IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received June 28, 2020, accepted July 26, 2020, date of publication July 29, 2020, date of current version August 10, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3012717

Toward Elderly Care: A Phase-Difference-of-Arrival Assisted Ultra-Wideband Positioning Method in Smart Home

YAN ZHANG[1] AND LINFU DUAN[2]
[1]College of Architecture and Civil Engineering, Chengdu University, Chengdu 6101061, China
[2]University of Electronic Science and Technology of China, Chengdu 611731, China

Corresponding author: Yan Zhang (zhangyan11@cdu.edu.cn)

This work was supported by the National Natural Science Foundation of China under Grant 61771114.

ABSTRACT Location-based services (LBSs) for elderly care is a trending topic in smart homes. The key issue is the high accurate positioning for the elderly. Ultra-wideband (UWB) is a centimeter-level positioning accuracy in line-of-sight (LOS) environments. However, most of existing UWB positioning methods need non-line-of-sight (NLOS) identification and compensation, and thus leading to severe deterioration in positioning accuracy in presence of complex indoor environments where the elderly lived. This article proposes a phase-difference-of-arrival (PDOA) assisted UWB positioning method (PDOA-UWB) for elderly care. In our positioning framework, we first calculate the phase difference of arrival from PDOA chip integrated in the UWB base stations (BSs) to obtain a coarse location of the elderly, which is further used to distinguish which nearby BSs are in LOS environments and which are in NLOS environments. Then, a PDOA-UWB positioning solution is derived to improve the positioning accuracy of the elderly. Compared with some existing methods, our method achieves higher accuracy with less NLOS compensation, and is easier to be implemented in complex indoor environments for simple practical engineering applications. Experimental results show the efficacy of our proposed method.

INDEX TERMS Phase-difference-of-arrival (PDOA), location-based services (LBSs), ultra-wideband (UWB) positioning, smart home, indoor positioning.

I. INTRODUCTION

The number of elderly people is increasing in developed countries and the healthcare services are being demanded to improve and maintain their health status and autonomy in homes or communities. It is estimated that the number of people at the age of 60 or over will reach 2 billion by the year 2050. Old age is associated with functional decline in selective aspects of cognitive performance, hence, the elderly care service is becoming more and more important in smart home applications [1]–[4].

Elderly care can be used in many applications such as medication reminders, mobile emergency response systems, fall detection systems, video surveillance systems, monitoring activities of daily life through communication with family, friends or health caregivers [1]. The key issue of the elderly care is to calculate the position of the elderly accurately. Several techniques have been proposed for the elderly positioning, including ultra-wideband (UWB) [5], WiFi [6], Bluetooth [7], and other techniques [8]. Among them, UWB is a well-known technique with centimeter-level positioning accuracy. It was widely used in assets and users management in factories, hospitals, smart homes, and other Internet-of-Things (IoT) application fields.

Although UWB is a popular positioning technique in the aforementioned fields, it needs line-of-sight signal (LOS) identification and non-line-of-sight signal (NLOS) and compensation [9] in general, and thus leading to performance deterioration in the accuracy and robustness of positioning, especially in some complex indoor scenarios where the elderly live. Some typical complex smart home environments consist of several walls, doors, and windows. Among them, doors and windows are the two main factors affecting the positioning accuracy of UWB techniques because the severe multipath propagation caused by doors and windows can result in severe NLOS propagation [10]. In this case, the existing LOS identification and NLOS compensation algorithms often fail to yield an accurate time-of-arrival (TOA) estimate,

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

which further results in location estimates with large bias. As we all known, elderly people's care needs more accurate positioning estimate than other people because most elderly people have poor health. When we provide specialized care services for the elderly, we need to know their specific location and whether they are in a falling down state, which requires their accurate position estimation.

In order to improve the service quality of the elderly, we designed a UWB BS by incorporating a phase-difference-of-arrival (PDOA) chip [11]. By using our BS, we can firstly estimate the coarse location of the elderly, which will be used to identify whether the required positioning BSs for positioning are in LOS environments or not. In this case, we only need to compensate the signals from the BSs in NLOS environments. Meanwhile, according to the coarse location of the PDOA, we can also assign higher weights to the signals from the BSs in LOS environments, and reduce the weights of the signals from the BSs in NLOS environments.

Below are the main contributions of this study:

1) We design a new hybrid positioning BS by integrating PDOA with UWB to improve the accuracy of the UWB-based positioning by fusing the coarse positioning of PDOA.
2) Although PDOA needs LOS propagation when positioning, it can easily calculate the coarse location of user with only one BS. That is to say, the probability that one BS is in LOS is much higher than the probability that multiple BSs are in LOSs. So, it can avoid the NLOS compensation for all BSs, thus reducing the positioning error of UWB-based method to some extent.
3) Unlike existing UWB-based positioning methods, which use all signals of detected BSs, our method only uses the measurements from the BSs with LOS for positioning. We just compensate NLOS for the nearest BS when the number of LOS BSs is insufficient. Hence, our method is very suitable for positioning the elderly in smart homes because the environment where they live is more complex.
4) Assisted by PDOA coarse location estimate, our proposed PDOA-UWB method can obtain an accurate location estimate of the elderly while efficiently reduces the computational time and complexity, which are very attractive in practical engineering applications.

We organize the remaining paper as follows. Section II presents some existing positioning methods for elderly care. We will detail the proposed elderly care method based on our new designed BS in Sections III. The experimental results are analyzed Section IV. And we finally draw conclusions in Section V.

II. RELATED WORKS

Elderly care has been a trending topic in the fields of architecture design [2], smart homes [3], [12], and the Internet of Things (IoT) fields in recent years [13], [14]. Location-based services (LBSs) are the main tasks for elderly care, which need to obtain the locations of the elderly in some typical complex and changing home environments full of obstacles [6], [15], [16].

There have been already many technologies such as WiFi [4], [16], [17], visible light communication [18], [19], pedestrian dead reckoning (PDR) [20], [21], and UWB [22], [23] adopted to locate targets in the aforementioned fields. For example, pedestrian dead reckoning (PDR) provides the direction and distance obtained from inertial sensors of users. The current position estimate is calculated based on the previously known position estimate. PDR based positioning methods can work well in a short moving distance. However, its performance may degenerate because the accumulated errors will be enlarged as the distance increases [5]. WiFi positioning is good for elderly care because it can provide Internet access services while positioning, but its positioning accuracy is only meter level and cannot meet the requirement of the high accurate positioning of elderly care [6], [15]. Visible light communication is also a good technology for indoor positioning, however, the Photo Diode (PD) receiver is not convenient to wear for the elderly [18].

