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A Hybrid Localization Algorithm Based on TOF and TDOA for Asynchronous Wireless Sensor Networks

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ABSTRACT Accuracy and energy consumption are two crucial assessment standards for localization systems. The positioning algorithm used in a single technique may not balance the accuracy and power problem due to its limitations. Moreover, the performance of the existing combined localization method is unsatisfactory. In this paper, taking the relative clock skew into account, we investigate the biased time-of-flight (TOF) compensation problem in the symmetric double-sided two-way ranging (SDS-TWR) method. We first estimate the relative clock skew among sensor nodes to improve the accuracy of the ranging result. We then combine with the time-difference-of-arrival (TDOA) algorithm and reduce the number of transmissions and receptions on the tag (a node that needs to be located) side. Finally, the tag location is determined by Newton's iteration method. A simulation is implemented to validate our theoretical analysis and the results show that our proposed hybrid localization algorithm improves the locating accuracy significantly, compared with that of the C-TDOA method. Furthermore, the proposed hybrid localization algorithm can overcome the shortcoming of high power cost in the conventional TOF-based algorithm.

INDEX TERMS Wireless sensor network, hybrid localization algorithm, time-difference-of-arrival (TDOA), time-of-flight (TOF), clock skew estimation.

I. INTRODUCTION

At present, there is an increasing number of studies focusing on wireless sensor networks (WSNs), mainly due to their rich applications in environmental monitoring, internet of things (IoT), military purposes and so on [1]–[6]. Localization plays one of the most important roles in WSNs. This is because a large number of operations of WSNs require the accurate localization of the individual nodes as a priori information to know where the metrics were measured [7]–[12]. Although global positioning systems (GPSs) are well-known methods for source localization, the accuracy provided by GPS is not always sufficient in harsh environments (e.g., urban canyons and indoor scenes). Moreover, the terminals in GPS-based localization systems require GPS receivers, which are uneconomical and unrealistic [13], [14]. For this reason, many source node localization algorithms applied to wireless sensor networks have recently been proposed in the literature.

Wireless sensor networks commonly contain two types of sensor nodes, referred to as anchor nodes and tag nodes. Anchors have perfectly known locations and are regarded as the referent nodes to locate tags. Tags have unknown locations and need to be located. The purpose of localization is to estimate the locations of tags via measurements among the sensor nodes [15]–[18]. In general, localization algorithms can be classified as range-based methods and range-free methods. This paper pays attention to the range-based methods because they tend to provide better performances. Four metrics can be used to implement range-based localization algorithms: angle-of-arrival (AOA) [19]–[21], received-signal-strength (RSS) [22]–[24], time-of-arrival (TOA) [25]–[27], and time-difference-of-arrival (TDOA) [28]–[30]. AOA requires antenna arrays equipped with sensor nodes, which limits the development of the scalability of wireless sensor networks. RSS methods are operated by an energy detector, but their performance is unstable due to sensitive channel conditions. On the other hand, with recent advances in digital

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communication and signal processing technologies, TOA or TDOA based on a broadband spread spectrum system, e.g., an ultra-wideband system (UWB), has become a promising ranging method owing to the high accuracy and potentially low-cost implementation [31]–[33]. For the time-based (TOA and TDOA) localization algorithms, it is of great importance to realize clock synchronization for the accurate and low-cost estimation of locations.

However, it is not easy to find the locations of tags because the range measurements present a nonlinear function with the coordinates of tags. In general, many combined ranging-based localization algorithms seem to improve the localization accuracy compared with the single technique due to the requirements (e.g., clock synchronization and antenna array) [12], [34]–[36]. In [12], a novel hybrid RSS and TOA positioning method is proposed. The authors combine RSS and TOA technologies with the path loss difference (PLD) when considering the multi-objective cooperative networks, outperforming both the conventional RSS and TOA algorithms. A combined TDOA and AOA localization algorithm is proposed in [34]. The method considers two stations and derives a closed-form solution using a new relationship between the two types of measurements, which is simple. In [35], the authors propose a hybrid system in both non-cooperative and cooperative 3D wireless sensor networks. The authors of [35] fuse signal strength and angle of arrival measurements and introduce a novel non-convex estimator by the least-squares (LS) method. The authors in [27] propose an accurate TOF-based localization algorithm, but there are many messages transmitted between tag-anchor pairs. Power efficiency is an important criterion for evaluating the performance of localization algorithms. In fact, many applications require low-power costs and need to work for a long period, especially in mobile environments. To reduce the power consumption, a combined TOF and TDOA localization algorithm is proposed in [36]. However, the clock skew is not considered, which leads to unsatisfactory ranging accuracy.

