Directional Target Localization in NLOS Environments Using RSS-TOA Combined Measurements

Peiliang Zuo, *Student Member, IEEE*, Han Zhang, Chen Wang, Hua Jiang, and Bin Pan, *Member, IEEE*

***Abstract*—This letter addresses the localization problem of a directional source in non-line-of-sight (NLOS) environments. To estimate both the position and the orientation of the source, we propose an iterative algorithm that skillfully adopts the received-signal-strength (RSS) and time-of-arrival (TOA) measurements. The algorithm is derived by converting the non-convex estimating problem into a generalized trust region subproblem (GTRS). The converted problem could be efficiently solved by a bisection process. Considering that the directivity of the target could greatly affect its RSS measurements in different directions, a preliminary estimate for the target's location is conducted using only the TOA measurements, based on which we then estimate the orientation of the source and the NLOS biases. The alternating process of the algorithm can converge quickly. Finally, the excellent performance of the proposed algorithm is demonstrated through simulations.**

***Index Terms*—Localization, directional source, RSS, TOA, GTRS.**

I. Introduction

Accurate positioning of the target is the premise of many technologies and applications, e.g., navigation, cognitive radio (CR) and wireless sensor networks (WSNs). Localization using typical measurements including RSS, TOA, angle-of-arrival (AOA) and time-difference-of-arrival (TDOA) therefore has drawn a lot of research attention [1], [2].

Many research work focuses on target localization in line-of-sight (LOS) conditions by utilizing single-type or mixed measurements [1]–[4], which might lose utility in the NLOS environment. In [5], a bisection based method was proposed to quickly localize the source using TOA measurements in NLOS conditions. Furthermore, channel correlations were employed by multivariate Gaussian mixture models in [6] for estimating position of the target using the same kind of measurement as in [5]. To localize the target with RSS-TOA hybrid measurements in NLOS conditions, the derived orientation information on the basis of RSS-TOA measurements were adopted in [10] for improving the accuracy of positioning. In order to mitigate the NLOS biases, a robust approach where they are treated as nuisance parameters was proposed in [17], the localization problem was then solved by the GTRS framework. Through using balancing parameters and semi-definite relaxation (SDR), the proposed method in [8] was shown to achieve the performance close to that of Cramer-Rao lower bounds (CRLB). Moreover, the source localization problem under unknown transmission power and time was considered in [9], which was addressed by using second-order cone programming.

With the continuous development of radio frequency technology, the non-uniform antenna gain patterns have been extensively utilized nowadays [11]. The above localization work may no longer be applicable. In [3], a heuristic method on the basis of image processing was proposed to estimate the position and orientation of the directional source using RSS measurements. Peng *et al.* [12] calculated both the parameters and estimation bounds of multiple directional targets with RSS measurements. In order to improve the accuracy of estimation, the RSS-AOA hybrid measurements were adopted in [13] for computing the parameters of the directional source. However, to the best of our knowledge, parameters of the directional source have never been estimated in NLOS environments.

This letter considers the localization problem of a directional source in NLOS environments using RSS-TOA hybrid measurements. The non-convex estimation problem is first converted into a GTRS framework. In view of that the unknown source direction may greatly affect the convergence rate of the estimation process if both kind of measurements are simultaneously utilized. We thus propose an iterative algorithm to avoid this situation.

II. Problem Formulation

Consider there are one directional source with unknown location $\boldsymbol{x}$ and orientation $\boldsymbol{\theta_0}$, and N anchors with known locations $\boldsymbol{a_i}$, $i = 1, \dots, N$ in the k-dimensional ($k = 2$ or 3) region of interest (ROI). In this letter, it is assumed that the transmission directionality of the source is generated by its directional antenna, and the antenna is provided with the Gaussian-shaped radiation pattern [11]

$$|G(\Delta\theta)|^2 = P_x \exp(-\frac{(\Delta\theta)^2}{2\beta^2}), \tag{1}$$

where P_x and β respectively represent the transmit power and main beam width of the source, while $\Delta\theta \in [0, \pi]$ denote the

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Peiliang Zuo is with the Department of Electronic and Communication Engineering, Beijing Institute of Electronic Science and Technology, Beijing 100070, China, and also with the State Key Laboratory of Integrated Services Networks, Xidian University, Xi'an 710126, China (e-mail: zplzpl88@bupt.cn).

Han Zhang is with the College of Communication Engineering, Xidian University, Xi'an 710126, Shaanxi, China (e-mail: zhanghdwork@163.com).

