An Improved NLOS Detection Scheme Using Stochastic Characteristics for Indoor Localization

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***Abstract*—Indoor localization scheme using sensor networks is expected to be applied in various fields, and the localization scheme using time of arrival (TOA) is well-known. However, the estimation accuracy of TOA localization is severely deteriorated in non-line-of-sight (NLOS) environments, and the NLOS mitigation scheme such as iterative minimum residual (IMR) scheme is required. The IMR scheme is often applied because of its lower calculation complexity. However, when an increased number of NLOS nodes exist, the NLOS detection errors increase in the IMR scheme and the estimation accuracy deteriorates. Therefore, in this paper, we propose a new scheme exploiting rough NLOS detection based on stochastic characteristics before the application of IMR scheme to improve the localization accuracy. The improved performance is shown by computer simulations.**

***Keywords*—sensor network; TOA position estimation; NLOS environment; iterative minimum residual scheme; stochastic characteristics**

I. Introduction

Indoor localization technique attracts much attention because of its expectation to be applied in various fields. For example, by obtaining the accurate position of products and workers in factory, the work efficiency and the reliability can be improved. Global positioning system (GPS) is the most famous localization system in which a location of the terminal can be detected by receiving the beacon from satellites. The outdoor location can be detected with high accuracy by the GPS. However, the GPS cannot be used indoors since the direct wave from satellites is blocked. Thus, other technologies need to be used for the indoor localization. The most popular one is that a few sensor nodes whose location is known receive the beacon from a target node whose location is unknown, and by more than three distance or two angle information of them, the target location is calculated by triangulation [1]. For the distance measurement, several schemes such as time of arrival (TOA), time difference of arrival (TDOA) or received signal strength (RSS) are used. RSS-based localization is applicable to various systems because of the simplicity for measurement and is used in many systems [2]. However, RSS-based localization is difficult to maintain high estimation accuracy because the performances deteriorates severely in noisy environments. In contrast, TOA-based localization is robust for the environmental noise, and the estimation accuracy is higher than that of RSS-based scheme [3]. For TOA-based localization, ultra wide band (UWB) signals whose time resolution is high are used and the higher estimation accuracy is achieved [3,4]. When the direct beacon between the target and the reference nodes is blocked by obstacles, which is called the non-line-of-sight (NLOS) environment, the estimation accuracy is largely deteriorated compared with line-of-sight (LOS) environments since the error of distance measurements becomes large by detecting only the reflected or diffracted signals. Specifically, the measured value under NLOS environments has large bias by wave detouring. Thus, the error mitigating schemes in NLOS environments are indispensable and several schemes are proposed. For example, one of the schemes applied to TOA-based localization is Rwgh (Residual weighting) [6]. In Rwgh scheme, the estimation is conducted using all sensor nodes including NLOS nodes, and the weight for each measured value is adaptively changed according to its reliability. The advantage of this algorithm is that the estimation is always available even if all nodes are in NLOS environments. However, the NLOS error cannot be perfectly removed and the estimation accuracy is degraded in general. For the performance improvement of those NLOS including schemes, NLOS identification schemes using the stochastic characteristics of measured data have been proposed [7,8]. However, the identification performance depends on the accordance of the error model and actual environment, and the effect is limited. On the other hand, an NLOS elimination scheme, in which the NLOS nodes are detected and the estimation is conducted only with LOS nodes, has been proposed. In this scheme the performance is not degraded by NLOS environments whenever NLOS nodes are correctly detected, and the better estimation performance is obtained. As one of the effective NLOS detection and elimination schemes, an iterative minimum residual (IMR) scheme has been proposed in [9]. In IMR scheme the node having inaccurate measurement distance is iteratively eliminated one-by-one, and thus, the IMR scheme does not require high calculation complexity and is suitable for systems having low calculation ability. Usually, TOA or RSS-based distance is used for IMR scheme but other measurements can also be used. However, when there are a lot of NLOS nodes, the NLOS detection error increases and the estimation accuracy deteriorates in the IMR scheme.

Therefore, in this paper, we exploit the NLOS detection scheme utilizing stochastic characteristics of measurement error, and propose a modified IMR scheme jointly using the stochastic characteristics to improve the estimation accuracy.

In the following, the TOA localization is described in Section II, and the IMR scheme is reviewed in Section III. In Section IV, the proposed scheme is introduced, and numeral results are shown in Section V. Finally, the conclusions are drawn in Section VI.

