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3-D Target Localization in Wireless Sensor Network Using TOA and AOA Measurements

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Abstract

This paper discusses a target location problem by using hybrid measurements of time-of-arrival (TOA) and angle of arrival (AOA) in a three-dimensional wireless sensor network (WSN). A novel non-convex estimator based on the least squares (LS) criterion is proposed. This estimator is transformed into a generalized trust region subproblem (GTRS) framework which tightly approximates the maximum likelihood (ML), therefore the optimal solution can be obtained by using the simple bisection method. Furthermore, a second-order cone relaxation method is also proposed to approximate the original non-convex problem into a convex optimization problem, and a suboptimal solution can be easily obtained. Finally, Cramer-Rao lower bound of the estimator based on hybrid measurements of time-of-arrival (TOA) and angle of arrival (AOA) in a three-dimensional wireless sensor network is also derived. Theoretical analysis and computer simulation results show that the proposed two methods provide good performance.

Keywords

Target Localization; Time of Arrival (TOA); Angle-of-Arrival (AOA); Wireless Sensor Networks (Wsns).

1. Introduction

Wireless Sensor Networks (WSN) generally refers to a Wireless communication network composed of multiple Sensor devices, which are assigned to a monitored area to measure some locally interesting information [1], [2]. In recent years, wireless sensor network (WSNS) have been used in a wide range of application, such as target tracking, navigation, emergency services, friends finding and, intelligent transportation [3], [4]. In these applications, getting positioning of the target position is crucial. GPS and other satellite systems can provide high-precision location information for outdoor targets. However, in some special environments, satellite positioning system cannot provide target location information. Therefore target localization methods based on Wireless Sensor Networks (WSN)attract more attention [5]. In these methods, sensor nodes with known location are called anchor nodes, and those that need to be located by anchor nodes are called target nodes. The main idea of sensor location is to determine the location of the target node by using the measurement data. Depending on the way the observed data are obtained, the target location methods can be divided into: time of arrival (TOA) [6], [7], Angle of arrival (AOA) [8], [9], time of arrival (TDOA) [10], [11], received signal strength (RSS) [12], [13], and combinations of them [19].

Target localization estimators based on a single kind of measurement have two main advantages due to their low complexity and cost [15], however, there exists great room for the estimation accuracy improvement, hybrid processing from the combined measurement systems has been proposed to improve the performance.

In [16], a target node localization problem based on TOA measurements was addressed by LS techniques. This method can reduce the computational complexity, however the methods mentioned above provide low estimation accuracy. To reduce the localization error, hybrid

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systems that use RSS and AOA measurements were presented in [14], However, the localization precision is sensitive to the channel environment and the model can be very difficult to be built in some cases. In [15], the authors propose a unified solution with a single model to locate the source using AOA, without requiring the knowledge whether the source is close to or far from the anchor nodes and then extend the analysis and the algorithm for hybrid AOA-TDOA localization. In [16], the least squares TOA and AOA localization algorithms based on Taylor series expansion are proposed in the two-dimensional space. This method employs Taylor-series expansion to make it linear, while the performance of this approach relies on the accuracy of the initial guess and its iterative process's convergence is not proved. In [17], the author proposes a TOA and AOA localization algorithm based on weighted linear least squares in two-dimensional space, and derives the Kramer lower bound of the algorithm, but it is not considered in three-dimensional space. In [18], the authors proposed two methods based on linear least squares (LS) and optimization are studied by making use of combined TOA and AOA measurements in three-dimensional space. The LS estimator is a relatively simple and well known estimator, while the optimization based estimator was solved by Davidson-Fletcher-Powell Algorithm. Although these two estimation methods are easy to implement, their estimation accuracy can be further improved.

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In this work, we propose a novel localization method in 3D WSNs by utilizing combined measurements of TOA and AOA. A new objective function for solving the hybrid positioning problem is established by using the weighted least squares criterion. Secondly, the generalized GTRS framework is used to transform the original non-convex optimization problem into a generalized trust domain sub-problem, which can be solved accurately by a simple bisection procedure. The operation complexity is low and the positioning performance is better. In addition, we show that the derived non-convex objective function can be transformed into a convex one, by using second order cone relaxation method. The simulation results show that the estimated performance of the proposed algorithm is significantly improved.

The following notations are adopted throughout the paper. Bold face lower case letters and bold face upper case letters denote the vectors and matrices, respectively. R^n denotes the set of n-dimensional real column vectors. r_i denotes the i-th entry of the vector r . In addition, $\|\bullet\|$ denotes the l_2 norm.

