Research Letter

NLOS Mitigation for TOA Location Based on a Modified Deterministic Model

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Wireless location becomes difficult due to contamination of measured time-of-arrival (TOA) caused by non-line-of-sight. In this letter, TOA measurements seen at base stations are adjusted by scale factors, and a modified deterministic model is built. An effective numerical solution is proposed to resolve the scale factors and mobile position. A simulation comparison of four algorithms indicates that the proposed algorithm outperforms the other three algorithms.

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1. INTRODUCTION

For outdoor wireless location, most time-of-arrival- (TOA-) based algorithms are derived from deterministic model. The mobile position is commonly modeled as the intersection of a set of circles defined by TOA ranges. Non-line-of-sight (NLOS) propagation is one of the major concerns. The field trials in [1] performed by Nokia showed that the positive range error due to NLOS is up to a thousand meters in some channel environments. NLOS is a key problem to improve location accuracy.

In recent years, very important contributions to the TOA-based location have been made to compute the mobile position using TOA measurements. And the least-square (LS) criterion is often used to compute the estimate of mobile position, which is optimal if the residual follows Gaussian distribution. For example, the “time of arrival data fusion” based on LS criterion in [2] is a closed-form solution for mobile position. A constrained nonlinear LS approach was proposed in [3] to minimize the residual. In [4], the quadric programming technique is used to find the ML estimation of the mobile position subjected to constraint from the inequalities introduced due to NLOS propagation. In the range scaling algorithm (RSA) in [5], the NLOS is mitigated using TOA adjustment by scaling NLOS-corrupted TOA measurements using factors that are estimated from

a constrained nonlinear optimization process. But RSA is only valid for three base stations (BSs) scenario, and the optimization process is very complex.

In this letter, scale factors are employed to adjust TOA measurements seen at base stations, and a modified deterministic model is proposed. An effective solution is used to resolve the mobile position, which does not require prior knowledge of NLOS distribution or time-based history measurements.

2. DETERMINISTIC MODEL FOR TOA-BASED LOCATION

It is assumed that M BSs are involved in the location process. The TOA-based range measurements are modeled as

$$r_i = d_i + L_i + v_i, \quad i = 1, \dots, M, \quad (1)$$

where r_i is the pseudorange between the i th BS and mobile station (MS), d_i is the LOS distance, and L_i is the excess distance due to NLOS. v_i is the sum of other errors caused by system delay, synchronization error, measurement noise, and so forth. Let the mobile position be $\mathbf{x} = [x, y]^T$, and let the position of the i th BS be $\mathbf{x}_i = [x_i, y_i]^T$. Define $e_i(\mathbf{x}) = r_i - \|\mathbf{x} - \mathbf{x}_i\|$ as the residual, where $\|\cdot\|$ denotes the norm operator, and $\|\mathbf{x} - \mathbf{x}_i\|$ represents the distance between vectors

FIGURE 1: The geometry of three circles shows the constraints on the scale factors.

$\mathbf{x}$ and $\mathbf{x}_i$. A generalized estimator normally used for TOA in determinate models is

$$\hat{\mathbf{x}} = \arg \min_{\mathbf{x}} \sum_{i \in S} \rho(e_i), \quad (2)$$

where S is the index set of BSs. $\rho(\cdot)$ is an optimal function of the residual. The determinate model in [3] was chosen as $\min_{\mathbf{x}} \sum_{i \in S} \alpha_i^2 e_i^2$, where α_i is the weight reflecting the reliability of the signal received at BS i , and $\rho(\cdot)$ in [6] was selected as a robust function with more tolerance for outliers. To locate mobile position in presence of NLOS propagation, an alternative way is to shift view to e_i in a modified deterministic model.

