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Hybrid TOA/AOA Localization with 1D Angle Estimation in UAV-assisted WSN

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Abstract-Unmanned aerial vehicles (UAVs) are considered as a great solution for a flexible and rapid deployment of wireless sensor networks (WSN) in emergency scenarios. Hybrid time-of-arrival (TOA) and angle-of-arrival (AOA) localization is widely used to estimate agents' positions in WSN. Conventional TOA/AOA localization methods normally require both elevation and azimuth AOA estimations to estimate agents' positions, leading to complicated L-shape antenna arrays and power-thirsty two-dimensional signal processing at the agents. We propose a hybrid TOA/1AOA localization approach which only requires elevation AOA estimations to combine with TOA measurements. A weighted least square algorithm is proposed to solve the nonlinear problem. The performance of the proposed method is compared with that of the conventional approach under various scenarios. Simulation results show that, by adjusting different parameters such as transmit power, signal bandwidth, and the number of anchors, the proposed method outperforms the conventional counterpart while significantly reduces the complexity of the agents.

Index Terms—Angle of arrival (AOA); time of arrival (TOA); target localization; wireless sensor network (WSN), unmanned aerial vehicles.

I. INTRODUCTION

Unmanned aerial vehicles (UAVs) have brought tremendous advantages in various applications, such as agriculture, aerial videography, and video surveillance to name a few. Recently, UAVs are also used as aerial anchors in flexible wireless sensor networks (WSN) to provide localization services in emergency scenarios, such as post-earthquake, fire, and military missions [1]. In such networks, UAVs fly in certain trajectories and periodically transmit beacons for unknown nodes or agents to estimate their relative positions.

The locations of unknown nodes can be derived based on the ranging information obtained from the beacons. Ranging information, such as time-of-arrival (TOA), angle-of-arrival (AOA) and received signal strength indicator (RSSI), is measured from the beacons and processed by localization algorithms implemented in the agents to derive their positions. If perfect ranging information was obtained, the exact agents' positions could be estimated by just one type of the above estimations. However, since measurement noise is unavoidable, a combination of the ranging information, such as AOA/RSSI [2]–[4],

AOA/TOA [5], [6] are normally used to obtain more accurate localization services.

Although RSSI is simple and readily available in every receiver, its accuracy is low when measuring signals emitted from UAVs. The reason is that, when aerial anchors are used, both the path-loss exponent and shadowing effect are significantly affected by the UAVs' altitude and their rotating wings [7]. Therefore, using TOA information can estimate the distance from agents to the UAVs more precisely, compared to RSSI.

Hybrid TOA/AOA localization has been extensively researched in literature [6], [8], [9]. In these publications, when estimating the agents' locations in a three dimensional (3D) space, the authors used both azimuth and elevation angles of arrivals. However, azimuth and elevation AOAs require the receiver to be equipped with two-dimensional signal processing as well as an L-shape antenna array [10]. This requirement results in a larger sized receiver front-end and more power consumption for the signal processing.

In this paper, we present a TOA/AOA localization method, called TOA/1AOA, to simplify the agents' complexity. Instead of combining TOA with both elevation and azimuth AOA information, or TOA/2AOA, as in the conventional approach, we use TOA and the elevation AOA measurement only. Since a fewer number of measurements is required in TOA/1AOA, its performance may be worse than the conventional method. Hence, the problem addressed in this paper is: *how to reduce the complexity of the agents using TOA/1AOA while ensuring the same level of precision as the conventional TOA/2AOA localization*?

This paper solves this problem by proposing a simple localization algorithm and by controlling other parameters of the WSN. In particular, the elevation AOA information is firstly used to determine the altitude of the agents. Then, the location of the agents in the xy-plane is found by solving the nonlinear system of equations using a weighted least square method. Cramer-Round lower bounds (CRLB) are derived to provide benchmarks for these methods. In addition, the impacts of other parameters of the WSN, such as signal bandwidth, transmit power, UAVs' altitude and the number of anchors are evaluated. Simulation results show that, by controlling

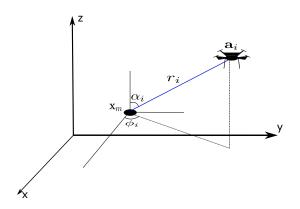


Fig. 1. Hybrid TOA/AOA localization: \mathbf{a}_i is the location of a UAV and \mathbf{x}_m is the location of an agent.

these parameters, TOA/1AOA can achieve the same or even significantly better performance, compared to the conventional method.

