JOINT TIME SYNCHRONIZATION AND LOCALIZATION FOR TARGET SENSORS USING A SINGLE MOBILE ANCHOR WITH POSITION UNCERTAINTIES

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ABSTRACT

Clock synchronization is required by most time-based localization methods in wireless sensor networks (WSNs). However, synchronization is often coupled with localization. Furthermore, the accuracy of anchor positions depends on several factors, and uncertainties may exist in the observed anchor positions. Thus, we propose a joint time and location estimation of target sensors using a single mobile anchor to reduce the deployment cost for WSNs. Taking anchor position uncertainties into account, we develop an expectation maximization (EM)-type method to solve the joint estimation problem. The simulation results verify the performance of the proposed EM method is superior than conventional methods, such as least squares (LS), weighted least squares (WLS) and generalized total least squares (GTLS) estimators.

***Index Terms*—** wireless sensor networks, expectation maximization, localization, synchronization, anchor position uncertainties

1. INTRODUCTION

Wireless sensor networks (WSNs) attract numerous attention because of their wide applications [1] [2]. The information gathered by sensors will be much more meaningful if it is tagged with sensor positions and timestamps to indicate where and when it is collected. Thus it is significant to solve localization and synchronization problems for WSNs. Time-based approaches are often adopted in localization for WSNs. However, time synchronization is always coupled with time-based localization. Furthermore, the sensor localization is usually aided by anchor nodes with known positions, which are often determined by global positioning system (GPS), inertial navigation system (INS) [3] or baseline localization systems [4]. The uncertainties of anchor positions are inevitable and degrade the localization and synchronization performance of target sensors.

In order to deal with the coupled problems, some research works propose to accomplish localization and time synchronization simultaneously. For instance, in [5] and [6], the joint estimation is accomplished by semi-definite programming (SDP). Moreover, a distributed belief propagation algorithm is developed in [7]. A novel two-step algorithm is described in [8]. However, none of these algorithms considers anchor position uncertainties. To cope with anchor position uncertainties, [9] and [10] propose the target position estimation for WSNs through SDP and expectation maximization (EM), respectively. However neither of them considers synchronization issues. In addition, some works propose to accomplish the joint estimation with anchor position uncertainties. In [11], whose clock skew is not considered, an semi-definite relaxation (SDR) method is proposed. Among the research works presented above, only [11] utilizes a single mobile anchor and others assume accurate knowledge of anchor positions. Our previous work introduced in [12] analyzes the characteristics of the single mobile anchor system. It discusses the joint estimation problem without anchor uncertainties.

In this paper, we use a single mobile node as an anchor node to assist the localization and synchronization of the target sensors. Instead of fixed anchor nodes, the mobile anchor decreases the anchor deployment cost and adds flexibility. Considering the anchor uncertainties, we propose the EM method to jointly estimate the clock skew and offset of the target sensor as well as its position. We also tailor the conventional least squares (LS), weighted LS (WLS) and generalized total LS (GTLS) estimators to compare with the proposed EM method. The simulation results show that the proposed EM algorithm has a better performance.

The rest of this paper is organized as follows. In Section 2, the system model of joint synchronization and localization in the presence of anchor position uncertainties is presented. In Section 3, we propose the EM algorithm and adjust the LS, WLS and GTLS algorithms for fair comparison. The performance of the proposed EM estimator is compared with the ones of the LS, WLS and GTLS algorithms in Section 4.

2. SYSTEM MODEL

We consider a scenario where a single mobile anchor is employed to localize and synchronize the target sensors in WSNs. As the proposed method is the same for all the sensor nodes, we exemplify the case of localization and synchronization of a single target sensor. The position and timestamp of the mobile anchor is recorded whenever it broadcasts a packet. If we assume that the mobile anchor has a standard clock with a reference time t, and the target sensor has an asynchronous clock with its local time $C(t)$, their relationship is

$$C(t) = \alpha t + \beta, \tag{1}$$

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where α is the clock skew, and β is the clock offset of the target sensor with respect to (w.r.t.) the mobile anchor. We define that the i-th packet is broadcast by the mobile anchor at t_i according to the standard clock. The current mobile anchor position is recorded as $\mathbf{a}_i$. Let us define the corresponding true position of the anchor as $\mathbf{a}_{io}$ and the position uncertainty as $\Delta\mathbf{a}_i$. The relationship among them is $\mathbf{a}_{io} = \mathbf{a}_i + \Delta\mathbf{a}_i$, where $[\Delta\mathbf{a}_i]_j \sim N(0, \sigma_a^2)$. The mobile anchor moves along a user-defined trajectory as shown in Fig. 1.