II. Time of arrival (TOA)-based localization

In TOA-based localization, the position of the target node is estimated by triangulation with more than three TOA measurement distances between the target node whose position is unknown and the sensor nodes whose position are known. Let (x, y) as the true position of target node, (x_i, y_i) as *i*-th sensor node position, d_i as the true distance between the target node and *i*-th sensor node. Then, the measured distance $\hat{d}_i$ is given by [10]

$$\hat{d}_i = d_i + \varepsilon_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} + \varepsilon_i \tag{1}$$

where ε_i is the noise component of *i*-th sensor node measurement, and is given by

$$\varepsilon_i = \varepsilon_{i,LOS} + \zeta_i \varepsilon_{i,NLOS} \tag{2}$$

Here, $\varepsilon_{i,LOS}$ is the noise component in LOS environments, $\varepsilon_{i,NLOS}$ is that in NLOS environments, and ξ_i is the switching parameter of 0 as LOS and 1 as NLOS. For $\varepsilon_{i,LOS}$, the main reason of TOA measurement error in LOS environments is the multipath reception of UWB pulses. It is reported in [11] that the small positive bias is added to the true distance when the narrow band UWB (such as 500 MHz) is used and the distance between the target and sensor nodes is relatively long (such as 10 m), because the multipath reception shifts the peak power in detection. Thus, TOA error in LOS environment $\varepsilon_{i,LOS}$ is modeled as a positive-mean Gaussian noise whose mean $\mu_{i,LOS}$ and variance $\sigma^2_{i,LOS}$ are given by

$$\mu_{i,LOS} = \mu_{LOS} \log(1 + d_i) \tag{3}$$

$$\sigma^2_{i,LOS} = \sigma^2_{LOS} \left[\log(1 + d_i)\right]^2 \tag{4}$$

where μ_{LOS} and σ^2_{LOS} are the parameters dependent on the signal bandwidth.

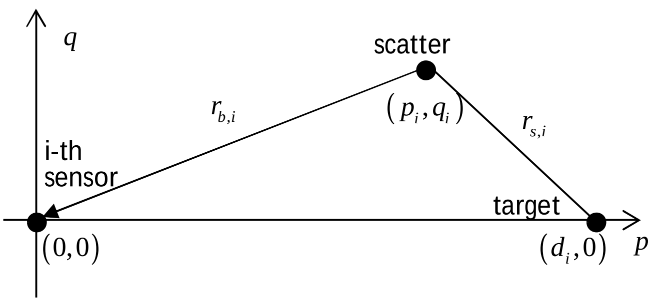


Fig. 1. Single scatter model in NLOS environment.

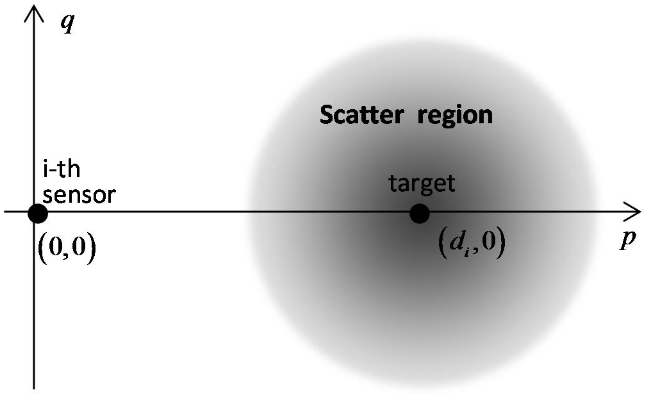


Fig. 2. Gaussian scatter density model in NLOS environment.

For the modeling of the error in NLOS environments, a single scatter model [12] is recognized as practical and well-known. In this study this model is used to calculate the NLOS noises. The single scatter model is a model in which the radio wave from the target node is reflected once by a scatter and is received by the sensor node. It is assumed that the multiple reflected wave is attenuated and can be ignored. Fig. 1 shows the single scatter model where the distance between the target and sensor nodes is d_i, the positions of the sensor and target nodes are $(0, 0)$ and $(d_i, 0)$, respectively, and the position of the scatter is (p_i, q_i). Then, the distance between the target node and the scatter $r_{s,i}$ and the distance between the sensor node and the scatter $r_{b,i}$ are, respectively, given by

