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Human Localization Using Multi-Source Heterogeneous Data in Indoor Environments

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ABSTRACT A human localization system using multi-source heterogeneous data in indoor environments is proposed in this paper. The system can be easily constructed with already deployed Wi-Fi and camera infrastructures and is able to make use of received signal strength samples, surveillance images, and room map information to achieve a comparable performance. In a corridor scenario, we optimize propagation model (PM) parameters with crowdsourcing data from only several locations and establish a data table of optimized parameters for trilateration localization. These crowdsourcing data are also used to correct trilateration localization results, through which localization performance can be greatly improved. In a room scenario, we locate a human object with a panoramic camera and room map. We first detect the human object on the observed image and search a pixel location that represents the object's location best. Then, the pixel location on the image is mapped to the room map using an artificial neural network. By this method, localization accuracy of sub-meter level can be obtained. We perform the proposed system in our experimental environment, and the experimental results show that our localization system not only requires no extensive time and labor cost, but also outperforms fingerprinting and PM localization systems.

INDEX TERMS Indoor localization, propagation model optimization, coordinate correction, object detection, location mapping.

I. INTRODUCTION

In global positioning system (GPS)-denied indoor environments, various indoor localization systems based on different techniques, such as ultra wideband (UWB), infrared, ultrasound, Wi-Fi, and vision processing, have been developed for location-based services (LBS) [1]–[3]. Because Wi-Fi infrastructures are ubiquitously deployed in indoor environments for communications, localization methods using Wi-Fi have been extensively researched like propagation model (PM), time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), and fingerprinting [3]–[6]. Meanwhile, cameras also proliferate fast in people's daily life for surveillance and localization methods with a single camera and camera network also have been presented in the past few years. Therefore, a heterogeneous design of Wi-Fi and camera-based localization is highly promising for accurate localization in indoor environments [7].

Among of the localization methods based on Wi-Fi, fingerprinting method is favored because it only needs software update without any hardware modification and outperforms the other methods under non-line-of-sight (NLOS) environments. However, it requires a process of data collection in the offline phase, which needs to collect location-labeled received signal strength (RSS) data by trained experts to build a database called radio-map [6]. The process requires considerable time and effort and therefore it limits the application potential of fingerprinting method. Although PM method needs no data collection and extra hardware, as a range-based localization method, the performance of PM method heavily depends on the estimated distances between a user and Wi-Fi access points (APs) for trilateration localization. So the performance of basic PM method is barely satisfactory.

In recent years, crowdsourcing approach has been proposed for radio-map establishment, in which common users, namely crowdsourcing participants, contribute location-labeled RSS data in a participatory sensing manner [8]. However, the problem of crowdsourcing-based radio-map establishment is that a considerable number of RSS data should be collected to compute an accurate localization result [9]. Thus, we apply crowdsourcing to PM localization method. In a corridor scenario, we mark crowdsourcing points (CPs) with two-dimensional (2-D) code stickers on the ground, so that crowdsourcing participants can freely scan the 2-D codes for location information and label collected RSS data with the location information. These crowdsourcing data are used for PM optimization and coordinate correction. Unlike fingerprinting method, our proposed crowdsourcing-based PM localization method only needs location-labeled RSS data collected at a few CPs. This amount of RSS data can be easily collected in a short time and usually are not enough for fingerprinting method.

Because crowdsourcing participants might not be allowed to enter rooms, we propose a human localization method using a panoramic camera and room map for room scenarios, which offers a localization accuracy of sub-meter level. The method first detects a human object observed with the panoramic camera on the room ceiling. Then the pixel location that represents the object's location best is searched and mapped to a corresponding pixel location on the room map to obtain a localization result.

Therefore, in this paper, we propose a human localization system using multi-source heterogeneous data for accurate localization in corridor and room scenarios. The main contributions of this paper are summarized:

1) We propose an indoor localization system using multi-source heterogeneous data that consist of RSS samples, surveillance images and room map information. The system not only can be easily constructed with already deployed Wi-Fi and camera infrastructures, but also is able to achieve a comparable localization performance.

