LETTER

Sensor Localization Based on AOA-Assisted NLOS Identification

Takahiro ASO[†], ***Student Member and*** **Teruyuki MIYAJIMA**[††a)], ***Member***

SUMMARY In ubiquitous sensor networks, the estimation accuracy of a node location is limited due to the presence of non-line-of-sight (NLOS) paths. To mitigate the NLOS effects, this letter proposes a simple algorithm where NLOS identification is carried out using angle-of-arrival (AOA). Simulation results show that the use of AOA improves NLOS identification rates and location estimation accuracy.

key words: *ubiquitous sensor network, positioning, NLOS error mitigation, time of arrival*

1. Introduction

In potential applications of ubiquitous sensor networks such as environmental monitoring and search-and-rescue operations, sensor node localization is a fundamental and crucial problem [1]. A major concern of the localization is the effect of non-line-of-sight (NLOS) situations where the transmitted signal only reaches the receiver through reflected paths. In the NLOS situations, large errors in range and angle measurements may occur and seriously degrade localization performance.

There have been various ways to mitigate adverse NLOS effects [2]–[7]. The first way is based on pattern matching that uses a database consisting of previously measured radio characteristics at known positions [2]. This approach requires high cost to set up and maintain the database especially in time-variant environments. The second way is to introduce an NLOS channel model and determine the node location from the model [3]. In practical situations, it is difficult to obtain an accurate model. In the third way [4], [5], initial estimates are determined from a set of range measurements and residual information is formed. The final estimate is obtained from a subset of selected measurements based on the residual information. In the residual weighting algorithm [4], since the initial estimates are computed for possible combinations of measurements, its computational complexity becomes higher as the number of anchors increases. An algorithm in [5] not only needs to set an appropriate threshold to identify an NLOS measurement using residual range errors, but also cannot provide satisfactory estimation performance because of its poor NLOS identification capability.

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[†]The author is with the Graduate School of Sci. and Eng., Ibaraki University, Hitachi-shi, 316-8511 Japan.
[††]The author is with the Faculty of Eng., Ibaraki University, Hitachi-shi, 316-8511 Japan.
a) E-mail: miyajima@mx.ibaraki.ac.jp

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This letter attempts to improve the performance of the algorithms in the third category. We propose a simple localization algorithm that uses residual angle-of-arrival (AOA) errors to identify NLOS measurements, instead of residual range errors as in [5]. Moreover, the proposed algorithm can determine a threshold automatically and requires only small computational effort.

2. Localization Algorithm

The unknown sensor location is denoted as $\mathbf{x} = [x\ y]^T$. Let there be M anchors whose location $\mathbf{X}_i = [X_i\ Y_i]^T$, $i = 1, 2, \cdots, M$, is known. Let t_i and θ_i be the ith measured time-of-arrival (TOA) and AOA, respectively. The measured TOA and AOA include the effects of measurement noise and NLOS propagation (if exists). The range measurement is denoted by $r_i = c \cdot t_i$ where c is the speed of light. If the ith path is NLOS, the AOA θ_i is assumed to take a value in an interval $[\phi_i - \Phi_0, \phi_i + \Phi_0]$ where ϕ_i is the eye direction from the sensor node to the ith anchor and we refer to Φ_0 as angular spread.

The proposed algorithm consists of three stages. In the first stage, the initial location estimate is obtained by the least squares (LS) method [6] with all range measurements as

$$\tilde{\mathbf{x}}_1 = \arg\min_{\tilde{\mathbf{x}}} J_{\mathcal{F}}(\tilde{\mathbf{x}}), \quad \mathcal{F} = \{1, \cdots, M\} \tag{1}$$

where, for a range measurement index set $C = \{i_1, i_2, \cdots, i_m\}$, the objective function is give by

