IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 20 October 2023, accepted 2 November 2023, date of publication 13 November 2023, date of current version 20 November 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3332482

RESEARCH ARTICLE

Joint Rigid Body Localization and Wireless Signal Transmission Parameter Estimation Under NLOS Environment

PENGWU WAN, WENJIE LI, JIAN WEI, AND YIFAN WEN
School of Communications and Information Engineering, Xi'an University of Posts and Telecommunications, Xi'an 710121, China
School of Artificial Intelligence, Xi'an University of Posts and Telecommunications, Xi'an 710121, China

Corresponding author: Pengwu Wan (wpw_lz@126.com)

This work was supported in part by the National Natural Science Foundation of China (NSFC) under Grant 62101441, and in part by the National Key Laboratory Foundation under Grant 6142411222203 and Grant 2022-JCJQ-LB-006.

ABSTRACT To improve the performance of the rigid body localization (RBL) in the non-line-of-sight (NLOS) environment, this paper delves into a joint estimation method about the wireless signal transmission parameter and the attitude parameters of the rigid body, employing Time Difference of Arrival (TDOA) and Received Signal Strength (RSS) measurements. In the initial phase, the rigid body sensors localization problem is transformed into a difference of convex (DC) programming based on the TDOA measurement, and the concave–convex procedure (CCCP) is adopted to solve the initial estimate of the rigid body sensors position. Subsequently, the positions of the rigid body sensors are estimated based on the RSS measurement, and the wireless signal transmission parameters are obtained by using the weighted least square method. Finally, the minimization objective function is reconstructed is reconstructed by incorporating modified RSS and TDOA measurements. The attitude parameters of the rigid body are then determined using a combination of the bisection method and singular value decomposition (SVD). Simulation results demonstrate the effectiveness of this proposed approach in significantly enhancing RBL accuracy under NLOS environments.

INDEX TERMS Rigid body localization, non-line-of-sight, difference of convex programming, concave–convex procedure.

I. INTRODUCTION

With the rapid development of wireless sensor network (WSN) and Internet of Things (IoT), coupled with the accelerated deployment of the fifth-generation mobile communication technology (5G) and the artificial intelligence (AI) technology, the demanding for high-precision position-based services is growing faster than expected, catering to an increasing variety of users and smart devices, which makes wireless localization technology becoming a major problem in the fields of wireless communication, information perception and signal processing [1], [2]. Traditionally, the WSN-based wireless localization technology takes the target as an independent point source in the two-dimensional (2)-D) or three-dimensional (3)-D) space. The position parameters contained in the signals received by the distributed sensors network are extracted, such as angle of arrival (AOA) [3], received signal strength (RSS) [4], time of arrival (TOA) and time difference of arrival (TDOA) [5], [6]. The position of the target is determined by combining them with the application scenarios, which playing an important role in the path planning, target tracking, attraction recommendation and other basic position services for users.

In recent years, driven by diverse user demands and the rapid advancements in AI technology, an increasing number of smart devices, including robots, robotic arms, space vehicles, and various rigid bodies, have found extensive application in areas such as unknown area exploration, smart factory manufacturing, and outer space exploration. To guarantee the application of the above devices for high

The associate editor coordinating the review of this manuscript and approving it for publication was Riccardo Carotenuto.

precision and real-time update of their status information, it is most important to accurately acquire the position parameters and the orientation information or motion direction [7], [8]. For instance, in industrial manufacturing, motion direction information is pivotal in determining the orientation of robot arms and other equipment, thus ensuring efficient and accurate industrial production. In navigation systems, motion direction data determines the orientation of unmanned aerial vehicles (UAVs), a critical factor for safe route planning and execution in unmanned systems [9], [10]. Additionally, orientation information directly influences the accuracy of a vehicle's flight attitude, aiding in trajectory adjustments and precise docking maneuvers in the aerospace sector. Consequently, the motion direction or orientation parameters of the smart devices play an essential role in controlling, maneuvering, safety and security. As a result, it presents a significant challenge for Wireless Sensor Network (WSN) localization technology to precisely estimate both the position parameters and orientation information for modern smart devices.

Obviously, the mentioned problem above is the technology of rigid body localization (RBL), which employs an array of sensors mounted on the rigid body with the external shape fixed and without deformation. The relative position of the sensors is determined, and the geometrical shape of the array is conforming to the rigid body, which can be called as rigid body conformal sensor array. When the smart device mentioned above is equipped with such an array, the position and orientation information of the device can be determined according to the localization results of the sensors array. In general, this process involves measuring wireless signals transmitted between the sensors and the anchors distributed within the surrounding environment to determine the array's attitude parameters. These attitude parameters, in turn, serve as the foundation for computing both the position parameters and the orientation data of the rigid body [11].

In reality, numerous advanced techniques have been introduced for estimating the attitude parameters of rigid bodies, such as visual recognition, global positioning system (GPS), laser radar, inertial navigation system (INS) and various fusion methods involving localization technologies [12]. Nevertheless, due to the application scenarios of the RBL are mostly in complex urban areas or indoor environments, the performance of the mentioned technologies is weakened for the obstruction or the interference factors. Specially, the non-line of sight (NLOS) transmission of the wireless signals and the increasing complexity of the wireless signal transmission environment usually lead to the localization performance deterioration significantly.

Therefore, to overcome the influence of the NLOS transmission channel and the complexity environment on the position and the orientation information estimation of the rigid body, a joint method is proposed to estimate the attitude parameters of the rigid body and the wireless signal transmission parameters under the NLOS environment in this paper, where the obtained transmission parameters are utilized to accurately refine the final results of the rigid body's position. The main contributions are summarized as follows.

- To improve the performance of the RBL in the NLOS environment based on WSN, the TDOA and RSS measurements are combined to jointly estimate the attitude parameters of the rigid body and the wireless signal transmission parameters.
- The rigid body sensors localization problem is transformed into a difference of convex (DC) programming based on the time domain measurement information, and the concave–convex procedure (CCCP) is adopted to solve the initial estimate of the rigid body sensors position.
- The MLE problem of rigid body sensors position solution is transformed into a generalized trust region subproblem (GTRS), which is solved by using the bisection method and the obtained wireless signal transmission parameters are employed to refine the final results.

The rest of this paper is organized as follows. The related works are provided in Section II. Section III constructs the RBL problem based on the WSN in the NLOS environment. Section IV presents the proposed method to estimate the attitude parameters of the rigid body. Section V simulates and compares the RBL performance of the proposed method with the existing methods in the NLOS environment. Section VI concludes the whole paper and provides an outlook on the subsequent work.

II. RELATED WORK

To accurately obtain the position and orientation information of the smart devices, RBL technology was first introduced by Chepuri et al. in [13]. By extracting the parameters contained in the wireless signal between the rigid body sensors and the anchors, the attitude information (including position and orientation) of the body can be estimated according to the geometrical relationship of the rigid body sensors and the body. Initially, the problem was primarily addressed in an ideal environment, neglecting error factors such as anchors position error, clock asynchronization between sensors, and the non-ideal channel of the wireless signal transmission. In recent years, some advanced methods about RBL problem in the non-ideal environment are proposed, which mainly consider the error factors above and have excellent performance. Unfortunately, the research about the influence of the NLOS in the wireless signal transmission on the RBL problem is rather scarce.

A. RBL IN IDEAL ENVIRONMENT

In the ideal environment, the error factors are left out of consideration, the existing methods mainly address the problem of accurately estimating the attitude parameters of the rigid body. The system model was firstly constructed in [13], which utilized both constrained least squares (CLS) and simplified constrained least squares methods to determine the attitude parameters of the rigid body, and the closed-form solution of the original objective equation was obtained. By using the AOA measurement information in ideal environment, Zhou et al. introduced the modified Newton iteration method, the participatory searching algorithm and the particle swarm optimization to determine the rigid body sensor position, respectively [20], [21], [22], where the attitude parameters of the rigid body were determined based on the unit quaternion and singular value decomposition (SVD) method. In [23], the RBL problem is formulated as a constrained weighted least squares problem, the global optimal solution was obtained by using the semidefinite relaxation (SDR) algorithm with a reasonable second-order cone constraint, which can be relaxed into a convex semidefinite programming problem and the localization performance can reach the Cramer-Rao lower bound (CRLB) at lower noise level. In [18], the SDR method and the projection matrix were introduced into the RBL problem to estimat the optimal solution of the rigid body attitude parameters, which can reach the CRLB performance. In order to solve the problem of RBL in the anchors-less deployment scenario, the literature [15] proposed a relative localization solution for two rigid body targets by using the multidimensional scalar analysis method and the CLS algorithm, which can overcome the effect caused by the distance measurements partially missing between all sensors on the two rigid body targets.

As for the moving rigid body, the parameters to be estimated in the RBL technology include not only the position information, but also the moving direction and the speed of the rigid body. Without multiple measurement information, the authors in the literature [14] investigated the dynamic rigid body tracking and localization problem in ideal environment based on the distance measurements and the Kalman filtering algorithm, which can significantly decrease the redundant information transmission and the computational complexity. By using the measurement information of distance and Doppler shift, Chen et al. employed the divide and conquer (DAC) method to estimate the initial solutions of the rigid body's attitude parameters in the stationary and moving scene respectively. Then a more accurate estimation of the attitude parameters was obtained according to the euler angles equation [16]. Furthermore, a two-step algorithm was proposed to solve the moving RBL problem in 2-D scenes [17]. In the algorithm, the initial position coordinates of the rigid body sensors were estimated firstly by using the weighted least squares (WLS), then the results were refined by introducing auxiliary constraint on the original problem to obtain the attitude parameters of the rigid body and the velocity. The algorithm is suitable for moving RBL scenarios with limited device resources and has lower computation complexity. In [19], the attitude parameters of the rigid body were estimated by using both the distance measurement parameters and the Doppler frequency shift, which method was not only able to achieve the CRLB at low noise level, but also has higher computational efficiency.