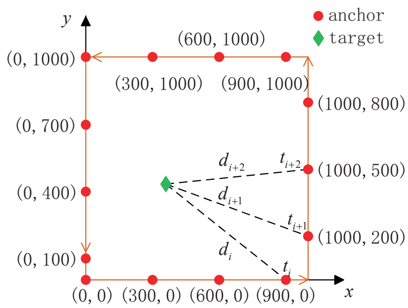

Fig. 1: An example of localizing a target sensor by a single mobile sensor.

Define the position of the target sensor as $\mathbf{x}$. According to the time of flight between the mobile anchor and the target sensor, the distance between them while the i-th packet is broadcast could be calculated as d_i, where $d_i = \|\mathbf{a}_{io} - \mathbf{x}\|$. We consider the system of two dimensions, which could be extended to the three dimensional case easily. The time stamp r_i is recorded when the i-th packet is received by the target sensor. We arrive at

$$r_i = \alpha(t_i + \frac{d_i + w_i}{c}) + \beta, \tag{2}$$

where c is the signal propagation speed related with environment conditions. The measurement noise is denoted as w_i, and $w_i \sim N(0, \sigma_w^2)$. We aim to estimate the position ($\mathbf{x}$) and clock parameters (α and β) of the target sensor using the timestamps (r_i and t_i) and the observations of anchor positions ($\mathbf{a}_i$).

Let us define $\theta_1 = \frac{1}{\alpha}$ and $\theta_2 = \frac{\beta}{\alpha}$, and assume that there are N packets received by the target sensor. We could linearize (2) as follows. Firstly, the equation (2) could be rewritten as $(r_i\theta_1 - \theta_2 - t_i)c = d_i + w_i$. Squaring both sides of the resulted equation, and according to $d_i = \|\mathbf{x} - \mathbf{a}_{io}\|$, we arrive at

$$\begin{aligned} &(r_i^2\theta_1^2 + \theta_2^2 + t_i^2 - 2r_i\theta_1\theta_2 - 2r_it_i\theta_1 + 2t_i\theta_2)c^2 \\ &= \|\mathbf{x}\|^2 - 2\mathbf{a}_{io}^T\mathbf{x} + \|\mathbf{a}_{io}\|^2 + 2d_iw_i + w_i^2. \end{aligned} \tag{3}$$

As $\mathbf{a}_{io} = \mathbf{a}_i + \Delta\mathbf{a}_i$, we have $\|\mathbf{a}_{io}\|^2 = -\|\mathbf{a}_i\|^2 + \|\Delta\mathbf{a}_i\|^2 + 2\mathbf{a}_i^T\mathbf{a}_{io}$. Taking it into account and rearranging (3), we achieve

$$\begin{aligned} &c^2t_i^2 + \|\mathbf{a}_i\|^2 \\ &= -2\mathbf{a}_{io}^T\mathbf{x} + 2c^2r_it_i\theta_1 - 2c^2t_i\theta_2 + 2c^2r_i\theta_1\theta_2 - c^2r_i^2\theta_1^2 \\ &+ \|\mathbf{x}\|^2 - c^2\theta_2^2 + 2\mathbf{a}_i^T\mathbf{a}_{io} + \|\Delta\mathbf{a}_i\|^2 + 2d_iw_i + w_i^2. \end{aligned} \tag{4}$$

As a result, we rewrite (4) into a vector form as follows.