In this paper, we propose a hybrid TOF and TDOA localization algorithm for asynchronous wireless sensor networks. Anchors have known positions and are used to locate tags, while tags' positions are unknown and need to be determined. The original TDOAs are stamped by anchors when a tag transmits a signal. Two anchors are selected to operate the TOF-based range algorithm to make the localization more accurate. Then, the solution of the tag localization is approximately solved by maximum likelihood estimation (MLE). All the timestamps are recorded with respect to the different internal clocks of the sensor nodes (both anchors and tags). To address the absence of clock synchronization, we introduce a relative clock skew estimator to compensate for the TOF measurements. Regarding the TDOA measurements, the relative clock offsets between anchors are eliminated in this paper. The main contribution of our proposed algorithm is combining the advantages of the TOF accuracy and TDOA low cast on the tag-side.

This paper is organized as follows. Section II introduces the model of the localization system and reviews the related work. Section III presents the proposed hybrid localization algorithm in detail. The simulation results are given in Section IV. Finally, we give our conclusions in Section V.

II. SYSTEM MODEL

In this section, the clock model used in our proposed algorithm is introduced. Then, the ranging models of the TOF-based and TDOA-based models are discussed. We also give the relationships between the ideal value and measurement value of the timestamps.

A. CLOCK MODEL

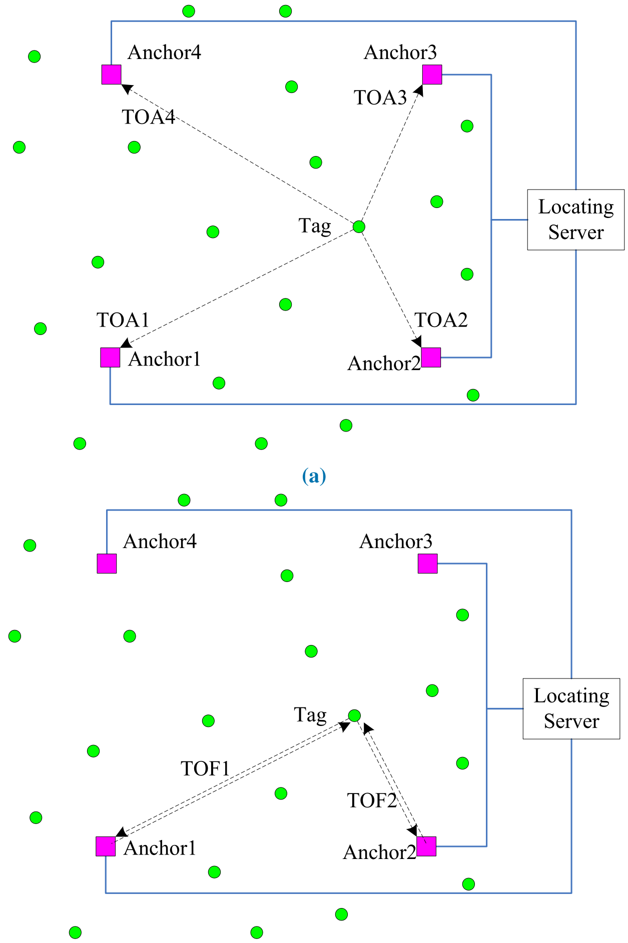
On the one hand, the measurements of time-of-emission (TOE) and TOA are stamped with the local clock inside the sensor nodes. Different nodes have different clock sources, which means deviations in the time displayed. On the other hand, the performance of localization is significantly affected by clock synchronization. In the range-based localization algorithms, a small errors deviating from the true value in time can result in a major error in location. Thus, the clock model we used is the affine clock model [37]. The display time of node i is:

$$T_i(t) = (1 + \alpha_i)t + \beta_i \tag{1}$$

where t denotes the standard ideal time, which is unique. $T_i(t)$ is the local time of node i. $(1 + \alpha_i)$ and β_i represent the clock skew and the starting clock offset, respectively, [37] indicates that the affine clock model is commonly used. It can be seen in [38] that the affine clock model is superior to other clock models (e.g., clock-offset model and discrete-valued clock model) when implementing a range-based algorithm (aimed at localization).