Comparatively speaking, UWB is known as centimeter positioning accuracy and is a high bandwidth short communication technique, exhibiting the properties of strong multipath resistance and to some extent penetrable for building materials, thus making it propitious for smart home application. However, in the UWB positioning, the received signals often reach BSs from multipath and reflection caused by doors and walls with different materials whose reflection coefficients are different, thus leading to a large positioning bias by using some conventional NLOS compensation methods. This phenomenon is especially remarkable in smart home positioning environments because the homes where the elderly live are often changing by opening/closing doors and windows, and people moving, etc. In these cases, some advanced convex optimization UWB positioning methods also result in large positioning errors [22], [23].

To improve the positioning accuracy in complex indoor environments, information fusion of different sensors has been addressed recently [8], [24], [25]. The existing fusion methods mainly developed for smartphones as they embed different kinds of sensors, such as GPS, WiFi, Bluetooth accelerometer, geomagnetism, camera, and barometer. For example, Lin *et al.* proposed an integrated service platform that can accommodate safety assurance, daily activity assistance, and health support services [24]. The developed platform can offer wandering detection by using GPS and other sensors embeded in smartphones. However, the positioning for smartphones is not a good technology for elderly care because most of the elderly do not carry their smartphones at all times. UWB-based watch can solve this problem well and is a popular solution in smart homes. For UWB positioning, the most popular fusion is UWB and inertial measurement unit [26]–[28]. Fan *et al.* proposed an INS/UWB positioning method by using Kalman filter (KF) and outliers eliminating techniques. Experimental results showed that the mean square error is reduced by 24.25 % as compared with the conventional KF methods [26]. Yang *et al.* proposed a residual based weighted least square algorithm for the indoor localization system to combine the merits of UWB and Bluetooth with relatively low cost to achieve a higher accuracy, which is validated by simulation results [29]. Zheng *et al.* proposed a probabilistic sensor fusion method to combine IMU, LiDAR, and UWB for robot navigation in tunnel-like Environments. Experimental results show that the proposed method can achieve a robust localization result inside a long straight tunnel [30].

PDOA is a simple and efficient measurement for positioning because it only needs two antennas. The PDOA positioning is recently a common and most sympathetic research topic in visible light positioning [31], [32]. Compared with TDOA positioning, PDOA is an energy-efficient and low-complexity positioning method without time synchronization among BSs [33]. A special PDOA chip was originally designed by Decawave in 2018 for calculating position directly from range and phase difference of arrival at two antennas, which is very suitable for coarse location estimate in LOS environments [11].

In summary, as the development of IoT related techniques, the UWB-based technique is a popular solution for elderly care due to its high accuracy. The UWB-based fusion positioning method is the main trendency to improve the positioning accuracy in severe NLOS environments like the living space of the elderly. However, the aforementioned UWB-based fusion methods were proposed for large scale environments, such as factories, shopping malls, and commercial centers. Additionally, these methods need the user be equipped with smartphones. For elderly care, most of them might have mild cognitive impairment, memory loss and cannot use smartphones all day. Furthermore, the existing UWB-based fusion methods, such as convex optimization, have heavy computational burden and cannot be used in real positioning systems because of limited computation resources and high energy consumption. Therefore, we propose a PDOA assisted UWB positioning method by combining their merits for elderly care in smart homes.

III. PROPOSED ELDERLY CARE BASED ON ACCURATE POSITIONING

A. POSITIONING PRINCIPLE BASED ON OUR DESIGNED BASE STATION

To improve the positioning accuracy of the elderly in some typical complex environments, we design a hybrid BS which integrates PDOA together with UWB as shown in Fig. 1. The integrated PDOA chip is from Decawave and it can measure the phase difference between two closed antennas by using interferometer direction finding principle. It aims to find the coarse location of the user to further distinguish whether the BSs around the elderly are LOS or not as shown in Fig. 2. Assuming that we have 10 BSs around the elderly, and all the 10 BSs can receive the signals transmitted from the watch the elderly wears, then from the coarse location estimate of the

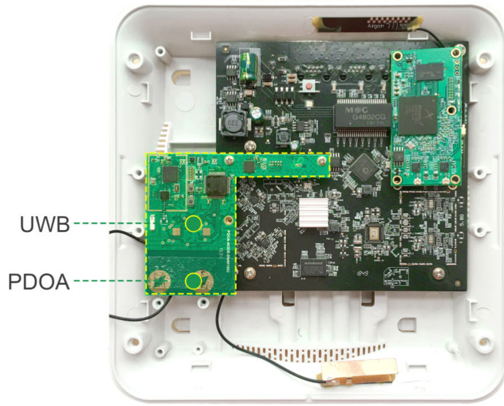


FIGURE 1. The designed PDOA-UWB BS.

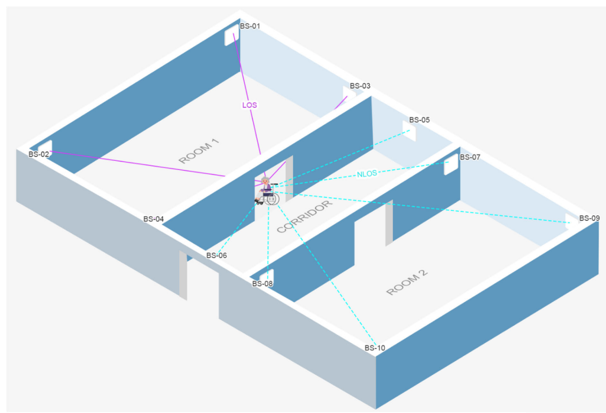
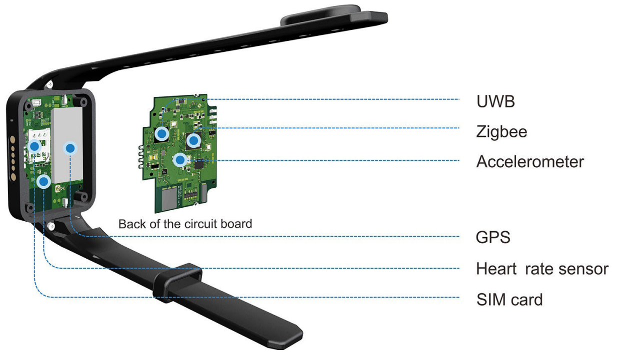


FIGURE 2. The schematic diagram of our positioning principle.