3. A MODIFIED DETERMINISTIC MODEL AND NUMERICAL SOLUTION

The fact that NLOS propagation causes positive range error means that the following inequality holds:

$$r_i - \|\mathbf{x} - \mathbf{x}_i\| \geq 0. \quad (3)$$

In order to change (3) into equality, let β_i be the scale factor on the range measurements, which yields

$$\beta_i r_i - \|\mathbf{x} - \mathbf{x}_i\| = 0. \quad (4)$$

Each β_i must be less than or equal to one. Furthermore, each β_i has a lower bound. For example, three BSs are involved in the location process, as seen in Figure 1. The mobile must lie in the overlapped region formed by I_1 , I_2 , and I_3 . Let η_i be the lower bound of β_i . We find that $\eta_1 = O_1 I_1 / r_1$. In a similar way, we get $\eta_2 = O_2 I_2 / r_2$ and $\eta_3 = O_3 I_3 / r_3$. Thus, β_i must be constrained by

$$\eta_i \leq \beta_i \leq 1, \quad i = 1, \dots, M. \quad (5)$$

Define $e'_i(\mathbf{x}) = \beta_i r_i - \|\mathbf{x} - \mathbf{x}_i\|$ as the modified residual in this letter. This residual will be zero or sufficient small if the scale factors are selected accurately. Thus, the modified deterministic model is defined as

$$\hat{\mathbf{x}} = \arg \min_{\mathbf{x}} \sum_{i=1}^M (\beta_i r_i - \|\mathbf{x} - \mathbf{x}_i\|)^2. \quad (6)$$

Subject to

$$\eta_i \leq \beta_i \leq 1. \quad (7)$$

Let the objective function which is minimized for TOA location be

$$g(\mathbf{x}) = \sum_{i=1}^M (\beta_i r_i - \|\mathbf{x} - \mathbf{x}_i\|)^2. \quad (8)$$

Clearly, (8) will be exactly zero with the true scale factors and true position. The sequential quadratic programming (SQP) technique is employed to study the performance surface of the objective function. We find that it has many local minimums in the overlapped region, and these minimums skirt the true mobile position.

Because of the difficulty in determining a closed-form solution for (8), we propose a numerical solution to resolve the scale factors and mobile position by the following steps.

- (1) Compute the lower bound η_i for $i = 1, \dots, M$.
- (2) Generate a random variable ε over $[0, 1]$ with a predefined distribution. The predefined distribution of ε is different in different channel environments. Typically, the channel environments can be classified as open area, mountains, suburban, urban, and bad urban.
- (3) Let the scale factors equal $\beta_i = \eta_i + (1 - \eta_i)\varepsilon$ for $i = 1, \dots, M$ and compute the mobile position as follows. Equation (8) is quadratic about x and y . Calculate the derivatives with respect to x and y , and let the derivatives be zero. The estimate of the mobile position is

$$\begin{aligned} \hat{x} &= \left(\sum_{i=1}^M \frac{e'_i}{\|\hat{\mathbf{x}} - \mathbf{x}_i\|} \right)^{-1} \sum_{i=1}^M \frac{x_i e'_i}{\|\hat{\mathbf{x}} - \mathbf{x}_i\|}, \\ \hat{y} &= \left(\sum_{i=1}^M \frac{e'_i}{\|\hat{\mathbf{x}} - \mathbf{x}_i\|} \right)^{-1} \sum_{i=1}^M \frac{y_i e'_i}{\|\hat{\mathbf{x}} - \mathbf{x}_i\|}. \end{aligned} \quad (9)$$

An interesting result from (9) is that the mobile position estimate is the linear combinations of the positions of all BSs. The tap weight of each linear combination is $(\sum_{i=1}^M (e'_i / \|\hat{\mathbf{x}} - \mathbf{x}_i\|))^{-1} (e'_i / \|\hat{\mathbf{x}} - \mathbf{x}_i\|)$. However, we must note that (9) is not the closed-form solution because $\|\hat{\mathbf{x}} - \mathbf{x}_i\|$ and e'_i are still functions of $\hat{x}$ and $\hat{y}$. Following the similar steepest descent technique as illustrated in [3], the estimate of mobile position is

$$\begin{aligned} \hat{\mathbf{x}}(k+1) &= \hat{\mathbf{x}}(k) - u_x \sum_{i=1}^M \frac{(\hat{\mathbf{x}}(k) - \mathbf{x}_i) e'_i(\hat{\mathbf{x}}(k))}{\|\hat{\mathbf{x}}(k) - \mathbf{x}_i\|}, \\ \hat{\mathbf{y}}(k+1) &= \hat{\mathbf{y}}(k) - u_y \sum_{i=1}^M \frac{(\hat{\mathbf{y}}(k) - \mathbf{y}_i) e'_i(\hat{\mathbf{x}}(k))}{\|\hat{\mathbf{x}}(k) - \mathbf{x}_i\|}, \end{aligned} \quad (10)$$

where u_x and u_y are the step sizes, and k is the iteration number.