B. WIRELESS SENSOR NETWORK MODEL

The localization system model used in this paper is shown in Fig. 1. In this paper, we consider a 2D localization system (the proposed algorithm can be extended to 3D systems directly). As Fig. 1 shows, anchors are connected to the locating server and stamp the TOAs and TOEs from the signals of anchors and tags. Then, the timestamp information is delivered to the locating server, where the ranging and localization algorithms are implemented. Suppose there are N anchors taking part in localization; $N \geq 3$ for TOF-based and $N \geq 4$ for TDOA-based. In this model, we consider four anchors placed at fixed, known positions. The deployment of anchors is relatively irregular and needs to guarantee only the area of localization. The coordinates of anchors can be defined as vector $\mathbf{x}_i$, where $i = 1, \ldots, N$. Since TOAs/TOEs arriving at sensor nodes are used to locate the tags independently, the proximity of tags is not considered. For simplicity, only one tag is considered for our proposed algorithm. We define the tag coordinate as $\mathbf{x}_0$, which is unknown and to be estimated.



(a)

(b)

FIGURE 1. Localization model of wireless sensor network: (a) for TDOA, (b) for TOF. (anchor nodes are represented by magenta rectangles and the tag is represented by small green circle).

As shown in Fig. 1(a), the TDOAs are obtained by anchors when the tag transmits a signal, which means only one emission for the tag. Although it can provide low energy consumption for tags, the localization results estimated by TDOA are unsatisfactory. For the TOF-based method, shown in Fig. 1(b), there are several multiple message exchanges among anchors and tags. To implement the symmetric double-sided two-way ranging method, three packets need to be transmitted for each anchor-tag pair. However, the TOF-based ranging method performs well, which leads to more precise localization than that of the TDOA-based methods. In this paper, we combine the advantages of TOF-based and TDOA-based localization, and propose a hybrid localization algorithm. When determining the TOF, the clock skews of anchor-tag pairs are estimated and used to compensate for the biased measured TOFs. Although the synchronization between anchor and tag is unnecessary for TDOA, the relative clock offsets among anchors need to be eliminated. The details of the proposed algorithm are described in the next section.

In this paper, the following assumptions are made for wireless sensor network localization problem:

- Due to the general low-cost crystal oscillators, the differences in sensor nodes clock skews are smaller than 10 ppm. That is, the α_i in (1) subject to $\alpha_i \leq 10^{-5}$.
- The maximum communication distance between nodes (anchors and tags) is 300 m, which means that the TOF is approximately smaller than 1 *ms*.
- This paper does not consider the power consumption of anchors because anchors are connected to the locating server and well powered. In addition, we suppose that the locating server has enough computing capability to address the proposed algorithm.
- The non-line-of-sight (NLOS) situation is not considered in this paper. The measurement error is mainly caused by noise.

III. PROPOSED HYBRID LOCALIZATION ALGORITHM

In this section, we analyse the processing of the proposed algorithm. First, the TOF-based ranging method is presented, where the relative clock skews between anchor-tag pairs are estimated to achieve clock synchronization. Second, the TDOA-based algorithm is shown. Third, we propose our hybrid TOF and TDOA algorithm.

A. TOF TECHNIQUE

The two-way ranging (TWR) and symmetric double-sided two-way ranging (SDS-TWR) methods introduced in IEEE 802.15.4a are existing methods used to estimate the time-of-flight (TOF). For the TWR method, the TOF is computed using the TOA/TOE measured by the anchors and tags when a signal travels around the sensor nodes. However, the performance of the TWR method suffers from the reply time and the relative clock skew due to the lack of clock synchronization. Different from the TWR method, the SDS-TWR method operates an extra signal transmission from the tag to the anchor,which can accommodate a much smaller error margin even with low-quality crystals.

The work flow of the SDS-TWR is depicted in Fig. 2. There are three message exchanges in Fig. 2, and we divide the SDS-TWR procedure into three steps.

Step 1: The tag transmits the POLL1 message and measures the time-of-emission t_1. Then, the anchor receives the message and measures the time-of-arrival t_2.

Step 2: After receiving the POLL1 message, the anchor waits for a reply time t_{replyB}. Then, the anchor sends the ACK message to the tag and measures the TOE t_3. The tag receives the ACK message and measures the TOA t_4.

Step 3: After receiving the ACK message, the tag also waits for a reply time t_{replyA}. Then, the tag sends the POLL2 message to the anchor and measures the TOE t_5. The anchor receives the POLL2 message and measures the TOA t_6.