Chen Wang and Hua Jiang are with the Department of Electronic and Communication Engineering, Beijing Institute of Electronic Science and Technology, Beijing 100070, China (e-mail: wc_victory@163.com; jhbesti@126.com).

Bin Pan is with the School of Statistics and Data Science, Nankai University, Tianjin 300071, China (e-mail: panbin@nankai.edu.cn).

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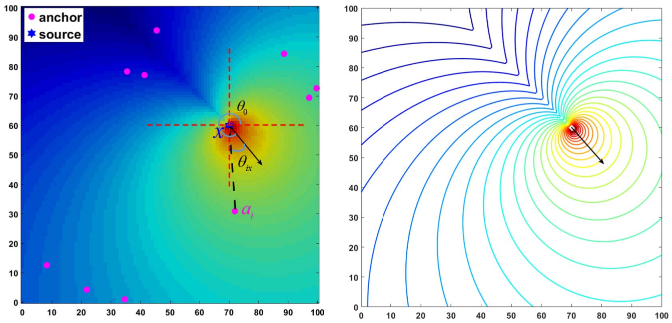

Fig. 1. The received energy topology in a noise-free environment and spatial relationship between the source and anchor *i*. The arrow indicates the orientation of the source, while the angle between it and the vector from the source to anchor *i* is denoted as θ_{ix}.

angle between the transmission orientation and any direction in the ROI. For ease of understanding, Fig. 1 shows the spatial relationship between the directional source and anchors, as well as the noise-free received energy topology in a two-dimensional space. We assume that the transmission power and transmission time of the target are known as a priory for the anchors. In addition, the anchors could extract the TOA and RSS measurements from the signal transmitted by the target, then the TOA and RSS measurements can be separately expressed as [14]

$$d_i = \|\boldsymbol{x} - \boldsymbol{a_i}\| + \eta_i + \tau_i, \tag{2}$$

$$P_i = P_0 - \mu_i - 10\alpha \log_{10}\left(\frac{\|\boldsymbol{x} - \boldsymbol{a_i}\|}{d_0}\right) - \frac{5\theta_{ix}^2}{\beta^2 \ln 10} + n_i, \tag{3}$$

where η_i and μ_i are respectively the NLOS biases in TOA and RSS measurements, which are bounded as $0 \le \eta_i, \mu_i \le b_{\max}(\text{m, dB})$ where $b_{\max}$ denotes the known maximum possible NLOS bias.[1] P_0 is the RSS in decibels (dB) at a reference distance d_0, α is the path loss exponent, $\theta_{ix} \in [0, \pi]$ denotes the angle between the transmission orientation $\boldsymbol{\theta_0}$ and the vector $\boldsymbol{\varphi_{ix}} = \boldsymbol{a_i} - \boldsymbol{x}$ from the source to the $\boldsymbol{i}$-th anchor. τ_i and n_i separately signify the measurement noises in TOA and RSS. According to [8]–[10], [14]–[17], they are commonly modeled as zero mean Gaussian random variable, i.e., $\tau_i \sim \mathcal{N}(0, \sigma_{\tau_i}^2)$ and $n_i \sim \mathcal{N}(0, \sigma_{n_i}^2)$. Meanwhile, the measurement noises in TOA measurements are considered to mainly include the synchronous error and multipath fading random processes [15]. σ_{τ_i} and σ_{n_i} respectively describe the joint nuisance of the multipath nature of the propagation channel and the measurement channel in TOA and RSS [15].

Considering that the experimental trials in [16] and [18] demonstrated that the TOA and RSS measurements extracted from the same radio signal are weakly correlated, the maximum likelihood (ML) estimator for the unknown parameters could be described as

$$\begin{aligned} \underset{\boldsymbol{x}, \boldsymbol{\theta_0}, \eta_i, \mu_i}{\arg\min} \; & \sum_{i=1}^{N} \frac{(d_i - \|\boldsymbol{x} - \boldsymbol{a_i}\| - \eta_i)^2}{\sigma_{\tau_i}^2} + \sum_{i=1}^{N} \\ & \frac{\left(P_i - P_0 + \mu_i + 10\alpha \log_{10}\left(\frac{\|\boldsymbol{x} - \boldsymbol{a_i}\|}{d_0}\right) + \frac{5\theta_{ix}^2}{\beta^2 \ln 10}\right)^2}{\sigma_{n_i}^2}. \end{aligned} \tag{4}$$

[1]It should be highlighted that this assumption does not imply anything about the distributions of the NLOS biases, since they are not known in general.