$$\mathbf{s} = \mathbf{G}\mathbf{y} - \mathbf{A}\mathbf{h}_o + \mathbf{e}, \tag{5}$$

where $[\mathbf{s}]_i = c^2t_i^2 + \|\mathbf{a}_i\|^2$, $\mathbf{G} = \begin{bmatrix} \mathbf{H}_o & \mathbf{R} \end{bmatrix}$, with $i = 1 \cdots N$,
$[\mathbf{H}_o]_{i,:} = -2\mathbf{a}_{io}^T$,
$[\mathbf{R}]_{i,:} = \begin{bmatrix} 2c^2r_it_i, & -2c^2t_i, & 2c^2r_i, & -c^2r_i^2, & 1 \end{bmatrix}$,
$\mathbf{y} = \begin{bmatrix} \mathbf{x}^T & \mathbf{z}^T \end{bmatrix}^T$, with
$\mathbf{z} = \begin{bmatrix} \theta_1, & \theta_2, & \theta_1\theta_2, & \theta_1^2, & \|\mathbf{x}\|^2 - c^2\theta_2^2 \end{bmatrix}^T$,

$$\mathbf{A} = \begin{bmatrix} \mathbf{a}_1^T & \mathbf{0}_2^T & \cdots & \mathbf{0}_2^T \\ \mathbf{0}_2^T & \mathbf{a}_2^T & \cdots & \mathbf{0}_2^T \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0}_2^T & \mathbf{0}_2^T & \cdots & \mathbf{a}_N^T \end{bmatrix}, \quad [\mathbf{h}_o] = vec(\mathbf{H}_o),$$

$[\mathbf{e}]_i = 2d_iw_i + w_i^2 + \|\Delta\mathbf{a}_i\|^2$.
We are interested in estimating $\mathbf{y}$. Considering the relationship between the elements of $\mathbf{H}_o$ and $\mathbf{h}_o$, (5) can also be rewritten as

$$\mathbf{s} = (\mathbf{I}_N \otimes \mathbf{x}^T - \mathbf{A})\mathbf{h}_o + \mathbf{R}\mathbf{z} + \mathbf{e}. \tag{6}$$

The unknown parameters to be estimated are $\mathbf{x}$ and $\mathbf{z}$. The accurate anchor positions are denoted by $\mathbf{h}_o$. The value of $\mathbf{h}_o$ is unknown due to the anchor uncertainties. The value of α and β could be recovered from $\mathbf{z}$ through $\hat{\alpha} = \frac{1}{[\mathbf{z}]_1}$, $\hat{\beta} = \frac{[\mathbf{z}]_2}{[\mathbf{z}]_1}$. The EM-based method will be developed based on (6) in the following sections.

3. THE PROPOSED EM-BASED METHOD

This section proposes the EM algorithm to estimate the clock parameters and position of the target sensor. We also tailor the LS, WLS and GTLS estimators to compare with the EM-based method.

3.1. The iterative steps of the EM method

The EM algorithm tries to find the maximum likelihood estimation through iterative steps. This iterative algorithm aims to complete the estimation with data dropouts. The system model (6) indicates that $\mathbf{y} = \begin{bmatrix} \mathbf{x}^T & \mathbf{z}^T \end{bmatrix}^T$ could be estimated if $\mathbf{s}$ and $\mathbf{h}_o$ are known. However, $\mathbf{h}_o$ is unknown due to anchor position uncertainties. Thus, we regard $\mathbf{h}_o$ as the hidden variable vector. We carry out the E step and M step of the EM algorithm respectively, after the initial value of $\mathbf{y}$ is determined by the LS estimator.

The E step

In this step, we compute the expectation to obtain the hidden variable vector estimation and the objective function of the EM algorithm. The estimation of $\mathbf{h}_o$ is determined by the expected value of $\mathbf{h}_o$ w.r.t. $\mathbf{s}$ and the previous estimate of $\mathbf{y}$ denoted as $\widehat{\mathbf{y}}(k-1)$. This estimator is also called minimum mean square error (MMSE) estimator. The error covariance of the MMSE estimator is calculated as (8).

$$\widehat{\mathbf{h}}_o(k) = \int_{\mathbf{h}_o} \mathbf{h}_o p(\mathbf{h}_o|\mathbf{s}, \widehat{\mathbf{y}}(k-1))d\mathbf{h}_o. \tag{7}$$

$$\begin{aligned} &\mathbf{C}_{\widehat{\mathbf{h}}_o}(k) \\ &= \int_{\mathbf{h}_o} (\mathbf{h}_o - \widehat{\mathbf{h}}_o(k))(\mathbf{h}_o - \widehat{\mathbf{h}}_o(k))^T p(\mathbf{h}_o|\mathbf{s}, \widehat{\mathbf{y}}(k-1))d\mathbf{h}_o. \end{aligned} \tag{8}$$

