. 2 The flowchart of the proposed algorithm

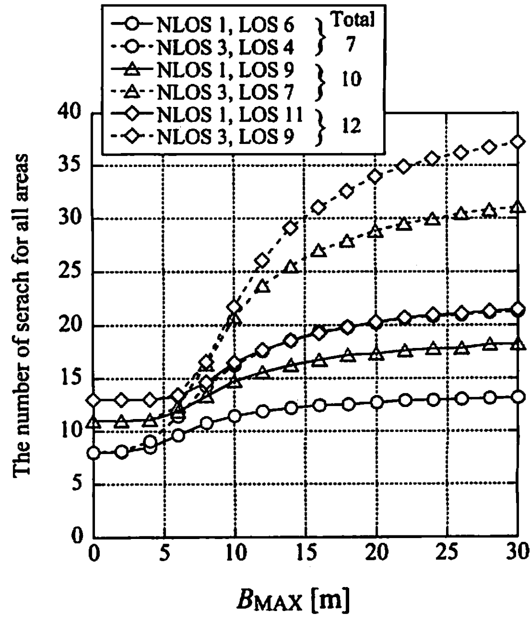

Fig. 3 B_{MAX} versus the number of searches for all areas in IMR

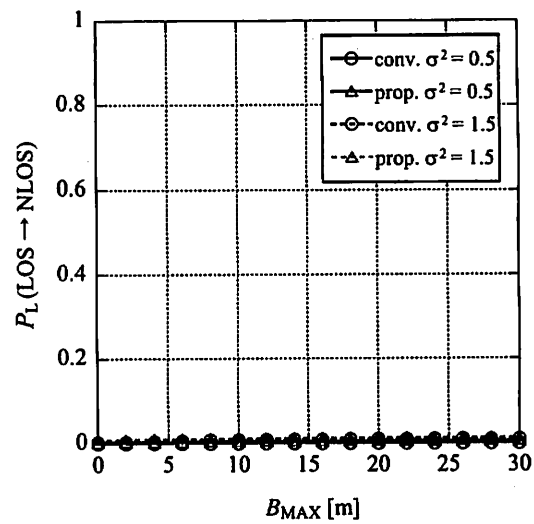

Fig. 4 B_{MAX} versus P_L(LOS → NLOS) when $(N_{NLOS}, N_{LOS}) = (1, 6)$, B_{MAX} is from 0 to 30 m

method to that of the IMR method. Secondly we evaluate the NLOS identification precision of the proposed method. Finally we evaluate the localization precision of the proposed method. The field is 30 m × 30 m at intervals of 1 m. We set a target and N nodes.

5.1 Amount of Calculation

Amount of calculation depends on the number of coordinates in the field for MMSE estimator greatly. The IMR and proposed methods search all areas for MMSE estimator, therefore we evaluate the amount of calculation by the number of searches for all areas.

In Fig. 3, we show the maximum value of NLOS error B_{MAX} versus the number of searches for all areas in IMR. We set the numbers of NLOS and LOS nodes to $(N_{NLOS}, N_{LOS}) = (1, 6), (3, 4), (1, 9), (3, 7), (1, 11), (3, 9)$ and $\sigma_k^2 (k = 1, \ldots, N) = \sigma^2 = 1.0$. B_{MAX} is from 0 to 30 m. We can see that the number of searches for all areas in IMR increases as B_{MAX} becomes larger. On the other hand, the number of searches in the proposed method is always one.Thus, we can see that the proposed method can reduce the amount of calculation.

In Figs. 4, 5, we show B_{MAX} versus miss determination probability, P_L(LOS → NLOS) and P_L(NLOS → LOS), where P_L(LOS → NLOS) and P_L(NLOS → LOS) are the probabilities of erroneous decision of NLOS and LOS, respectively. We consider the case where $(N_{NLOS}, N_{LOS}) = (1, 6)$, $\sigma_k^2 (k = 1, \ldots, N) = \sigma^2 = 0.5, 1.5$ and B_{MAX} is from 0 to 30 m. We can see that P_L(LOS → NLOS) and P_L(NLOS → LOS) of the proposed

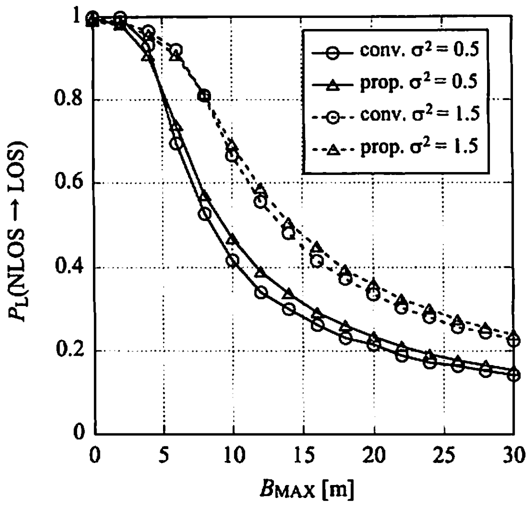

Fig. 5 B_{MAX} versus P_L(NLOS → LOS) when $(N_{NLOS}, N_{LOS}) = (1, 6)$, B_{MAX} is from 0 to 30 m