It can be concluded that problem (4) is highly non-convex. Moreover, it is clearly underdetermined, as the number of known factors is $2N$, and the number of factors to be estimated is $2(N + k) - 1$. In the next section, we will introduce an algorithm to simplify the estimation process.

III. Proposed Estimator

Considering that we can not well distinguish the biases of NLOS links, we simplify equations (2) and (3) to

$$d_i = \|\boldsymbol{x} - \boldsymbol{a_i}\| + \eta + \tau_i, \tag{5}$$

$$P_i = P_0 - \mu - 10\alpha \log_{10}\left(\frac{\|\boldsymbol{x} - \boldsymbol{a_i}\|}{d_0}\right) - \varepsilon\theta_{ix}^2 + n_i, \tag{6}$$

respectively, where $\varepsilon = 5/\beta^2 \ln 10$, η and μ instead of η_i and μ_i can be regarded as balancing parameters. This simplification operation greatly reduces the number of parameters to be estimated, i.e., from $2(N + k) - 1$ to $2k + 1$, and the effect of this operation is that the NLOS biases are homogenized.[2]

Equation (5) could be converted into

$$d_i - \eta = \|\boldsymbol{x} - \boldsymbol{a_i}\| + \tau_i. \tag{7}$$

By squaring both sides of the equation, we get

$$\tau_i + \frac{\tau_i^2}{2\|\boldsymbol{x} - \boldsymbol{a_i}\|} = \frac{(d_i - \eta)^2 - \|\boldsymbol{x} - \boldsymbol{a_i}\|^2}{2\|\boldsymbol{x} - \boldsymbol{a_i}\|}. \tag{8}$$

In addition, we can rearrange (6) as

$$\|\boldsymbol{x} - \boldsymbol{a_i}\| \phi_i \rho_{ix} = d_0 \times 10^{\frac{P_0 - \mu}{10\alpha}} \times 10^{\frac{n_i}{10\alpha}}, \tag{9}$$

where $\phi_i = 10^{\frac{P_i}{10\alpha}}$ and $\rho_{ix} = 10^{\frac{\varepsilon\theta_{ix}^2}{10\alpha}}$. According to the first order Taylor expansion $e^t \approx 1 + t$ when t is a small value, we have

$$\|\boldsymbol{x} - \boldsymbol{a_i}\| \phi_i \rho_{ix} \approx \gamma + \chi_i, \tag{10}$$

with $\gamma = d_0 \times 10^{\frac{P_0 - \mu}{10\alpha}}$ and $\chi_i \sim \mathcal{N}(0, (\gamma \frac{\ln 10}{10\alpha} \sigma_{n_i})^2)$. Further, we can get

$$\chi_i - \frac{\chi_i^2}{2\phi_i \rho_{ix} \|\boldsymbol{x} - \boldsymbol{a_i}\|} \approx \frac{\phi_i^2 \rho_{ix}^2 \|\boldsymbol{x} - \boldsymbol{a_i}\|^2 - \gamma^2}{2\phi_i \rho_{ix} \|\boldsymbol{x} - \boldsymbol{a_i}\|}. \tag{11}$$

By ignoring the second-order noise terms[3] in equations (8) and (11), and utilizing the WLS criterion, the estimator could be reorganized as

$$\begin{aligned} \underset{\boldsymbol{x}, \boldsymbol{\theta_0}, \eta, \mu}{\arg\min} \; & \sum_{i=1}^{N} w_i \left(\frac{\|\boldsymbol{x} - \boldsymbol{a_i}\|^2 - \tilde{d}_i^2}{2\|\boldsymbol{x} - \boldsymbol{a_i}\|}\right)^2 + \sum_{i=1}^{N} \\ & w_i \left(\frac{\phi_i^2 \rho_{ix} \|\boldsymbol{x} - \boldsymbol{a_i}\|^2 - \gamma^2/\rho_{ix}}{2\phi_i \|\boldsymbol{x} - \boldsymbol{a_i}\|}\right)^2, \end{aligned} \tag{12}$$

[2]Note that this simplification as the same in [7], [8] and [9] might be somewhat arbitrary, but we could estimate both η and μ together with the location and orientation of the target.