$$r_{s,i} = \sqrt{(d_i - p_i)^2 + q_i^2} \tag{5}$$

$$r_{b,i} = \sqrt{p_i^2 + q_i^2} \tag{6}$$

From (5) and (6), the error $\varepsilon_{i,NLOS}$ in NLOS environments is given by

$$\varepsilon_{i,NLOS} = r_{b,i} + r_{s,i} - d_i \tag{7}$$

To obtain the averaged characterisitcs of NLOS error, the distribution of the scatter position (p_i, q_i) is needed. As the scatter distribution, circular scattering model (CSM) for outdoor environments, elliptical scattering model (ESM) for indoor environments, and Gaussian scatter density model (GSDM) for both indoor and outdoor environments [13] have been proposed. GSDM is a model of two-dimensional Gaussian distribution centered at the target node position $(d_i, 0)$ illustrated in Fig. 2. The joint probability density function $P(p_i, q_i)$ of scatter position (p_i, q_i) is given by

$$P(p_i, q_i) = \frac{1}{2\pi\sigma_s^2} \exp\left(- \frac{\sqrt{(p_i - d_i)^2 + q_i^2}}{2\sigma_s^2} \right) \tag{12}$$

where the standard deviation σ_s is given by

$$\sigma_s = \frac{d}{D_s} \tag{13}$$

and D_s is the constant parameter determined from propagation environments. In this study GSDM is adopted to derive the NLOS errors.

III. Iterative minimum residual (IMR) scheme

IMR scheme is an iterative NLOS elimination scheme in which the target location is iteratively estimated using some combinations of measured data and the inaccurate node is detected by comparing the residual estimation error [9]. By iterating this operation, the nodes having inaccurate data are eliminated as NLOS node one-by-one. The IMR algorithm is conducted by the following steps:

(i) Initialization:
Let N_d as the number of sensor nodes used for estimation and set

$$N_d = N, \quad r = \left\{ \hat{d}_i, 1 \le i \le N \right\} \tag{14}$$

where r is the observed distance set. Define the threshold δ as a small positive number.

(ii) Least square-based estimation:
Find the least squares (LS) estimated location $(\hat{x}, \hat{y})$ using the observation data r and calculate the normalized residual error $\bar{\varepsilon}(\hat{x}, \hat{y})$. They are given by

$$(\hat{x}, \hat{y}) = \arg\min_{\hat{x},\hat{y}} \sum_{i=1}^{N_d} \left\{ \hat{d}_i - \sqrt{(\hat{x} - x_i)^2 + (\hat{y} - y_i)^2} \right\}^2 \tag{15}$$

$$\bar{\varepsilon}(\hat{x}, \hat{y}) = \frac{1}{N_d} \sum_{i=1}^{N_d} \left\{ \hat{d}_i - \sqrt{(\hat{x} - x_i)^2 + (\hat{y} - y_i)^2} \right\}^2 \tag{16}$$

Set $\bar{\varepsilon}_{N_d} = \bar{\varepsilon}(\hat{x}, \hat{y})$.

(iii) Iteration:
Find the LS estimation $(\hat{x}, \hat{y})^{(k)}$ and the normalized residual error $\bar{\varepsilon}(\hat{x}, \hat{y})^{(k)}$, $1 \le k \le N_d$, for N_d combinations of N_d distances in r taking $N_d - 1$ at a time. Denote the position with the minimum normalized residual error as $(\hat{x}_m, \hat{y}_m)$, $\bar{\varepsilon}_m = \bar{\varepsilon}(\hat{x}_m, \hat{y}_m)$ and r_m as the set of distances used in $(\hat{x}_m, \hat{y}_m)$.
If $\bar{\varepsilon}_{N_d} - \bar{\varepsilon}_m > \delta$, then $(\hat{x}, \hat{y}) = (\hat{x}_m, \hat{y}_m)$; else return $(\hat{x}, \hat{y})$.
If $N_d > 3$, then $N_d = N_d - 1$, $r = r_m$, $\bar{\varepsilon}_{N_d} = \bar{\varepsilon}_m$, repeat (iii); else return $(\hat{x}, \hat{y})$.

In IMR scheme the estimation accuracy of location is degraded when NLOS detection is failed. In particular, when there are a lot of NLOS nodes, the residual error becomes fluctuant and the NLOS detection error tend to happen.