2) We propose a crowdsourcing-based PM localization method in corridor scenarios. A data table that consists of optimized PM parameters of different CPs is first established to estimate accurate distances between a user and APs for trilateration localization. Then the distance between the user and a nearby CP is also estimated to correct the localization coordinates, through which localization errors can be reduced greatly.

3) We propose a panoramic camera-based localization method in room scenarios. The method first detects a human object on the observed image and searches the pixel location that can represent the object location best. With room map information, the found pixel location is mapped to the map using artificial neural network (ANN) to locate the object. The proposed panoramic camera-based localization method has a localization accuracy of sub-meter level.

4) We verify the proposed localization system in a real office environment and compared it with popular fingerprinting and PM-based localization systems. The experimental results confirm that our system outperforms the localization systems using fingerprinting and PM methods.

The rest of this paper is organized as follows. Section II reviews the related works of our proposed localization system. The system overview is given and every component of it is described in details in Section III. The experimental setup, results and analyses are given in Section IV. Finally, Section V concludes this paper.

II. RELATED WORKS

A. *Wi-Fi* INDOOR LOCALIZATION USING CROWDSOURCING

In the beginning, crowdsourcing participants contributed location-labeled RSS samples for radio-map establishment with indoor electronic maps [8], [10]. Then Mirowski *et al.* [11] deployed a number of 2-D code labels in their experimental area for users to scan and obtain location information. Wu *et al.* [12] recorded numerous trajectories of crowdsourcing participants and then matched the trajectories with RSS data using multidimensional scaling (MDS). In [13], a survey-free algorithm called Chameleon was proposed to filter out altered APs with crowdsourcing data. Wang *et al.* [14] proposed an indoor sub-area localization method that constructed sub-area radio-map with crowdsourcing data and related them to indoor layouts. Jiang *et al.* [9] proposed a probabilistic radio-map construction for crowdsourcing-based fingerprinting method. The method required a large number of RSS samples. Unlike above-mentioned literatures that focused on crowdsourcing-based fingerprinting localization, Zhuang *et al.* [15] estimated PM parameters with crowdsourcing data for AP localization. Then localization coordinates were computed with trilateration localization. The system required a certain number of crowdsourcing data collected from the participants' daily life. By contrast, our proposed crowdsourcing-based PM localization method only needs crowdsourcing data from a few CPs, which can be easily collected in a short time.

B. CAMERA-BASED INDOOR LOCALIZATION

So far, many camera-based localization systems have been proposed. With 2-D image physical properties, locations and heights of people were estimated by a constrained optimization process in multiple calibrated camera network [16]. Liu *et al.* [17] first focused on the localization-oriented coverage of camera network and then formulated the localization problem using Bayesian estimation to compute a needed camera density. Liu *et al.* [18] proposed a location-constrained maximum *a posteriori* algorithm for camera-based localization through incorporating camera parameters and location information. Pflugfelder and Bischof [19] formulated camera-based localization and trajectory reconstruction as an optimization problem that could be solved by singular value decomposition (SVD). Also, Lin *et al.* [20] presented a series of image transforms based on the vanishing point of vertical lines, which improved their probabilistic occupancy map (POM)-based localization method. Compared with the camera-based indoor localization methods above, our method is capable to cover an area and locate people with only one panoramic camera.