[3]It should be noted that the premises that the impact of these simplifications can be ignored are $\tau_i \ll 2\|\boldsymbol{x} - \boldsymbol{a_i}\|$ and $\chi_i \ll 2\phi_i \rho_{ix} \|\boldsymbol{x} - \boldsymbol{a_i}\|$, respectively. This means that the approximation operations will result in performance degradation, for quite large measurement noises or for very short range communication. In fact, the high measurement noises can be avoided at the calibration phase [19]. Moreover, the degradation owing to partial short-range measurements could be compensated by the hybrid utilization of RSS and TOA measurements as validated in Section IV.

where $w_i = 1 - \tilde{d}_i / \sum_{i=1}^{N} \tilde{d}_i$ with $\tilde{d}_i = d_i - \eta$, which means that the estimator pays more attention to nearby links.[4] In the light of (12) still belonging to highly non-convex problem, we adjust the denominators of the two parts of the estimator using $\tilde{d}_i \approx \|\boldsymbol{x} - \boldsymbol{a_i}\|$. This approximation is reasonable, since the measurement noise τ_i is small. Now we have

$$\arg\min_{\boldsymbol{x}, \boldsymbol{\theta_0}, \eta, \mu} A + B \tag{13}$$

with

$$A \triangleq \sum_{i=1}^{N} w_i \left(\frac{\|\boldsymbol{x} - \boldsymbol{a_i}\|^2 - \tilde{d}_i^2}{2\tilde{d}_i} \right)^2, \tag{14}$$

$$B \triangleq \sum_{i=1}^{N} w_i \left(\frac{\phi_i^2 \rho_{ix} \|\boldsymbol{x} - \boldsymbol{a_i}\|^2 - \gamma^2/\rho_{ix}}{2\phi_i \tilde{d}_i} \right)^2. \tag{15}$$

It can be observed that problem (13) could be solved directly by the bisection procedure if parameters μ, η and ρ_{ix} are known.[5] Note here that the first term of problem (13) has nothing to do with the transmission direction of the target. Taking into account the above observations, we consider a) using an alternating process to estimate the unknown parameters; b) acquiring the estimation of the target's location first by the TOA measurements, based on which then estimating the orientation of the target using the RSS measurements; c) finally using both RSS and TOA measurements to further estimate the target's position. Mathematically, problem (13) can be divided into three subproblems, which are separately

$$SP1: \quad \arg\min_{\boldsymbol{x}, \eta} A, \tag{16}$$

$$SP2: \quad \arg\min_{\boldsymbol{\theta_0}, \mu} B, \tag{17}$$

$$SP3: \quad \arg\min_{\boldsymbol{x}} A + B. \tag{18}$$

Firstly, SP1 can be solved by the following steps.

1) Initialize η: $\hat{\eta} = 0$, and define $\hat{d}_i = \tilde{d}_i|_{\hat{\eta}}$.

2) By expanding the numerator of A, we can get

$$\underset{\boldsymbol{y} = [\boldsymbol{x}^T, \|\boldsymbol{x}\|^2]^T}{\text{minmize}} \left\{ \| \boldsymbol{W}(\boldsymbol{D}\boldsymbol{y} - \boldsymbol{q})\|^2 : \boldsymbol{y}^T \boldsymbol{M} \boldsymbol{y} + 2\boldsymbol{p}^T \boldsymbol{y} = 0 \right\} \tag{19}$$

where $\boldsymbol{W} = diag(\frac{\sqrt{w_1}}{2\hat{d}_1^2}, \frac{\sqrt{w_2}}{2\hat{d}_2^2}, \ldots, \frac{\sqrt{w_N}}{2\hat{d}_N^2})$, $\boldsymbol{M} = \begin{bmatrix} \boldsymbol{I_k} & \boldsymbol{0}_{k\times 1} \\ \boldsymbol{0}_{1\times k} & 0 \end{bmatrix}$, $\boldsymbol{D} = \begin{bmatrix} 2\boldsymbol{a_1}^T & -1 \\ 2\boldsymbol{a_2}^T & -1 \\ \vdots & \vdots \\ 2\boldsymbol{a_N}^T & -1 \end{bmatrix}$, $\boldsymbol{q} = \begin{bmatrix} \|\boldsymbol{a_1}\|^2 - \hat{d}_1^2 \\ \|\boldsymbol{a_2}\|^2 - \hat{d}_2^2 \\ \vdots \\ \|\boldsymbol{a_N}\|^2 - \hat{d}_N^2 \end{bmatrix}$, $\boldsymbol{p} = \begin{bmatrix} \boldsymbol{0}_{k\times 1} \\ -0.5 \end{bmatrix}$. Equation (19) belongs to the category of GTRS, and it can be exactly solved by a bisection process.

3) By utilizing the estimate of $\boldsymbol{x}$, $\hat{\boldsymbol{x}}$, we have $\hat{\eta} = \frac{\sum_{i=1}^{N} (d_i - \|\hat{\boldsymbol{x}} - \boldsymbol{a_i}\|)}{N}$.