PDOA chip we can know the location of the elderly in room 1 with high probability. Based on this information, we know the BSs 1 to 4 being the LOS environments, and other stations being the NLOS environments. In this case, we can directly remove all the measurements from the BSs with NLOS, and just use the four BSs with LOS to localize the elderly without any NLOS compensation. If there are less than 4 BSs with LOS around the elderly, we can select the nearest BSs with LOS and perform dedicated NLOS compensation for the BSs with NLOS for positioning. In other words, we do not need to perform NLOS compensation for all BSs, thus reducing the complexity of the positioning algorithm and improving the accuracy of the elderly positioning simultaneously. This is the key idea of this paper. Fig. 3 is the watch shaped UWB tag for the elderly to be localized in our BS. Except for the 3D accurate UWB positioning, the watch can also monitor the blood pressure and heart rate of the elderly from the embeded sensors as shown in Fig. 3(a). The sim card in the watch can send and receive text or voice information to the relatives or friends of the elderly. The MIC interface provides a voice channel for the elderly to communicate with others. The GPS module can work for positioning when the elderly moves out of buildings, which guarantees a seamless positioning for them. We have also successfully integrated an



(a) The internal structure of our UWB watch

(b) The external shape of our UWB watch

FIGURE 3. The UWB watch for elderly positioning.

IMU into the watch by introducing the ZigBee protocol for two-way transmission of the IMU data (because UWB watch can only work on uplink), thus offering two benefits: (1) it can improve the positioning accuracy of the watch by fusing accelerometer and UWB data, and (2) the movement status of the watch can be monitored through the accelerometer data. When the watch is in a stationary state, the signal transmission frequency of the watch can be reduced for the purpose of lowering energy consumption. The battery life of the watch is up to 6 months at 1Hz date rate. Fig. 3(b) shows the external shape of the watch, which can display the real information about the elderly via a LCD.

B. COARSE LOCATION ESTIMATE USING PDOA-BASED POSITIONING

Using two receiver antennas, the unknown location $\boldsymbol{x} = [x, y]^T$ of an elderly person with a UWB watch can be found by using TOA to get the distance r to the watch and using the difference in phase of arrival as shown in Fig. 4. Assuming that we have two antennas spacing of $d \leq \frac{\lambda}{2}$ with λ being the wavelength, the signal travels a distance r to arrive antenna A and a distance $r - p$ to arrive antenna B.

1) ESTIMATION OF p

The phase difference p can be found by using the difference at the time of arrival of the earliest signal path of a received frame at two of the antennas A and B. Specifically, taking antenna B as reference point, we have

$$u_B(t) = s(t) \tag{1}$$

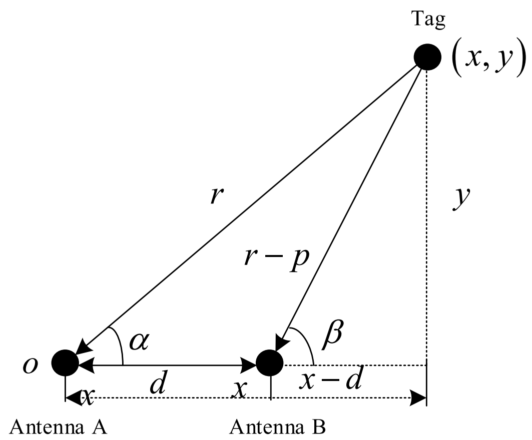


FIGURE 4. A radio signal arrives at two antennas in PDOA module separated by d.

and

$$u_A(t) = s(t)e^{-j\phi} = s(t)e^{-j2\pi f \varsigma}, \tag{2}$$

where $s(t)$ is the transmitted signal from the watch, f is the carrier frequency, and ϕ is the phase difference. The phase difference can be estimated by

$$\hat{\phi} = \text{angle}\left(\frac{u_B(t)}{u_A(t)}\right), \tag{3}$$

and the corresponding time delay ς can be estimated by

$$\hat{\varsigma} = \frac{\hat{\phi}}{2\pi f}. \tag{4}$$

With the estimated $\hat{\varsigma}$, the difference between the distances of two antennas can be given by

$$\hat{p} = c\hat{\varsigma}. \tag{5}$$

2) COARSE LOCATION ESTIMATE USING PDOA

Given the estimated $\hat{p}$, using cosine formula, we have

$$\cos(\alpha) = \frac{x}{r} = \frac{r^2 + d^2 - (r - \hat{p})^2}{2rd}. \tag{6}$$

Simplify Eq. (6), we obtain

$$x = \frac{d^2 + 2r\hat{p} - \hat{p}^2}{2d} = \left(r - \frac{\hat{p}}{2}\right)\frac{\hat{p}}{d} + \frac{d}{2}. \tag{7}$$

Consider that $x^2 + y^2 = r^2$, hence, we can obtain y by

$$y = \pm\sqrt{r^2 - x^2}. \tag{8}$$

Substituting Eq. (7) into Eq. (8), we further obtain

$$y = \pm \frac{\sqrt{\left(1 - \left(\frac{\hat{p}}{d}\right)^2\right)\left(4r^2 - 4r\hat{p} + \hat{p}^2 - d^2\right)}}{2}. \tag{9}$$

Note that d is small compare to r, so d^2 is very small compare to r^2 and can be neglected, so we have

$$y \approx \pm\left(r - \frac{\hat{p}}{2}\right)\sqrt{1 - \left(\frac{\hat{p}}{d}\right)^2}. \tag{10}$$

The maximum error by using the approximation is 0.22mm for a 6.5GHz carrier and a receiver antenna separation of $\lambda/2$. We can calculate the coarse location estimates x and y of the UWB watch if we can know the path difference p for the signal arriving at the antennas because r can be given by TOA measurement and d is known by using Eqs. (7) and (8) or (7) and (10).

C. ACCURATE POSITIONING USING UWB

For the UWB module in the BS, due to the multipath resolution capability of UWB signals, the received signal can be expressed as

$$u(t) = h(t) \otimes s(t) + n(t) = \sum_{l=0}^{L-1} h(t) s(t - \tau_l), \quad (11)$$

where $h(t)$ is the channel impulse response (CIR), $s(t)$ is the transmitted signal, $n(t)$ is the additive noise, and $\otimes$ is the convolution operator.