The remainder of this paper is organized as follows. Section II introduces system models and the conventional TOA/2AOA localization algorithm. Section III presents the proposed TOA/1AOA estimator and derives the CRLB. In Section IV, the performance of the proposed method is evaluated and compared with that of the conventional TOA/2AOA counterpart under different parameters of the WSN. Finally, Section V concludes the paper.

II. SYSTEM DESCRIPTION

Consider a WSN including N anchors whose locations are known at $\mathbf{a}_i = [a_{ix}, a_{iy}, a_{iz}]^T$, $i = 1, \ldots, N$ and M unknown agents at $\mathbf{x}_m = [x_{mx}, x_{my}, x_{mz}]^T$, $m = 1, \ldots, M$ as in Fig. 1. The anchors can be deployed by N UAVs in a delay-free system, or just one UAV to fly and hover at N predetermined locations in a delay-tolerant WSN. In this paper, we focus on the positioning algorithm implemented in the agents to calculate their locations based on the received beacons from the anchors. Therefore, the problem of designing the optimal trajectories for the anchors is not considered here. Further, we assume that all anchors are within the communication ranges of the agents so that they can receive the beacon packets from anchors, which indicate the transmit timestamp and the anchors' locations. From the received timestamp, the agents calculate the TOA and determine the distances to the *i*-th anchor, which can be expressed as

$$r_i = d_i + n_i \text{ for } i = 1, \dots, N \tag{1}$$

where d_i is the real distance from the agent to the *i*-th anchor, i.e., $d_i = \sqrt{(x_{mx} - a_{ix})^2 + (x_{my} - a_{iy})^2 + (x_{mz} - a_{iz})^2}$, and n_i is the measurement error. The agent also performs AOA estimations, including azimuth and elevation angles, denoted as ϕ_i and α_i , respectively. Due to estimation errors, these angles are represented as

$$\phi_{i} = \tan^{-1} \frac{x_{my} - a_{iy}}{x_{mx} - a_{ix}} + m_{i}$$

$$\alpha_{i} = \cos^{-1} \frac{z - z_{i}}{d_{i}} + v_{i}$$
(2)

where m_i, v_i are the azimuth and elevation angle estimation noises, respectively. n_i, m_i and v_i are modeled as zeromean Gaussian random variables with standard deviations σ_{n_i} (m) and $\sigma_{m_i}, \sigma_{v_i}$ (degrees), respectively, i.e., $n_i \sim \mathcal{N}(0, \sigma_{n_i}^2), m_i \sim \mathcal{N}(0, \sigma_{m_i}^2), v_i \sim \mathcal{N}(0, \sigma_{v_i}^2)$.

It was shown in [11] that the TOA estimation error depends on the number of antenna elements, the received signal-tonoise ratio (SNR), and the bandwidth of the transmitted signal, i.e.,

$$\sigma_{n_i}^2 \ge \frac{c^2}{2KSNR_i B^2} \tag{3}$$

where c is the speed of light, K is the number of antenna elements in the array, and B is the bandwidth of the transmitted signal. Meanwhile, the azimuth and elevation angle estimations errors, σ_{mi} and σ_{vi} , have their lower bounds as [11]

$$\sigma_{m_{i}}^{2} \geq \frac{3\lambda^{2}}{4\pi^{2}l^{2}K(K-1)(2K-1)SNR_{i}\sin^{2}\phi_{i}} \qquad (4)$$
$$\sigma_{v_{i}}^{2} \geq \frac{3\lambda^{2}}{4\pi^{2}l^{2}K(K-1)(2K-1)SNR_{i}\sin^{2}\alpha_{i}}$$

where l is the distance between two adjacent antenna elements and λ is the wavelength of the received signal. Assuming that all anchors transmit signals with the same bandwidth B and power P_T . As shown in [12], the path-loss from UAV to the ground in a line-of-sight (LOS) environment is calculated by

$$PL = 20\log_{10}(d) + 20\log_{10}(f_c) + 20\log_{10}(\frac{4\pi}{c}) + \eta \quad (5)$$

where f_c is the carrier frequency of the transmitted signal and η is the additional attenuation factor to account for the air-toground channel.