IV. Proposed NLOS detection scheme

For the TOA measurements, the target node sends beacon M times and the averaged measurement data are used for estimation, which is given by

$$\hat{d}_i = \frac{1}{M} \sum_{m=1}^{M} \hat{d}_{i,m} \tag{17}$$

where $\hat{d}_{i,m}$ is m-th measured distance of i-th sensor node and M is the number of measurements before estimation. By this operation, the Gaussian noise in the measurements is mitigated. Furthermore, using this M-time measurement, the error variance can be calculated. The estimated variance of measurement in i-th sensor node is given by

$$\sigma_{i,est}^2 = \frac{1}{M-1} \sum_{m=1}^{M} \left(\hat{d}_{i,m} - \hat{d}_i \right)^2 \tag{18}$$

Here, if the true variance of LOS measurement of (3) is known in advance, the environment of i-th sensor node can be estimated by comparing (19) with (3). The estimated distance D_i between the target node and i-th sensor node derived by the error variance is given by

$$D_i = \exp\left(\frac{\sigma_{i,est}}{\sigma_{LOS}} \right) \tag{19}$$

(19) is derived by the assumption that $\sigma_{i,est}$ ideally coincides $\sigma_{i,LOS}$ and by (3). Thus, on every M measurements, the averaged measurement distance $\hat{d}_i$ and the estimated distance D_i derived by the estimated variance are obtained. The NLOS bias is added to $\hat{d}_i$ in the NLOS environments, while D_i is not affected by the NLOS environments. Utilizing this property NLOS environments can be detected by comparing $\hat{d}_i$ with D_i such as

$$\hat{d}_i - D_i > \alpha_i \tag{20}$$

where α_i is a threshold. When (20) is satisfied, i-th sensor node is detected as NLOS environment, and eliminated for position estimation in IMR scheme. Different from the original IMR scheme, in which the NLOS detection in conducted by a combination search, (20) can be conducted for each i alone. However, when M is small, D_i becomes noisy and the NLOS detection accuracy using (20) is decreased. Hence, we propose the combination of this stochastic scheme and IMR scheme to improve the NLOS detection performance as follows.

The proposed algorithm of IMR scheme with the stochastic NLOS detection is shown in Fig. 3. First, $\hat{d}_i$ of (17) and D_i of (19) are calculated using M time measurements for all N sensor nodes. Next, the NLOS detection is conducted by (20) and the detected NLOS nodes are eliminated for position

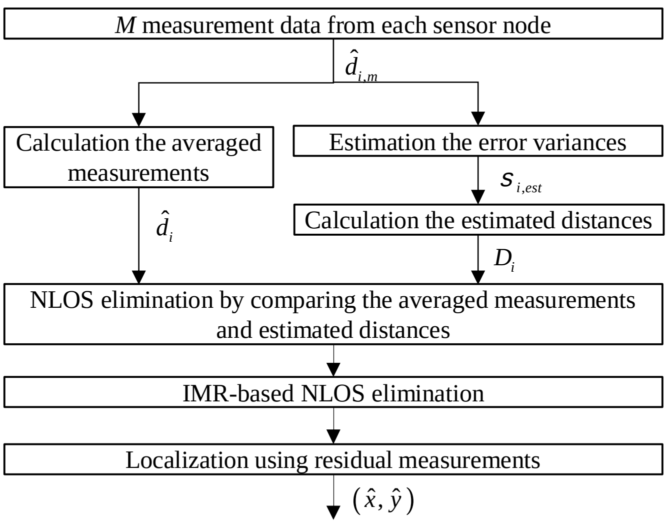


Fig. 3. Algorithm of the proposed scheme.

estimation. Here, because the accuracy of (20) is relatively low, the threshold a_i is configured as a large number not to eliminate LOS nodes. Then, some NLOS nodes may not be detected and remain. These residual NLOS nodes are then eliminated by IMR scheme conducted after the stochastic scheme. The IMR scheme has less detection performance when the number of NLOS nodes is large. However, this performance disadvantage will be solved by the proposed scheme because the nodes having large error is already eliminated.