Based on Eq. (11), the optimal TOA estimate can be obtained using the ML or Bayesian criterion depending on the level of a priori knowledge [10]. The IEEE 802.15.4a UWB CIR $h(t)$ is based on an extended version of the classical Saleh-Valenzuela (SV) indoor channel model, where multipath components arrive at the receiver in clusters following the Poisson point process. According to the SV model, the complex baseband CIR is given by [34]

$$h(t,\tau) = \sum_{k=1}^{K} \sum_{l=1}^{L} a_{k,l} e^{j\phi_{k,l}} \delta\left(t - T_k - \tau_{k,l}\right), \quad (12)$$

where $a_{k,l}$ and $\phi_{k,l}$ are the multipath gain and phase. T_k is the arrival time of the first path of the k-th cluster, and $\tau_{k,l}$ is the delay of the l-th ray inside the k-th cluster relative to T_k with K and L being the total number of clusters and multipath. In the SV model, the phases of multipath component $\phi_{k,l}$ are modeled as independent uniform random variables in $[0, 2\pi)$, and the amplitude $a_{k,l}$ is an independent Rayleigh random variable with power delay profile (PDP)

$$E\{a_{k,l}^2\} = E\{a_{0,0}^2\} e^{-T_k/\Gamma} e^{-\tau_{k,l}/\gamma}, \quad (13)$$

where Γ and γ are the constant decay rates for clusters and rays, respectively. The cluster and ray arrival times are represented by Poisson distributed random variables with arrival rates Λ and λ, respectively, according to the following probability density functions (PDFs):

$$p(T_k | T_{k-1}) = \Lambda e^{-\Lambda (T_k - T_{k-1})} \quad (14)$$

and

$$p\left(\tau_{k,l} | \tau_{k,l-1}\right) = \lambda e^{-\lambda\left(\tau_{k,l} - \tau_{k,l-1}\right)}. \quad (15)$$

Given the received signal $r(t)$, the TOA τ can be estimated by maximum likelihood (ML) as

$$\hat{\tau}_{ML} = \arg\max_{\tau} \int_0^T u(t) s(t - \tau)\, d\tau, \quad (16)$$

which suggests the typical implementation of the estimator based on a filter matched to the transmitted signal $s(t)$ followed by a device which searches the time instant corresponding to the maximum peak of the output signal over the observation interval T. When signals propagate through the channel, an NLOS effect may emerge if the LOS signal component is obstructed by objects across the direct path between the transmitter and the receiver. NLOS propagation is often encountered in harsh indoor and urban environments. For time-based localization, NLOS propagation induces extra delay to the TOA measurement, which results in location estimation errors. Although different NLOS identification and mitigation algorithms have been proposed in the past decades, large TOA estimate errors always exists in some complex real environments, thus further leading to large positioning errors.

Assuming that we have M BSs with known coordinates $\boldsymbol{p}_i = [x_i, y_i, z_i]^T$ $(i = 1, 2, \cdots, M)$, and the location of the elderly with the watch $\boldsymbol{p}_0 = [x, y, 0]^T = \left[\boldsymbol{x}^T, 0\right]^T$ is to be estimated, we have

$$\hat{\Delta} r_{1j} = \hat{r}_j - \hat{r}_1 = c\left(\hat{\tau}_j - \hat{\tau}_1\right), \quad j = 2, \cdots, M, \quad (17)$$

where

$$\hat{r}_j = \|\boldsymbol{p}_0 - \hat{\boldsymbol{p}}_j\| \quad r_j = \|\boldsymbol{p}_0 - \boldsymbol{p}_j\| \quad (18)$$

with r_j being the jth true range between the watch and the jth BS. According to [16], the TOA measurement can be described by an additive noise model, so the estimated range can be written as

$$\hat{r}_i = r_i + v_i, \quad (19)$$

where v_i is the range error, which can be expressed as

$$v_i = \epsilon_i + \chi, \quad (20)$$

where $\epsilon_i \sim \mathcal{N}\left(0, \sigma_i^2\right)$ is independent of ϵ_i for $i \neq j$ and χ is the synchronization bias, here we assume that all the BSs have the same bias. With the vector form, we have

$$\boldsymbol{\epsilon} \sim \mathcal{N}\left(\boldsymbol{0}, \mathrm{diag}\left(\sigma_1^2, \sigma_2^2, \cdots, \sigma_M^2\right)\right), \quad (21)$$

where $\boldsymbol{\epsilon} = [\epsilon_1, \epsilon_2, \cdots, \epsilon_M]^T$. We can also write the distance difference

$$\hat{\Delta}_{1j} = \Delta_{1j} + \epsilon_{1j}, \quad j = 2, 3, \cdots, M, \quad (22)$$

where $\epsilon_{1j} = \epsilon_j - \epsilon_1$ is the error in the estimated range-difference between the first and the jth BS and $\Delta_{1j} = r_j - r_1$ is the corresponding true range-difference.

Expanding Eq. (17), we have

$$\hat{\Delta} r_{1j} = \sqrt{\left(x_j - x_0\right)^2 + \left(y_j - y_0\right)^2 + \left(z_j - z_0\right)^2} - \sqrt{(x_1 - x_0)^2 + (y_1 - y_0)^2 + (z_1 - z_0)^2} \quad (23)$$

Simplify Eq. (23), we have

$$\boldsymbol{A}\boldsymbol{x} = \boldsymbol{b}, \quad (24)$$

where

$$\boldsymbol{A}=\begin{bmatrix} x_{21}\hat{\Delta}r_{13}-x_{31}\hat{\Delta}r_{12} & y_{21}\hat{\Delta}r_{13}-y_{31}\hat{\Delta}r_{12} \\ x_{21}\hat{\Delta}r_{14}-x_{41}\hat{\Delta}r_{12} & y_{21}\hat{\Delta}r_{14}-y_{41}\hat{\Delta}r_{12} \\ \vdots & \vdots \\ x_{21}\hat{\Delta}r_{1M}-x_{M1}\hat{\Delta}r_{12} & y_{21}\hat{\Delta}r_{1M}-y_{M1}\hat{\Delta}r_{12} \end{bmatrix} \tag{25}$$

and

$$\boldsymbol{b}=\frac{1}{2}\begin{bmatrix} \hat{\Delta}r_{12}\hat{\Delta}r_{13}\hat{\Delta}r_{23}+k_{12}\hat{\Delta}r_{13}-k_{13}\hat{\Delta}r_{12} \\ \hat{\Delta}r_{12}\hat{\Delta}r_{14}\hat{\Delta}r_{24}+k_{12}\hat{\Delta}r_{14}-k_{14}\hat{\Delta}r_{12} \\ \vdots \\ \hat{\Delta}r_{12}\hat{\Delta}r_{1M}\hat{\Delta}r_{2M}+k_{12}\hat{\Delta}r_{1M}-k_{1M}\hat{\Delta}r_{12} \end{bmatrix}, \tag{26}$$

where

$$\hat{\Delta}r_{23}=\hat{\Delta}r_{12}-\hat{\Delta}r_{13} \tag{27}$$
$$\hat{\Delta}r_{24}=\hat{\Delta}r_{12}-\hat{\Delta}r_{14} \tag{28}$$
$$\hat{\Delta}r_{2M}=\hat{\Delta}_{12}-\hat{\Delta}r_{1M} \tag{29}$$
$$x_{j1}=x_1-x_j \tag{30}$$
$$y_{j1}=y_1-y_j \tag{31}$$
$$z_{j1}=z_1-z_j \tag{32}$$
$$a_j^2=x_j^2+y_j^2+z_j^2 \tag{33}$$
$$k_{1,j}=a_1^2-a_j^2 \tag{34}$$