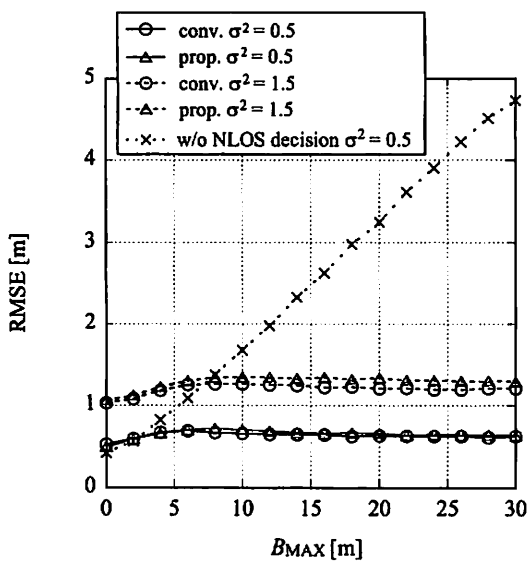

Fig. 6 B_{MAX} versus RMSE of IMR, the proposed method, and without NLOS identification method, when B_{MAX} is from 0 to 30 m

method are close to those of of IMR, respectively. Thus, the proposed method achieves almost the same NLOS identification precision as the IMR with low complexity.

In Fig. 6, we show B_{MAX} versus RMSE of IMR, the proposed method, and MMSE without NLOS identification. We consider the case where $(N_{NLOS}, N_{LOS}) = (1, 6)$, $\sigma_k^2(k = 1, \dots, N) = \sigma^2 = 0.5, 1.5$ and B_{MAX} is from 0 to 30 m. We can see that the RMSE increases as B_{MAX} becomes larger for MMSE without NLOS identification. On the other hand there is a little increase of RMSE of IMR and the proposed method. These results clearly demonstrate that when one of the distance measurements has a large error, IMR

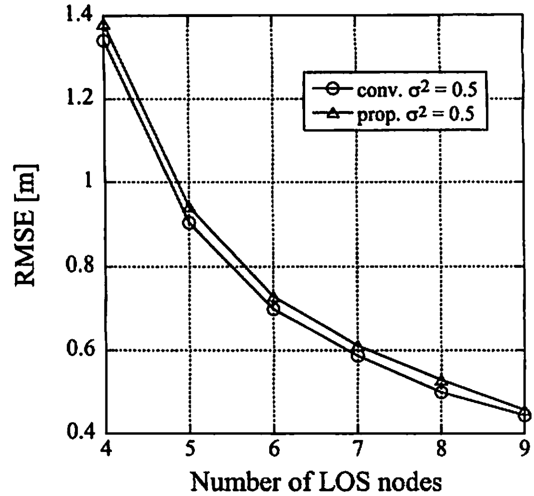

Fig. 7 The number of LOS nodes versus RMSE of IMR and the proposed method where $N_{NLOS} = 1$, N_{LOS} is from 4 to 9, and $B_{MAX} = 10$

and the proposed method can significantly improve location estimation accuracy by rejecting erroneous measurement data. No significant difference is observed between the performances of IMR and the proposed method in this simulation. Therefore, the proposed method achieves almost the same RMSE as the IMR with less complexity.

In Fig. 7, we show the number of LOS nodes versus RMSE of IMR and the proposed method. We consider the case where $N_{NLOS} = 1$, N_{LOS} is from 4 to 9, $\sigma_k^2(k = 1, \dots, N) = \sigma^2 = 0.5$, and $B_{MAX} = 10$. In Fig. 8, we show the number of NLOS nodes versus RMSE of IMR and the proposed method. We consider the case where $N_{LOS} = 10$, N_{NLOS} is from 1 to 6, $\sigma_k^2(k = 1, \dots, N) = \sigma^2 = 0.5$, and $B_{MAX} = 10$. We can see that no significant difference is observed between the performances of the IMR and the proposed method for any number of NLOS and LOS nodes. Therefore, the proposed method achieves almost the same RMSE as IMR with less complexity.

In Figs. 4–8, we can see that the precisions of NLOS identification and localization of the proposed method are close to those of IMR, respectively. This performance can be explained as follows. We use only three nodes for calculating a temporal target location in the proposed method. Therefore, the number of sets that do not include NLOS nodes increases, and we can get high precision estimation of the temporal target location. As a result, the proposed method can achieve almost the same performance as IMR with less complexity.

6. Conclusions

In this paper we proposed a low complexity TOA localization algorithm for NLOS environments and presented the RMSE perfor-

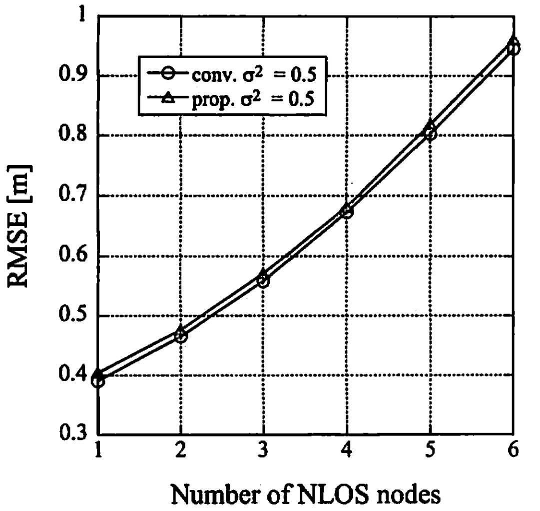

Fig. 8 The number of NLOS nodes versus RMSE of IMR and the proposed method where $N_{\mathrm{LOS}} = 10$, N_{NLOS} is from 1 to 6, and $B_{\mathrm{MAX}} = 10$

mance at the proposed method. The proposed method can reduce the amount of calculation when a lot of NLOS nodes or total nodes exist. Also the proposed method can reduce the amount of calculation when the NLOS error is large. In addition, the proposed method can achieve almost the same localization precision as IMR without depending on the number of LOS nodes, NLOS nodes, measurement error, and NLOS error.

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