B. RBL IN NON-IDEAL ENVIRONMENT

The research results about RBL problem mentioned above mainly were conducted in the ideal environment, where the anchors' position are known exactly and the clock errors are not considered. However, there are many error factors in the wireless signal transmission processing under non-ideal environment, which lead to performance deterioration of the rigid body localization accuracy.

To overcome the effect caused by the anchors position error, Hao et al. introduced a calibration source into the RBL system to accurately estimate the position and the orientation information of the target rigid body [24]. According to the proposed method, the highly non-convex RBL equation was firstly transformed into an unconstrained optimization problem by using the Euler angles parametric rotation matrix, then three different maximum likelihood estimation (MLE) methods were proposed to determine the attitude parameters. Finally, a closed-form solution was given based on the DAC algorithm and SDR algorithm to calculate the global optimal solution in the anchors' position error environment. The RBL method based on TOA measurement information requires strict clock synchronization between anchors and rigid body sensors, but it is difficult to guarantee in the practical application scenario. Therefore, Ke et al. investigated the deterioration of RBL performance due to the clock asynchronization in the anchors network [25]. The method utilized the SDR algorithm to estimate the attitude parameters of the rigid body, and the clock offset parameters were calculated to compensate the localization errors. Then the constrained CRLB in the present of the clock deviation was derived to evaluate the localization performance of the proposed algorithm.

With the increasingly complex channel environment of the wireless signal transmission, and the fact that RBL technology is mostly used in the complex urban or indoor environments. It is difficult to guarantee the line of sight (LOS) transmission of wireless signals between the anchors and the rigid body sensors, which makes the transmission delay increasing due to NLOS transmission of wireless signals or the signal transmitting power declining on a large scale. Therefore, the RBL performance would be worsened due to the NLOS environment. In [39], we formulated the RBL problem in the NLOS environment based on the TOA measurement between the anchors and the rigid body sensors, the original MLE problem was converted into a difference of convex (DC) programming. By introducing the modified CCCP algorithm and the SVD algorithm, the precise estimation of the position and orientation information of the rigid body was determined, which can obtain the NLOS parameters meantime. However, there are some other error factors such as the clock asynchronous and the dynamic wireless transmission parameters combining together in the NLOS environment, which would seriously affect the performance of the RBL in the complexty application scenarios.

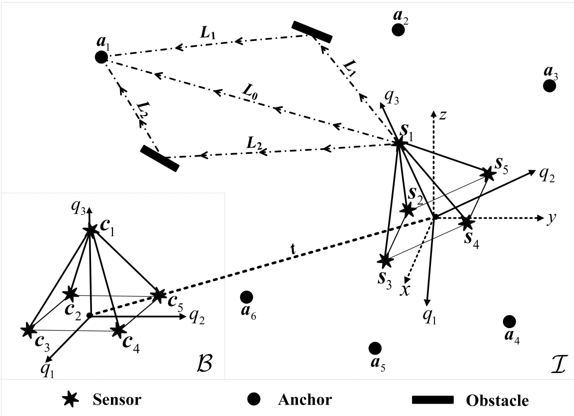


FIGURE 1. 3-D scenario of rigid body localization in the NLOS environment.

III. PROBLEM FORMULATION

Considering in a K dimensional ($K = 2$ or 3) space, N sensors are mounted on the rigid body and conformal with it, their positions are known in the local coordinate system $\mathcal{B}$ and denoted as $\boldsymbol{c}_i \in \mathbb{R}^K$, $i = 1, 2, \ldots, N$. When the rigid body target goes through with the rotation matrix $\boldsymbol{Q} \in \mathbb{R}^{K\times K}$ and the translation vector $\boldsymbol{t} \in \mathbb{R}^K$, the positions of all rigid body sensors in the global coordinate system $\mathcal{L}$ are denoted as $\boldsymbol{s}_i \in \mathbb{R}^K$, $i = 1, 2, \ldots, N$. According to the Stiefel manifold function, $\boldsymbol{s}_i$ can be expressed as [26]

$$\boldsymbol{s}_i = \boldsymbol{Q}\boldsymbol{c}_i + \boldsymbol{t} \tag{1}$$

where $\boldsymbol{Q}$ and $\boldsymbol{t}$ are the parameters of the rigid body attitude to be estimated in the RBL problem. In addition, the rotation matrix $\boldsymbol{Q}$ must satisfy the special orthogonality relation $\mathrm{SO}(K) = \left\{\boldsymbol{Q} \in \mathbb{R}^{K\times K} : \boldsymbol{Q}^{\mathrm{T}}\boldsymbol{Q} = \boldsymbol{I}, \det(\boldsymbol{Q}) = 1\right\}$, and $\boldsymbol{I}$ is the unit matrix [27].

In 3-D scenario ($K = 3$), the RBL problem based on the conformal sensor array in the NLOS environment is shown in Figure 1. M anchors are employed to determine the rigid body's attitude parameters. Their positions are precisely known in the global coordinate system $\mathcal{L}$, and denoted as $\boldsymbol{a}_m \in \mathbb{R}^K$, $m = 1, 2, \ldots, M$. Assuming that the wireless channel between the rigid body sensor and anchor contains both LOS and NLOS transmissions. For example, L_0 is the LOS path of the radiation signal, L_1 and L_2 are both the NLOS paths caused by the reflection of the radiation signal from obstacles between $\boldsymbol{s}_1$ and $\boldsymbol{a}_1$. Assuming that all rigid body sensors are capable of actively sending wireless signals to anchors, the anchors record the RSS measurements and TDOA measurements of the radiated signals, denoted as

$$P_{mi} = P_i - 10\gamma\log_{10}\frac{\|\boldsymbol{a}_m - \boldsymbol{s}_i\|}{r_0} + l_{mi} - e_{mi} \tag{2}$$

$$d_{mi} = \|\boldsymbol{a}_m - \boldsymbol{s}_i\| - \|\boldsymbol{a}_1 - \boldsymbol{s}_i\| + n_{mi} + b_{mi} \tag{3}$$

where $\|\boldsymbol{a}_m - \boldsymbol{s}_i\|$ represents the true distance between the i-th rigid body sensor and the m-th anchor, $l_{mi} \sim \mathcal{N}\left(0, \sigma_{l_{mi}}^2\right)$ is the RSS log-shadow fading, $n_{mi} \sim \mathcal{N}\left(0, \sigma_{n_{mi}}^2\right)$ is the TDOA measurement error, it is assumed that the measurement errors and the log-shadow fading are independent at different sensors. P_i is the transmitted signal of the rigid body sensor $\boldsymbol{s}_i$ at the reference distance r_0, γ is the transmission path loss factor, e_{mi} and b_{mi} are the NLOS error factors in the RSS measurement and TDOA measurement, and their maximum values are denoted as $e_{\max}$ and $b_{\max}$, respectively [28]. It is worth to mentioning that the transmission parameters of P_i and γ are different for different channel in the complex NLOS environment, which will be taken as unknowns to to estimated in the following section.

According to the Stiefel manifold function, the MLE problem for estimating the rigid body attitude parameters $\boldsymbol{Q}$ and $\boldsymbol{t}$, the signal strength P_i emitted from the rigid body sensors, and the wireless signal transmission path loss coefficient γ is expressed as

$$\begin{aligned}\min_{\boldsymbol{Q},\boldsymbol{t},P_i,\gamma} &\left[\sum_{m=2}^{M}\sum_{i=1}^{N}\frac{\left(d_{mi}-\|\boldsymbol{a}_m-\boldsymbol{Q}\boldsymbol{c}_i-\boldsymbol{t}\|+\|\boldsymbol{a}_1-\boldsymbol{Q}\boldsymbol{c}_i-\boldsymbol{t}\|-b_{mi}\right)^2}{\sigma_{n_{mi}}^2}\right.\\ &\left.+\sum_{m=1}^{M}\sum_{i=1}^{N}\frac{\left(P_{mi}-P_i+10\gamma\log_{10}\frac{\|\boldsymbol{a}_m-\boldsymbol{Q}\boldsymbol{c}_i-\boldsymbol{t}\|}{r_0}+e_{mi}\right)^2}{\sigma_{l_{mi}}^2}\right]\\ \text{s.t. } &\boldsymbol{Q}^{\mathrm{T}}\boldsymbol{Q} = \boldsymbol{I}, \det(\boldsymbol{Q}) = 1\end{aligned} \tag{4}$$

Obviously, the problem in (4) is a highly non-convex problem without closed-form analytical solution, which is difficult to be solved directly to determine the unknown parameters. Therefore, it is necessary to split and transform the original problem in a reasonable manner to estimate the unknown parameters, including $\boldsymbol{Q}$, $\boldsymbol{t}$, P_i and γ.

IV. PROPOSED RBL ALGORITHM

In the complex electromagnetic environment, due to the complex and variable channel state during the wireless signal transmission, it is difficult to directly distinguish if the wireless signal received by the anchors array belongs to LOS or NLOS in the practical applications, which makes it hard to determine the value of NLOS error in the measurement information, and further leads to serious degradation of RBL accuracy.

To accurately estimate the attitude parameters $\boldsymbol{Q}$ and $\boldsymbol{t}$ of the target rigid body, an alternate methods is proposed by using the TDOA and RSS measurements respectively in this paper, which has been demonstrated that information fusion can obtain accurate performance than single measurement in [29].

Specifically, the TDOA measurements in NLOS environment are firstly employed to initially determine the position coordinates of the rigid body sensors. Then, the initial estimation of the rigid body sensors position is coupled with the RSS measurements to construct a DRSS localization model, which is solved by using the WLS method to determine the transmission path loss coefficient of the wireless signal. By substituting the obtained parameters into the RSS localization model, the signal strength emitted from the rigid body sensors is solved iteratively. Finally, the RSS localization model is reconstructed based on the determined transmit signal strength and the path loss coefficient, and the minimization objective function of the RBL problem is constructed by combining the TDOA localization model. The rigid body's attitude parameters are determined according to the the bisection method and SVD method.