The location estimate can be given by

$$\hat{\boldsymbol{x}}=\left(\boldsymbol{A}^T\boldsymbol{A}\right)^{-1}\boldsymbol{A}^T\boldsymbol{b}, \tag{35}$$

For the hybrid positioning, we have

$$\hat{\boldsymbol{x}}=\left(\boldsymbol{A}^T\boldsymbol{W}^{-1}\boldsymbol{A}\right)^{-1}\boldsymbol{A}^T\boldsymbol{W}^{-1}\boldsymbol{b}, \tag{36}$$

where the weighting matrix $\boldsymbol{W}$ can be given by

$$\boldsymbol{W}=\begin{bmatrix} \boldsymbol{W}_{M_1} & 0 \\ 0 & \boldsymbol{W}_N \end{bmatrix} \tag{37}$$

where $\boldsymbol{W}_{M_1}=\mathrm{diag}\left(\sigma_1^2,\cdots,\sigma_{M_1}^2\right)$ is the $M_1\times M_1$ matrix with σ_i^2 is the range measurement variance of the i-th BS with LOS, and $\boldsymbol{W}_N=\mathrm{diag}\left(\sigma_{M_1+1}^2,\cdots,\sigma_M^2\right)$ is the $(M-M_1)\times(M-M_1)$ matrix with σ_j^2 is the range measurement variance of the j-th BS with NLOS.

Instead of using the estimated $\hat{\tau}$ directly, the workflow of our proposed PDOA-UWB is illustrated in Fig. 5, and the PDOA-UWB positioning algorithm is also summarized in Algorithm 1.

Note that some existing convex optimization positioning algorithms [23], [36] can also be chosen as a candidate for UWB positioning in our framework, however, to ease the practical engineering application, we only list the above simple linear solution in order to avoid the heavy burden of the convex-based algorithms.

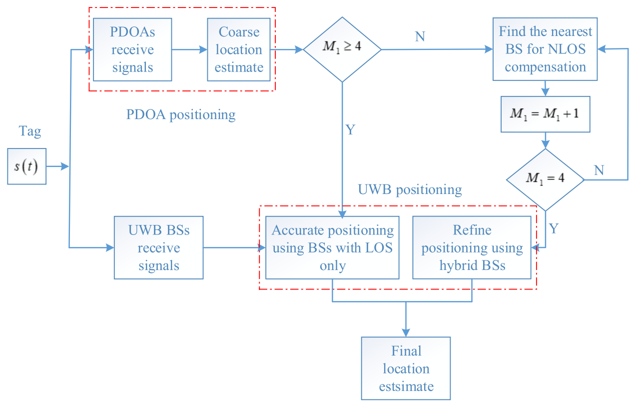


FIGURE 5. The workflow of our proposed PDOA-UWB positioning method.

Algorithm 1 PDOA-UWB

Input: 1) The transmitted signal from the UWB watch $s(t)$, $t=1,2,\cdots,T$; 2) The antenna space d in PDOA; 3) The coordinates of BSs $\boldsymbol{p}_i$; 4) The number of BSs M;
Output: The location estimate $\hat{\boldsymbol{x}}$ of the elderly

PDOAs receive signals $u_A(t)$, $u_B(t)$ and UWBs receive signals $u(t)$
Calculate the distance r using TOF [35]
Calculate the phase difference $\hat{\phi}$ using Eq. (3)
Calculate the time delay $\hat{\varsigma}$ using Eq. (4)
Calculate the distance difference p using Eq. (5)
Estimate the coarse location $[\hat{x},\hat{y}]^T$ using Eqs. (7) and (9)
Determine the number of LOS BS M_1 based on $[\hat{x},\hat{y}]^T$
for $i=1,2,\cdots,M$ **do**
    Estimate the TOA τ_i using Eq. (16)
    if $M_1 \geq 4$ **then**
        Calculate the location of the people $\hat{\boldsymbol{p}}$ using Eq. (35) without compensation
    else
        repeat
            Find the nearest BS for NLOS compensation
            $M_1=M_1+1$
        until $M_1=4$
        Refine positioning the elderly $\hat{\boldsymbol{x}}$ using Eq. (37) hybrid BSs
    end if
end for
return Final location estimate $\hat{\boldsymbol{x}}$

IV. EXPERIMENTAL RESULTS

Here, we conduct an experiment in a real home of the elderly and compare the performance of our method with several related approaches. As shown in Fig. 6, the real home has 2 bedrooms, 1 living room, kitchen, vestibule, and balconies, totaling 63.5 square meters. Note that the unit of length in Fig. 6 is millimetre (mm). A total of $M=9$ BSs was installed to mainly cover all the space of the house. To evaluate the effectiveness of the proposed algorithm, we use

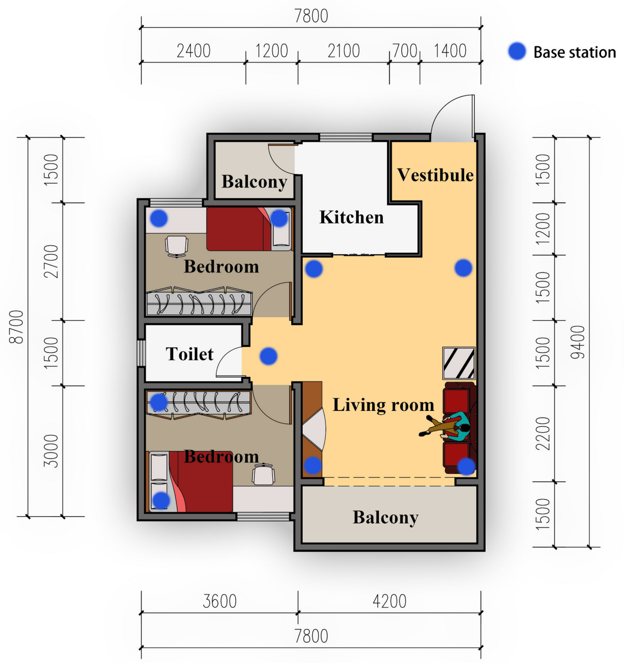


FIGURE 6. The experimental environment in an elderly home.

the root mean square error (RMSE) as a metric, which is defined as

$$\mathrm{RMSE}=\sqrt{\frac{1}{J}\sum_{j=1}^{J}\left[(\hat{x}_j-x)^2+(\hat{y}_j-y)^2+(\hat{z}_j-z)^2\right]}, \tag{38}$$

where $[\hat{x}_j, \hat{y}_j, \hat{z}_j]^T$ represents the j-th location estimate, $[x, y, z]^T$ is the true location of source, and J is the number of experiment trials.