[4] It should be emphasized that the estimated range based on RSS measurement may have obvious deviation due to the transmission direction of the source, the RSS-related second part of the estimator also uses weights based on TOA measurements, i.e., w_i, $i = 1, \ldots, N$.

[5] It should be highlighted that ρ_{ix} is related to both the position and orientation of the target, and we could not separate $\boldsymbol{x}$ or $\boldsymbol{\theta_0}$ from ρ_{ix}. Here we assume that ρ_{ix} is known to mean that its estimation error is relatively small.

Through repeating 2) and 3) steps, we can get the convergence result of the target's position, which can be used for solving SP2. With the estimated $\hat{\eta}$ and $\hat{\boldsymbol{x}}$, we can observe that problem SP2 (i.e., equation (17)) is still highly non-convex, and has no closed-form solution. In view of this, this letter adopts the Multiresolution (MR) search approach [4] to obtain the estimate of $\boldsymbol{\theta_0}$, $\hat{\boldsymbol{\theta}}_0$ under the condition of setting $\hat{\gamma} = \gamma|_{\hat{\mu}}$, and $\hat{\mu}$ is initialized to 0. Note that the MR search method has been proved to be more efficient than those methods of exhaustive search classes. Then we can acquire

$$\hat{\mu} = \frac{\sum_{i=1}^{N} \left(P_0 - P_i - 10\alpha \log_{10} \frac{\|\hat{\boldsymbol{x}} - \boldsymbol{a_i}\|}{d_0} - \varepsilon \hat{\theta}_{ix}^2 \right)}{N}, \tag{20}$$

with $\hat{\theta}_{ix} = \theta_{ix}|_{\boldsymbol{\theta_0} = \hat{\boldsymbol{\theta}}_0, \boldsymbol{x} = \hat{\boldsymbol{x}}}$. Both $\hat{\boldsymbol{\theta}}_0$ and $\hat{\mu}$ will converge on the basis of repeating the MR search step and equation (20).

With $\hat{\boldsymbol{x}}$, $\hat{\mu}$, $\hat{\eta}$ and $\hat{\boldsymbol{\theta}}_0$, the estimated position of the target can be further optimized by solving SP3 using the following steps.

1) Define $\hat{\rho}_{ix} = \rho_{ix}|_{\boldsymbol{\theta_0} = \hat{\boldsymbol{\theta}}_0, \boldsymbol{x} = \hat{\boldsymbol{x}}}$.

2) By expanding the numerators of A and B, we have

$$\underset{\boldsymbol{y} = [\boldsymbol{x}^T, \|\boldsymbol{x}\|^2]^T}{\text{minmize}} \left\{ \| \boldsymbol{W}'(\boldsymbol{D}'\boldsymbol{y} - \boldsymbol{q}')\|^2 : \boldsymbol{y}^T \boldsymbol{M} \boldsymbol{y} + 2\boldsymbol{p}^T \boldsymbol{y} = 0 \right\} \tag{21}$$

where $\boldsymbol{W}' = diag(\frac{\sqrt{w_1}}{2\hat{d}_1^2}, \frac{\sqrt{w_2}}{2\hat{d}_2^2}, \ldots, \frac{\sqrt{w_N}}{2\hat{d}_N^2}, \frac{\sqrt{w_1}}{2\hat{d}_1^2}, \frac{\sqrt{w_2}}{2\hat{d}_2^2}, \ldots, \frac{\sqrt{w_N}}{2\hat{d}_N^2})$,

$$\boldsymbol{D}' = \begin{bmatrix} \vdots & \vdots \\ 2\phi_i^2 \hat{\rho}_{ix} \boldsymbol{a_i^T} & -\phi_i^2 \hat{\rho}_{ix} \\ \vdots & \vdots \\ 2\boldsymbol{a_i^T} & -1 \\ \vdots & \vdots \end{bmatrix}, \ \boldsymbol{q}' = \begin{bmatrix} \vdots \\ \phi_i^2 \hat{\rho}_{ix} \|\boldsymbol{a_i}\|^2 - \frac{\hat{\gamma}^2}{\hat{\rho}_{ix}} \\ \vdots \\ \|\boldsymbol{a_i}\|^2 - \hat{d}_i^2 \\ \vdots \end{bmatrix}.$$

Similarly, problem (21) can be quickly and accurately solved by a bisection process.