To obtain the TOF between the tag and anchor, the tag must transmit two messages and receive one message. If there are N anchors, ranging to all anchors requires $2N$ transmission and N reception to perform the distance calculation.

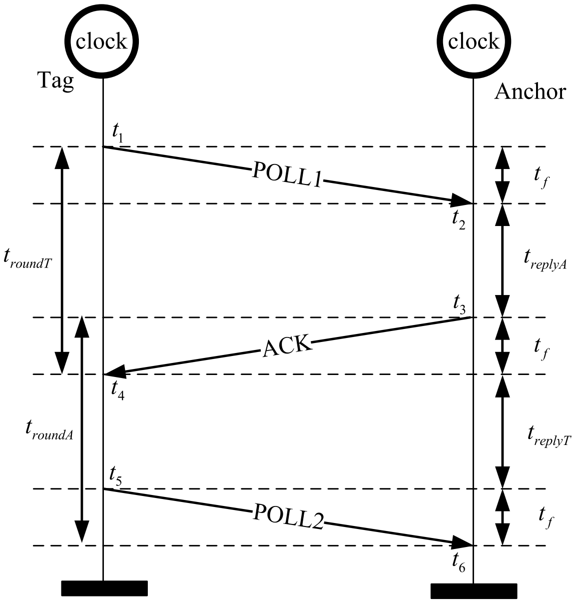


FIGURE 2. **A workflow of the SDS-TWR method.**

We define the t_f as the TOF of the tag and anchor, and the round trip time t_{roundT} and t_{roundA} can be expressed using *TOFs*. Then, t_{replyT} and t_{replyA} are:

$$t_{roundT} = 2t_f + t_{replyA} \tag{2}$$

$$t_{roundA} = 2t_f + t_{replyT} \tag{3}$$

Combining the (2) and (3) and isolating the t_f, we have

$$4t_f = t_{roundT} - t_{replyT} + t_{roundA} - t_{replyA} \tag{4}$$

Then, the distance between anchor and tag d can be computed by the TOF and the light speed c.

$$d = t_f \times c \tag{5}$$

However, the internal clocks of the node are imperfect. The period of time stamped by different nodes maybe deviate from the true value due to the clock skew. We define $(1+\alpha_T)$ and $(1+\alpha_A)$ as the clock skews of the tag and anchor. Based on the affine clock model and (1), the estimated TOF $\hat{t}_f$ can be expressed as:

$$4\hat{t}_f = (t_{roundT} - t_{replyT})(1+\alpha_T) + (t_{roundA} - t_{replyA})(1+\alpha_A) \tag{6}$$

Combining (4) and (6), we can get the estimation error using the SDS-TWR method.

$$\omega_{SDS} = \hat{t}_f - t_f = \frac{1}{2} t_f(\alpha_T + \alpha_A) + \frac{1}{4}\Delta_{reply}(\alpha_T - \alpha_A) \tag{7}$$

where

$$\Delta_{reply} = t_{replyA} - t_{replyT} \tag{8}$$

The the terms of reply time Δ_{reply} is known to the anchor and tag. Assume that the communication range is smaller than 300 m and the clock skew $\alpha_T, \alpha_A \le 10^{-5}$, we have $\frac{1}{2} t_f(\alpha_T + \alpha_A) \le 10^{-11}$, which can be ignored (the estimated error caused by the ignorance is smaller than 3 mm). Equation (7) becomes:

$$\omega_{SDS} \approx \frac{1}{4}\Delta_{reply}\Delta\alpha_{T,A} \tag{9}$$

where $\Delta\alpha_{T,A} = \alpha_T - \alpha_A$ is the relative clock skew between the tag and anchor. To obtain a more accurate ranging result, we need to estimate the relative clock skews [27].

Subtract (2) from (3), we have

$$t_{roundT} - t_{roundA} = t_{replyA} - t_{replyT} \tag{10}$$

Considering the impact of the clock skew, (10) is reshaped based on the clock model and Fig. 2.

$$\frac{t4 - t1}{1+\alpha_T} - \frac{t6 - t3}{1+\alpha_A} = \frac{t3 - t2}{1+\alpha_A} - \frac{t5 - t4}{1+\alpha_T} \tag{11}$$

where $t1 \sim t6$ denote the measured TOAs/TOEs. Equation (11) can be transformed as follows:

$$(t5 - t1) - (t6 - t2) = \alpha_T(t6 - t2) - \alpha_A(t5 - t1) \tag{12}$$

Assume that the clock skew is smaller than 10ppm, we have $(\alpha_T + \alpha_A) \le 2 \times 10^{-5} \ll 1$. Thus, we can make an approximation as follows:

$$(t5 - t1) - (t6 - t2) \approx (1 - \alpha_T - \alpha_A)[(t5 - t1) - (t6 - t2)] \tag{13}$$