C. INDOOR LOCALIZATION USING MULTI-SOURCE HETEROGENEOUS DATA

To offer accurate location information for users, people have tried to exploit multi-source heterogeneous data for indoor localization. The expressions of the Cramer-Rao lower bound (CRLB) were given using heterogeneous information under NLOS conditions, which showed that the condition of localizability could be almost always fulfilled for connected range bearing networks [21]. Nguyen *et al.* [7] presented a vision-enhanced wireless localization method that successfully integrated vision information and TOA measurements of UWB for cooperative localization in harsh indoor environments. In [22], Denis *et al.* emulated a multi-mode terminal based on ZigBee and orthogonal frequency division multiplexing (OFDM). Their experimental results proved that more accurate location of the terminal could be estimated through cooperation, data fusion and node detection. Liu *et al.* [23] proposed a peer assisted localization approach using RSS and acoustic signals. The approach could reduce the maximum error to 2m. Chen *et al.* [24] presented a smartphone inertial sensor-based localization and tracking approach using Wi-Fi and iBeacon. The localization accuracy of the approach was 1.39m. Unlike [24], using Wi-Fi and FM wireless fingerprints, a system proposed in [25] only had a localization accuracy of room level. Therefore, although various localization systems using heterogeneous data have been developed, to the best of our knowledge, no indoor localization system using Wi-Fi, panoramic camera and map information has been proposed so far.

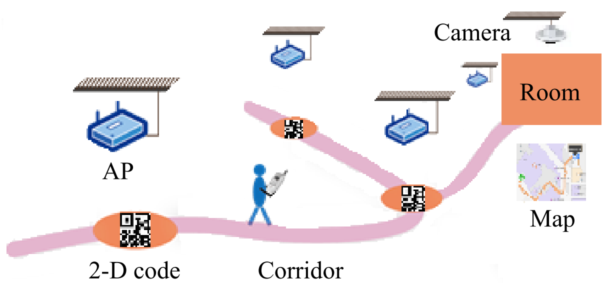

FIGURE 1. Human localization using multi-source data in indoor environments.

III. INDOOR HUMAN LOCALIZATION USING MULTI-SOURCE HETEROGENEOUS DATA

A. SYSTEM OVERVIEW

As shown in Fig. 1, we propose a localization system using RSS samples, surveillance images and room map information to offer accurate location coordinates for users in corridor and room scenarios, which are two kinds of typical indoor scenarios.

In the corridor scenario, we optimize a PM for trilateration localization with crowdsourcing data. Our method is able to make use of already deployed Wi-Fi APs and achieve a satisfactory localization performance without intensive labor and time cost. We first select several CPs that are marked with 2-D code stickers on the ground. Crowdsourcing participants can scan the 2-D codes to obtain location information, with which the collected RSS data are labeled. These location-labeled RSS data can be uploaded to a server. Then PM parameters of each CP are optimized with the crowdsourcing data collected at each CP. By this way, a data table of optimized PM parameters can be established. When a user scans a 2-D code at a CP, location coordinates of the CP are searched in the data table and optimized PM parameters of the CP can be derived for trilateration localization. Even after the user walks away from the CP, the distance between the user and CP can also be estimated as a restrictive condition to correct the localization coordinates of trilateration localization.

In the room scenario, when the user enters a room and is observed by the mounted panoramic camera. The pixel differences between the observed image and modeled background image are computed. According to a given threshold, the foreground object, that is the user, can be detected. Then the foreground pixel location that can represent the user's location best is searched and mapped from the observed image to a corresponding location on the room map. Finally, the pixel location is transformed to a localization result in the coordinate system we construct with linear equations.

Therefore, in indoor environments, the proposed localization system in this paper is able to make use of available heterogeneous data to improve localization performance without extensive labor and time cost.

B. PROPAGATION MODEL OPTIMIZATION AND COORDINATE CORRECTION

We assume that K APs are deployed in an indoor environment and J CPs are marked with 2-D code stickers on the ground. Crowdsourcing participants collect E RSS samples at each CP and label them with location coordinates, which can be denoted as $\left(\boldsymbol{r}_1^{(j)}, \boldsymbol{r}_2^{(j)}, \cdots, \boldsymbol{r}_E^{(j)}, x_{\mathrm{CP}}^{(j)}, y_{\mathrm{CP}}^{(j)}\right), j \in \{1, 2, \cdots, J\}$. Because RSS data from only three APs are needed for trilateration localization, the top three strongest crowdsourcing RSS data are selected to optimize the PM parameters of each CP. Then mean values of optimized parameters of each CP are calculated. These mean values and location information of each CP are compiled into a data table. If a user is at CP j and scans the 2-D code on the ground, the corresponding optimized parameters in the data table can be found to estimate distances for trilateration localization. These parameters will be adopted until the user moves to another CP and scans the 2-D code there. Meanwhile, the crowdsourcing data of CP j are also exploited to estimate the distance between the user and CP j as a restrictive distance. If the distance between the localization coordinates and CP j is greater than the restrictive distance, then the localization coordinates