V. Numerical results

The position estimation performance of the proposed scheme in NLOS environments is evaluated through computer simulations. The root mean square error (RMSE) is calculated and compared with the original IMR scheme. In the simulation, the target node is located at all area of the sensor field in Fig. 4 on every 0.1m grid in x and y directions, and at each target location the proposed scheme for NLOS detection and RMSE calculation are conducted. Here, the threshold for the proposed NLOS detection scheme a_i is configured by heuristic search as

$$a_i = 0.7\sqrt{(\hat{x}_0 - x_i)^2 + (\hat{y}_0 - y_i)^2} \tag{21}$$

where $(\hat{x}_0, \hat{y}_0)$ is estimated position calculated with all N sensor nodes, the number of sensor nodes N is 9, the number of NLOS nodes is 4, the number of measurements M is 30, and the number of trials for RMSE calculation is 1000. The signal bandwidth is assumed as 500MHz and the channel parameters of (3) and (4) are set as $m_{LOS} = 0.21$ and $s_{LOS} = 0.269$ [10]. For the NLOS channel model, Gaussian scatter density model (GSDM) [13] is used and its variance parameter is set as $D_s = 3$.

Fig. 5 shows the RMSE performance of the proposed scheme and conventional IMR scheme. In Fig. 5, the RMSE value is shown as a color bar between red (1m, highest) and blue (0m, lowest). In Fig. 5(a), there are some red region that means the lower estimation accuracy, while in Fig. 5(b), the performance is overall improved because of the improvement of the NLOS detection. The average RMSE in the whole sensor field of Fig. 5(a) and (b) is 0.569 [m] and 0.494 [m], respectively. This RMSE improvement of the proposed scheme is obtained by the accurate NLOS detection and elimination.

VI. Conclusions

In this paper, we proposed a new NLOS detection scheme by comparing the estimated variances of measurements and proposed a modified IMR scheme with joint NLOS detection. The RMSE performance of the proposed scheme was evaluated by computer simulations and it was confirmed that the RMSE was decreased compared to the conventional IMR scheme.

In future studies, the performance improvement by increasing the accuracy of stochastic detection scheme will be considered.

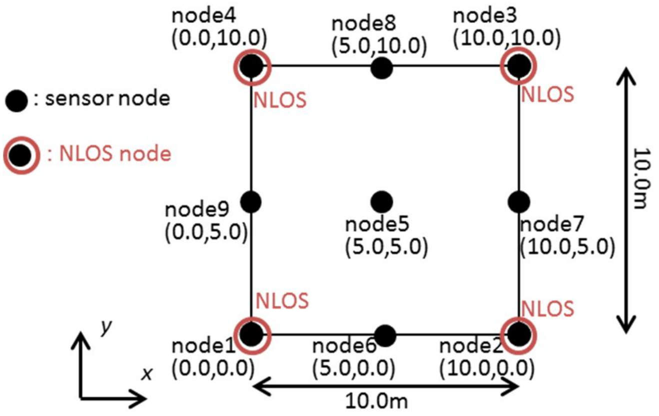
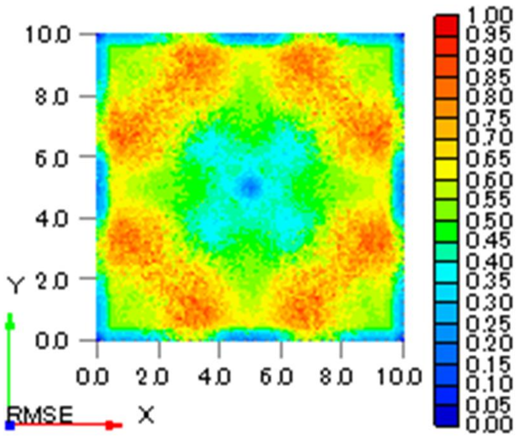
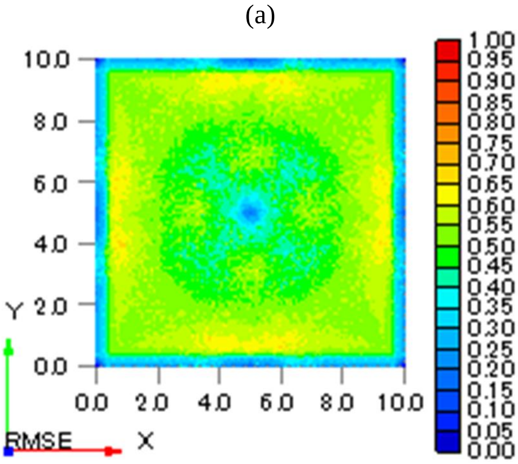


Fig. 4. Sensor field.



(a)



(b)

Fig. 5. RMSE performances;
(a) conventional IMR scheme, (b) proposed scheme.

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