The rest of the paper is organized as follows. Section II discusses the TOA and AOA models, and also proposes the localization problem. Section III presents the proposed localization methods. In Section IV, the complexity of the algorithm is analyzed. Section V derived CRLB of the algorithm analysis , Section VI provides computer simulation results and analyzes the performances of the proposed methods. Finally, the main conclusions are concluded in Section VII.

2. System Model and Problem Formulation

2.1. A. System Model

In this section, we consider a three-dimensional WSNs with N anchor nodes and one target node, where the location of the anchor nodes, noted as $s_1, s_2, \cdots, s_N$, are known, but the location of the target node, noted as x ,is unknown. For simplicity and without loss of generality, we assume that the anchor nodes are equipped with omnidirectional antennas. Under a centralized processing mode, all sensors convey to the central processor their TOA and AOA measurements with respect to the target node for the location, during which the locations of all the sensor nodes are supposed to be unchanged. As show in Fig.1, $x=(x_1, x_2, x_3)$ and $s_i=(s_{i1}, s_{i2}, s_{i3})$ are respectively the unknown coordinates of the target and the known coordinates of the i_{th} anchor node. d_i , ϕ_i , α_i respectively represent the distance, azimuth angle and elevation angle between the target and the i_{th} anchor. Assuming that the target node sends a signal to the anchor node, then the anchor node can extract the information of TOA and AOA from the received signal. Knowledge, the application of simple geometric structure TOA measurement information d_i and AOA measurements (azimuth angle ϕ_i and elevation angle α_i) can be modeled as [20], [21].

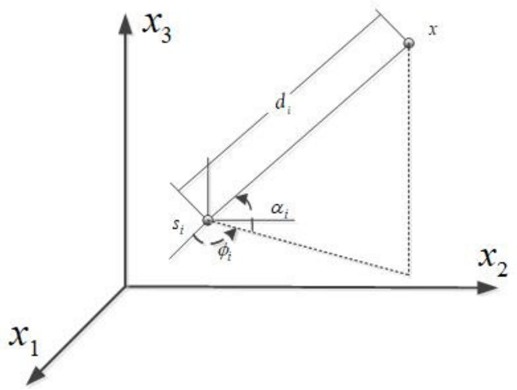

Fig 1. Illustration of the link between the target node and the i_{th} and anchor node in 3D WSNs

$$d_i = \| x - s_i \| + n_i \tag{1}$$

$$\phi_i = \arctan\left(\frac{x_2 - s_{i2}}{x_1 - s_{i1}}\right) + m_i \tag{2}$$

$$\alpha_i = \arctan\left(\frac{x_3 - s_{i3}}{(x_3 - s_{i3})\cos\phi_i + (x_2 - s_{i2})\sin\phi_i}\right) + v_i \tag{3}$$

Where $\| x - s_i \|$ is the true distance between the i-th anchor node and the target node, and n_i follows a Zero-mean Gaussian distribution i.e., $n_i \sim N(0, \sigma_n^2)$, where m_i and v_i represent the errors of azimuth and elevation respectively, modeled as zero mean Gaussian random variables, i.e., $m_i \sim N(0, \sigma_m^2)$, and i.e., $v_i \sim N(0, \sigma_v^2)$, For the sake of simplicity, in the rest of this paper, we assume the following variances of all noise $\sigma_{n_i}^2 = \sigma_n^2 ; \sigma_{m_i}^2 = \sigma_m^2 ; \sigma_{v_i}^2 = \sigma_v^2$, for $i = 1, \cdots, N$.

2.2. B. Problem Formulation

Given the observation vector $\theta=\left(d^T,\phi^T,\alpha^T\right)^T$, $\theta\in R^{3N}$, where $d=\left[d_1,d_2,\cdots,d_N\right]^T$, $\phi=\left[\phi_1,\phi_2,\cdots,\phi_N\right]^T$, $\alpha=\left[\alpha_1,\alpha_2,\cdots,\alpha_N\right]^T$. the resulting joint Maximum Likelihood (ML) estimation of target location x can be formulated as:

$$\min_x \sum_{i-1}^{3N}\frac{\left(\theta_i-f_i\left(x\right)\right)^2}{\sigma_i^2} \tag{4}$$

Where $\sigma_i=[\sigma_{n_i},\sigma_{m_i},\sigma_{v_i}]^T$ and

$$f_i(x)=[\|x-s_i\|,\arctan(\frac{x_2-s_{i2}}{x_1-s_{i1}}),\arctan(\frac{x_3-s_{i3}}{(x_3-s_{i3})\cos\phi_i+(x_2-s_{i2})\sin\phi_i})]^T$$

Although the ML estimator is approximately the minimum variance unbiased estimator, the ML estimator is non-convex and no closed-from solution. In order to overcome the non-convexity and nonlinearity of ML estimation, it is proved that the maximum likelihood problem (4) can be solved by the suboptimal estimation method. In the following paper, we proposed a suboptimal estimator based on GTRS approach, which can be solve exactly by a simple bisection procedure and a convex optimization method which can be solved efficiently by interior-point algorithms.