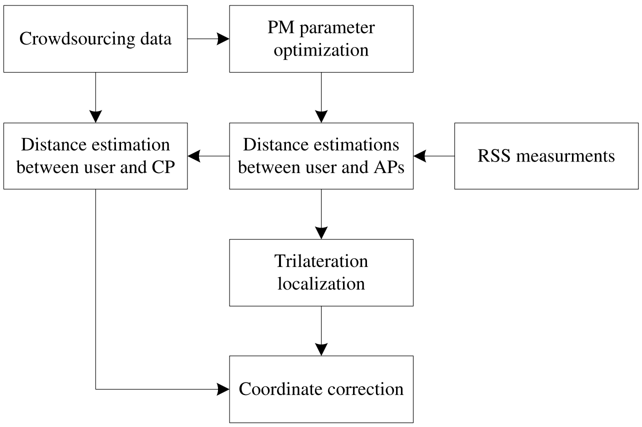

FIGURE 2. Frame of the proposed crowdsourcing-based PM localization method.

should be corrected. The frame of proposed method is shown in Fig. 2.

1) PROPAGATION MODEL OPTIMIZATION

In this paper, we select a site-general model to predict the radio propagation loss between a terminal device and AP [26], which can be denoted by:

$$P_{\mathrm{Loss}} = 20\lg f + N\lg d + L_f(n) - 28, \tag{1}$$

where P_{Loss} in dB is the radio propagation loss between the terminal device and AP, d in meter is the separation distance between the terminal device and AP ($d > 1$m), f in MHz is the frequency, L_f in dB is the floor penetration loss factor, n is the number of floors between the terminal device and AP ($n \geq 1$), and N is the distance power loss coefficient, which equals 30 at 2.4GHz in office environments.

In this paper, all the APs we deployed are on the same floor as our experimental environment, so the term $L_f(n)$ can be removed from (1). If we let $P_{\mathrm{Tr}}^{(k)}$ and $P_{\mathrm{Re}}^{(k,j)}$ denote the transmitted power of AP k and received power measured by a terminal device at CP j, respectively, and also replace the constant 28 with parameter $X^{(k,j)}$, then (1) can be rewritten as:

$$P_{\mathrm{Tr}}^{(k)} - P_{\mathrm{Re}}^{(k,j)} = 20\lg f + N^{(k,j)}\lg d^{(k,j)} - X^{(k,j)}. \tag{2}$$

In practical application, the power $P_{\mathrm{Tr}}^{(k)}$ and $P_{\mathrm{Re}}^{(k,j)}$ in dBm can be derived from AP configurations and measured RSS samples by the terminal device, respectively. The distance between the user at CP j and AP k can be computed by:

$$d^{(k,j)} = 10^{\frac{P_{\mathrm{Tr}}^{(k)} - P_{\mathrm{Re}}^{(k,j)} - 20\lg f + X^{(k,j)}}{N^{(k,j)}}}. \tag{3}$$

In order to improve localization performance, we first optimize PM parameters $X^{(k,j)}$ and $N^{(k,j)}$ and then establish a data table of the optimized parameters. Let the location coordinates of AP k and CP j be $(x_{\mathrm{AP}}^{(k)}, y_{\mathrm{AP}}^{(k)})$ and $(x_{\mathrm{CP}}^{(j)}, y_{\mathrm{CP}}^{(j)})$, respectively, then the horizontal distance $d_{\mathrm{Horz}}^{(k,j)}$ between them can be calculated by:

$$d_{\mathrm{Horz}}^{(k,j)} = \sqrt{\left(x_{\mathrm{AP}}^{(k)} - x_{\mathrm{CP}}^{(j)}\right)^2 + \left(y_{\mathrm{AP}}^{(k)} - y_{\mathrm{CP}}^{(j)}\right)^2}. \tag{4}$$