As the probability density distribution of $\mathbf{h}_o$ is Gaussian, we could obtain

$$\mathbf{C}_{\widehat{\mathbf{h}}_o}(k) = (\mathbf{C}_{\mathbf{h}_o}^{-1} + (\mathbf{I}_N \otimes \mathbf{x}^T - \mathbf{A})^T\mathbf{C}_{\mathbf{e}}{}^{-1}(\mathbf{I}_N \otimes \mathbf{x}^T - \mathbf{A}))^{-1}, \tag{9}$$

$$\begin{aligned} &\widehat{\mathbf{h}}_o(k) \\ &= \mathbf{C}_{\widehat{\mathbf{h}}_o}(k)((\mathbf{I}_N \otimes \mathbf{x}^T - \mathbf{A})\mathbf{C}_{\mathbf{e}}{}^{-1}(\mathbf{s} - \mathbf{R}\mathbf{z} - \mathbf{E}\{\mathbf{e}\}) + \mathbf{C}_{\mathbf{h}_o}^{-1}\mathbf{h}), \end{aligned} \tag{10}$$

where $\mathbf{h} = \left[\begin{array}{ccc} -2\mathbf{a}_1^T & \cdots & -2\mathbf{a}_N^T \end{array} \right]^T$. The objective function of the EM algorithm is the expected value of $log\ p(\mathbf{s}, \mathbf{h}_o|\mathbf{y})$ w.r.t. the conditional distribution of $\mathbf{h}_o$ given $\mathbf{s}$ under $\widehat{\mathbf{y}}(k-1)$. Denote the expected value of the log likelihood as $Q(\mathbf{y}|\widehat{\mathbf{y}}(k-1))$, we arrive at

$$Q(\mathbf{y}|\widehat{\mathbf{y}}(k-1)) = \int_{\mathbf{h}_o} (log\ p(\mathbf{s}, \mathbf{h}_o|\mathbf{y}))\ p(\mathbf{h}_o|\mathbf{s}, \widehat{\mathbf{y}}(k-1))d\mathbf{h}_o. \tag{11}$$

Since $p(\mathbf{s}, \mathbf{h}_o|\mathbf{y}) = p(\mathbf{s}|\mathbf{h}_o, \mathbf{y})p(\mathbf{h}_o|\mathbf{y})$ and $\mathbf{h}_o$ is independent from $\mathbf{y}$, we can simplify the calculation of $Q(\mathbf{y}|\widehat{\mathbf{y}}(k-1))$ without the constant terms. The following equation can be easily obtained.

$$Q(\mathbf{y}|\widehat{\mathbf{y}}(k-1)) \propto \int_{\mathbf{h}_o} (log\ p(\mathbf{s}|\mathbf{h}_o, \mathbf{y}))\ p(\mathbf{h}_o|\mathbf{s}, \widehat{\mathbf{y}}(k-1))d\mathbf{h}_o. \tag{12}$$

Using the Taylor expansion, (12) has a linear approximation at $\widehat{\mathbf{h}}_o(k)$, which is the current estimate of $\mathbf{h}_o$. As the higher-order terms are equal to zero, only the first two derivatives remain. Denote $\mathbf{C}_\mathbf{e}$ as the covariance matrix of $\mathbf{e}$, and $\mathbf{c}_l$ as the l-th column vector of the square root of $\mathbf{C}_\mathbf{e}$. Therefore, $[\mathbf{c}_l]_i = \begin{cases} \frac{1}{\sqrt{4d_i^2\sigma_w^2 + 2\sigma_w^4 + 2\sigma_a^4}}, & i = l \\ 0, & i \neq l \end{cases}$. Using (7) and (8), we could simplify $Q(\mathbf{y}|\widehat{\mathbf{y}}(k-1))$ as a quadratic function w.r.t. $\mathbf{y}$