A. INITIAL ESTIMATION OF THE RIGID BODY SENSORS

Theoretically, a continuous function $\mathrm{F}(x)$ is called a DC function if it can be expressed as the difference form of two convex functions $f(x)$ and $g(x)$ in its convex domain $\mathbb{D}$, the programming problem dealing with DC functions called DC programming [30]. For the DC programming problem, it can be solved by using the CCCP algorithm to find out the optimal solution of the objective function [31].

Therefore, the MLE function of the rigid body sensors position estimation problem based on TDOA measurements can be expressed as

$$\min_{\boldsymbol{s}_i} \sum_{m=2}^{M} \sum_{i=1}^{N} \left[f_{mi}(\boldsymbol{s}_i) - g_{mi}(\boldsymbol{s}_i) - h_{mi}(\boldsymbol{s}_i)\right] \tag{5}$$

where

$$f_{mi}(\boldsymbol{s}_i) = (d_{mi} - b_{mi})^2 + \|\boldsymbol{a}_m - \boldsymbol{s}_i\|^2 + \|\boldsymbol{a}_1 - \boldsymbol{s}_i\|^2 \tag{6}$$

$$g_{mi}(\boldsymbol{s}_i) = 2\|\boldsymbol{a}_m - \boldsymbol{s}_i\| \cdot \|\boldsymbol{a}_1 - \boldsymbol{s}_i\| \tag{7}$$

$$h_{mi}(\boldsymbol{s}_i) = 2(d_{mi} - b_{mi}) \cdot (\|\boldsymbol{a}_m - \boldsymbol{s}_i\| - \|\boldsymbol{a}_1 - \boldsymbol{s}_i\|) \tag{8}$$

Obviously, f_{mi} is a convex function, g_{mi} and h_{mi} are nonconvex functions that consist of a parametric product and a parametric difference, respectively. In order to convert the MLE problem in equation (5) into a DC programming problem, auxiliary variables μ_{mi} and ϑ_{mi} are introduced to compensate the non-convex part in g_{mi} and h_{mi}, so that $f_{mi}(\boldsymbol{s}_i) - \mu_{mi}(\boldsymbol{s}_i) - \vartheta_{mi}(\boldsymbol{s}_i)$, $g_{mi}(\boldsymbol{s}_i) - \mu_{mi}(\boldsymbol{s}_i)$ and $h_{mi}(\boldsymbol{s}_i) - \vartheta_{mi}(\boldsymbol{s}_i)$ become convex functions. Therefore, the original objective function in (5) can be converted as

$$\min_{\boldsymbol{s}_i} \sum_{m=2}^{M} \sum_{i=1}^{N} \left[F_{mi,1}(\boldsymbol{s}_i) - F_{mi,2}(\boldsymbol{s}_i)\right] \tag{9}$$

where,

$$F_{mi,1}(\boldsymbol{s}_i) = f_{mi}(\boldsymbol{s}_i) - \mu_{mi}(\boldsymbol{s}_i) - \vartheta_{mi}(\boldsymbol{s}_i) \tag{10}$$

$$F_{mi,2}(\boldsymbol{s}_i) = g_{mi}(\boldsymbol{s}_i) - \mu_{mi}(\boldsymbol{s}_i) + h_{mi}(\boldsymbol{s}_i) - \vartheta_{mi}(\boldsymbol{s}_i) \tag{11}$$

Defining the auxiliary variables μ_{mi} and ϑ_{mi} as

$$\mu_{mi} = -2(\boldsymbol{a}_m - \boldsymbol{s}_i)^{\mathrm{T}}(\boldsymbol{a}_1 - \boldsymbol{s}_i) \tag{12}$$

$$\vartheta_{mi} = -2 \cdot (d_{mi} - b_{mi})\|\boldsymbol{a}_1 - \boldsymbol{s}_i\|^2 \tag{13}$$

Therefore,

$$g_{mi}(\boldsymbol{s}_i) - \mu_{mi}(\boldsymbol{s}_i) = 2\Big[\|\boldsymbol{a}_m - \boldsymbol{s}_i\| \cdot \|\boldsymbol{a}_1 - \boldsymbol{s}_i\| + (\boldsymbol{a}_m - \boldsymbol{s}_i)^{\mathrm{T}}(\boldsymbol{a}_1 - \boldsymbol{s}_i)\Big] \tag{14}$$

$$h_{mi}(\boldsymbol{s}_i) - \vartheta_{mi}(\boldsymbol{s}_i) = 2(d_{mi} - b_{mi}) \cdot (\|\boldsymbol{a}_m - \boldsymbol{s}_i\| - \|\boldsymbol{a}_1 - \boldsymbol{s}_i\|) - 2 \cdot (d_{mi} - b_{mi})\|\boldsymbol{a}_1 - \boldsymbol{s}_i\|^2 \tag{15}$$

According to the theoretical derivation, it can be verified that both equation (14) and equation (15) are convex functions [33]. It is further shown that $F_{mi,1}(\boldsymbol{s}_i)$ and $F_{mi,2}(\boldsymbol{s}_i)$ in equation (9) are also convex functions, thus the problem is a DC programming problem, which can be solved iteratively using the CCCP algorithm and the initial estimate $\tilde{\boldsymbol{s}}_i$ of the rigid body sensors position can be obtained.

Obviously, the obtained $\tilde{\boldsymbol{s}}_i$ can be substituted directly into (1) to calculate the attitude parameters $\boldsymbol{Q}$ and $\boldsymbol{t}$ of the target rigid body, but due to the existing of the NLOS error and the measurement error, the performance will be very poor. Therefore, the unknown wireless transmission parameters are estimated firstly in the follow section, and the fusion method of TDOA and RSS is introduced to accurate estimate the attitude parameters of the target rigid body.

B. CONSTRUCTING THE DRSS LOCALIZATION MODEL

Substituting the initial estimate of the rigid body sensors position $\tilde{\boldsymbol{s}}_i$ into the RSS localization model in equation (2), taking $\boldsymbol{a}_1$ as the reference anchor, the DRSS measurement information between anchors $\boldsymbol{a}_m$ and the reference anchor $\boldsymbol{a}_1$ to the rigid body sensors $\boldsymbol{s}_i$ is expressed as [34]

$$\bar{P}_{mi} = P_{mi} - P_{1i} = 10\gamma \log_{10}\left(\frac{\|\boldsymbol{a}_1 - \tilde{\boldsymbol{s}}_i\|}{\|\boldsymbol{a}_m - \tilde{\boldsymbol{s}}_i\|}\right) + \Delta l_{mi} + \Delta e_{mi} \tag{16}$$

where $\Delta l_{mi} = l_{mi} - l_{1i}$, $\Delta e_{mi} = e_{1i} - e_{mi}$.

C. ESTIMATION THE TRANSMISSION PATH LOSS FACTORS γ

Replacing the NLOS error difference Δe_{mi} in the DRSS measurements with its average value Δe_i. Letting $P'_{mi} = \bar{P}_{mi} - \Delta e_i$, according to the WLS criterion, the minimization objective function of the transmission path loss coefficient is constructed as

$$\min_{\gamma, \Delta e_m} \sum_{m=2}^{M} \omega_{P'_{mi}}\left[P'_{mi} - 10\gamma \log_{10}\left(\frac{\|\boldsymbol{a}_1 - \tilde{\boldsymbol{s}}_i\|}{\|\boldsymbol{a}_m - \tilde{\boldsymbol{s}}_i\|}\right)\right]^2 \tag{17}$$

where $\omega_{P'_{mi}}$ is the weight factor of DRSS measurements. And for DRSS information between the i-th rigid body sensors $\boldsymbol{s}_i$ and the array of M anchors that exists

$$\omega_{P'_{mi}} = P'_{mi} \Big/ \sum_{m=2}^{M} P'_{mi} \tag{18}$$

$$\Delta e_i = \frac{1}{M-1} \sum_{m=2}^{M} \Delta e_{mi} \tag{19}$$

According to (17), all DRSS measurements between the M anchors and the i-th rigid body sensors $\boldsymbol{s}_i$ are collated into the matrix form

$$\min_{\gamma, \Delta e_i} \|\boldsymbol{W}(\boldsymbol{A}\gamma - \boldsymbol{H})\|^2 \tag{20}$$

where the weighting matrix $\boldsymbol{W}$ is

$$\boldsymbol{W} = \mathrm{diag}\left[\sqrt{\omega_{P''_{2i}}}, \sqrt{\omega_{P''_{3i}}}, \cdots, \sqrt{\omega_{P''_{Mi}}}\right] \tag{21}$$

The matrices $\boldsymbol{A}$ and $\boldsymbol{H}$ in the objective function are

$$\boldsymbol{A}=\left[-10\log_{10}\left(\frac{\|\boldsymbol{a}_1-\tilde{\boldsymbol{s}}_i\|}{\|\boldsymbol{a}_2-\tilde{\boldsymbol{s}}_i\|}\right),-10\log_{10}\left(\frac{\|\boldsymbol{a}_1-\tilde{\boldsymbol{s}}_i\|}{\|\boldsymbol{a}_3-\tilde{\boldsymbol{s}}_i\|}\right),\cdots,-10\log_{10}\left(\frac{\|\boldsymbol{a}_1-\tilde{\boldsymbol{s}}_i\|}{\|\boldsymbol{a}_M-\tilde{\boldsymbol{s}}_i\|}\right)\right]^{\mathrm{T}} \tag{22}$$

$$\boldsymbol{H}=\left[-P''_{2i},-P''_{3i},\cdots,-P''_{Mi}\right]^{\mathrm{T}} \tag{23}$$

where $P''_{mi}=P'_{mi}\big|_{\Delta e_i=\Delta\hat{e}_i}$.