III. TOA/AOA LOCALIZATION

A. Conventional TOA/AOA Localization

When TOA measurement and azimuth and elevation AOA estimations are available, the position of the agent can be calculated based on a system of linear equations as [13]

$$x_{mx} = a_{ix} - r_i \sin \alpha_i \cos \phi_i$$

$$x_{my} = a_{iy} - r_i \sin \alpha_i \sin \phi_i$$

$$x_{mz} = a_{iz} - r_i \cos \alpha_i, \text{ for } i = 1, \dots, N.$$
(6)

Eq. (6) can be expressed in the matrix form as

$$\mathbf{A}_I \mathbf{x}_m = \mathbf{b}_I \tag{7}$$

where $\mathbf{A}_I = \text{diag}\{\mathbf{e}_N, \mathbf{e}_N, \mathbf{e}_N\}$ is a $\mathbb{R}^{3N \times 3}$ matrix, where the column vector \mathbf{e}_N contains N ones,

$$\mathbf{b}_{I} = \begin{bmatrix} a_{1x} - r_{1} \sin \alpha_{1} \cos \phi_{1} \\ \vdots \\ a_{Nx} - r_{N} \sin \alpha_{N} \cos \phi_{N}, \\ a_{1y} - r_{1} \sin \alpha_{1} \sin \phi_{1}, \\ \vdots \\ a_{Ny} - r_{N} \sin \alpha_{N} \sin \phi_{N} \\ a_{1z} - r_{1} \cos \alpha_{1} \\ \vdots \\ a_{Nz} - r_{N} \cos \alpha_{N} \end{bmatrix}$$

and $\mathbf{x}_m = [x_{mx}, x_{my}, x_{mz}]^T$. A popular solution of the least square (LS) problem (7) is using the normal equation as

$$\hat{\mathbf{x}}_m = (\mathbf{A}_I^T \mathbf{A}_I)^{-1} \mathbf{A}_I^T \mathbf{b}_I.$$
(8)

To improve the precision of (8), different weights, denoted as $w_i, i = 1, ..., N$, are applied to emphasize the importance of nearby links which are proved to be more reliable in [14]. The weighted LS solution of (7) is presented as

$$\hat{\mathbf{x}}_m = (\mathbf{A}_I^T \mathbf{W} \mathbf{A}_I)^{-1} \mathbf{A}_I^T \mathbf{W} \mathbf{b}_I \tag{9}$$

where $\mathbf{W} = \text{diag}\{\sqrt{w_1}, \dots, \sqrt{w_N}\}$, and $w_i = 1 - \frac{r_i}{\sum_{i=1}^N r_i}$. This solution is herein denoted as *T2A*.

B. Proposed TOA/1AOA Localization

In order to reduce both hardware and computational complexities of each agent's terminal, we propose to use only the elevation AOA estimation to combine with the TOA measurement. Therefore, only one antenna array is needed, rather than the dual antenna array or the L-shape antenna array. The reasons of using the elevation angle instead of the azimuth one are follows. Firstly, the antenna array for the elevation AOA estimation is placed in the z direction which is more convenient for the operations of first responders. Secondly, it can be seen from (2) that by using the elevation angle, the agent's altitude can be calculated easily. Hence, for TOA/1AOA localization, we have a set of nonlinear equations as

$$(x_{mx} - a_{ix})^2 + (x_{my} - a_{iy})^2 + (x_{mz} - a_{iz})^2 = r_i^2$$

$$x_{mz} = a_{iz} - r_i \cos \alpha_i, \text{ for } i = 1, \dots, N.$$
(10)

Since this is an overdetermined problem, there are many possible solutions as listed and evaluated in [15]. In this paper, we present a simple method as follows.

From the last N equations of (10), the estimation \hat{x}_{mz} can be readily found as $\hat{x}_{mz} = \frac{1}{N} \sum_{i=1}^{N} (a_{iz} - r_i \cos \alpha_i)$. The first N equations in (10) can be written as

$$(x_{mx} - a_{ix})^2 + (x_{my} - a_{iy})^2 = r_i^2 \sin^2 \alpha_i \text{ for } i = 1, \dots, N.$$
(11)

Eq. (11) is equivalent to a problem of localizing agents in a 2D plane with N anchors located at $(a_{ix}, a_{iy}), i = 1, ..., N$, while the distances from the agent to anchors are $(r_i \sin \alpha_i)$.