Combining (12) and (13), we can get

$$(t5 - t1) - (t6 - t2) = \alpha_T(t5 - t1) - \alpha_A(t6 - t2) \tag{14}$$

Adding (12) into (14), we have

$$2[(t5 - t1) - (t6 - t2)] = \Delta\alpha_{T,A}[(t5 - t1) + (t6 - t2)] \tag{15}$$

where $\Delta\alpha_{T,A}$ is the relative clock skew between the tag and the anchor. From (15), the estimation of $\Delta\alpha_{T,A}$ is

$$\hat{\Delta}\alpha_{T,A} = \frac{2[(t5 - t1) - (t6 - t2)]}{(t5 - t1) + (t6 - t2)} \tag{16}$$

Then, the result of (16) is used to compensate the biased TOF.

Based on (6), (9) and (17), the estimated distance between the anchor and the tag is

$$\hat{d} = (\hat{t}_f - \frac{1}{4}\Delta_{reply}\hat{\Delta}\alpha_{T,A}) \times c \tag{17}$$

where

$$\hat{t}_f = \frac{(t4 - t1) - (t3 - t2) + (t6 - t3) - (t5 - t4)}{4} \tag{18}$$

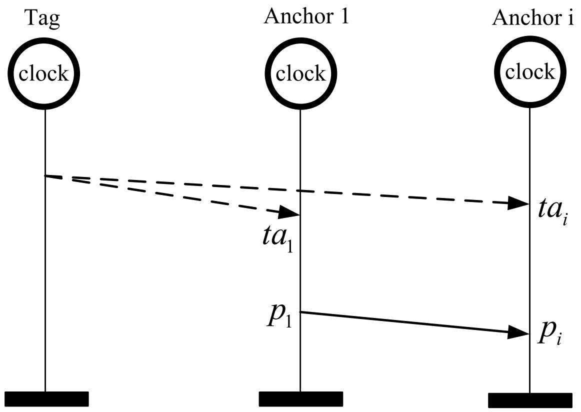


FIGURE 3. A workflow of the TDOA method.

B. TDOA TECHNIQUE

The TDOA-based method is efficient and simple for the tag side, requiring only one signal transmission for the tag. However, clock synchronization is a crucial problem for TDOA-based localization. When a tag sends a signal, the anchors receive it and measure the arrival time of the signal, and different TOAs can be used to determine the difference ranges of tag-anchor pairs. Due to a lack of synchronization, the relative clock offset among the anchors affects the localization accuracy significantly (a 10 ns error in time can lead to a 3 m error in the localization result). In contrast to [36], we propose an improved clock offset estimation method for TDOA-based localization, where the clock skew and the clock drift are both considered.

The procedure of the TDOA-based algorithm is shown in Fig. 3. First, the tag transmits a signal, and the anchors record the TOAs (i.e., ta_i, where $i = 1, \dots, N$). Then, the original TDOAs are obtained. However, the original TOAs are biased because of the relative clock offset among the anchors. To obtain accurate localization, estimation of the clock offset is necessary. Second, after all the anchors receive the tag's signal, anchor 1 sends a signal to the other anchor $i, i = 2, \dots, N$. Then, the clock offsets are estimated. Third, the TDOAs are compensated by the clock offset estimation and used to locate the tag.

The deviation of the TDOA-based localization is presented as follows. From Fig. 3, the original biased TDOAs z_i can be expressed as:

$$z_i = ta_1 - ta_i \tag{19}$$

where $i = 2, \dots, N$. Then, the estimated relative clock offset at time of p_1 is

$$\phi_{1,i} = p_1 - (p_i - \|\mathbf{x}_1 - \mathbf{x}_i\|/c) \tag{20}$$

where $\|\cdot\|$ represents the Euclidean norm, and $\phi_{1,i}$ is the relative clock offset between anchor 1 and anchor i. Based on (19) and (20), the compensated TDOA $\hat{td}_i$ is