Firstly, the average covariance Δe_i of the NLOS error difference in the DRSS measurements is initialized as $\Delta e_i = 0$. Then, according to the defined P'_{mi} and P''_{mi}, the value of the wireless signal transmission path loss coefficient $\hat{\gamma}$ can be estimated by using the iterative WLS algorithm [35]. Coupling equation (24), the estimation of the NLOS error difference average parameter can be obtained as

$$\Delta\hat{e}_i=\frac{\sum_{m=2}^{M}\left[P''_{mi}-10\hat{\gamma}\log_{10}\left(\frac{\|\boldsymbol{a}_1-\tilde{\boldsymbol{s}}_i\|}{\|\boldsymbol{a}_m-\tilde{\boldsymbol{s}}_i\|}\right)\right]}{M-1}. \tag{24}$$

Then, substituting $\Delta\hat{e}_i$ into P'_{mi} and repeating the above processing, as long as the termination condition is satisfied, the final estimate of the loss coefficient $\hat{\gamma}$ is output. Where the termination condition is $\left|\hat{\gamma}^{(\mathrm{t})}-\hat{\gamma}^{(\mathrm{t}-1)}\right|/\hat{\gamma}^{(\mathrm{t}-1)}<\varepsilon$, ε is a positive number tending to zero, and t is the number of iterations times.

D. ESTIMATION THE RECEIVED SIGNAL STRENGTH P_I

Substituting the initial estimated rigid body sensors position $\tilde{\boldsymbol{s}}_i$ in subsection IV-A and the estimated transmission path loss factor $\hat{\gamma}$ determined in subsection IV-C above into the RSS localization model, replacing the NLOS error e_{mi} with the average parameter e_i, the modified RSS measurement is expressed as

$$\tilde{P}_{mi}=P_i-10\hat{\gamma}\log_{10}\frac{\|\boldsymbol{a}_m-\tilde{\boldsymbol{s}}_i\|}{r_0}+l_{mi}-e_i \tag{25}$$

where $e_i=\frac{1}{M}\sum_{m=1}^{M}e_{mi}$.

Letting $\tilde{P}'_{mi}=\tilde{P}_{mi}+e_i$, the expression for determining the signal strength P_i emitted from the rigid body sensors is reconstructed as

$$\hat{P}_i=\frac{\sum_{m=1}^{M}\left[\tilde{P}''_{mi}+10\tilde{\gamma}\log_{10}\frac{\|\boldsymbol{a}_m-\tilde{\boldsymbol{s}}_i\|}{r_0}\right]}{M} \tag{26}$$

where $\tilde{P}''_{mi}=\tilde{P}'_{mi}\Big|_{e_i=\hat{e}_i}$.

The NLOS error averaging e_i in equation (25) is initialized as $e_i = 0$. Based on the defined $\tilde{P}'_{mi}$ and $\tilde{P}''_{mi}$, the emitted signal strength $\hat{P}_i$ of the rigid body sensors by equation (26) can be calculated. Then substitute it into equation (27) to get the estimated value of the NLOS error average parameter as

$$\hat{e}_i=\frac{\sum_{m=1}^{M}\left[\hat{P}_i-\tilde{P}_{mi}-10\hat{\gamma}\log_{10}\frac{\|\boldsymbol{a}_m-\tilde{\boldsymbol{s}}_i\|}{r_0}\right]}{M} \tag{27}$$

Finally, substituting $\hat{e}_i$ into $\tilde{P}'_{mi}$ and repeating the above operation, the final estimation result $\hat{P}_i$ of the signal strength emitted from the rigid body sensors is obtained.

E. DETERMINING THE RIGID BODY SENSORS' POSITIONS

In the RBL problem with unknown the priori information about the wireless channel, the emitted signal strength P_i and the wireless signal transmission path loss factor γ of the rigid body sensors array have been determined in the above subsections. Therefore, according to the MLE expression constructed by equation (4), only the unknown parameters $\boldsymbol{Q}$ and $\boldsymbol{t}$ of the rigid body's attitude parameters still need to be solved.

However, due to the strong coupling between the rotation matrix $\boldsymbol{Q}$ and translation vector $\boldsymbol{t}$ of the rigid body, along with the highly nonlinear relationship between the parameters to be estimated and the measured parameters, solving the objective equation becomes challenging. Therefore, in this subsection, the MLE problem of rigid body sensors position solution is transformed into a generalized trust region subproblem (GTRS), and then the bisection method is employed to get the optimal solution of the rigid body sensors position. Finally, the rotation matrix $\boldsymbol{Q}$ and translation vector $\boldsymbol{t}$ of the rigid body are determined by using the procrustes analysis and Stiefel manifold function [36].

By substituting the estimated signal strength P_i of the rigid body sensors and the wireless signal transmission path loss factor γ into the RSS localization model expressed in equation (2), replacing the NLOS error b_{mi} in the TDOA measurements with the average parameter b_i, replacing the NLOS error e_{mi} in the RSS measurement with the average parameter e_i, the modified TDOA measurements and RSS measurements are reformulated as

$$\bar{P}_{mi}=P_i-10\gamma\log_{10}\frac{\|\boldsymbol{a}_m-\boldsymbol{s}_i\|}{r_0}+l_{mi}-e_i \tag{28}$$

$$\bar{d}_{mi}=\|\boldsymbol{a}_m-\boldsymbol{s}_i\|-\|\boldsymbol{a}_1-\boldsymbol{s}_i\|+n_{mi}+b_i \tag{29}$$

Although the above approximation processing loss part of the NLOS error information, the mean values e_i and b_i can be estimated with the rigid body sensors position $\boldsymbol{s}_i$ as the optimization variables in parallel, which make the RBL problem become determined and can be resolved. Furthermore, the obtained mean error can be employed to refine the final results.

By transferring and removing logarithms, equation (28) can be transformed into

$$\frac{\xi_{mi}^2\|\boldsymbol{a}_m-\boldsymbol{s}_i\|^2-\zeta_i^2}{2\xi_{mi}\|\boldsymbol{a}_m-\boldsymbol{s}_i\|}\approx\ell_{mi}-\frac{\ell_{mi}^2}{2\xi_{mi}\|\boldsymbol{a}_m-\boldsymbol{s}_i\|} \tag{30}$$

where $\zeta_i = r_0\cdot 10^{\frac{P_i-e_i}{10\gamma}}$, $\ell_{mi} = l_{mi}\cdot\left(r_0\cdot 10^{\frac{P_i-e_i}{10\gamma}}\right)\cdot(\ln 10/10\gamma)$, $\xi_{mi}=10^{\frac{\bar{P}_{mi}}{10\gamma}}$.

By transferring the mean NLOS error b_i to the left side of (29), and squaring both sides to get

$$\begin{aligned}(\bar{d}_{mi}-b_i)^2 = \|\boldsymbol{a}_m-\boldsymbol{s}_i\|^2+\|\boldsymbol{a}_1-\boldsymbol{s}_i\|^2 \\ -2\,\|\boldsymbol{a}_m-\boldsymbol{s}_i\|\cdot\|\boldsymbol{a}_1-\boldsymbol{s}_i\| \\ +2n_{mi}\left(\|\boldsymbol{a}_m-\boldsymbol{s}_i\|-\|\boldsymbol{a}_1-\boldsymbol{s}_i\|\right)+n_{mi}^2 \end{aligned} \tag{31}$$

Dividing both sides of (31) by $2\left(\|\boldsymbol{a}_m-\boldsymbol{s}_i\|-\|\boldsymbol{a}_1-\boldsymbol{s}_i\|\right)$, and transferring the relevant term containing the TDOA measurement error n_{mi} to the right side of the equation, one has

$$\begin{aligned}\frac{(\bar{d}_{mi}-b_i)^2-(\boldsymbol{a}_m-\boldsymbol{a}_1)^2}{2\left(\|\boldsymbol{a}_m-\boldsymbol{s}_i\|-\|\boldsymbol{a}_1-\boldsymbol{s}_i\|\right)} \\ = n_{mi}+\frac{n_{mi}^2}{2\left(\|\boldsymbol{a}_m-\boldsymbol{s}_i\|-\|\boldsymbol{a}_1-\boldsymbol{s}_i\|\right)}\end{aligned} \tag{32}$$

According to the principle that the weight factor of the anchors closer to the rigid body sensors is larger, i.e., the weight increases with the increasing of RSS measurements P_{mi} of the anchors, and decreases with the increasing of TDOA measurements d_{mi} of the anchors. Defining the weights of RSS and TDOA measurements as $\omega_{\mathrm{R}_{mi}} = 1-r'_{mi}\Big/\sum_{m=1}^{M} r'_{mi}$ and $\omega_{\mathrm{T}_{mi}} = 1-d'_{mi}\Big/\sum_{m=2}^{M} d'_{mi}$, respectively. The MLE function to estimate $\boldsymbol{s}_i$, b_i and e_i is expressed as

$$\begin{aligned}\min_{\boldsymbol{s}_i,b_i,e_i}\sum_{m=1}^{M}\sum_{i=1}^{N}\left[\omega_{\mathrm{R}_{mi}}\left(\frac{\xi_{mi}^2\|\boldsymbol{a}_m-\boldsymbol{s}_i\|^2-\zeta_i^2}{2\xi_{mi}\,\|\boldsymbol{a}_m-\boldsymbol{s}_i\|}\right)^2\right] \\ +\sum_{m=2}^{M}\sum_{i=1}^{N}\left[\omega_{\mathrm{T}_{mi}}\left(\frac{d'^{\,2}_{mi}-(\boldsymbol{a}_m-\boldsymbol{a}_1)^2}{2\left(\|\boldsymbol{a}_m-\boldsymbol{s}_i\|-\|\boldsymbol{a}_1-\boldsymbol{s}_i\|\right)}\right)^2\right]\end{aligned} \tag{33}$$

where $r'_{mi}=r_0 10^{(P_i-\bar{P}_{mi}-e_i)/10\gamma}$, $d'_{mi}=\bar{d}_{mi}-b_i$.