Therefore, parameters $X^{(k,j)}$ and $N^{(k,j)}$ are optimized to minimize the difference of the real and estimated distances between AP k and CP j denoted by (5), which can be considered as an unconstrained nonlinear multivariable optimization problem:

$$\begin{cases} \left(\hat{X}^{(k,j)}, \hat{N}^{(k,j)}\right) = \underset{\left(X^{(k,j)}, N^{(k,j)}\right)}{\arg\min} \left|d_{\mathrm{Real}}^{(k,j)} - d^{(k,j)}\right| \\ d_{\mathrm{Real}}^{(k,j)} = \sqrt{\left(d_{\mathrm{Horz}}^{(k,j)}\right)^2 + \Delta h^2} \end{cases}, \tag{5}$$

where Δh is the height difference between the AP and user's terminal device and it is set to be a fixed value in this paper. To solve the optimization problem, we select Nelder-Mead simplex algorithm and the starting values of parameters $X^{(k,j)}$ and $N^{(k,j)}$ are set equal to 28 and 30, respectively. In order to establish the data table of optimized parameters, mean values $\bar{\hat{X}}_{\mathrm{Tab}}^{(j)}$ and $\bar{\hat{N}}_{\mathrm{Tab}}^{(j)}$ of CP j are calculated with the crowdsourcing data of CP j. In case no matched optimized parameters are available for trilateration localization, mean values $\bar{\hat{X}}_{\mathrm{All}} = \sum_{j=1}^{J} \bar{\hat{X}}_{\mathrm{Tab}}^{(j)}$ and $\bar{\hat{N}}_{\mathrm{All}} = \sum_{j=1}^{J} \bar{\hat{N}}_{\mathrm{Tab}}^{(j)}$ of all the two optimized parameters are also computed.

With optimized PM parameters, localization coordinates are calculated by trilateration localization. We assume that the user stands at $(\hat{x}, \hat{y})$, the user's terminal device measures RSS samples from three APs that are deployed at locations $\left(x_{\mathrm{AP}}^{(i)}, y_{\mathrm{AP}}^{(i)}\right)$, $i \in \{a, b, c\}$ and the horizontal distances between the user and these APs are $d^{(i)}$, $i \in \{a, b, c\}$, then we can have (6). The location coordinates $(\hat{x}, \hat{y})$ can be computed through solving the equations as follows:

$$\begin{cases} \sqrt{\left(\hat{x} - x_{\mathrm{AP}}^{(a)}\right)^2 + \left(\hat{y} - y_{\mathrm{AP}}^{(a)}\right)^2} = d^{(a)} \\ \sqrt{\left(\hat{x} - x_{\mathrm{AP}}^{(b)}\right)^2 + \left(\hat{y} - y_{\mathrm{AP}}^{(b)}\right)^2} = d^{(b)} \\ \sqrt{\left(\hat{x} - x_{\mathrm{AP}}^{(c)}\right)^2 + \left(\hat{y} - y_{\mathrm{AP}}^{(c)}\right)^2} = d^{(c)} \end{cases}. \tag{6}$$

2) COORDINATE CORRECTION WITH CROWDSOURCING DATA

As shown in Fig. 3, After the user scans the 2-D code at CP j, even when the user walks to location i, a restrictive distance between the user at location i and CP j can be still estimated to correct localization coordinates. Let $P_{\mathrm{Re}}^{(1,i)}$ and $P_{\mathrm{Re}}^{(1,j)}$ be the received powers from AP 1 measured at location i and CP j, respectively. The received power $P_{\mathrm{Re}}^{(1,i)}$ can be denoted with the optimized parameters in the data table:

$$P_{\mathrm{Re}}^{(1,i)} = P_{\mathrm{Tr}}^{(1)} - 20\lg f - \bar{\hat{N}}_{\mathrm{Tab}}^{(j)}\lg d^{(1,i)} + \bar{\hat{X}}_{\mathrm{Tab}}^{(j)}. \tag{7}$$