We finally summarize the proposed estimator in Algorithm 1, where the estimates of the position and orientation of the target could be acquired through solving subproblems SP1, SP2 and SP3 reasonably. The complexity of Algorithm 1 is $O((\log_2 M)(T_{\max} + T_{\max}^{SP_1}) + T_{\max} T_{\max}^{SP_2} \sum_{i=1}^{3} R_i^2 + N(T_{\max} + T_{\max} \times T_{\max}^{SP_2} + T_{\max}^{SP_1}))$, where R_i denotes the number of searches at the *i*-th resolution in the MR search method, while M is the search space size of the bisection process. In addition, we notice that all three loops in Algorithm 1 can converge quickly in the simulations. Specifically, $T_{\max}^{SP1}, T_{\max}^{SP2}, T_{\max} \leq 2$. Therefore, the complexity can be described as $O(4\log_2 M + 6N + 4\sum_{i=1}^{3} R_i^2)$. Considering that $R_1 = 12, R_2 = 6, R_3 = 5$ and $M = 10000$ in the simulation, the complexity of Algorithm 1 is low, and the estimation results can be obtained quickly.

IV. Simulation and Analysis

This section verifies the performance of the proposed estimator. We randomly deploy N sensors in a 2-dimensional region of 100m×100m with one randomly placed directional source in each Monte Carlo (MC) run. We set $P_0 = 20$dBm, $\alpha = 2.8, \beta = \frac{\pi}{3}, d_0 = 1$. The multi-resolution orientations of the MR method in Algorithm 1 are successively set as $\frac{\pi}{6}$rad, $\frac{\pi}{36}$rad and $\frac{\pi}{180}$rad. Without loss of generality, the NLOS biases

Algorithm 1: The Proposed Estimation Algorithm

Input: α, d_0, P_0, β, the observations d_i, P_i, $i = 1, 2, \ldots, N$.
Output: $\hat{\boldsymbol{x}}$ and $\hat{\boldsymbol{\theta}}_{\mathbf{0}}$.

1 Initialize $\hat{\eta} = 0$, $\hat{\mu} = 0$;
2 **for** $t_1 = 1 : 1 : T_{\max}^{SP1}$ **do**
3 Update $\hat{d}_i = \tilde{d}_i\big|_{\hat{\eta}}$, and acquire $\hat{\boldsymbol{x}}$ by solving (19) using a bisection process.
4 Obtain $\hat{\eta} = \sum_{i=1}^{N} \left(d_i - \|\hat{\boldsymbol{x}} - \boldsymbol{a_i}\|\right) \Big/ N$.
5 **end**
6 **for** $t = 1 : 1 : T_{max}$ **do**
7 **for** $t_2 = 1 : 1 : T_{\max}^{SP2}$ **do**
8 Update $\hat{\gamma} = \gamma|_{\hat{\mu}}$, $\boldsymbol{x}$=$\hat{\boldsymbol{x}}$, and acquire $\hat{\boldsymbol{\theta}}_{\mathbf{0}}$ from (17) using the MR search method.
9 Update $\hat{\theta}_{ix} = \theta_{ix}|_{\boldsymbol{\theta_0}=\hat{\boldsymbol{\theta}}_{\mathbf{0}}, \boldsymbol{x}=\hat{\boldsymbol{x}}}$.
10 Obtain $\hat{\mu} = \sum_{i=1}^{N} \left(P_0 - P_i - 10\alpha\log_{10}\frac{\|\hat{\boldsymbol{x}}-\boldsymbol{a_i}\|}{d_0} - \varepsilon\hat{\theta}_{ix}^2\right) \Big/ N$.
11 **end**
12 Update $\hat{\rho}_{ix} = \rho_{ix}|_{\boldsymbol{\theta_0}=\hat{\boldsymbol{\theta}}_{\mathbf{0}}, \boldsymbol{x}=\hat{\boldsymbol{x}}}$.
13 Obtain $\hat{\boldsymbol{x}}$ by solving (21) using a bisection process.
14 Update $\hat{\eta} = \sum_{i=1}^{N} \left(d_i - \|\hat{\boldsymbol{x}} - \boldsymbol{a_i}\|\right) \Big/ N$ and $\hat{d}_i = \tilde{d}_i\big|_{\hat{\eta}}$.
15 **end**