$$\hat{td}_i = z_i - \phi_{1,i} \tag{21}$$

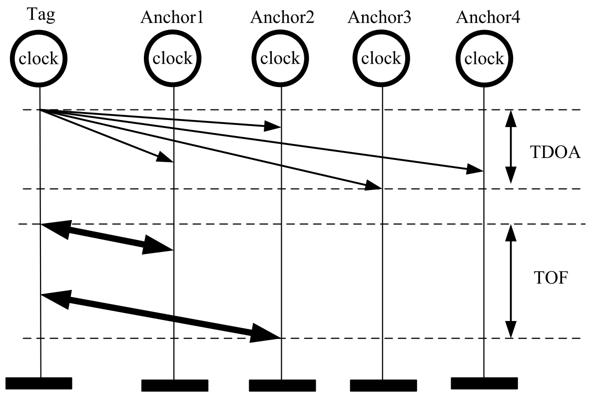


FIGURE 4. A workflow of the hybrid TOF and TDOA methods.

C. HYBRID LOCALIZATION ALGORITHM

In this subsection, the TOF and TDOA methods are combined to locate the tag. The hybrid localization algorithm workflow is shown in Fig. 4. First, the tag sends a signal to obtain the compensated TDOAs, as described in Section III-B. Assume that $\mathbf{x}_i$, $i = 1, \dots, 4$, denotes the coordinates of the anchor, which are known to the localization system. $\mathbf{x}_0 = (x_0, y_0)$ denotes the coordinate of the tag, which is unknown and need to be determined. Based on (21), we obtain three TDOA information td_i, $i = 2, \dots, 4$. Then, the relationship between TDOAs and the difference distance of anchors and the tag is

$$\Delta d_i = td_i * c = \|\mathbf{x}_1 - \mathbf{x}_0\| - \|\mathbf{x}_i - \mathbf{x}_0\|, \quad i = 2, 3, 4 \tag{22}$$

Second, the tag operates TOF-based ranging with anchor 1 and anchor 2, as described in Section III-A. Based on (17) and (18), we obtain two ranges between anchors and the tag. Then, the relationship of coordinate and the range is

$$\hat{d}_{0,i} = \|\mathbf{x}_i - \mathbf{x}_0\|, \quad i = 1, 2 \tag{23}$$

Stack (22) and (23) into the nonlinear multilateration problem, which can be solved by Newton's iteration method. Based on the least-squares criterion, the estimation of tag coordinate can be expressed as:

$$\hat{\mathbf{x}}_0 = \arg\min_{\mathbf{x}_0} \left[(\mathbf{s} - f(\mathbf{x}_0))^T (\mathbf{s} - f(\mathbf{x}_0)) \right] \tag{24}$$

where $\mathbf{s} = [\Delta d_2 \ \Delta d_3 \ \Delta d_4 \ d_{0,1} \ d_{0,2}]^T$. The function of $f(\mathbf{x}_0)$ is determined by (22) and (23), and it has no closed-form solution. Then, a successive linearization procedure [39] is as follows:

1) $\hat{\mathbf{x}}_0(m)$ denotes the *mth* estimation of $\mathbf{x}_0(m)$, so we have $\mathbf{x}_0 = \hat{\mathbf{x}}_0(m) + \Delta(m)$. Linearizing $f(\mathbf{x}_0)$ around $\hat{\mathbf{x}}_0(m)$

$$f(\mathbf{x}_0) \approx f(\hat{\mathbf{x}}_0(m)) + G(\hat{\mathbf{x}}_0(m))\Delta(m) \tag{25}$$

where $\mathbf{G}(\hat{\mathbf{x}}_0(m))$ denotes the Jacobian matrix

$$\mathbf{G}(\mathbf{x}_0) = \frac{\partial f(\mathbf{x}_0)}{\partial \mathbf{x}_0} \tag{26}$$

Substituting (25) into (24) and solving the linearized minimization problem for $\Delta(m)$ yields

$$\hat{\Delta}(m) = \left[\mathbf{G}^T(\hat{\mathbf{x}}_0(m))\mathbf{G}(\hat{\mathbf{x}}_0(m))\right]^{-1} \cdot \mathbf{G}^T(\hat{\mathbf{x}}_0(m))\left[\mathbf{s} - f_t(\hat{\mathbf{x}}_0(m))\right] \quad (27)$$

where

$$\mathbf{G}(\mathbf{x}_0) = \left[\mathbf{r}_1^T(\mathbf{x}_0) - \mathbf{r}_2^T(\mathbf{x}_0), \mathbf{r}_1^T(\mathbf{x}_0) - \mathbf{r}_3^T(\mathbf{x}_0), \mathbf{r}_1^T(\mathbf{x}_0) - \mathbf{r}_4^T(\mathbf{x}_0), \mathbf{r}_1^T(\mathbf{x}_0), \mathbf{r}_2^T(\mathbf{x}_0)\right]^T \quad (28)$$