Obviously, equation (33) is highly nonconvex and hard to be solved directly. While it can be transformed into

$$\begin{aligned}\min_{\boldsymbol{s}_i,b_i,e_i}\sum_{m=1}^{M}\sum_{i=1}^{N}\left[\omega_{\mathrm{R}_{mi}}\left(\frac{\xi_{mi}^2\|\boldsymbol{a}_m-\boldsymbol{s}_i\|^2-\zeta_i^2}{2\xi_{mi}r'^{\,2}_{mi}}\right)^2\right] \\ +\sum_{m=2}^{M}\sum_{i=1}^{N}\left[\omega_{\mathrm{T}_{mi}}\left(\frac{d'^{\,2}_{mi}-(\boldsymbol{a}_m-\boldsymbol{a}_1)^2}{2d'^{\,2}_{mi}}\right)^2\right]\end{aligned} \tag{34}$$

With the obtained estimation of $\hat{e}_i$ and $\hat{b}_i$, equation (34) can be transformed into GTRS and solved by using the bisection method. The process is expressed as follows [37].

Defining the variables $\zeta'_i=\zeta_i|_{e_i=\hat{e}_i}$, $r''_{mi}=r'_{mi}|_{e_i=\hat{e}_i}$, $d''_{mi}=d'_{mi}|_{b_i=\hat{b}_i}$. Expanding and constructing (34) as

$$\min_{\boldsymbol{Y}=\left[\boldsymbol{s}_i^{\mathrm{T}}\,\|\boldsymbol{s}_i\|^2\right]^{\mathrm{T}}}\left\{\|\boldsymbol{W}(\boldsymbol{A}\boldsymbol{Y}-\boldsymbol{P})\|^2:\boldsymbol{Y}^{\mathrm{T}}\boldsymbol{D}\boldsymbol{Y}+2\boldsymbol{G}^{\mathrm{T}}\boldsymbol{Y}=0\right\} \tag{35}$$

where

$$\boldsymbol{W}=\begin{bmatrix}\boldsymbol{W}_{\mathrm{R}} & 0_{MN\times(M-1)N}\\ 0_{(M-1)N\times MN} & \boldsymbol{W}_{\mathrm{T}}\end{bmatrix} \tag{36}$$

$$\begin{aligned}\boldsymbol{W}_{\mathrm{R}}=\mathrm{diag}\Bigg[\frac{\sqrt{\omega_{\mathrm{R}_{11}}}}{2\xi_{11}r''_{11}},\frac{\sqrt{\omega_{\mathrm{R}_{21}}}}{2\xi_{21}r''_{21}},\cdots,\frac{\sqrt{\omega_{\mathrm{R}_{M1}}}}{2\xi_{M1}r''_{M1}}, \\ \cdots,\frac{\sqrt{\omega_{\mathrm{R}_{1N}}}}{2\xi_{1N}r''_{1N}},\frac{\sqrt{\omega_{\mathrm{R}_{2N}}}}{2\xi_{2N}r''_{2N}},\cdots,\frac{\sqrt{\omega_{\mathrm{R}_{MN}}}}{2\xi_{MN}r''_{MN}}\Bigg]\end{aligned} \tag{37}$$

$$\begin{aligned}\boldsymbol{W}_{\mathrm{T}}=\mathrm{diag}\Bigg[\frac{\sqrt{\omega_{\mathrm{T}_{11}}}}{2d''_{11}},\frac{\sqrt{\omega_{\mathrm{T}_{21}}}}{2d''_{21}},\cdots,\frac{\sqrt{\omega_{\mathrm{T}_{M1}}}}{2d''_{M1}}, \\ \cdots,\frac{\sqrt{\omega_{\mathrm{T}_{1N}}}}{2d''_{1N}},\frac{\sqrt{\omega_{\mathrm{T}_{2N}}}}{2d''_{2N}},\cdots,\frac{\sqrt{\omega_{\mathrm{T}_{MN}}}}{2d''_{MN}}\Bigg]\end{aligned} \tag{38}$$

The matrices in the constraints are respectively

$$\boldsymbol{D}=\begin{bmatrix}\boldsymbol{I}_K & 0_{K\times1}\\ 0_{1\times K} & 0\end{bmatrix},\boldsymbol{G}=\begin{bmatrix}0_{K\times1}\\ -\frac{1}{2}\end{bmatrix} \tag{39}$$

The matrices in the minimization objective function are respectively

$$\boldsymbol{A}=\begin{bmatrix}\boldsymbol{A}_{\mathrm{R}}\\ 0_{(M-1)N\times(K+1)}\end{bmatrix},\quad \boldsymbol{P}=\begin{bmatrix}\boldsymbol{P}_{\mathrm{R}}\\ \boldsymbol{P}_{\mathrm{T}}\end{bmatrix} \tag{40}$$

$$\boldsymbol{A}_{\mathrm{R}}=\begin{bmatrix}2\xi_{11}^2\boldsymbol{a}_1^{\mathrm{T}} & -\xi_{11}^2\\ 2\xi_{21}^2\boldsymbol{a}_2^{\mathrm{T}} & -\xi_{21}^2\\ \vdots & \vdots\\ 2\xi_{M1}^2\boldsymbol{a}_M^{\mathrm{T}} & -\xi_{M1}^2\\ \vdots & \vdots\\ 2\xi_{1N}^2\boldsymbol{a}_1^{\mathrm{T}} & -\xi_{1N}^2\\ 2\xi_{2N}^2\boldsymbol{a}_2^{\mathrm{T}} & -\xi_{2N}^2\\ \vdots & \vdots\\ 2\xi_{MN}^2\boldsymbol{a}_M^{\mathrm{T}} & -\xi_{MN}^2\end{bmatrix} \tag{41}$$

$$\boldsymbol{P}_{\mathrm{R}}=\begin{bmatrix}\xi_{11}^2\|\boldsymbol{a}_1\|^2-\zeta_1'^2\\ \xi_{21}^2\|\boldsymbol{a}_2\|^2-\zeta_1'^2\\ \vdots\\ \xi_{M1}^2\|\boldsymbol{a}_M\|^2-\zeta_1'^2\\ \vdots\\ \xi_{1N}^2\|\boldsymbol{a}_1\|^2-\zeta_N'^2\\ \xi_{2N}^2\|\boldsymbol{a}_2\|^2-\zeta_N'^2\\ \vdots\\ \xi_{MN}^2\|\boldsymbol{a}_M\|^2-\zeta_N'^2\end{bmatrix} \tag{42}$$

$$\boldsymbol{P}_{\mathrm{T}}=\begin{bmatrix}\|\boldsymbol{a}_2-\boldsymbol{a}_1\|^2-d''^{\,2}_{21}\\ \|\boldsymbol{a}_3-\boldsymbol{a}_1\|^2-d''^{\,2}_{31}\\ \vdots\\ \|\boldsymbol{a}_M-\boldsymbol{a}_1\|^2-d''^{\,2}_{M1}\\ \vdots\\ \|\boldsymbol{a}_2-\boldsymbol{a}_1\|^2-d''^{\,2}_{2N}\\ \|\boldsymbol{a}_3-\boldsymbol{a}_1\|^2-d''^{\,2}_{3N}\\ \vdots\\ \|\boldsymbol{a}_M-\boldsymbol{a}_1\|^2-d''^{\,2}_{MN}\end{bmatrix} \tag{43}$$

It can be seen from (35) that the above problem belongs to GTRS, which can be solved by using the bisection method to obtain the estimated value $\hat{\boldsymbol{Y}}$ containing the information on the position of the rigid body sensors $\boldsymbol{s}_i$. According to the definition $\boldsymbol{Y} = \left[\boldsymbol{s}_i^{\mathrm{T}} \ \|\boldsymbol{s}_i\|^2\right]^{\mathrm{T}}$, the estimated coordinates of the rigid body sensors positions can be obtained as

$$\hat{\boldsymbol{s}}_i = \hat{\boldsymbol{Y}}(1:3) \tag{44}$$

To improve the estimation performance of the rigid body sensors' positions, an iterative program is introduced, which alternately estimate the NLOS error factors and the positions to refine the results. The iterative estimation steps are summarized as follows.

Step 1: Initializing the NLOS error mean e_i, b_i and iteration times t, $e_i^{(0)} = 0$, $b_i^{(0)} = 0$, $\mathrm{t} = 1$.

Step 2: Calculating the variables ζ', r''_{mi} and d''_{mi} by using e_i and b_i, respectively.

Step 3: Substituting the values of ζ', r''_{mi} and d''_{mi} into equation (35), and obtaining the t-th rigid body sensors position estimate $\hat{\boldsymbol{s}}_i^{(\mathrm{t})}$.