$$\begin{aligned} &Q(\mathbf{y}|\widehat{\mathbf{y}}(k-1)) \\ &\propto (\mathbf{s} - (\mathbf{I}_N \otimes \mathbf{x}^T - \mathbf{A})\widehat{\mathbf{h}}_o(k) - \mathbf{Rz} - \mathbf{E}\{\mathbf{e}\})^T \mathbf{C}_e^{-1} \\ &(\mathbf{s} - (\mathbf{I}_N \otimes \mathbf{x}^T - \mathbf{A})\widehat{\mathbf{h}}_o(k) - \mathbf{Rz} - \mathbf{E}\{\mathbf{e}\}) \\ &+ \sum_{l=1}^{N} \mathbf{c}_l^T (\mathbf{I}_N \otimes \mathbf{x}^T - \mathbf{A})\mathbf{C}_{\widehat{\mathbf{h}}_o}(k)(\mathbf{I}_N \otimes \mathbf{x}^T - \mathbf{A})^T \mathbf{c}_l. \end{aligned} \tag{13}$$

The M step

In this step, $\widehat{\mathbf{y}}(k)$ is achieved by maximizing (13). The estimate $\widehat{\mathbf{y}}(k)$ could be obtained if the derivative of (13) w.r.t. $\mathbf{y}$ equals to zero. Let us define $\widehat{\mathbf{G}}(k) = \left[\begin{array}{cc} \widehat{\mathbf{H}}_o(k) & \mathbf{R} \end{array} \right]$. As a result, we obtain the estimate of $\mathbf{y}$ in the current iteration as follows.

$$\begin{aligned} &\widehat{\mathbf{y}}(k) \\ &= ((\widehat{\mathbf{G}}(k))^T \mathbf{C}_e^{-1} \widehat{\mathbf{G}}(k) + \sum_{k=1}^{N} \mathbf{P}^T (\mathbf{c}_l^T \otimes \mathbf{I}_2)\mathbf{C}_{\widehat{\mathbf{h}}_o(k)}(\mathbf{c}_l \otimes \mathbf{I}_2)\mathbf{P})^{-1} \\ &((\widehat{\mathbf{G}}(k))^T \mathbf{C}_e^{-1}(\mathbf{s} + \mathbf{A}\widehat{\mathbf{h}}_o(k) - \mathbf{E}\{\mathbf{e}\}) \\ &+ \sum_{k=1}^{N} \mathbf{P}^T (\mathbf{c}_l^T \otimes \mathbf{I}_2)\mathbf{C}_{\widehat{\mathbf{h}}_o}(k)\mathbf{A}^T \mathbf{c}_l), \end{aligned} \tag{14}$$

where $\mathbf{P} = \left[\begin{array}{cc} \mathbf{I}_2 & \mathbf{0}_{2\times 5} \end{array} \right]$, and $\mathbf{x} = \mathbf{Py}$.

In summary, the estimation process consists of two steps. Firstly, $\widehat{\mathbf{h}}_o(k)$ and $\mathbf{C}_{\widehat{\mathbf{h}}_o}(k)$ is derived according to (9) and (10) and we arrive at (13). Secondly, we could obtain $\widehat{\mathbf{y}}(k)$ through (14). The two steps are repeated alternately. The EM algorithm terminates when $\|\widehat{\mathbf{x}}(k) - \widehat{\mathbf{x}}(k-1)\| \leq 0.001$. The initial value $\widehat{\mathbf{y}}(0)$ comes from an LS estimator.

3.2. The tailored LS, WLS and GTLS estimators

In this section, we tailor the LS, WLS and GTLS estimators for joint synchronization and localization with anchor position uncertainties. The performance of the three algorithms could be compared with the proposed EM-based method.

The LS and WLS algorithm

Let us define $[\boldsymbol{\rho}]_i = c^2t_i^2 - \|\mathbf{a}_i\|^2$, $[\boldsymbol{\epsilon}]_i = 2d_iw_i + w_i^2 + \|\Delta\mathbf{a}_i\|^2 + 2\mathbf{a}_i^T\Delta\mathbf{a}_i$, $\bar{\mathbf{y}} = \mathbf{y} + \Delta\bar{\mathbf{y}}, \Delta\bar{\mathbf{y}} = \left[\begin{array}{cc} \mathbf{0}_6^T & \sigma_w^2 + 2\sigma_a^2 \end{array} \right]^T$ and rewrite (5). We obtain the system model for the LS estimator and the LS estimate of $\bar{\mathbf{y}}$ as follows.