To validate the efficacy of our method, we compare our methods with two conventional TDOA-based position methods, i.e., Chan method [37] and Convex method [23]. The Chan's method is a typical closed form solution for TDOA positioning, which is sensitive to NLOS measurement errors. Comparatively, convex-based methods need semidefinite relax (SDR) for convex optimization, and thus showing computational burden as compared with the closed form solutions.

We randomly select $J = 120$ test points in our experiment to calculate the RMSEs. The cumulative distribution functions (CDFs) of the RMSEs of different positioning algorithms are illustrated in Fig. 7.

It shows that the probability of our proposed PDOA-UWB method achieving positioning error of less than 1m is 92.77%. The probability of positioning error of less than 1m for Convex+UWB (9BSs, NLOS compensation) (i.e., using Convex algorithm based on TDOA measurements of 9 BSs with NLOS compensation), Convex+UWB (9BSs, no NLOS compensation) (i.e., using Convex algorithm based on TDOA measurements of the UWB with NLOS compensation), Chan+UWB (9BSs, NLOS compensation) (i.e., using Chan algorithm based on TDOA measurements of 9BSs with

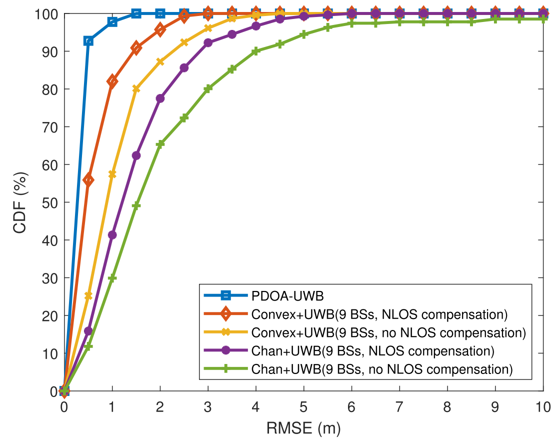


FIGURE 7. The CDF curves for different compared methods.

NLOS compensation), and Chan+UWB (9BSs, no NLOS compensation) (i.e., using Chan algorithm based on TDOA measurements of 9BSs without NLOS compensation) are 80.87%, 55.87%, 41.33%, and 29.89%, respectively. From the results, we find our method more superior to the other methods in positioning accuracy.

Fig. 8 shows the histogram of the RMSEs of different localization algorithms, indicating that the RMSEs of PDOA-UWB, Convex+UWB (9BSs, NLOS compensation), Convex+UWB (9BSs, no NLOS compensation), Chan+UWB (9BSs, NLOS compensation), and Chan+UWB (9BSs, no NLOS compensation) are 0.5145m, 1.4371m, 2.2469m, 2.7791m, and 3.0562m, respectively. For convenience purposes, we used abbreviations, for example, "9BSs, NLOS compensation" is abbreviated as "comp", and "9BSs, no NLOS compensation" is abbreviated as "no comp". Note that our proposed PDOA-UWB algorithm needs only 4 BSs for accurate positioning, and other compared methods use all the measurements of BSs to achieve their accuracy. That is to say, our method can obtain better performance by avoiding the unnecessary NLOS compensation, which is attributed to the use of PDOA coarse location.

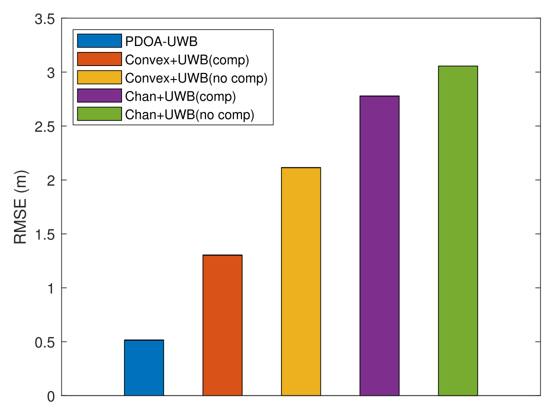


FIGURE 8. The histogram of different positioning methods.

Figure 9 shows the RMSEs of different methods under different number of BSs. We can find that the RMSEs decrease as the number of BSs involved in positioning increases.

TABLE 1. The complexities and average running time of the three typical methods.

Algorithms	Complexity	Ave Time (s)
SDP [36]	$\mathcal{O}\left(\sqrt{M}\left((M+4)^4+(M+4)(M+1)^3\right)\right)$	1.9237
SDP-R [23]	$\mathcal{O}\left((M+6)^{6.5}\right)$	2.5762
Our method	$\mathcal{O}(M)^3$	0.0013

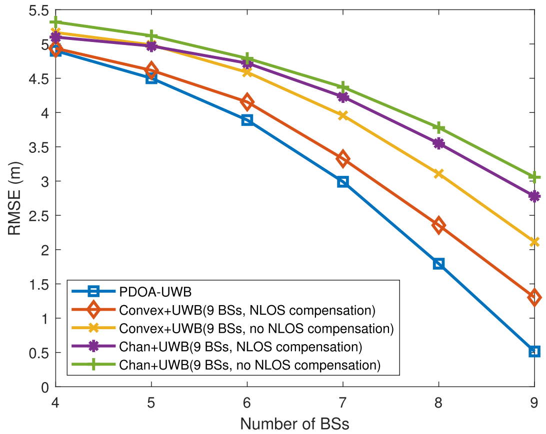


FIGURE 9. The RMSEs under different number of BSs.

Comparatively, our method shows better positioning accuracy because our algorithm can make full use of the signals from the BSs with LOS and efficiently compensate the BSs with NLOS from the nearest locations based on the coarse positioning of the PDOA positioning procedure.

To show the robustness of our proposed method, Fig. 10 illustrates the RMSEs of our method under different NLOS propagation cases. Note that our method needs only four BSs for positioning, so we test the performance of our method with different LOS and NLOS combinations. It can be seen that the more LOS BSs, the better the performance of our method. The probability of RMSEs of less than 0.45m is 95.38% in four LOS BSs case.