Selecting an anchor as a reference, denoted as $\mathbf{a}_r, 1 \le r \le N$, and subtracting other equations in (11) from the *r*-th one, we have

 $\mathbf{A}_{II}\mathbf{x}_m = \mathbf{b}_{II}$

(12)

where

$$\mathbf{A}_{II} = 2 \begin{bmatrix} a_{1x} - a_{rx} & a_{1y} - a_{ry} \\ \vdots & \vdots \\ a_{Nx} - a_{rx} & a_{Ny} - a_{ry} \end{bmatrix},$$
$$\mathbf{b}_{II} = \begin{bmatrix} r_r^2 \sin^2 \alpha_r - r_1^2 \sin^2 \alpha_1 - k_r + k_1 \\ \vdots \\ r_r^2 \sin^2 \alpha_r - r_N^2 \sin^2 \alpha_N - k_r + k_N \end{bmatrix},$$

and $k_i = a_{ix}^2 + a_{iy}^2$, i = 1, ..., N. As proved in [16], the reference anchor should be chosen to have the closest distance to the agent. It means that a_r is selected if $r_r \sin \alpha_r \rightarrow min$. This least square problem can be solved by the normal equation as in (8). A WLS solution can also be applied to improve the accuracy of the algorithm as

$$\hat{\mathbf{x}}_m = (\mathbf{A}_{II}^T \mathbf{W}_{II} \mathbf{A}_{II})^{-1} \mathbf{A}_{II}^T \mathbf{W}_{II} \mathbf{b}_{II}$$
(13)

where $\mathbf{W}_{II} = \text{diag}\{\sqrt{w'_1}, \dots, \sqrt{w'_{r-1}}, \sqrt{w'_{r+1}}, \dots, \sqrt{w'_N}\}$, and

$$w'_i = 1 - \frac{|r_i \sin \alpha_i|}{\sum_i |r_i \sin \alpha_i|}, i = 1, \dots, N, \text{ and } i \neq r.$$

This solution is denoted as *T1A*.

C. Cramer-Rao Lower Bound Derivation

Cramer-Rao Lower Bound (CRLB) is derived to compare the performances of the two localization methods. CRLB is calculated from the Fisher information matrix (FIM) which contains the expected value of the observed ranging information. Define a generalized measurement vector $\boldsymbol{\theta}$ as

$$\boldsymbol{\theta} = \mathbf{f}(\mathbf{x}) + \mathbf{n} \tag{14}$$

where f(.) is a nonlinear function of the agents' positions x and n is an additive zero-mean noise vector. Since both TOA and AOA measurements are used, θ for the case of TOA/2AOA, denoted as θ_{T2A} , is presented as

$$\boldsymbol{\theta}_{T2A} = [r_1, \dots, r_N, \alpha_1, \dots, \alpha_N, \phi_1, \dots, \phi_N]^T$$
(15)

From (1) and (2), we have the nonlinear function of TOA/2AOA $\mathbf{f}_{T2A}(\mathbf{x})$ as

$$\mathbf{f}_{T2A}(\mathbf{x}) = \left[d_1, \dots, d_N, \cos^{-1}\frac{x_z - a_{1z}}{d_1}, \dots, \cos^{-1}\frac{x_z - a_{Nz}}{d_N}\right]^T$$
$$\tan^{-1}\left(\frac{x_y - a_{1y}}{x_x - a_{1x}}\right), \dots, \tan^{-1}\left(\frac{x_y - a_{Ny}}{x_x - a_{Nx}}\right)^T \in \mathbb{R}^{3N \times 1}$$
(16)

As proved in [17], when the measurement noise in (14) is zero-mean Gaussian distributed, the FIM for TOA/2AOA, denoted as $I_{T2A}(\mathbf{x})$ can be calculated from the first-order

derivative of $\mathbf{f}_{T2A}(\mathbf{x})$ over \mathbf{x} and the covariance matrix \mathbf{C}_{T2A} of the noise vector \mathbf{n} as

$$\mathbf{I}_{T2A}(\mathbf{x}) = \left[\frac{\partial \mathbf{f}_{T2A}(x)}{\partial \mathbf{x}}\right]^T \mathbf{C}_{T2A}^{-1} \left[\frac{\partial \mathbf{f}_{T2A}(\mathbf{x})}{\partial \mathbf{x}}\right]$$
(17)

where $\mathbf{C}_{T2A} \in \mathbb{R}^{3N \times 3N}$ and

$$\mathbf{C}_{T2A} = \text{diag}\{\sigma_{n_1}^2, \dots, \sigma_{n_N}^2, \sigma_{v_1}^2, \dots, \sigma_{v_N}^2, \sigma_{m_1}^2, \dots, \sigma_{m_N}^2\}.$$
(18)