$\mathbf{r}_i(\mathbf{x}_0)$ is defined as the unit-norm direction vectors:

$$\mathbf{r}_i(\mathbf{x}_0) = \frac{\mathbf{x}_0 - \mathbf{x}_i}{\|\mathbf{x}_0 - \mathbf{x}_i\|}, \quad i = 1, \ldots, 4 \quad (29)$$

2) The $(m+1)th$ iteration of $\mathbf{x}_0(m)$ can be estimated as:

$$\hat{\mathbf{x}}_0(m+1) = \hat{\mathbf{x}}_0(m) + \hat{\Delta}(m) \quad (30)$$

A two step process, starting with a coarse grid search and continuing with an iterative procedure, is adopted to search for the global minimum. To prevent numerical instability, $\|\hat{\Delta}(m)\|$ must not exceed 1% of the maximum propagation distance of sensor nodes during iterative computation.

IV. SIMULATION RESULT

In this section, we simulate our proposed algorithm to verify the performance. We consider four anchors in the 2D scene of a 100 m×100 m area. The coordinates of the anchors are (0,0) m, (0,100) m, (100,0) m, and (100,100) m, and the tag is placed at (70,40) m. The deployment of the localization system in this paper is similar to that in [27]. First, a simulation is conducted to test the impact of measurement noise. For a given noise level, we operate 1000 independent simulations. Second, we compare the proposed algorithm with the pure TDOA (P-TDOA) method in [36], the combined TOF/TDOA (C-TDOA) method in [36] and the method in [27] to test the impact of the clock skew parameter. Then, the energy consumption is also compared for all the above considered methods.

Fig. 5 shows the cumulative distribution function (CDF) of the localization errors for our proposed algorithm. The measurement noise level varies from 0.1 *ns* to 4 *ns*. From Fig. 5, the performance of the proposed algorithm is affected significantly when the noise increases. For $\sigma_n = 0.5\,ns$, the localization error has a probability of 90 % within 0.35 *m*. This result occurs because the TOF and TDOA information is obtained based on the stamped TOAs/TOEs, and the time stamps are disturbed by the measurement noise, which leads to a localization error.

Fig. 6 shows a performance comparison between the proposed hybrid localization algorithm and the P-TDOA method, the C-TDOA method, and the method in [27]. As shown in Fig. 6, the performance of the method in [27] is better than that of our proposed algorithm. This outcome occurs because the method in [27] is TOF-based, and the clock skew is estimated to compensate for the biased TOFs of four anchor-tag pairs, which results in a more accurate TOF estimation. However, the number of messages sent or received by the tag side in [27] is larger than in the proposed method, which means that the implementation is very costly for the tag in terms of energy consumption. Fig. 6 also indicates that the proposed hybrid localization algorithm outperforms the combined TOF/TDOA (C-TDOA) method in [36]. On the one hand, the relative clock skew of the tag and anchor in this paper is estimated to compensate for the biased TOF result, while this does not occur in the C-TDOA method. On the other hand, the rough TOF estimation of anchors is used to eliminate the relative clock offset in the C-TDOA method. However, to obtain a more accurate relative clock offset, we use the true value of the distance between anchors directly. The P-TDOA method has the worst performance, which is expected.

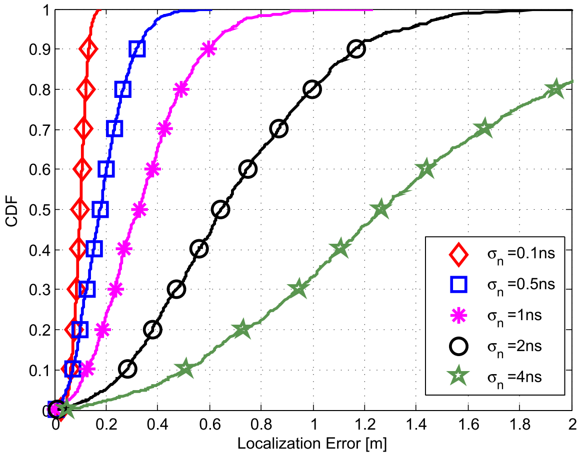


FIGURE 5. CDFs of the localization error versus different measurement noise.