- (4) Substitute the scale factors β_i and mobile position estimate $[\hat{x}, \hat{y}]$ into (8), and calculate the exact value of $g(\hat{x}, \hat{y})$.
- (5) Repeat steps, (2)–(4) N times. We get a set of the scale factors $\Pi_\beta = \{\beta_{1n}, \beta_{2n}, \dots, \beta_{Mn}, n = 1, \dots, N\}$, a set of mobile position $\Pi_{x,y} = \{\hat{x}_n, \hat{y}_n, n = 1, \dots, N\}$, and a set of exact value of objective function $\Pi_J = \{g_n(\hat{x}_n, \hat{y}_n), n = 1, \dots, N\}$.
- (6) Find the minimum $g_p(\hat{x}_p, \hat{y}_p)$ in Π_J , where p is the index. Then, $(\hat{x}_p, \hat{y}_p)$ in $\Pi_{x,y}$ is the final estimate for mobile position, and $\{\beta_{1p}, \beta_{2p}, \dots, \beta_{Mp}\}$ in Π_β are the final estimates for scale factors.

The random variable ε controls the step size of the scale factors while we search them in solution space. Without any prior knowledge, we apply the same ε on each scale factor in step (3) to limit the solution space. In step (6), both the scale factors and the mobile position that minimizes the objective function are taken as the final estimates. This scheme to select scale factors is reasonable because it follows the physical meaning of the modified deterministic model. Clearly, the final estimates cannot make the objective function exactly zero. But, they can guarantee it to be a relatively small number. A notable advantage of the numerical process is that compared to the complex nonlinear optimization processes as illustrated in RSA [5], the complexity to search the scale factors is reduced. In addition, the proposed algorithm can be applied to the scenarios of more than three BSs; however, RSA is difficult to be applied in these scenarios.

4. SIMULATIONS

The simulations are conducted in a cellular network composed of hexagonal cells with radius of 1000 meters. The mobile station is assumed uniformly distributed in the central cell. And the mobile position is computed based on TOA measurements from the six nearest BSs. In scenario 1, the excess range L_i due to NLOS propagation is modeled as positive random variables over $[0 \ 400]$ meters, generated according to CDSM [5, 7]. To study the performance in a high NLOS environment, the “reverse” CDSM is used. Without knowledge of the channel environment, the variable ε in the proposed algorithm is uniformly generated over $[0 \ 1]$, and the number of attempts is 10, that is, $N = 10$. The range error v_i is caused by system delay, synchronization error, measurement noise and is typically smaller in magnitude than NLOS error. As an example, v_i is modeled as a Gaussian variable with mean 100 meters and variance 30 meters. The performances are compared with the LS algorithm, that is, “time of arrival data fusion” algorithm in [2], the algorithm in [3], and the Huber-estimator mentioned in [6]. The root mean square errors of the four algorithms with the two NLOS models are shown in Figure 2.

In scenario 2, another model considered is a range-dependent NLOS model [8]. The NLOS error is proportional to the BS-MS range, that is, the NLOS error for the i th BS is taken to be $L_i = \chi d_i$, where χ is a proportionality constant. The root mean square errors with the proportional

FIGURE 2: The root mean square errors with CDSM and reverse CDSM.

FIGURE 3: The root mean square errors with range-dependent model.

NLOS model are shown in Figure 3. It is found that the performance of the other three algorithms degrade greatly with increasing χ , and the proposed algorithm is robust with χ .

5. CONCLUSIONS

A modified deterministic model with a new residual is built to compute the mobile position. Due to the difficulty to find a closed-form solution, an effective numerical solution is proposed to resolve the scale factors and the mobile position. A simulation comparison among four algorithms is conducted to evaluate their performance. The results indicate that the proposed algorithm can deal with NLOS effectively and is simple to be implemented.

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