(i.e., η_i and μ_i, $i = 1, 2, \ldots, N$) are drawn from a uniform distribution among $[0, b_{\max}]$ for each MC run. Except for the CRLB, we also adopt a total of eight comparison methods, i.e., NR [16], ImageP [3], the brute force (BF) method, $\mathrm{A1_{TOA}}$ and $\mathrm{A1_{RSS\&TOA}}$, CKF [20], UKF [21], $\mathrm{WLS_{OI}}$ [10]. The position of the target could be easily estimated through the range estimations by the NR method.[6] For the BF method, the search resolutions of location and orientation are respectively set to 1m and $\frac{\pi}{180}$rad. In view of the need to verify each candidate value, the BF method is too time-consuming and evidently infeasible in practical application. In $\mathrm{A1_{TOA}}$, the TOA measurements are utilized for the localization, i.e., only Steps 1-5 of Algorithm 1 are performed. $\mathrm{A1_{RSS\&TOA}}$ means that both RSS and TOA measurements are directly employed to estimate the position of the target, i.e., Steps 1-5 of Algorithm 1 are abandoned, and the position estimation is performed prior to the orientation estimation in the loop. On the basis of Kalman filtering, CKF and UKF are both typical nonlinear estimation methods. In each iteration, we set their number of observations to 4, including two random RSS measurements and two TOA measurements. Besides, owing to the fact that the transmission directivity greatly affects the RSS measurements and degrades the positioning performance, only the TOA measurements are utilized in $\mathrm{WLS_{OI}}$. We adopt the root mean squared error (RMSE) as the performance metric, and all results shown in this section are averaged over 2000 randomized trials.

Fig. 2 and Fig. 3 respectively illustrate the RMSE of position and orientation estimations versus the number of anchor nodes (i.e., N). The orientation estimation performance of NR, $A1_{\mathrm{TOA}}$ and $\mathrm{WLS_{OI}}$ methods is not shown in Fig. 3, since they can only estimate the location of the target. As expected, the estimation error decreases with the increase of the number of observations. Interestingly, $\mathrm{A1}_{RSS\&TOA}$ performs evidently inferior to $A1_{\mathrm{TOA}}$, even though the RSS measurements are additionally employed by the former. This is because the RSS measurements are simultaneously affected by the position and orientation of the target, and the estimation process of $\mathrm{A1_{RSS\&TOA}}$ is prone to fall into the local optimal state, if the error of the initial value of $\hat{\boldsymbol{x}}$ or $\hat{\boldsymbol{\theta}}_{\mathbf{0}}$ is large. Moreover, thanks to the derived extra orientation information, performance of $\mathrm{WLS_{OI}}$ is better than that of $A1_{\mathrm{TOA}}$. CKF and UKF methods show similar performance in position estimation, but have obvious difference in orientation estimation. On the whole, their performance is relatively insensitive to changes in the number of anchors, and compared with the proposed Algorithm 1, they show better performance when the number of sensors is 3. Algorithm 1 successively outperforms $\mathrm{WLS_{OI}}$ and $A1_{\mathrm{TOA}}$, as it skillfully processes the TOA and RSS hybrid measurements. It also nearly attains the lower bound set by the BF method. Meanwhile, owing to the quantization error, the BF's performance is slightly inferior to the CRLB.

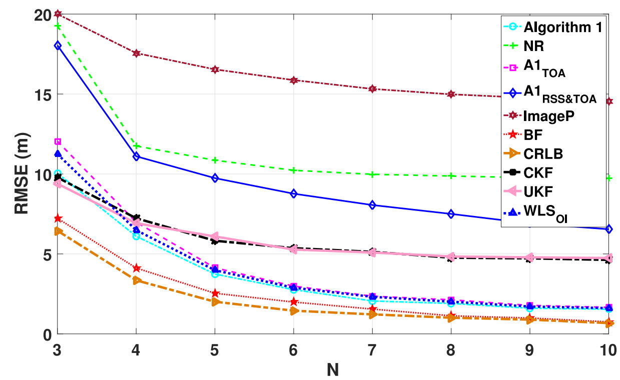

Fig. 2. RMSE of position estimation versus N comparison, when $\sigma_{n_i} = 3$m, $\sigma_{\tau_i} = 3$dB, $b_{\max} = 6$(m, dB).

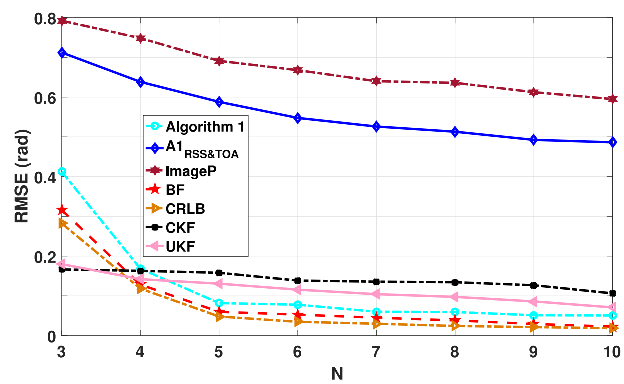

Fig. 3. RMSE of orientation estimation versus N comparison, when $\sigma_{n_i} = 3$m, $\sigma_{\tau_i} = 3$dB, $b_{\max} = 6$(m, dB).