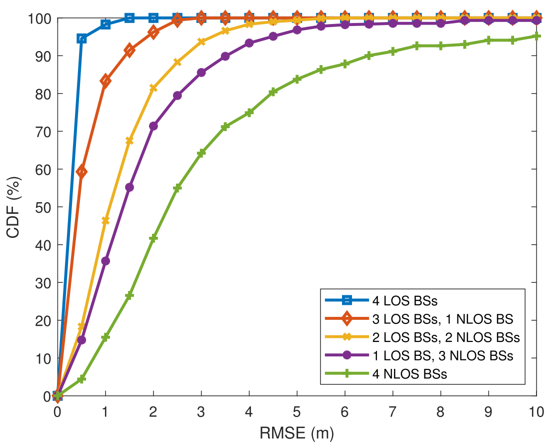


FIGURE 10. The RMSEs under different NLOS cases.

To compare the computational burden of our proposed algorithm with other existing methods, we list the computational complexity and average time of our method and SDP [36], robust SDP [23] (denoted as SDP-R) in Table 1. The average time is calculated based on the 1000 independent runs under MATLAB 2018 and Pentium I7 processors. Note that the main computational burden of our method is the inverse of a $M \times M$ matrix because other operators are linear. Other two compared method consume more running time on convex solution finding, so our method show superiority in practical engineering applications.

V. CONCLUSION AND FUTURE WORKS

This article proposed a PDOA assisted UWB positioning method (PDOA-UWB) for location-based user service in smart home. In our positioning framework, we first calculated the phase difference of arrival from PDOA chip integrated in the UWB BSs to obtain a coarse location of the elderly. This is used to distinguish which nearby BSs are in a LOS environment and those in a NLOS environment. Combined with the UWB positioning method, we proposed a PDOA assisted UWB (PDOA-UWB) positioning method to improve the positioning accuracy of the elderly. Compared with some existing methods, our method can achieve higher accuracy with less NLOS compensation, and is easier to be implemented in complex practical indoor environments.

The proposed PDOA-UWB method can efficiently select the minimal and optimal BSs for positioning, thus avoiding the blind compensation and calculation burden of the traditional UWB positioning methods. Our proposed method is mainly designed for fast and robust practical engineering applications, which reduce the computational burden of the convex-based methods greatly without remarkable performance loss. The proposed positioning scheme can not only solve the problem of elderly care in smart homes, it also has better application prospects for other complex positioning environments, such as factories, parking, and airports.

REFERENCES

[1] G. Gaoan and Z. Zhenmin, "Heart rate measurement via smart phone acceleration sensor," in *Proc. IEEE Int. Conf. Smart Comput.*, Nov. 2014, pp. 295–300.

[2] M. Prado, J. Reina-Tosina, and L. Roa, "Distributed intelligent architecture for falling detection and physical activity analysis in the elderly," in *Proc. IEEE EMBS-BMES*, vol. 3, Oct. 2002, pp. 1910–1911.

[3] J. M. Canas, S. Marugán, M. Marrón, and J. C. Garcia, "Visual fall detection for intelligent spaces," in *Proc. IEEE Int. Symp. Intell. Signal Process.*, Aug. 2009, pp. 157–162.

[4] X. Guo, N. Ansari, F. Hu, Y. Shao, N. R. Elikplim, and L. Li, ''A survey on fusion-based indoor positioning,'' *IEEE Commun. Surveys Tuts.*, vol. 22, no. 1, pp. 566–594, 1st Quart., 2020.

[5] M. Alzantot and M. Youssef, ''UPTIME: Ubiquitous pedestrian tracking using mobile phones,'' in *Proc. IEEE Wireless Commun. Netw. Conf. (WCNC)*, Shanghai, China, Apr. 2012, pp. 3204–3209.

[6] X. Guo, S. Zhu, L. Li, F. Hu, and N. Ansari, ''Accurate WiFi localization by unsupervised fusion of extended candidate location set,'' *IEEE Internet Things J.*, vol. 6, no. 2, pp. 2476–2485, Apr. 2019.

[7] L. Aalto, N. Göthlin, J. Korhonen, and T. Ojala, ''Bluetooth and WAP push based location-aware mobile advertising system,'' in *Proc. 2nd Int. Conf. Mobile Syst., Appl., Services*, 2004, pp. 49–58.

[8] X. Xu, M. Wang, L. Luo, Z. Meng, and E. Wang, ''An indoor pedestrian localization algorithm based on multi-sensor information fusion,'' *J. Comput. Commun.*, vol. 5, no. 3, pp. 102–115, 2017.

[9] I. Guvenc and C.-C. Chong, ''A survey on TOA based wireless localization and NLOS mitigation techniques,'' *IEEE Commun. Surveys Tuts.*, vol. 11, no. 3, pp. 107–124, 3rd Quart., 2009.

[10] K. Yu and Y. J. Guo, ''Statistical NLOS identification based on AOA, TOA, and signal strength,'' *IEEE Trans. Veh. Technol.*, vol. 58, no. 1, pp. 274–286, Jan. 2009.

[11] *PDOA*. Accessed: Sep. 3, 2019. [Online]. Available: hhttps://www.decawave.com/technology1/

[12] A. Gaddam, S. Mukhopadhyay, and G. S. Gupta, ''Smart home for elderly care using optimized number of wireless sensors,'' in *Proc. 4th Int. Conf. Comput. Devices Commun. (CODEC)*, Dec. 2009, pp. 1–4.

[13] H. Yan, H. Huo, Y. Xu, and M. Gidlund, ''Wireless sensor network based e-health system–implementation and experimental results,'' *IEEE Trans. Consum. Electron.*, vol. 56, no. 4, pp. 2288–2295, Nov. 2010.

[14] B. M. C. Silva, J. J. P. C. Rodrigues, T. M. C. Simões, S. Sendra, and J. Lloret, ''An ambient assisted living framework for mobile environments,'' in *Proc. IEEE-EMBS Int. Conf. Biomed. Health Informat. (BHI)*, Jun. 2014, pp. 448–451.

[15] X. Guo, L. Li, F. Xu, and N. Ansari, ''Expectation maximization indoor localization utilizing supporting set for Internet of Things,'' *IEEE Internet Things J.*, vol. 6, no. 2, pp. 2573–2582, Apr. 2019.

[16] X. Guo, N. R. Elikplim, N. Ansari, L. Li, and L. Wang, ''Robust WiFi localization by fusing derivative fingerprints of RSS and multiple classifiers,'' *IEEE Trans. Ind. Informat.*, vol. 16, no. 5, pp. 3177–3186, May 2020.