Step 4: Substituting the position estimates $\hat{\boldsymbol{s}}_i^{(\mathrm{t})}$ into equations (45) and (46), and determining the t-th NLOS error estimation $\hat{e}_i^{(\mathrm{t})}$ and $\hat{b}_i^{(\mathrm{t})}$.

$$\hat{e}_i^{(\mathrm{t})} = \frac{\sum_{m=1}^{M}\left(P_i - \bar{P}_{mi} - 10\gamma\log_{10}\frac{\left\|\boldsymbol{a}_m - \hat{\boldsymbol{s}}_i^{(\mathrm{t})}\right\|}{r_0}\right)}{M} \tag{45}$$

$$\hat{b}_i^{(\mathrm{t})} = \frac{\sum_{m=2}^{M}\left(\bar{d}_{mi} - \left\|\boldsymbol{a}_m - \hat{\boldsymbol{s}}_i^{(\mathrm{t})}\right\| + \left\|\boldsymbol{a}_1 - \hat{\boldsymbol{s}}_i^{(\mathrm{t})}\right\|\right)}{M-1} \tag{46}$$

Step 5: Substituting the NLOS mean error estimates obtained from Step 4 into Step 2, updating $\mathrm{t} = \mathrm{t} + 1$, and iterate the above operation steps until the termination condition is satisfied, then output the final rigid body sensors position estimates $\hat{\boldsymbol{s}}_i$. $\left|\hat{\boldsymbol{s}}_i^{(\mathrm{t})} - \hat{\boldsymbol{s}}_i^{(\mathrm{t}-1)}\right| \Big/ \hat{\boldsymbol{s}}_i^{(\mathrm{t}-1)} < \varepsilon$ or $\mathrm{T}_{\max} < \mathrm{t}$ is the termination condition, where ε is a positive number converging to zero, $\mathrm{T}_{\max}$ is the maximum times of iteration.

F. DETERMINING THE RIGID BODY'S ATTITUDE PARAMETERS

The position information of the rigid body sensors in the local coordinate $\mathcal{B}$ and global coordinate $\mathcal{L}$ systems are represented as $\boldsymbol{c}_i$ and $\boldsymbol{s}_i$, respectively. $\boldsymbol{c}_i$ is known and $\boldsymbol{s}_i$ is obtained in the above subsection. According to (1), determining the rotation matrix $\mathbf{Q}$ and translation vector $\mathbf{t}$ between two sets of data points in different coordinate systems can be formulated as a least squares minimization problem [38]

$$\begin{aligned} &\min_{\boldsymbol{Q},\boldsymbol{t}} \sum_{i=1}^{N} \|\boldsymbol{s}_i - (\boldsymbol{Q}\boldsymbol{c}_i + \boldsymbol{t})\|^2 \\ &\text{s.t. } \boldsymbol{Q} \in \mathrm{SO}(K) \end{aligned} \tag{47}$$

The rigid body has the same center of mass in the local and global coordinate systems, which can be expressed as

$$\bar{\boldsymbol{c}} = \frac{\sum_{i=1}^{N}\boldsymbol{c}_i}{N}, \quad \bar{\boldsymbol{s}} = \frac{\sum_{i=1}^{N}\boldsymbol{s}_i}{N} \tag{48}$$

Let $\bar{\boldsymbol{s}}_i = \boldsymbol{s}_i - \bar{\boldsymbol{s}}$, $\bar{\boldsymbol{c}}_i = \boldsymbol{c}_i - \bar{\boldsymbol{c}}$, and substituting them into the above equation to get

$$\sum_{i=1}^{N}\|\bar{\boldsymbol{s}}_i - \boldsymbol{Q}\bar{\boldsymbol{c}}_i\|^2 = \sum_{i=1}^{N}\left(\bar{\boldsymbol{s}}_i^{\mathrm{T}}\bar{\boldsymbol{s}}_i + \bar{\boldsymbol{c}}_i^{\mathrm{T}}\bar{\boldsymbol{c}}_i - 2\bar{\boldsymbol{s}}_i^{\mathrm{T}}\boldsymbol{Q}\bar{\boldsymbol{c}}_i\right) \tag{49}$$

When the last term in (49) is maximized, the equation is minimized, which is equivalent to maximizing Trace $(\boldsymbol{QH})$. The correlation matrix $\boldsymbol{H}$ is defined as

$$\boldsymbol{H} = \sum_{i=1}^{N}\bar{\boldsymbol{c}}_i\bar{\boldsymbol{s}}_i^{\mathrm{T}} \tag{50}$$

The singular value decomposition of the matrix $\boldsymbol{H} = \boldsymbol{U}\Lambda\boldsymbol{V}^{\mathrm{T}}$, and the optimal solution of the rotation matrix is

$$\boldsymbol{Q} = \boldsymbol{V}\mathrm{diag}\left(\left[\mathbf{1}, \det\left(\boldsymbol{V}\boldsymbol{U}^{\mathrm{T}}\right)\right]^{\mathrm{T}}\right)\boldsymbol{U}^{\mathrm{T}} \tag{51}$$

where the length of $\mathbf{1}$ is $K-1$, the rotation matrix is guaranteed to satisfy $\det(\boldsymbol{Q}) = 1$. Due to the center of mass for the rigid target also satisfies the relationship in equation (1), the translation vector can be calculated by

$$\boldsymbol{t} = \bar{\boldsymbol{s}} - \boldsymbol{Q}\bar{\boldsymbol{c}} \tag{52}$$

Thus, the final estimation results of the rigid body attitude parameters can be determined. The solution process of the above proposed RBL method for wireless signal transmission parameter estimation can be summarized as follows

Solution steps : Proposed RSS-TDOA Fusion RBL Method

i. Extracting time domain measurement information d_{mi}, energy domain measurement information p_{mi};
ii. Introducing auxiliary variables μ_{mi} and ϑ_{mi} in d_{mi} to construct the DC function;
iii. Using the CCCP algorithm to estimate the initial value of the rigid body sensors position $\tilde{\boldsymbol{s}}_i$;
iv. Constructing the DRSS measurement information $\bar{P}_{mi}$;
v. Estimating transmission path loss factor $\hat{\gamma}$, wireless signal transmit power $\hat{P}_i$;
vi. Modifying energy domain measurement information $\bar{P}_{mi}$, time domain measurement information $\bar{d}_{mi}$.
vii. Estimating NLOS error average parameter $\hat{e}_i$ and $\hat{b}_i$.
viii. Substituting $\hat{e}_i$ and $\hat{b}_i$ into the GTRS problem and solve it iteratively, until the termination condition is satisfied and output the optimal estimation result $\hat{\boldsymbol{s}}_i$ of the rigid body sensors position.
ix. Determining the parameters of rigid body's attitude parameters by SVD method.

V. SIMULATION RESULTS

To fully verify the rigid body localization performance of the proposed method based on the fusion of RSS and TDOA in the NLOS environment with unknown priori information of the wireless signal transmission, computer simulations are carried out based on the Matlab software. Specifically, the proposed RSS-TDOA fusion localization algorithm (RSS-TDOA-Ref), the initial TDOA estimation results (TDOA-Initial) in subsection IV-A, the DAC [16] and SDR [19] methods are compared to demonstrate the performance of the proposed method. It is should be noted that both of the DAC and SDR methods are utilize the range measurements, in which the NLOS error are treated as the measurement error in the simulation.

The simulation parameters are set as follow [19]. The anchors number is set $M = 6$, all anchors are uniformly and randomly distributed in a cube of length 100 m with the global coordinate system $\mathcal{L}$ origin as the center. To avoid the poor anchors distribution structure affecting the localization performance, the minimum distance between anchors is required to be large than 20 m. Assuming that the local coordinate system $\mathcal{B}$ and the global coordinate system $\mathcal{L}$ coincide at the initial position, the rigid body sensors in the local coordinate system have the topological matrix

$$\boldsymbol{C} = \begin{bmatrix} -3 & -3 & 2 & 7 & 7 \\ -5 & 5 & 2 & -5 & 5 \\ -3 & -3 & 4 & -3 & -3 \end{bmatrix}, \tag{53}$$

where the i-th column parameter in $\boldsymbol{C}$ denotes the 3D coordinates of the rigid body sensor $\boldsymbol{c}_i$. In the global coordinate system $\mathcal{I}$, the rigid target is rotated 10°, 25° and −20° around the x, y and z axes, respectively. The translation vector is $\boldsymbol{t} = [25, -25, 30]^{\mathrm{T}}$ m.

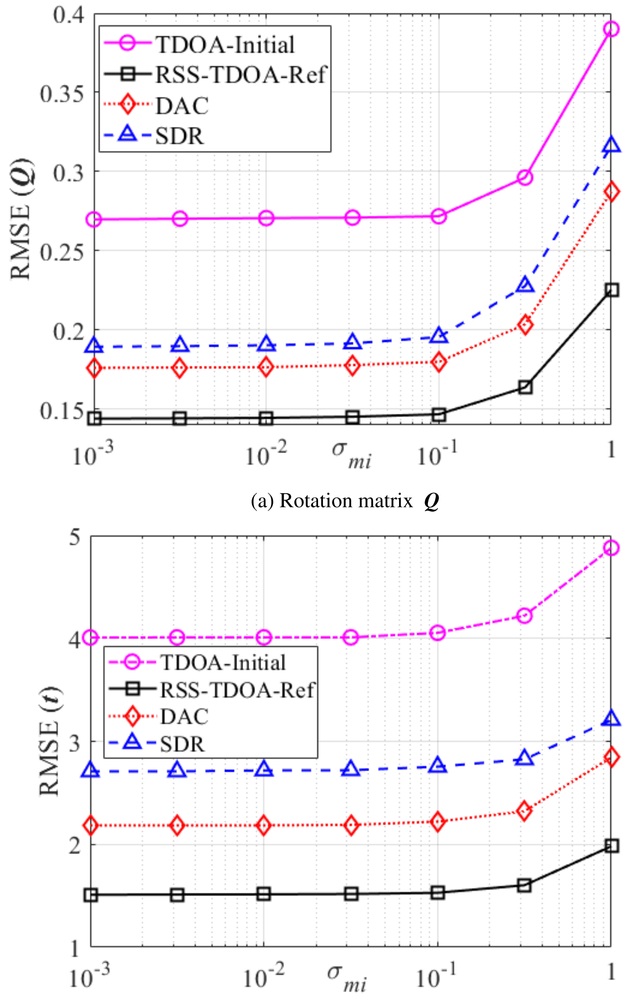
The number of Monte Carlo simulation experiments is $L = 2000$ times, wireless signal transmitting power is $P_i = 50$ (dBm), transmission path loss coefficient is $\gamma = 3$, and the reference distance is $r_0 = 1$ m. The NLOS error factor (containing RSS measurements and TDOA measurements) in each simulation experiment is uniformly distributed between $[0, bias_{\max}]$. The localization performance of the rigid body's attitude parameters is expressed by root mean square error (RMSE)

$$\mathrm{R}MSE\,(*) = \sqrt{\frac{1}{L}\sum_{l=1}^{L}\left\| \left(\hat{*}\right)^{(l)} - (*) \right\|^2}, \tag{54}$$

where $\left(\hat{*}\right)^{(l)}$ denotes the estimated value of the l-th Monte Carlo simulation experiment on $(*)$. When $(*)$ is a vector, $\|\cdot\|$ denotes the Euclidean parametrization. when $(*)$ is a matrix, $\|\cdot\|$ denotes the Frobenius parametrization. The estimation error of transmission path loss coefficient and wireless signal transmit power parameters is expressed by average deviation (AD)

$$\mathrm{AD}\,(*) = \frac{1}{L}\sum_{l=1}^{L}\left| \left(\hat{*}\right)^{(l)} - (*) \right|, \tag{55}$$

where $|\cdot|$ denotes the absolute value.