$$\begin{aligned} J_C(\tilde{\boldsymbol{x}}) &= \sum_{i \in C} \sum_{\substack{j \in C \\ j > i}} (a_{ij}\tilde{x} + b_{ij}\tilde{y} - c_{ij})^2 \\ &= \|\boldsymbol{A}\tilde{\boldsymbol{x}} - \boldsymbol{c}\|^2 \end{aligned} \tag{2}$$

where $a_{ij} = X_i - X_j$, $b_{ij} = Y_i - Y_j$, $c_{ij} = \{(X_i^2 - X_j^2) + (Y_i^2 - Y_j^2) - (r_i^2 - r_j^2)\}/2$, $\tilde{\boldsymbol{x}} = [\tilde{x}\ \tilde{y}]^T$, and

$$\boldsymbol{A} = \begin{bmatrix} a_{i_1 i_2} & a_{i_1 i_3} & \ldots & a_{i_1 i_m} & a_{i_2 i_3} & \ldots & a_{i_{m-1} i_m} \\ b_{i_1 i_2} & b_{i_1 i_3} & \ldots & b_{i_1 i_m} & b_{i_2 i_3} & \ldots & b_{i_{m-1} i_m} \end{bmatrix}^T$$

$$\boldsymbol{c} = \begin{bmatrix} c_{i_1 i_2} & c_{i_1 i_3} & \ldots & c_{i_1 i_m} & c_{i_2 i_3} & \ldots & c_{i_{m-1} i_m} \end{bmatrix}^T.$$

In the second stage, NLOS measurements are identified and the initial estimate is refined. The eye direction from the initial location estimate to the ith anchor is defined as

$$\tilde{\phi}_i = \arctan(\mathbf{X}_i - \tilde{\mathbf{x}}_1), \quad i = 1, 2, \ldots, M \tag{3}$$

where arctan(·) denotes four-quadrant inverse tangent with the result in the interval $[-\pi, \ \pi]$. The angle residual error can be formed as

$$e_i = \theta_i - \tilde{\phi}_i. \tag{4}$$

As shown in Fig. 1, the eye direction $\tilde{\phi}_i$ largely differs from the AOA θ_i in the presence of NLOS as long as the initial estimate $\tilde{\mathbf{x}}_1$ is not so far from the true location $\mathbf{x}$. Based on this observation, NLOS measurements are identified by the following rule:

$$\xi_i = \begin{cases} \text{NLOS} & \text{if } e_i^2 > T \\ \text{LOS} & \text{if } e_i^2 \leq T \end{cases} \tag{5}$$

where T denotes the threshold determined by

$$T = \frac{1}{|\mathcal{F}|} \sum_{i \in \mathcal{F}} e_i^2. \tag{6}$$

Next, we can form a set $\mathcal{L} = \{j; \xi_j = \text{LOS}\}$ by removing the measurements identified as NLOS. The sensor location is re-estimated by LS with the selected range measurements as

$$\tilde{\mathbf{x}}_2 = \arg\min_{\tilde{\mathbf{x}}} J_{\mathcal{L}}(\tilde{\mathbf{x}}). \tag{7}$$

A large angle spread Φ_0 is preferable to distinguish NLOS from LOS. When the angular spread Φ_0 is small it is anticipated that the performance of the NLOS identification degrades. In addition, interestingly, the removal of the NLOS measurements does not necessarily improve estimation accuracy [6]. These facts suggest that $\tilde{\mathbf{x}}_2$ is not always a better estimate than $\tilde{\mathbf{x}}_1$. Thus, in the third stage, we select a better one from the two estimates $\tilde{\mathbf{x}}_1$ and $\tilde{\mathbf{x}}_2$. We evaluate how good an estimate is by the mean squared residual range error

$$S_{C}(\tilde{\mathbf{x}}) = \frac{1}{|C|} \sum_{i \in C} (r_i - \|\tilde{\mathbf{x}} - \mathbf{X}_i\|)^2 \tag{8}$$

where $|C|$ denotes the number of entries of a measurement index set C. The final estimate is determined by

$$\hat{\mathbf{x}} = \begin{cases} \tilde{\mathbf{x}}_1 & \text{if } S_{\mathcal{F}}(\tilde{\mathbf{x}}_1) \leq S_{\mathcal{L}}(\tilde{\mathbf{x}}_2) \\ \tilde{\mathbf{x}}_2 & \text{if } S_{\mathcal{F}}(\tilde{\mathbf{x}}_1) > S_{\mathcal{L}}(\tilde{\mathbf{x}}_2) \end{cases}. \tag{9}$$