3. Proposed Techniques

In the section, we develop two estimators by using appropriate relaxation techniques, namely GTRS and SOCP for 3-D target positioning.

Move the measurement noise n_i in equation (1) to the left side of the equation and square the equations. By ignoring the noise quadratic term, we can get the approximate formula (5):

$$d_i-2d_in_i\approx\|x-s_i\|^2 \tag{5}$$

With simple manipulations, we have

$$\frac{d_i^2-\left\|x-s_i\right\|^2}{2d_i}\approx n_i \tag{6}$$

Similarly, for the sufficiently small noise, (2) and (3) can be rewritten in approximation from (7) and (8) below, respectively.

$$-\sin\phi_i\left(x_1-s_{i1}\right)+\cos\phi_i\left(x_2-s_{i2}\right)\approx 0 \tag{7}$$

$$-\cos\phi_i\sin\alpha_i\left(x_1-s_{i1}\right)-\sin\phi_i\sin\alpha_i\left(x_2-s_{i2}\right)+\cos\alpha_i\left(x_3-s_{i3}\right)\approx 0 \tag{8}$$

For the sake of expression, (7) and (8) can be written as vector from:

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$$g_{\phi_i}^T\left(x-s_i\right)\approx 0 \tag{9}$$

$$g_{\alpha_i}^T\left(x-s_i\right)\approx 0 \tag{10}$$

Where $g_{\phi_i}=\left[-\sin\phi_i,\cos\phi_i,0\right]^T$ and $g_{\alpha_i}=\left[-\cos\phi_i\sin\alpha_i,-\sin\phi_i\cos\alpha_i,\cos\alpha_i\right]^T$.

3.1. A. Proposed GTRS Method

In this part, designs a fast target location algorithm for solving problem (4). The specific process is as follows: in order to given more importance to nearby links, we introduce weights similarly to [22]:

$$\omega_i=\sqrt{1-\frac{d_i}{\sum_{i=1}^{N}d_i}} \tag{11}$$

Where $d_i=\|x-s_i\|+n_i$ is the measurement of the distance between anchor node and target node.

Then, base on the weighted least square (WLS) criterion and (6), (9), (10), we can derive:

$$\min_x\sum_{i=1}^{N}\omega_i\left(\frac{d_i^2-\|x-s_i\|^2}{2d_i}\right)^2+\sum_{i=1}^{N}\omega_i\left(g_{\phi_i}^T(x-s_i)\right)^2+\sum_{i=1}^{N}\omega_i\left(g_{\alpha_i}^T(x-s_i)\right)^2 \tag{12}$$

Although the problem (12) is no convex and has no closed from solution. In the following part, we can transform (12) into an equivalent quadratic programming problem with a quadratic constraint whose global solution can be computed efficiently.

Using the substitution $y=\left[x^T\quad \|x\|^2\right]^T$,We can rewrite (12) as a GTRS:

Where $W=I_3\otimes diag(\omega)$, $A=\begin{bmatrix}\frac{s_i^T}{d_i} & 1\\ g_{\phi_i}^T & 0\\ g_{\alpha_i}^T & 0\end{bmatrix}$, $b=\begin{bmatrix}-\frac{d_i}{2}+\frac{\|s_i\|^2}{2d_i}\\ g_{\phi_i}^T s_i\\ g_{\alpha_i}^T s_i\end{bmatrix}$,, $D=\begin{bmatrix}I_3 & 0_{3\times1}\\ 0_{1\times3} & 0\end{bmatrix}$, $l=\begin{bmatrix}0_{3\times1}\\ -\frac{1}{2}\end{bmatrix}$

Although problem (12) is still non-convex, both the objective function and the constraint in (12) are quadratic. This is a typical quadratic programming problem with quadratic constraint, and can be solved by using the bisection method [23].