Taking partial derivations of $\mathbf{f}_{T2A}(\mathbf{x})$ over the three dimensions x, y and z, we have $\frac{\partial \mathbf{f}_{T2A}(\mathbf{x})}{\partial \mathbf{x}} \in \mathbb{R}^{3N \times 3}$ as

$$\frac{\partial \mathbf{f}_{T2A}(\mathbf{x})}{\partial \mathbf{x}} = \begin{bmatrix} \frac{x_x - a_{ix}}{d_i} & \frac{x_y - a_{iy}}{d_i} & \frac{x_z - a_{iz}}{d_i} \\ \vdots & \vdots & \vdots \\ \frac{(x_x - a_{ix})(x_z - a_{iz})}{d_{2,i}d_i^2} & \frac{(x_y - a_{iy})(x_z - a_{iz})}{d_{2,i}d_i^2} & -\frac{d_{2,i}}{d_i} \\ \vdots & \vdots & \vdots \\ -\frac{(x_y - a_{iy})}{d_{2,i}^2} & -\frac{(x_x - a_{ix})}{d_{2,i}^2} & 0 \end{bmatrix}$$
for $i = 1, \dots, N$ (19)

where $d_{2,i} = \sqrt{(x_x - a_{ix})^2 + (x_y - a_{iy})^2}$, i = 1, ..., N. From (17), (18), and (19), $\mathbf{I}_{T2A}(\mathbf{x})$ is determined. Similarly, the FIM matrix for the case of TOA/1AOA, denoted as $\mathbf{I}_{T1A}(\mathbf{x})$, can be derived from (17) using the derivation of the nonlinear function $\mathbf{f}_{T1A}(\mathbf{x})$ over \mathbf{x} and the covariance matrix \mathbf{C}_{T1A} . Since TOA/1AOA only requires the distance measurement and elevation estimation, $\frac{\partial \mathbf{f}_{T1A}(\mathbf{x})}{\partial \mathbf{x}} \in \mathbb{R}^{2N \times 3}$ is obtained by taking the first 2N rows of $\frac{\partial \mathbf{f}_{T2A}(\mathbf{x})}{\partial \mathbf{x}}$ and $\mathbf{C}_{T1A} = \text{diag}\{\sigma_{n_1}^2, \ldots, \sigma_{n_N}^2, \sigma_{v_1}^2, \ldots, \sigma_{v_N}^2\} \in \mathbb{R}^{2N \times 2N}$. Finally, the CRLBs of the two methods, denoted as $CRLB_{T1A}$ and $CRLB_{T2A}$, are obtained by

$$CRLB_{j} = \sqrt{E\left\{\frac{1}{3M}\sum_{m=1}^{M}\sum_{l=1}^{3}\mathbf{I}_{j}^{-1}(\mathbf{x})_{l,l}^{(m)}\right\}}$$
(20)

where $E\{.\}$ denotes expectation over all Monte Carlo iterations, j denotes T1A and T2A, and l = 1, 2, 3.

IV. PERFORMANCE EVALUATION

A. Simulation Setup

Simulations are conducted using MATLAB to evaluate and compare the precision of the proposed approach with that of the conventional TOA/2AOA. A WSN with N anchors is randomly deployed at the altitude h to transmit beacons for 1000 agents randomly appearing in the area of 1000 m × 1000 m. The agents are equipped with antenna arrays including 10 elements and the space between elements is half of the received signal wavelength. Noise power spectral density at all agents are set at -174 dBm/Hz. The additional attenuation factor η is 3 dB [18]. Using these parameters, the received SNR at each agent can be calculated and the variance of estimation noises σ_{n_i} , σ_{m_i} , σ_{v_i} are obtained from (3) and (4).

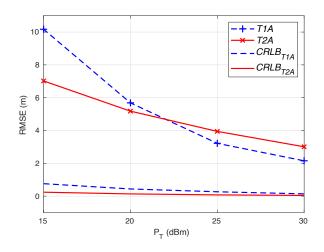


Fig. 2. RMSE versus transmit power, B = 1 MHz.

To evaluate the accuracy of different localization methods, we use the root mean square error (RMSE), defined as

$$RMSE = \sqrt{E\left\{\frac{1}{M}\sum_{m=1}^{M} (\Delta r_m)^2\right\}}$$
(21)

where $E\{.\}$ stands for expectation over Monte Carlo simulations, and $\Delta r_m = \sqrt{(x_{mx} - \hat{x}_{mx})^2 + (x_{my} - \hat{x}_{my})^2 + (x_{mz} - \hat{x}_{mz})^2}$ is the distance from the estimated location to the real location of the *m*-th agent. In the following simulations, 1000 Monte Carlo runs will be performed to estimate the locations of 1000 agents in each run.