[17] L. Li, X. Guo, N. Ansari, and H. Li, ''A hybrid fingerprint quality evaluation model for WiFi localization,'' *IEEE Internet Things J.*, vol. 6, no. 6, pp. 9829–9840, Dec. 2019.

[18] X. Guo, F. Hu, N. R. Elikplim, and L. Li, ''Indoor localization using visible light via two-layer fusion network,'' *IEEE Access*, vol. 7, pp. 16421–16430, 2019.

[19] S. V. Tiwari, A. Sewaiwar, and Y.-H. Chung, ''Color coded multiple access scheme for bidirectional multiuser visible light communications in smart home technologies,'' *Opt. Commun.*, vol. 353, pp. 1–5, Oct. 2015.

[20] Y.-L. Hsu, P.-H. Chou, H.-C. Chang, S.-L. Lin, S.-C. Yang, H.-Y. Su, C.-C. Chang, Y.-S. Cheng, and Y.-C. Kuo, ''Design and implementation of a smart home system using multisensor data fusion technology,'' *Sensors*, vol. 17, no. 7, p. 1631, Jul. 2017.

[21] A. Cenedese, G. A. Susto, G. Belgioioso, G. I. Cirillo, and F. Fraccaroli, ''Home automation oriented gesture classification from inertial measurements,'' *IEEE Trans. Autom. Sci. Eng.*, vol. 12, no. 4, pp. 1200–1210, Oct. 2015.

[22] G. Wang, S. Cai, Y. Li, and N. Ansari, ''A bias-reduced nonlinear WLS method for TDOA/FDOA-based source localization,'' *IEEE Trans. Veh. Technol.*, vol. 65, no. 10, pp. 8603–8615, Oct. 2016.

[23] G. Wang, W. Zhu, and N. Ansari, ''Robust TDOA-based localization for IoT via joint source position and NLOS error estimation,'' *IEEE Internet Things J.*, vol. 6, no. 5, pp. 8529–8541, Oct. 2019.

[24] Q. Lin, D. Zhang, H. Ni, X. Zhou, and Z. Yu, ''An integrated service platform for pervasive elderly care,'' in *Proc. IEEE Asia–Pacific Services Comput. Conf.*, Dec. 2012, pp. 165–171.

[25] P. A. Moreno, M. E. Hernando, and E. J. Gomez, ''Design and technical evaluation of an enhanced location-awareness service enabler for spatial disorientation management of elderly with mild cognitive impairment,'' *IEEE J. Biomed. Health Informat.*, vol. 19, no. 1, pp. 37–43, Jan. 2015.

[26] Q. Fan, B. Sun, Y. Sun, and X. Zhuang, ''Performance enhancement of MEMS-based INS/UWB integration for indoor navigation applications,'' *IEEE Sensors J.*, vol. 17, no. 10, pp. 3116–3130, May 2017.

[27] L. Zwirello, X. Li, T. Zwick, C. Ascher, S. Werling, and G. F. Trommer, ''Sensor data fusion in UWB-supported inertial navigation systems for indoor navigation,'' in *Proc. IEEE Int. Conf. Robot. Autom.*, Karlsruhe, Germany, May 2013, pp. 3154–3159.

[28] P. K. Yoon, S. Zihajehzadeh, B.-S. Kang, and E. J. Park, ''Robust biomechanical model-based 3-D indoor localization and tracking method using UWB and IMU,'' *IEEE Sensors J.*, vol. 17, no. 4, pp. 1084–1096, Feb. 2017.

[29] S. Yang and B. Wang, ''Residual based weighted least square algorithm for Bluetooth/UWB indoor localization system,'' in *Proc. 36th Chin. Control Conf. (CCC)*, Dalian, China, Jul. 2017, pp. 5959–5963.

[30] W. Zhen and S. Scherer, ''Estimating the localizability in tunnel-like environments using LiDAR and UWB,'' in *Proc. Int. Conf. Robot. Autom. (ICRA)*, May 2019, pp. 4903–4908.

[31] S. Zhang, P. Du, C. Chen, W.-D. Zhong, and A. Alphones, ''Robust 3D indoor VLP system based on ANN using hybrid RSS/PDOA,'' *IEEE Access*, vol. 7, pp. 47769–47780, 2019.

[32] A. Naz, H. M. Asif, T. Umer, and B.-S. Kim, ''PDOA based indoor positioning using visible light communication,'' *IEEE Access*, vol. 6, pp. 7557–7564, 2018.

[33] B. Sackenreuter, N. Hadaschik, M. Fassbinder, and C. Mutschler, ''Low-complexity PDoA-based localization,'' in *Proc. Int. Conf. Indoor Positioning Indoor Navigat. (IPIN)*, Sapporo, Japan, Oct. 2016, pp. 1–6.

[34] Z. Sahinoglu, *Ultra-Wideband Positioning Systems*. Cambridge, U.K.: Cambridge Univ. Press, 2008.

[35] T. Gädeke, J. Schmid, M. Krüger, J. Jany, W. Stork, and K. D. Müller-Glaser, ''A bi-modal ad-hoc localization scheme for wireless networks based on RSS and ToF fusion,'' in *Proc. 10th Workshop Positioning, Navigat. Commun. (WPNC)*, Dresden, Germany, Mar. 2013, pp. 1–6.

[36] S. Venkatesh and R. M. Buehrer, ''NLOS mitigation using linear programming in ultrawideband location-aware networks,'' *IEEE Trans. Veh. Technol.*, vol. 56, no. 5, pp. 3182–3198, Sep. 2007.

[37] Y. T. Chan and K. C. Ho, ''A simple and efficient estimator for hyperbolic location,'' *IEEE Trans. Signal Process.*, vol. 42, no. 8, pp. 1905–1915, Aug. 1994.

YAN ZHANG received the B.Eng. degree from the Southwest University of Science and Technology, Mianyang, China, in 2007, and the M.Eng. degree from Southwest Jiaotong University, Chengdu, China, in 2010. She is currently an Assistant Professor with the College of Architecture and Civil Engineering, Chengdu University, Chengdu. Her research interests include architecture design, smart homes, elderly building design, and the Internet of Things.

LINFU DUAN received the B.Eng., M.Eng., and Ph.D. degrees from the University of Electronic Science and Technology of China (UESTC), Chengdu, China, in 2009, 2018, and 2012, respectively. He is currently a Research Fellow of the UESTC. His research interests include wireless positioning and ultra-wideband positioning.