3.2. B. Proposed SOCP Method

In this section, we proposed an effective target localization algorithm based on convex optimization. The specific process is as follows: By squaring both sides of the equation (1), and ignoring the quadratic term of noise that:

$$\frac{d_i^2-\|x-s_i\|^2}{2\|x-s_i\|}\approx n_i \tag{13}$$

Then, base on the weighted least square (WLS) criterion and (13), (9), (10), we can derive:

$$\min_x \sum_{i=1}^{N} \omega_i \left(\frac{d_i^2 \left\| x - s_i \right\|^2}{2\left\| x - s_i \right\|} \right)^2 + \sum_{i=1}^{N} \omega_i \left(g_{\phi_i}^T (x - s_i) \right)^2 + \sum_{i=1}^{N} \omega_i \left(g_{\alpha_i}^T (x - s_i) \right)^2 \tag{14}$$

The problem in (14) is highly non-convex and has no closed from solution, it can be transformed into a convex problem by using some technique. In this section, we introduce auxiliary variable $r_i = \left\| x - s_i \right\|, z_i = \frac{d_i^2 - \left\| x - s_i \right\|^2}{2\left\| x - s_i \right\|}, u_i = g_{\phi_i}^T \left(x - s_i \right), h_i = g_{\alpha_i}^T \left(x - s_i \right)$,Then (14) can be transformed into the following optimization problem.

$$\min_x \sum_{i=1}^{N} \omega_i \left(\frac{d_i^2 - \left\| x \right\|^2 + 2s_i^T x - \left\| s_i \right\|^2}{2\left\| x - s_i \right\|} \right)^2 + \sum_{i=1}^{N} \omega_i \left(g_{\phi_i}^T (x - s_i) \right)^2 + \sum_{i=1}^{N} \omega_i \left(g_{\alpha_i}^T (x - s_i) \right)^2 \tag{15}$$

For the sake of relaxation, we also introduce the slack variable r_i, z_i, h_i, can be relaxed as:

$$\begin{aligned} &\min_{x,r,z_i,u_i,h_i} z_i + u_i + h_i \\ &\textbf{s.t. } n\left\| x - s_i \right\| \le r_i \\ &\left\| x \right\|^2 \le y \\ &\frac{\omega_i \left(d_i^2 - \left\| x \right\|^2 + 2s_i^T x - \left\| s_i \right\|^2 \right)^2}{4\left\| x - s_i \right\|^2} \le z_i \\ &\omega_i \left(g_{\phi_i}^T \left(x - s_i \right) \right)^2 \le u_i \\ &\omega_i \left(g_{\alpha_i}^T \left(x - s_i \right) \right)^2 \le h_i \end{aligned} \tag{16}$$

The minimization problem (16) is still non-convex and has no closed form solution. However, by relaxing $r_i = \| x - s_i \|, y = \| x \|^2, \| x - s_i \| \le r_i, \| x \|^2 \le y$, respectively, we can obtain the following convex SOCP estimator, which can be expressed as:

$$\begin{aligned} &\min_{x,r,z_i,u_i,h_i} z_i + u_i + h_i \\ &\textbf{s.t. } \| x - s_i \| \le r_i \\ &\left\| \begin{bmatrix} 2x \\ y-1 \end{bmatrix} \right\| \le y + 1 \\ &\left\| \begin{bmatrix} 2\omega_i (d_i^2 - y + 2s_i^T x - \| s_i \|^2) \\ 4(d_i^2 - y + 2s_i^T x - \| s_i \|^2) - z_i \end{bmatrix} \right\| \le 4(d_i^2 - y + 2s_i^T x - \| s_i \|^2) + z_i \\ &\left\| \begin{bmatrix} 2\omega_i (g_{\phi_i}^T (x - s_i)) \\ u_i - 1 \end{bmatrix} \right\| \le u_i + 1 \\ &\left\| \begin{bmatrix} 2\omega_i (g_{\alpha_i}^T (x - s_i)) \\ h_i - 1 \end{bmatrix} \right\| \le h_i + 1 \end{aligned} \tag{17}$$

The Problem in (17) is a SOCP problem, which can be efficiently solved by the CVX package for specifying and solving convex programs.