B. Agents in 2D space

In the first scenario, all agents are assumed to move in a 2D space only. For example, the agents are all moving on the ground. Four anchors are deployed at random positions at the altitude h = 200 m. Fig. 2 shows the performance of the two localization methods over different levels of the transmit power, while the bandwidth is fixed at B = 1 MHz. Clearly, when P_T is higher than 25 dBm, TOA/1AOA is better than TOA/2AOA. We also see that $CRLB_{T1A}$ approaches $CRLB_{T2A}$ when P_T is large.

In the second simulation, we consider the impact of the transmit bandwidth on the performance of the two methods. The RMSEs of the two algorithms for different values of B are compared in Fig. 3. We can see that the TOA/1AOA's precision is improved significantly when B increases. Meanwhile, the performance of the conventional TOA/2AOA deteriorates when a wider bandwidth is used. This is because a wider bandwidth leads to a smaller TOA estimation error (cf. (3)). However, it increases the noise power at the receivers, causing a higher AOA estimation error (cf. (4)) and hence reduces the performance of the TOA/2AOA method. The inset in this figure presents a closer look of the CRLBs. Obviously, when a wider bandwidth is used, $CRLB_{T1A}$ will meet $CRLB_{T2A}$.

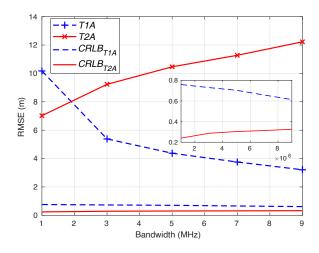


Fig. 3. RMSE versus transmit bandwidth, $P_T = 15$ dBm.

C. Agents in 3D space

In the second scenario, the agents are considered in a 3D space where first responders operate in mountainous areas or skyscrapers. In this case, the agents can randomly appear in the area at any height from 0 m to h. Unlike in the 2D space case when a higher altitude of the anchors leads to a lower SNR at the agents and hence increases the RMSE of both methods, in the 3D space, the altitude of the anchors may impact the performance of the two methods differently. We evaluate three plans of anchors' altitude as follows. Firstly, all anchors are deployed at the middle of the space, i.e., $a_{iz} = h/2, i = 1, ..., N$. Secondly, all anchors are at the top of the space, i.e., $a_{iz} = h, i = 1, ..., N$. Finally, all anchors are evenly deployed in the range from 0 m to h, i.e.,

$$a_{iz} = h_i = i\frac{h}{N}, i = 1, \dots, N.$$

All anchors transmit beacons with $P_T = 20$ dBm and 1 MHz bandwidth.

The performances of the two methods for the three deployment plans of the anchors are represented in Fig. 4. It can be seen that both *T1A* and *T2A* perform best when anchors are deployed at the centre of the space. This is because, in this case, the averaged distance from anchors to agents is smallest. We can also see that *T1A* outperforms *T2A* in all cases of anchor deployments when $N \ge 6$. It is also worth noting that *T1A* is improved significantly with the increased number of anchors.

These analyses confirm that, in UAV-assisted WSN, the complexity of agents using the TOA/2AOA localization can be mitigated significantly by the proposed TOA/1AOA method. For example, by using TOA/1AOA, an L-shape antenna array including 10 elements required in TOA/2AOA localization can be reduced to a 5 elements array placed in the z direction. In addition, 2D signal processing used in TOA/2AOA can also be simplified to 1D one. TOA/1AOA can achieve higher level of precision than TOA/2AOA by controlling WSN parameters, such as the number of anchors, their transmit power, their altitude, and signal bandwidth. Hence, understanding the impacts

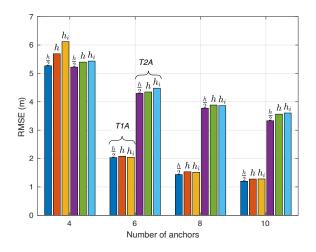


Fig. 4. RMSE versus number of anchors when agents in 3D space.

of these parameters helps to optimize the efficiency of the WSN.

V. CONCLUSION

This paper proposes a hybrid TOA/AOA localization method to simplify the complexity of the agents by requiring 1D AOA estimations only. A simple WLS solution is presented to locate the agents. The CRLBs have been derived to provide benchmarks for the two methods. The impacts of different parameters in the networks have been evaluated to show that the trade-off among these parameters can be adjusted to achieve the same level of precision as in the conventional TOA/AOA network while significantly reducing the complexity of the agents.

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