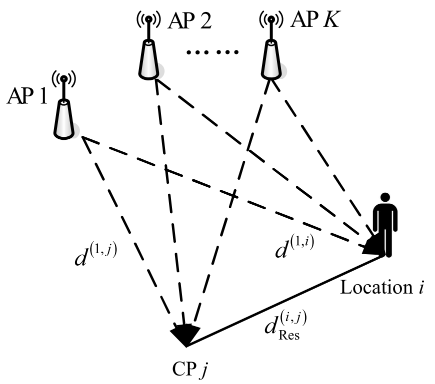

FIGURE 3. Distance estimation between a user and crowdsourcing point.

Using the similar equation for $P_{\text{Re}}^{(1,j)}$, then we can have:

$$P_{\text{Re}}^{(1,j)} - P_{\text{Re}}^{(1,i)} = \bar{\hat{N}}_{\text{Tab}}^{(j)} \lg \frac{d^{(1,i)}}{d^{(1,j)}}. \tag{8}$$

As shown in Fig. 3, the restrictive distance $d_{\text{Res}}^{(i,j)}$ between location i and CP j should not be less than $\left|d^{(1,i)} - d^{(1,j)}\right|$, so we can have:

$$d_{\text{Res}}^{(i,j)} \geq \left|d^{(1,i)} - d^{(1,j)}\right| = \left|10^{\frac{P_{\text{Re}}^{(1,j)} - P_{\text{Re}}^{(1,i)}}{\bar{\hat{N}}_{\text{Tab}}^{(j)}}} - 1\right| d^{(1,j)}. \tag{9}$$

When RSS samples from K APs are measured, (9) is applicable to all the K APs and the real distance between AP k and CP j can be calculated with their horizontal distance and height difference, so we can conclude that:

$$d_{\text{Res}}^{(i,j)} \simeq \left(\max_{k \in \{1,\cdots,K\}} \left|10^{\frac{P_{\text{Re}}^{(k,j)} - P_{\text{Re}}^{(k,i)}}{\bar{\hat{N}}_{\text{Tab}}^{(j)}}} - 1\right| \sqrt{\left(d_{\text{Horz}}^{(k,j)}\right)^2 + \Delta h^2} \right). \tag{10}$$

Even though the PM is optimized, due to radio propagation variations and multi-path effect, localization coordinates calculated by PM method may deviate from the real location greatly. The estimated distance $d_{\text{Res}}^{(i,j)}$ can be used as a restrictive distance to correct the localization coordinates. After localization coordinates $\left(\hat{x}_i, \hat{y}_i\right)$ are estimated by trilateration localization, the distance $\hat{d}^{(i,j)}$ between the localization coordinates $\left(\hat{x}_i, \hat{y}_i\right)$ and CP j is calculated. If $\hat{d}^{(i,j)}$ is greater than $d_{\text{Res}}^{(i,j)}$, then the localization coordinates are corrected to a location on a circle with center point at CP j and radius $d_{\text{Res}}^{(i,j)}$ as well as in the same direction as $\left(\hat{x}_i, \hat{y}_i\right)$. The final localization coordinates $\left(\hat{x}_i', \hat{y}_i'\right)$ can be calculated by:

$$\begin{cases} \hat{x}_i' = \dfrac{\left(\hat{x}_i - x_{\text{CP}}^{(j)}\right) d_{\text{Res}}^{(i,j)}}{\hat{d}^{(i,j)}} + x_{\text{CP}}^{(j)} \\ \hat{y}_i' = \dfrac{\left(\hat{y}_i - y_{\text{CP}}^{(j)}\right) d_{\text{Res}}^{(i,j)}}{\hat{d}^{(i,j)}} + y_{\text{CP}}^{(j)} \end{cases}. \tag{11}$$