3. Simulation Results

There are four anchors ($M = 4$) which are located at [0 0], [0 100], [100 0], and [100 100], respectively. The path from one of anchors is assumed to be NLOS and is longer by R_0 than the corresponding LOS path. There is one sensor node set at random in the area surrounded by the square formed by the anchors. The AOA of the NLOS path is chosen uniformly from $[\phi_i - \Phi_0, \ \phi_i + \Phi_0]$. A range measurement noise is assumed to be modeled as a zero-mean Gaussian variable with the standard deviation $\sigma_{\text{r}} = 1$ (m) which is common among anchors. Similarly, an AOA measurement noise has the common standard deviation $\sigma_{\text{a}} = 2.5$ (deg). A performance measure is the mean squared position error defined as

$$\varepsilon = \frac{1}{K} \sum_{k=1}^{K} \|\hat{\mathbf{x}}_k - \mathbf{x}_k\|^2 \tag{10}$$

where K is the number of trials, which is set to 1,000. For the purpose of comparison, we also evaluate an algorithm in [5], which uses the range residual error to identify an NLOS measurement and requires a predetermined threshold.

In Fig. 2, NLOS identification rates of the proposed and conventional algorithms as a function of NLOS error are shown where the angle spread is set to $\Phi_0 = 15°, 45°, 90°$, and $180°$. As expected, the performance of the proposed algorithm improves as the angle spread increases. Clearly, the proposed algorithm outperforms the conventional range residual error based method. The reason of the performance degradation of the conventional algorithm is as follows. In the presence of an NLOS path, the initial estimated location tends to be away from the anchor with the NLOS path and thus the range residual error (difference between measured and estimated range) becomes small. Then the NLOS measurement is likely to be misjudged to be a LOS measurement. On the other hand, in the proposed AOA-based

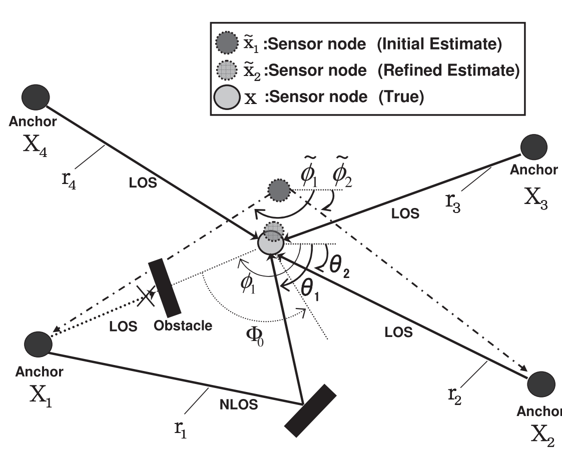

Fig. 1 LOS and NLOS paths in a sensor network.

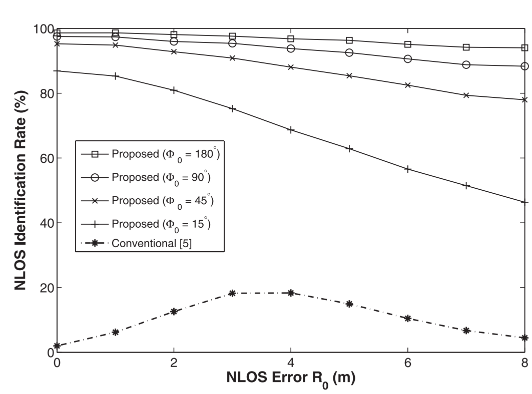

Fig. 2 NLOS identification rates.