$$\boldsymbol{\rho} = \mathbf{G}\bar{\mathbf{y}} + \boldsymbol{\epsilon} - \mathbf{E}\{\boldsymbol{\epsilon}\} = \mathbf{G}\bar{\mathbf{y}} + \boldsymbol{\epsilon} - (\sigma_w^2 + 2\sigma_a^2)\mathbf{1}_N, \tag{15}$$

$$\widehat{\bar{\mathbf{y}}}_{LS} = (\mathbf{G}^T\mathbf{G})^{-1}\mathbf{G}^T\boldsymbol{\rho}. \tag{16}$$

Note that the accurate anchor position is unknown because of anchor position uncertainties. The value of $\mathbf{a}_{io}$ in submatrix $\mathbf{H}_o$ of $\mathbf{G}$ is replaced by $\mathbf{a}_i$ during the estimation process.

When the accurate positions of the mobile anchor are known, we denote $[\boldsymbol{\zeta}]_i = c^2t_i^2 - \|\mathbf{a}_{io}\|^2$, $[\boldsymbol{\eta}]_i = 2d_iw_i + w_i^2$, $\tilde{\mathbf{y}} = \mathbf{y} + \Delta\tilde{\mathbf{y}}$, $\Delta\tilde{\mathbf{y}} = \left[\begin{array}{cc} \mathbf{0}_6^T & \sigma_w^2 \end{array} \right]^T$. We arrive at

$$\boldsymbol{\zeta} = \mathbf{G}\tilde{\mathbf{y}} + \boldsymbol{\eta}. \tag{17}$$

Denote the covariance matrix of $\boldsymbol{\eta}$ as $\mathbf{C}_{\boldsymbol{\eta}}$, which is a diagonal matrix and $[\mathbf{C}_{\boldsymbol{\eta}}]_{i,i} = 4d_i^2\sigma_w^2 + 2\sigma_w^4$. The value of d_i is decided by $d_i = \|\widehat{\bar{\mathbf{x}}}_{LS} - \mathbf{a}_{io}\|$ from (16). The LS and WLS estimate $\widehat{\tilde{\mathbf{y}}}_{LS-I}$ and $\widehat{\tilde{\mathbf{y}}}_{WLS}$ are as follows, respectively.

$$\widehat{\tilde{\mathbf{y}}}_{LS-I} = (\mathbf{G}^T\mathbf{G})^{-1}\mathbf{G}^T\boldsymbol{\zeta}, \tag{18}$$

$$\widehat{\tilde{\mathbf{y}}}_{WLS} = (\mathbf{G}^T\mathbf{C}_{\boldsymbol{\eta}}^{-1}\mathbf{G})^{-1}\mathbf{G}^T\mathbf{C}_{\boldsymbol{\eta}}^{-1}\boldsymbol{\zeta}. \tag{19}$$

The GTLS algorithm

Referring to [13], the GTLS solves the linear parameter estimation problem while the observation matrix are with Gaussian noise of zero mean. The equation (5) is equivalent to (20) while $\vec{\mathbf{y}} = [\mathbf{y}]_{1:6}, \mathbf{W} = [\mathbf{G}]_{:,1:6}, [\boldsymbol{\varepsilon}]_i = 2d_iw_i + w_i^2 + \|\Delta\mathbf{a}_i\|^2 + 2\mathbf{a}_i^T\Delta\mathbf{a}_i + \|\mathbf{x}\|^2 - c^2\theta_2^2$.

$$\boldsymbol{\rho} = \mathbf{W}\vec{\mathbf{y}} + \boldsymbol{\varepsilon}. \tag{20}$$

The expected value of $\boldsymbol{\varepsilon}$ is not equal to zero. Therefore, we substract $\mathbf{E}\{\boldsymbol{\varepsilon}\}$ from both sides of (20). Let us define $\boldsymbol{\varrho} = \boldsymbol{\rho} - \mathbf{E}\{\boldsymbol{\varepsilon}\}$. Considering the LS estimator is unbiased, the estimate of $\mathbf{E}\{\boldsymbol{\varepsilon}\}$ could be obtained by $[\widehat{\bar{\mathbf{y}}}_{LS}]_7$. Then, the following equation could be derived.