4. Complexity Analysis

The computational complexity of the discussed methods is analyzed in this section. The estimator for the worst-case complexity of the mixed SD/SOCP [25] is used to analyse the complexities of our proposed estimator and other considered estimators in this paper. The formula of computing complexities is given here

$$O\left(\sqrt{L}\left(m\sum_{i=1}^{N_{sd}} n_i^{sd^3} + m^2\sum_{i=1}^{N_{sd}} n_i^{sd^2} + m^2\sum_{i=1}^{N_{soc}} n_i^{soc} + \sum_{i=1}^{N_{soc}} n_i^{soc^2} + m^3\right)\right) \tag{18}$$

Where L is the number of iterations of the algorithm, m is the number of equality constrains, N_{sd}, N_{soc} are respectively the number of the semidefinite cone (SDC) and second order (SOC) constrains, and n_i^{sd}, n_i^{soc} are the number of dimensions of the i_{th} SDC and i_{th} SOC, respectively. Assuming that $K_{\max}$ is the maximum number of steps in the bisection procedure used in [18]. The formula (17) and Table I shows that the computational complexity of the discussed methods depends mainly on the network size, i.e., the number of anchors.

Table 1. Summary of the Considered Methods

Method	Description	Complexity
LS	The LS approach in [18]	$O(N)$
GTRS	The proposed GTRS method based on LS in(12)	$2\bullet O(K_{\max}N)$
SOCP	The proposed SOCP relaxation method in (17)	$O(N^{3.5})$
CRLB	Lower limit on the variance of any unbiased estimators	$O(N)$

As can be seen from Table 1, the proposed SOCP method is the most expensive in terms of computational cost, as expected. In addition, we can see that the proposed GTRS method has higher computational requirements than the current method. This is because the GTRS method is iteratively executed. However, it can be seen from the simulation analysis that the higher computational cost of the proposed method is very reasonable because of their superior performance in terms of estimation accuracy.

5. Cramer-Rao Lower Bound Analysis

In this section ,We would like to drive the CRLB of the parameter vector $\theta = \left[d^T, \phi^T, \alpha^T\right]$,when the TOA measurement noise n and AOA measurement noise vectors m, v are independent. The measurement noise vectors n, m, v are all Gaussian and they are independent of each other. The conditional probability density function(pdf) is given as:

$$p(\theta|x)=\sum_{i=1}^{3N}\frac{1}{\sqrt{2\pi\sigma_i^2}}\exp\left\{\frac{(\theta_i-f_i(x))^2}{2\sigma_i^2}\right\} \quad (19)$$

For the target location x_i , the ML estimator $\hat{x}_i$ in the (2) is an unbiased estimator, i.e., $E\left(\hat{x}_i\right)=x_i$,,as the are essentially based on (1) Then, the covariance matrix of $\hat{x}_i$ is subject to the CRLB as $VAR\left(\hat{x}_i\right)\geq F^{-1}$.where F is the Fisher information matrix (FIM). Accordingly, we are defined the CRLB on RMSE by computing the root trace of F^{-1}.As proved following, the CRLB can be defined as

$$CRLB(x)=\sqrt{tr\left(F^{-1}\right)} \quad (20)$$

The FIM are computed as :

$$F=\left[\left(\frac{\partial\theta_i}{\partial x}\right)^T \quad \left(\frac{\partial\phi_i}{\partial x}\right)^T \quad \left(\frac{\partial d_i}{\partial x}\right)^T\right]^T Q^{-1}\left[\left(\frac{\partial\theta_i}{\partial x}\right)^T \quad \left(\frac{\partial\phi_i}{\partial x}\right)^T \quad \left(\frac{\partial d_i}{\partial x}\right)^T\right]^T \quad (21)$$

Where

$$\begin{aligned}
&diag\left\{\sigma_{n_i}^2,\sigma_{m_i}^2,\sigma_{v_i}^2\right\}\\
&\frac{\partial\theta_i}{\partial x}=[-\frac{x_2-s_{i_2}}{r_i^2\cos^2\Phi_i} \quad \frac{x_1-s_{i_1}}{r_i^2\cos^2\Phi_i} \quad 0]\\
&\frac{\partial\phi_i}{\partial x}=[-\frac{(x_1-s_{i_1})(x_3-s_{i_3})}{r_i^3\cos^2\phi_i} \quad -\frac{(x_2-s_{i_2})(x_3-s_{i_3})}{r_i^3\cos^2\phi_i} \quad \frac{\cos\phi_i}{r_i}]\\
&\frac{\partial d_i}{\partial x}=\left[\frac{x_1-s_{i_1}}{r_i} \quad \frac{x_2-s_{i_2}}{r_i} \quad \frac{x_3-s_{i_3}}{r_i}\right]
\end{aligned} \quad (22)$$

$r_i=\|x-s_i\|$ is the distance from the source to the i_{th} senor.