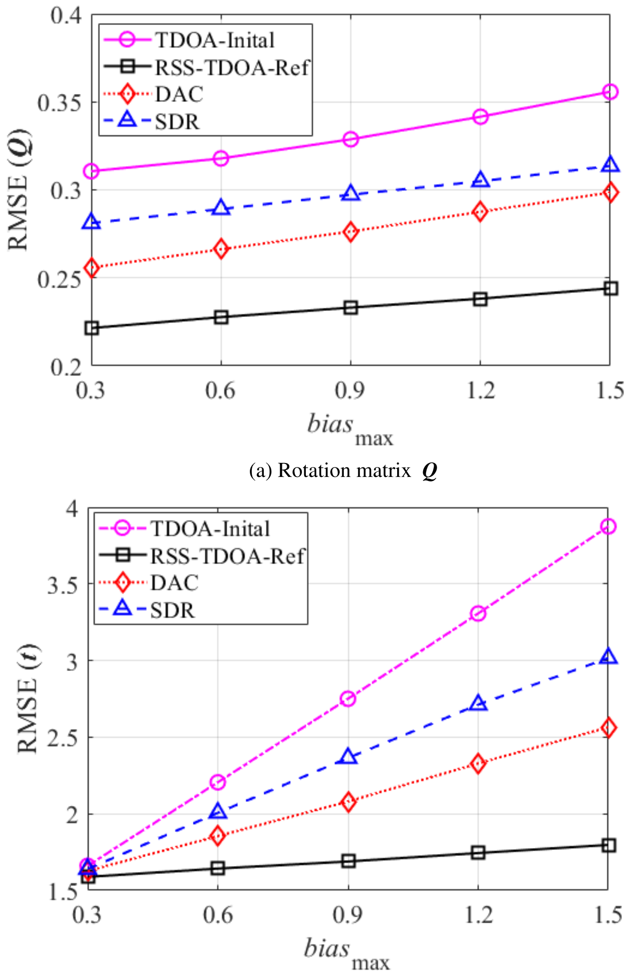
(a) Rotation matrix $\boldsymbol{Q}$

(b) Translation vector $\boldsymbol{t}$

FIGURE 2. Performance curves of RMSE of rigid body's attitude parameters estimation with measurement error σ_{mi} in 3-D scenario.

Simulation 1: NLOS error maximum $bias_{\max} = 2$ (dB·m), measurements error σ_{mi} varies between 10^{-3} and 1 (dB·m). The results of rigid body's attitude parameters estimation are shown in Figure 2.

The estimated performance curves of the rotation matrix $\boldsymbol{Q}$ are shown in Figure 2(a), and the translation vector $\boldsymbol{t}$ is shown in Figure 2(b). It is shown that the localization accuracy of each method gradually decreases as the measurement error σ_{mi} increases. When the measurements error is greater than 10^{-1} m, the localization performance of the rigid body's attitude parameters of each method deteriorates severely, but the proposed method has better localization performance in the NLOS environment compared with the initial estimation results of the proposed method, the DAC method and the SDR method. Specifically, due to the effective handling of the NLOS error, the performance of the proposed algorithm is better than that of the initial TDOA estimation results. Although the NLOS error is taken as the measurement error for the DAC and SDR methods, the performance are better



(a) Rotation matrix $\boldsymbol{Q}$

(b) Translation vector $\boldsymbol{t}$

FIGURE 3. Performance curves of RMSE of rigid body's attitude parameters estimation with NLOS error maximum $bias_{\max}$ in 3-D scenario.

than the inttial TDOA estimation results, which means both method have some robustness about the measurement errors.

Simulation 2: The measurement error is $\sigma_{mi} = 1$ (dB·m), the NLOS error maximum $bias_{\max}$ varies between 0.3 and 1.5, the rigid body's attitude parameters estimation results are shown in Figure 3.

The estimation performance curves of the rotation matrix $\boldsymbol{Q}$ are shown in Figure 3(a), and the displacement vector $\boldsymbol{t}$ is shown in Figure 3(b). It is shown that the localization accuracy of each method gradually decreases as the NLOS error maximum $bias_{\max}$ increases, but the proposed RBL method has more accurate results of the rigid body's attitude parameters estimation in the NLOS environment compared with the initial estimation results of the proposed method, DAC method and SDR method. Meanwhile, the performance of the DAC method is better than the SDR method, which because that the SDR method is more effective in lower niose. However, the NLOS error is taken as the measurement error in the simulation, which makes the error is higher.

TABLE 1. Estimation results of transmission path loss factor γ and wireless signal transmit power P_i in case of variation of measurement error σ_{mi} in 3-D scenario.

σ_{mi}/m	$\hat{P}_i$	AD (P_i)	$\hat{\gamma}$	AD (γ)
10^{-3}	48.1592	1.8408	2.9267	0.0733
$10^{-2.5}$	51.8227	1.8227	3.0746	0.0746
10^{-2}	51.9046	1.9046	3.0823	0.0823
$10^{-1.5}$	47.9695	2.0305	2.8956	0.1044
10^{-1}	50.2891	2.2891	3.1375	0.1375
$10^{-0.5}$	47.4063	2.5937	2.8208	0.1792
1	46.8631	3.1369	2.7719	0.2281

TABLE 2. Estimation results of transmission path loss factor γ and wireless signal transmit power P_i in case of variation of measurement error σ_{mi} in 3-D scenario.

$bias_{\max}$ /m	$\hat{P}_i$	AD (P_i)	$\hat{\gamma}$	AD (γ)
0.3	47.8651	2.1349	2.8473	0.1527
0.6	52.4296	2.4296	3.1854	0.1854
0.9	47.2736	2.7264	2.7508	0.2492
1.2	53.1918	3.1918	3.3101	0.3101
1.5	53.6527	3.6527	3.3704	0.3704

In addition, the proposed method not only achieves the estimation of the rigid body's attitude parameters in the NLOS environment, but also obtains the estimates of the wireless signal transmit power P_i and the path loss coefficient γ in the transmission channel. The estimation results are shown in Table 1 and Table 2 for Simulation 1 and Simulation 2, respectively.

Analysis of the data in both tables reveals the capability of the proposed method to accurately estimate wireless signal transmission parameters. As the measurement error or NLOS error increases, there is a subsequent rise in the estimation error of these transmission parameters. Nevertheless, the obtained transmission parameters can be utilized in the RSS measurement, which method is combined with TDOA measurement to estimate the attitude parameters of the target rigid body. The results unequivocally demonstrate that the proposed method effectively mitigates the adverse effects of unknown transmission parameters on rigid body localization in NLOS environments. The simulation outcomes under these conditions affirm that when prior knowledge of wireless signal characteristics is lacking, the Rigid Body Localization (RBL) method, which leverages the fusion of RSS and TDOA measurements, adeptly mitigates the degradation of RBL performance stemming from NLOS signal propagation.

VI. CONCLUSION

In the absence of prior knowledge concerning the wireless signal transmission channel, in order to overcome the influence of the NLOS error on the localization performance of the rigid body, this paper treats the wireless signal prior information and the NLOS error as the parameters for estimation. Through an iterative algorithm, the sensors position of the rigid body is modified. Subsequently, the SVD method is applied to accurately determine the rigid body's attitude parameters. Computer simulations show that in the application scenario where the priori information of the wireless signal transmission channel is unknown, the proposed method can effectively reduce the RBL performance loss owing to the NLOS propagation of the wireless signal. In future research endeavors, the integration of modern optimization algorithms can be explored to minimize computational complexity and further enhance the localization performance for RBL challenges in NLOS environments.

REFERENCES

[1] S. Dwivedi, R. Shreevastav, F. Munier, J. Nygren, I. Siomina, Y. Lyazidi, D. Shrestha, G. Lindmark, P. Ernström, E. Stare, S. M. Razavi, S. Muruganathan, G. Masini, Å. Busin, and F. Gunnarsson, "Positioning in 5G networks," *IEEE Commun. Mag.*, vol. 59, no. 11, pp. 38–44, Nov. 2021.

[2] J. Sanusi, O. Oshiga, S. Thomas, S. Idris, S. Adeshina, and A. M. Abba, "A review on 6G wireless communication systems: Localization and sensing," in *Proc. 1st Int. Conf. Multidisciplinary Eng. Appl. Sci. (ICMEAS)*, Abuja, Nigeria, Jul. 2021, pp. 1–5.

[3] J. He and Y. J. Chun, "Performance analysis for AOA-based localization under millimeter-wave wireless networks," *IEEE Access*, vol. 10, pp. 17221–17230, 2022.