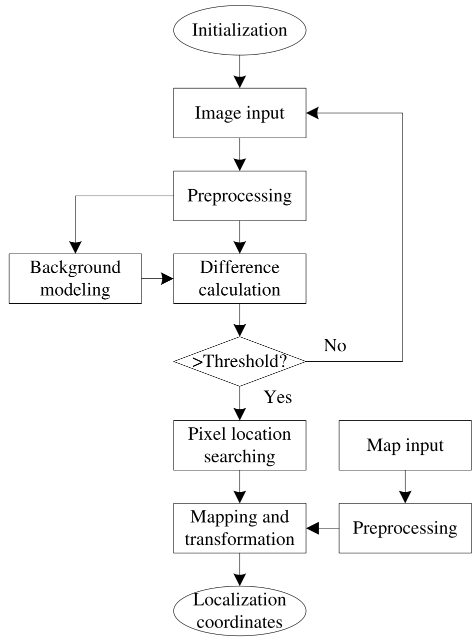

FIGURE 4. Flow chart of panoramic camera-based localization method.

C. HUMAN DETECTION AND LOCALIZATION USING PANORAMIC CAMERA

In our room scenario, instead of using Wi-Fi, we locate people with a panoramic camera mounted on the room ceiling. There are two phases in our proposed localization process: object detection and coordinate calculation. In the first phase, observed images are first preprocessed with some basic image processing operations and then a human object on the observed image can be detected. In the second phase, the object pixel location that represents the human object's location best is first searched and then mapped to a corresponding pixel location on the map. Finally, localization coordinates can be obtained in our constructed coordinate system using linear equations. The flow chart of the proposed panoramic camera-based localization method is shown in Fig. 4.

1) HUMAN OBJECT DETECTION

In this phase, an observed image derived from a surveillance video is first preprocessed with basic image processing operations, such as resizing, rotation, gray processing, and reverse color processing, in order to reduce calculation complexity and extract morphological characteristics [27]. Then we detect the human object with background subtraction method [28] because there is no greatly varying illumination in the our experimental environment and background subtraction method has a fast computation speed.

Background subtraction method detects a human object through separating the foreground object, that is the human object, from the background image. It first models the background image that is approximate to the static observed scene without foreground objects. So the differences between the modeled background image and observed image can be computed. With a given threshold, foreground object pixels can be determined.

In the process of background modeling, we first assume that an image sequence after preprocessing is denoted as $\{\mathbf{F}_1, \mathbf{F}_2, \cdots, \mathbf{F}_t\}$, then the background pixel value $B_t(x, y)$ at location (x, y) on the image can be averaged by:

$$B_t(x, y) = \frac{1}{L}\sum_{i=0}^{L-1} F_{t-i}(x, y), \tag{12}$$

where $F_{t-i}(x, y)$ is the pixel value at location (x, y) on image $\mathbf{F}_{t-i}$ and L is the number of observed images used for computing mean value $B_t(x, y)$. Using (12), all the background pixel values on the image can be computed. So we can obtain the background image $\mathbf{B}_t$.

Then we assume that $F_t(x, y)$ is the pixel value at location (x, y) on the observed image, so we can have:

$$|B_t(x, y) - F_t(x, y)| > T, \tag{13}$$

where T is a threshold to determine whether the pixel belongs to the foreground object or not. If (13) is satisfied, then the pixel at location (x, y) is considered as a foreground pixel, or it is a background pixel.