6. Simulation Results

In this part, computer simulation results are used to compared the performance of the proposed methods with the LS methods [18]. The proposed algorithm was solved by using the MATLAB package CVX, where the solver is SeDuMi[24]. We are use the propagation model (1), (2), (3) to generate the rang and angle measurement. The anchors are assumed uniformly located at a circle with radius 20m, while the unknown target node is uniformly and randomly chosen from a region of size $20\times 20m^2$ in each Monte carlo (Mc) runs. As the performance metric we used the root mean error (RMSE), defined as:

$$RMSE=\sqrt{\frac{1}{M_c}\sum_{i=1}^{M_c}\|\hat{x}_i-x_i\|^2} \quad (23)$$

where $\hat{x}_i$ is the estimated location of the i_{th} Monte carlo runs.

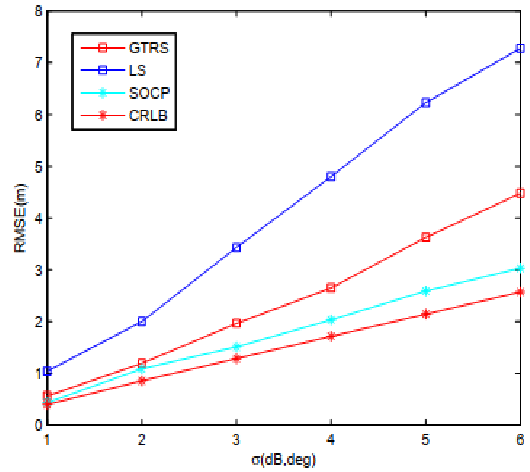

Fig 2. RMSE versus the σ when the number of anchor N is fixed and $N = 8$

Figure 2 compares the RMSE versus the noise standard deviation for different methods, when $N = 6$. From Fig.2, It is observed that the RMSE grows in nature as the standard derivation increases for all the methods. Moreover, it is seen that the performance gap between approaches increase with noise standard deviation. It also shows that the proposed methods is outperform the other methods for different noise stand deviation, reducing the estimation error for roughly 4m (SOCP) and 3m(GTRS), for σ=6(m,deg). It is clear that our proposed "SOCP" estimator outperforms of the existing estimators and is the closest to CRLB among the discussed estimators. This result shows that the proposed estimator is the closest RMSE to CRLB.

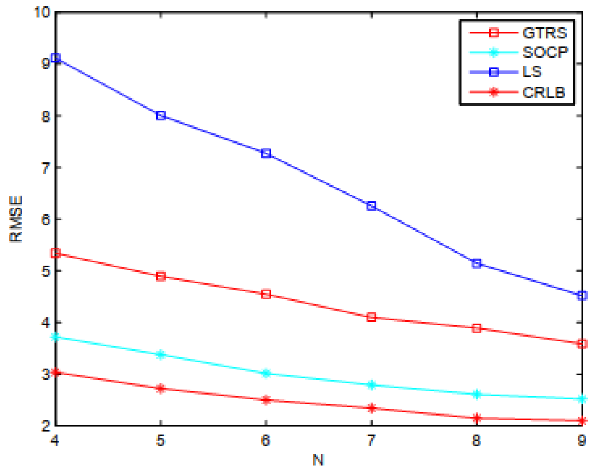

Fig 3. Effect of RESE versus of sensor number N when $\sigma = 4dB$

Fig.3 compares the RMSE versus the number N of the anchor nodes, when σ=6(m,deg). The figure shows that the RMSE of all the discussed methods decreases when the number of anchor nodes increases. It is clear that the new approaches outperform considerably the existing one for all choices of N. Moreover, the RMSE of the proposed algorithm has a slow decline with the increase of the number of anchor nodes, indicating that the proposed method is more robust.

This result shows that the proposed estimator is the closest RMSE to CRLB, and the proposed method has better positioning performance better than the other discussed estimator.

In summary, simulation and theoretical results verify that the proposed estimator provide the best performance versus the noise standard deviation and the number of anchor respectively.

7. Conclusion

In this paper, we investigated a hybrid localization system which combines range and angle measurements for target node localization in 3-D space. In order to avoid the ML estimator convergence problem, we derive a novel non-convex estimator based on the least squares (LS) criterion, and we derived two estimators that tightly approximate the ML estimator for small noise, namely SOCP and GTRS. This method effectively reduces the positioning error and improves the accuracy of the positioning. Simulation results show that the proposed methods outperform other discussed methods in estimation accuracy in various system settings.

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