$$\boldsymbol{\varrho} = \mathbf{W}\vec{\mathbf{y}} + \boldsymbol{\varepsilon} - [\widehat{\bar{\mathbf{y}}}_{LS}]_7\mathbf{1}_N. \tag{21}$$

Denote the errors in $\mathbf{H}_o$ and $\boldsymbol{\varrho}$ as $[\mathbf{F}]_{i,:} = \left[\begin{array}{cc} -2\Delta\mathbf{a}_{io}^T & [\boldsymbol{\varepsilon}]_i - [\widehat{\bar{\mathbf{y}}}_{LS}]_7 \end{array} \right]$ and $\mathbf{C}_\mathbf{F} = \mathbf{E}\{\mathbf{F}^T\mathbf{F}\}$. $\mathbf{R}_\mathbf{C}$ is the Cholesky decomposition of $\mathbf{C}_\mathbf{F}$. Therefore, the GTLS algorithm is proposed as

$$\begin{aligned} &\arg\min_{\widehat{\mathbf{H}}_o, \widehat{\boldsymbol{\varrho}}} \left\| \left[\begin{array}{cc} \mathbf{H}_o - \widehat{\mathbf{H}}_o & \boldsymbol{\varrho} - \widehat{\boldsymbol{\varrho}} \end{array} \right] \mathbf{R}_\mathbf{C}{}^{-1} \right\| \\ &s.t.\ Range(\widehat{\boldsymbol{\varrho}}) \subseteq Range(\widehat{\mathbf{W}}). \end{aligned} \tag{22}$$

The detailed solution of this problem is described in [13].

4. PERFORMANCE EVALUATION

In this section, we evaluate the performance of the EM method through simulations for underwater WSNs. The positions of the mobile anchor are decided by GPS when it is on the sea surface and INS underwater. The positions of the mobile anchor consist uncertainties. As the depth of the target sensor could be measured by pressure sensors, we consider the localization system of two dimensions. The accurate positions where the mobile anchor transmits signals are shown in Fig. 1. The signal propagation speed is $c = 1500$ m/s, which is the average speed of the acoustic signal underwater. The coordinates of the target sensor are uniformly distributed inside the square in Fig. 1. The clock parameters α and β are uniformly distributed in the range $[-0.3, 0.3]$ and $[1 - 10^{-3}, 1 + 10^{-3}]$, respectively. We run 5000 rounds of Monte Carlo trails to obtain the simulation results.

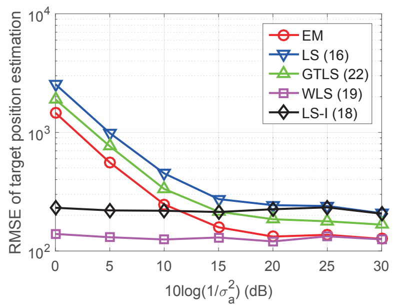

Fig. 2: RMSE of the target sensor position estimation

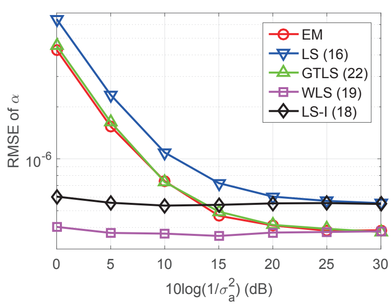

Fig. 3: RMSE of α estimation

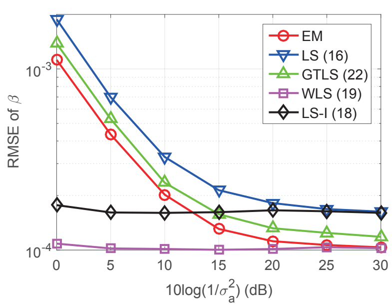

Fig. 4: RMSE of β estimation

Fig. 2 shows the position estimation performance versus different anchor position uncertainties, when $\sigma_w^2 = 10$ m^2. The EM estimator achieves the best performance compared with the LS and GTLS estimators. Because it explores the priori information about the anchor position and noise. The GTLS estimator performs better than the LS estimator as expected. The WLS estimator has a lower root mean square error (RMSE) than the LS-I estimator though both of them are carried out based on accurate anchor positions. Because the variances of the observations are unequal in our system. The EM algorithm performs better than the LS estimator even though the anchor position uncertainties are low. It is clear that the EM estimator has a better performance than LS-I while $1/\sigma_a^2$ is greater than 10 dB. Figs. 3 and 4 show the performance of clock skew and offset estimation under the same settings as in Fig. 2. The trend is similar to Fig. 2.