[4] N. Podevijn, D. Plets, J. Trogh, A. Karaagac, J. Haxhibeqiri, J. Hoebeke, L. Martens, P. Suanet, and W. Joseph, "Performance comparison of RSS algorithms for indoor localization in large open environments," in *Proc. Int. Conf. Indoor Positioning Indoor Navigat. (IPIN)*, Nantes, France, Sep. 2018, pp. 1–6.

[5] S. Zhao, N. Guo, X.-P. Zhang, X. Cui, and M. Lu, "Closed-form two-way TOA localization and synchronization for user devices with motion and clock drift," *IEEE Signal Process. Lett.*, vol. 29, pp. 100–104, 2022.

[6] S. Cao, X. Chen, X. Zhang, and X. Chen, "Combined weighted method for TDOA-based localization," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 5, pp. 1962–1971, May 2020.

[7] Y. Wang, G. Wang, S. Chen, K. C. Ho, and L. Huang, "An investigation and solution of angle based rigid body localization," *IEEE Trans. Signal Process.*, vol. 68, pp. 5457–5472, 2020.

[8] Y. Zhang, K. Song, J. Yi, P. Huang, Z. Duan, and Q. Zhao, "Absolute attitude estimation of rigid body on moving platform using only two gyroscopes and relative measurements," *IEEE/ASME Trans. Mechatronics*, vol. 23, no. 3, pp. 1350–1361, Jun. 2018.

[9] N. A. Chaturvedi, A. K. Sanyal, and N. H. McClamroch, "Rigid-body attitude control," *IEEE Control Syst. Mag.*, vol. 31, no. 3, pp. 30–51, Jun. 2011.

[10] Y. Zeng, R. Zhang, and T. J. Lim, "Wireless communications with unmanned aerial vehicles: Opportunities and challenges," *IEEE Commun. Mag.*, vol. 54, no. 5, pp. 36–42, May 2016.

[11] S. P. Chepuri, G. Leus, and A.-J. van der Veen, "Position and orientation estimation of a rigid body: Rigid body localization," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process.*, Vancouver, BC, Canada, May 2013, pp. 5185–5189.

[12] K. Bengler, K. Dietmayer, B. Farber, M. Maurer, C. Stiller, and H. Winner, "Three decades of driver assistance systems: Review and future perspectives," *IEEE Intell. Transp. Syst. Mag.*, vol. 6, no. 4, pp. 6–22, Winter 2014.

[13] S. P. Chepuri, G. Leus, and A.-J. van der Veen, "Rigid body localization using sensor networks," *IEEE Trans. Signal Process.*, vol. 62, no. 18, pp. 4911–4924, Sep. 2014.

[14] S. P. Chepuri, A. Simonetto, G. Leus, and A.-J. van der Veen, "Tracking position and orientation of a mobile rigid body," in *Proc. 5th IEEE Int. Workshop Comput. Adv. Multi-Sensor Adapt. Process. (CAMSAP)*, Martin, France, Dec. 2013, pp. 37–40.

[15] A. Pizzo, S. P. Chepuri, and G. Leus, "Towards multi-rigid body localization," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Shanghai, China, Mar. 2016, pp. 3166–3170.

[16] S. Chen and K. C. Ho, "Accurate localization of a rigid body using multiple sensors and landmarks," *IEEE Trans. Signal Process.*, vol. 63, no. 24, pp. 6459–6472, Dec. 2015.

[17] S. Chen and K. C. Ho, "Localization of a mobile rigid sensor network," in *Proc. 24th Eur. Signal Process. Conf. (EUSIPCO)*, Budapest, Hungary, Aug. 2016, pp. 1368–1372.

[18] J. Jiang, G. Wang, and K. C. Ho, "Accurate rigid body localization via semidefinite relaxation using range measurements," *IEEE Signal Process. Lett.*, vol. 25, no. 3, pp. 378–382, Mar. 2018.

[19] J. Jiang, G. Wang, and K. C. Ho, "Sensor network-based rigid body localization via semi-definite relaxation using arrival time and Doppler measurements," *IEEE Trans. Wireless Commun.*, vol. 18, no. 2, pp. 1011–1025, Feb. 2019.

[20] B. Zhou, M. Zhang, Y.-Q. Chen, N. Xiong, Y. Tian, and S. Ahmed, "Efficient AoA-based rigid body localization via single base station for Internet of Things applications," *IEEE Access*, vol. 7, pp. 171140–171152, 2019.

[21] B. Zhou, X. Yao, L. Yang, S. Yang, S. Wu, Y. Kim, and L. Ai, "Accurate rigid body localization using DoA measurements from a single base station," *Electronics*, vol. 8, no. 6, p. 622, Jun. 2019.

[22] B. Zhou, L. Ai, X. Dong, and L. Yang, "DoA-based rigid body localization adopting single base station," *IEEE Commun. Lett.*, vol. 23, no. 3, pp. 494–497, Mar. 2019.

[23] G. Wang and K. C. Ho, "Accurate semidefinite relaxation method for 3-D rigid body localization using AOA," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Barcelona, Spain, May 2020, pp. 4955–4959.

[24] B. Hao, K. C. Ho, and Z. Li, "Range-based rigid body localization with a calibration emitter for mitigating anchor position uncertainties," *IEEE Trans. Wireless Commun.*, vol. 18, no. 12, pp. 5734–5748, Dec. 2019.

[25] X. Ke, Y. Wang, and L. Huang, "Three-dimensional rigid body localization in the presence of clock offsets," *IEEE Signal Process. Lett.*, vol. 27, pp. 96–100, 2020.

[26] L. Eldén and H. Park, "A Procrustes problem on the Stiefel manifold," *Numerische Math.*, vol. 82, no. 4, pp. 599–619, Jun. 1999.

[27] J. Diebel, "Representing attitude: Euler angles, unit quaternions, and rotation vectors," *Matrix*, vol. 58, nos. 15–16, pp. 1–35, 2006.

[28] J. Zhang, L. Ding, Y. Wang, and L. Hu, "Measurement-based indoor NLoS ToA/RSS range error modelling," *Electron. Lett.*, vol. 52, no. 2, pp. 165–167, Jan. 2016.

[29] P. Wan, Q. Yan, G. Lu, J. Wang, and Q. Huang, "Robust localization of signal source based on information fusion," *IEEE Syst. J.*, vol. 15, no. 2, pp. 1764–1775, Jun. 2021.

[30] R. Horst and N. V. Thoai, "DC programming: Overview," *J. Optim. Theory Appl.*, vol. 103, no. 1, pp. 1–43, Oct. 1999.

[31] A. L. Yuille and A. Rangarajan, "The concave-convex procedure," *Neural Comput.*, vol. 15, no. 4, pp. 915–936, Apr. 2003.

[32] X. Ma, T. Ballal, H. Chen, O. Aldayel, and T. Y. Al-Naffouri, "A maximum-likelihood TDOA localization algorithm using difference-of-convex programming," *IEEE Signal Process. Lett.*, vol. 28, pp. 309–313, 2021.

[33] A. W. Roberts, "Convex functions," in *Handbook of Convex Geometry*, vol. 1081, P. M. Gruber, Ed. Amsterdam, The Netherlands: Elsevier, 1993, pp. 1083–1104.

[34] Y. Chen, J. Li, and Q. Yan, "Robust DRSS based localization in sensor networks with generalized Gaussian noise," *IEEE Commun. Lett.*, vol. 26, no. 12, pp. 2909–2913, Dec. 2022.

[35] A. Zaeemzadeh, M. Joneidi, B. Shahrasbi, and N. Rahnavard, "Robust target localization based on squared range iterative reweighted least squares," in *Proc. IEEE 14th Int. Conf. Mobile Ad Hoc Sensor Syst. (MASS)*, Orlando, FL, USA, Oct. 2017, pp. 380–388.

[36] S. Umeyama, "Least-squares estimation of transformation parameters between two point patterns," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 13, no. 4, pp. 376–380, Apr. 1991.

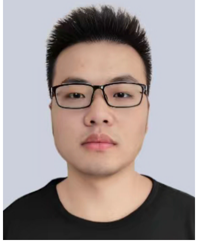
[37] J. J. More, "Generalizations of the trust region problem," *Optim. Methods Softw.*, vol. 2, nos. 3–4, pp. 189–209, Jan. 1993.

[38] D. W. Eggert, A. Lorusso, and R. B. Fisher, ''Estimating 3-D rigid body transformations: A comparison of four major algorithms,'' *Mach. Vis. Appl.*, vol. 9, pp. 272–290, Mar. 1997.

[39] P. Wan, J. Wei, J. Wang, and Q. Huang, ''Wireless sensor network-based rigid body localization for NLOS parameter estimation,'' *Sensors*, vol. 22, no. 18, p. 6810, Sep. 2022.

PENGWU WAN received the Ph.D. degree in wireless communication and information system from Xidian University, Xi'an, China, in 2018.

He is currently an Associate Professor with the School of Communication and Information engineering, Xi'an University of Posts and Telecommunications, Xi'an. His research interests include localization and tracking based on wireless sensor networks or unmanned aerial vehicle, and rigid body localization.



WENJIE LI received the B.E. degree from West Anhui University, Anhui, China, in 2021. He is currently pursuing the degree in communication and information system with the Xi'an University of Posts and Telecommunications.

His current research interests include source localization and wireless sensor networks.

JIAN WEI received the B.E. degree from the Xi'an University of Posts and Telecommunications, Xi'an, China, in 2020, where he is currently pursuing the degree in communication and information system.

His current research interests include rigid body localization and wireless sensor networks.

YIFAN WEN received the B.E. degree from the Xi'an University of Posts and Telecommunications, Xi'an, China, in 2022, where she is currently pursuing the degree in electronic information.

Her current research interests include rigid body localization and wireless sensor networks.