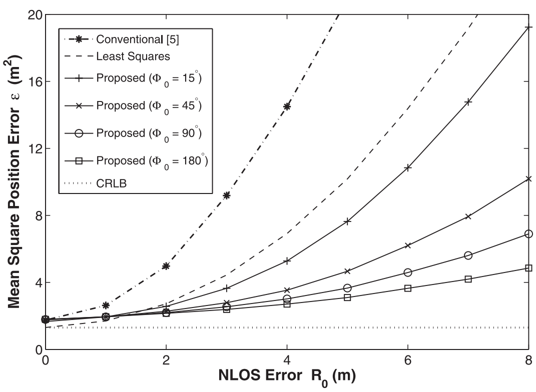

Fig. 3 Location estimation error performances.

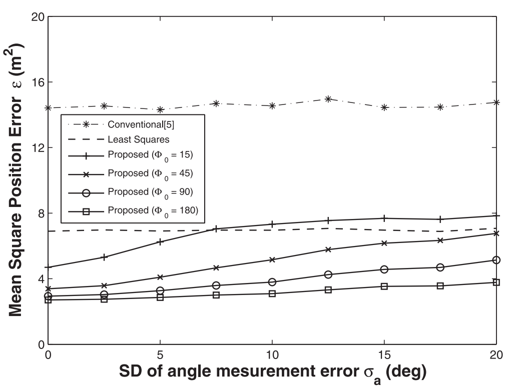

Fig. 4 Position error when NLOS error $R_0 = 4$ m.

algorithm, the angle residual error tends not to be affected by the initial location estimation error.

Figure 3 shows the location estimation errors as a function of NLOS error. It also contains the results of the LS, i.e., $\hat{\mathbf{x}}_1$, that of the conventional algorithm with a carefully chosen threshold of 0.95, and a lower bound of ε obtained from the Cramér-Rao lower bound (CRLB). Assuming the range measurement noise is spatially white, the range measurement $\boldsymbol{r} = [r_1 \ \cdots \ r_M]^T$ obeys a multivariate Gaussian distribution with mean $\boldsymbol{\mu}(\mathbf{x})$ and covariance matrix $\sigma_\mathrm{r}^2\boldsymbol{I}$ where the ith entry of $\boldsymbol{\mu}(\mathbf{x})$ is $\sqrt{(x - X_i)^2 + (y - Y_i)^2}$. The CRLB sets a lower limit for the estimate error covariance matrix and is given by the inverse of the Fisher information matrix as $\sigma_\mathrm{r}^2(\boldsymbol{G}^T\boldsymbol{G})^{-1}$ where $\boldsymbol{G} = \partial\boldsymbol{\mu}(\mathbf{x})/\partial\mathbf{x}$. The trace of the CRLB matrix provides a lower bound for ε. We can observe that the performance strongly depends on the angle spread Φ_0 and becomes better as Φ_0 increases. The conventional algorithm is worse than even LS because of its poor NLOS identification capability.

In Fig. 4, the location estimation errors as a function of the standard deviation of AOA measurement noise σ_a are shown when NLOS error is $R_0 = 4$ (m). We can observe that the proposed algorithm significantly outperforms the conventional algorithm for all σ_a values and becomes better than LS when σ_a is less than about a half of the angle spread Φ_0.

4. Conclusion

In this letter, we have proposed a simple sensor localization algorithm based on NLOS identification using AOA residual errors. Simulation results have shown that the performance of the proposed algorithm becomes better as the angle spread of AOA increases. Though not shown, the proposed algorithm can also be applied to cases where there are more than one NLOS paths.

If the initial location estimate is poor, the proposed algorithm may fail to identify NLOS measurements. The factors making impact on the initial estimate are range measurement noise, anchor geometry, and a location estimation method. Although we used LS, which may provide poor initial estimate for a certain geometry, we can adopt any location estimation method. The use of other than the LS method with range measurements in stages 1 and 2 would improve the performance in various situations.

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