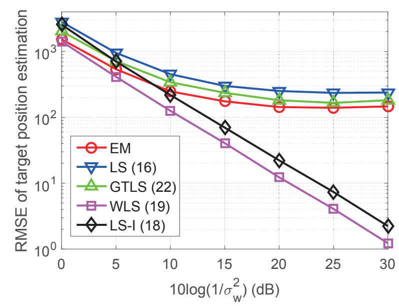

Fig. 5: RMSE of the target sensor position estimation

If we set $\sigma_a^2 = 10$ m^2, the RMSE of localization under different measurement noises could be illustrated in Fig.5. The WLS estimator has a lower RMSE than LS-I and the gap between their performance stays constant. The error floors are determined by the anchor position uncertainties. The performance trend of clock skew and offset estimation under the same settings as in Fig. 5 is similar to the position estimation. Thus, we omit their figures.

A. APPENDIX

A.1. The covariance matrix $\mathbf{C_e}$ and $\mathbf{C_{h_o}}$

As $w_i \sim N(0, \sigma_w^2)$ and $[\Delta \mathbf{a}_i]_j \sim N(0, \sigma_a^2)$, the expectation and covariance matrix of $\mathbf{e}$ can be modeled as follows.

$$\mathbf{E}\{[\mathbf{e}]_i\} = \mathbf{E}\{2d_i w_i + w_i^2 + \|\Delta \mathbf{a}_i\|^2\} = \sigma_w^2 + 2\sigma_a^2, \tag{23}$$

$$\begin{aligned}[\mathbf{C_e}]_{i,j} &= \mathbf{E}\{[\mathbf{e}]_i[\mathbf{e}]_j\} - \mathbf{E}\{[\mathbf{e}]_i\}\mathbf{E}\{[\mathbf{e}]_j\} \\ &= \begin{cases} 4d_i^2\sigma_w^2 + 2\sigma_w^4 + 2\sigma_a^4 & i = j \\ 0 & i \neq j \end{cases}, \end{aligned} \tag{24}$$

$\mathbf{C_e}$ is related to the distance d_i, and it should be updated upon the current estimate of $\mathbf{x}$ and $\mathbf{a}_{io}$ every iteration.The covariance matrix $\mathbf{C}_{\mathbf{h}_o}$ of $\mathbf{h}_o$ can be derived as $[\mathbf{C}_{\mathbf{h}_o}]_{i,j} = \begin{cases} 4\sigma_a^2, & i = j \\ 0, & i \neq j \end{cases}$.

A.2. The covariance matrix $\mathbf{C}_{\boldsymbol{\varepsilon}}$ and $\mathbf{C_F}$

The value of $\mathbf{C}_{\boldsymbol{\varepsilon}}$ and $\mathbf{C_F}$ could be computed as

$$[\mathbf{C}_{\boldsymbol{\varepsilon}}]_{i,j} = \begin{cases} 4d_i^2\sigma_w^2 + 2\sigma_w^4 + 4\sigma_a^4 + 4\sigma_a^2\|\mathbf{a}_i\|^2, & i = j \\ 0, & i \neq j \end{cases} \tag{25}$$

$$\mathbf{C_F} = \begin{bmatrix} 4N\sigma_a^2\mathbf{I}_2 & \mathbf{u} \\ \mathbf{u}^T & \sum_{i=1}^{N}\sum_{j=1}^{N}[\mathbf{C}_{\boldsymbol{\varepsilon}}]_{i,j} \end{bmatrix}, \text{with } \mathbf{u} = \begin{bmatrix} 4\sigma_a^2 \sum_{i=1}^{N}[\mathbf{a}_i]_1 \\ 4\sigma_a^2 \sum_{i=1}^{N}[\mathbf{a}_i]_2 \end{bmatrix}. \tag{26}$$

B. REFERENCES

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