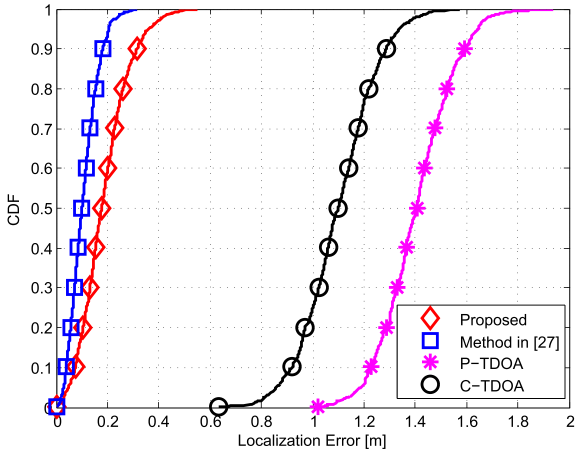


FIGURE 6. CDFs of the localization error compared with the existing methods.

Table 1 shows a comparison of the power consumption for the tag side under four anchors. Based on [36], the energy consumption of the reception operation for a tag is usually twice that of a transmission. Although our proposed algorithm is not as good as the method in [27], the energy

TABLE 1. A comparison of the power consumption for the tag side under four anchors (κ is the energy consumption of a transmission).

Method	Energy Consumption (μA)	Relative to Method in [27]
In [27]	16κ	100%
Proposed	6κ	37.5%
P-TDOA	1κ	6.3%
C-TDOA	4κ	25%

TABLE 2. A comparison of the power consumption for the tag side under seven anchors.

Method	Energy Consumption (μA)	Relative to Method in [27]
In [27]	28κ	100%
Proposed	6κ	21.4%
P-TDOA	1κ	3.6%
C-TDOA	4κ	14.3%

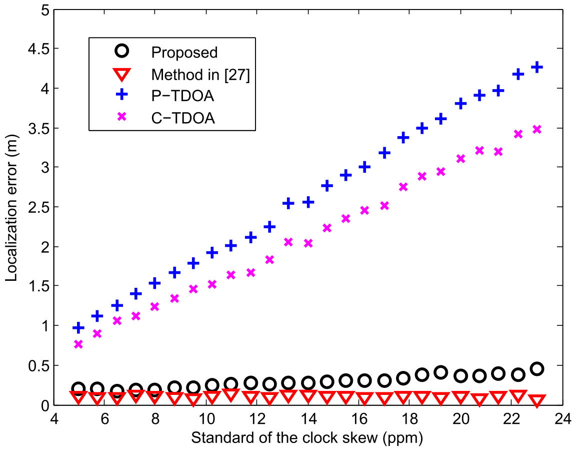


FIGURE 7. Localization error compared with the existing methods versus different clock skews.

consumption of the proposed method requires only 37.5% of the energy needed in [27]. As we can see, the P-TDOA method is an energy-efficient method in terms of the tag side, and only a 6.3% consumption relative to the method in [27] is needed.

Table 2 shows a comparison of the power consumption for the tag side under seven anchors. The energy consumption of the method in [27] is directly proportional to the anchor number. This observation indicates that the power benefit increases relative to the number of anchors. In addition, the difference of the related rate to the pure TOF method decreases as the anchor number increases.

Fig. 7 shows the localization error compared with the existing methods versus different clock skews. As the clock skew increases, the impact of the proposed method and the method in [27] is relatively weak. However, the P-TDOA and C-TDOA methods seem to be sensitive to the influence of the clock skew. This is because the first two methods estimate the clock skew, while the latter two methods do not consider the clock skew. The results in Fig. 7 coincide with the results in Fig. 6.

V. CONCLUSION

In this paper, a novel hybrid localization algorithm based on the TDOA and TOF techniques for asynchronous wireless sensor networks is proposed. For the TOF procedure, we estimate the relative clock skew and compensate for the biased TOF information. For the TDOA procedure, only one transmission is required for the tag, which means that it has the least power dissipation. Moreover, the relative clock offset among the anchors is eliminated. The proposed hybrid algorithm extends the high accuracy of the TOF and the energy efficiency of the TDOA to our system. The simulation results show that our proposed algorithm outperforms the existing methods and is suitable for the accurate and low-cost requirement in asynchronous WSNs.

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