Fig. 4 and Fig. 5 separately show the RMSE of position and orientation estimations versus the maximum value of the NLOS biases (i.e., b_{max}). As can be seen, for each method, the accuracy of estimation decreases gradually with b_{max}. Since the estimation process of the ImageP method is roughly based on image processing technology, its performance is far

[6] We set the values of $\sigma_{\tau_i}^2$, $\sigma_{n_i}^2$, η_i and μ_i $(i = 1, 2, \ldots, N)$ to be known for this method, as it requires knowledge about them.

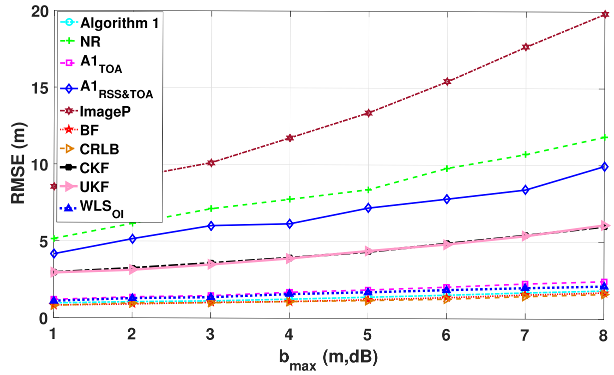

Fig. 4. RMSE of position estimation versus $b_{\max}$ comparison, when $\sigma_{n_i} = 3$m, $\sigma_{\tau_i} = 3$dB, $N = 8$.

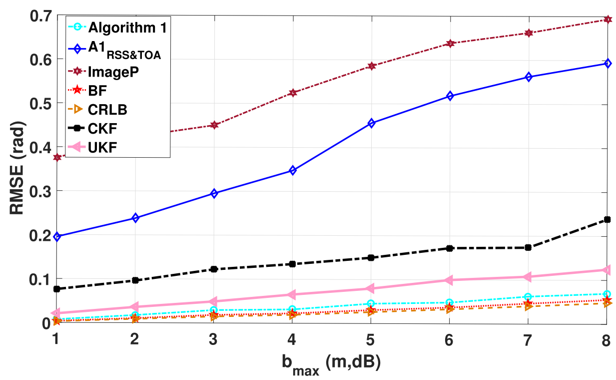

Fig. 5. RMSE of orientation estimation versus $b_{\max}$ comparison, when $\sigma_{n_i} = 3$m, $\sigma_{\tau_i} = 3$dB, $N = 8$.

inferior to other comparison methods. Similarly, performance of CKF is comparable to that of UKF in terms of position estimation, but there is a clear gap in the orientation estimation. In general, the performance of proposed estimator (i.e., Algorithm 1) is superior to that of $\mathrm{WLS_{OI}}$, $A1_{\mathrm{TOA}}$, UKF, CKF, $\mathrm{A1_{RSS\&TOA}}$, NR and ImageP in sequence, and has little difference with the lower bounds (i.e., BF and CRLB). To gain some intuition, the RMSE of position estimation of CRLB, BF, Algorithm 1, $\mathrm{WLS_{OI}}$, $A1_{\mathrm{TOA}}$, UKF, CKF, $\mathrm{A1_{RSS\&TOA}}$, NR and ImageP are respectively 1.147m, 1.221m, 1.432m, 1.694m, 1.865m, 4.675m, 4.682m, 7.191m, 8.392m and 13.394m, while RMSE of orientation estimation of CRLB, BF, Algorithm 1, UKF, CKF, $\mathrm{A1_{RSS\&TOA}}$ and ImageP are separately 0.027rad, 0.031rad, 0.045rad, 0.079rad, 0.149rad, 0.456rad and 0.586rad when $b_{max} = 5$(m, dB).

V. Conclusion

As opposed to previous related work, this letter considered localizing a directional target in NLOS environments based on RSS-TOA combined measurements. By combining the operation of converting the non-convex estimating problem into a GTRS, an skillfully estimator was proposed, where the position, orientation of the target and the NLOS biases are estimated alternately. Simulation results have demonstrated the superiority of the estimator, and shown that its performance is close to the lower bounds set by the brute force method and the CRLB.

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