2) LOCALIZATION COORDINATE CALCULATION

In the second phase, we assume that the foreground object detected in the first phase consists of R pixels and the panoramic camera is at location $(x_{\mathrm{Cam}}, y_{\mathrm{Cam}})$ on the image. Because the panoramic camera is deployed near the central area of the room ceiling, we find that the foreground pixel that is the nearest to location $(x_{\mathrm{Cam}}, y_{\mathrm{Cam}})$ can represent the detected object's location best. Therefore, we calculate the Euclidean distances $D_i, i \in \{1, 2, \cdots, R\}$ between every foreground pixel and the pixel of the panoramic camera at location $(x_{\mathrm{Cam}}, y_{\mathrm{Cam}})$ and then search the pixel location with minimum Euclidean distance D_r. The searched pixel coordinates $\boldsymbol{L}_r = (x_r, y_r)$ are considered as the location coordinates of the foreground object $\boldsymbol{L}_{\mathrm{Img}} = \left(x_{\mathrm{Img}}, y_{\mathrm{Img}}\right)$ on the image, which are computed by:

$$\begin{cases} D_i = \sqrt{(x_i - x_{\mathrm{Cam}})^2 + (y_i - y_{\mathrm{Cam}})^2} \\ D_r = \min(D_i) \\ \boldsymbol{L}_{\mathrm{Img}} = \boldsymbol{L}_r \end{cases}, i \in \{1, \cdots, R\}. \tag{14}$$

Then an accurate room map is also resized and binarized to obtain a binary map $\mathbf{I}_{\mathrm{Map}}$ for coordinate mapping. We model the mapping relationship between pixel locations on the image and map as $f(\cdot)$. Because ANN has been widely used for nonlinear mapping, a three-layer perceptron trained by back propagation (BP) is applied in this paper [29]. The inputs of the ANN are the pixel coordinates $\boldsymbol{L}_{\mathrm{Img}} = \left(x_{\mathrm{Img}}, y_{\mathrm{Img}}\right)$ on the image and outputs are the coordinates $\boldsymbol{L}_{\mathrm{Map}} = \left(x_{\mathrm{Map}}, y_{\mathrm{Map}}\right)$ on the map. The proposed structure of the ANN is shown in Fig. 5.

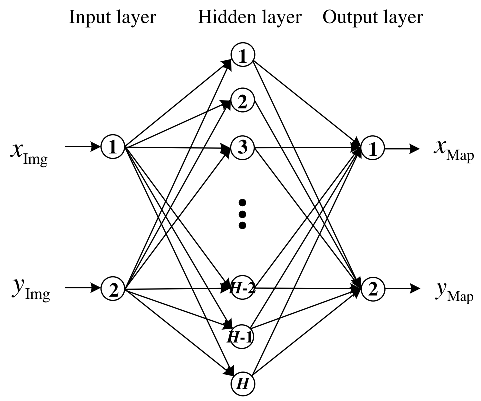

FIGURE 5. ANN structure for coordinate mapping.

We train the ANN with observed images of the human object at several specific locations, whose location coordinates are known. The relationship between pixel coordinates on the image and map can be modeled by the ANN as:

$$\boldsymbol{L}_{\mathrm{Map}} = f\left(\boldsymbol{L}_{\mathrm{Img}}\right). \tag{15}$$

The outputs in layer l of the ANN can be given by:

$$\begin{cases} y_l^{(j)} = g\left(u_l^{(j)}\right) \\ u_l^{(j)} = \sum\limits_{i=1}^{I} \omega_{l-1,l}^{(i,j)} x_{l-1,l}^{(i,j)} - \theta_l^{(j)} \\ \begin{cases} j = 1, 2, \cdots, H; I = 2, l = 2 \\ j = 1, 2; I = H, l = 3 \end{cases} \end{cases}, \tag{16}$$

where $\omega_{l-1,l}^{(i,j)}$ is the weight from neuron i in layer $(l-1)$ to neuron j in layer l, $\theta_l^{(j)}$ is the threshold of neuron j in layer l, $x_{l-1,l}^{(i,j)}$ is the input from neuron i in layer $(l-1)$ to neuron j in layer l, $y_l^{(j)}$ is the output of neuron j in layer l, H is the number of neurons in the hidden layer, and $g(\cdot)$ is the activation function of the ANN.

BP algorithm propagates computed errors backwards to update the weights and thresholds of the ANN. The updating will continue until termination criterions for iteration are satisfied. With the basic BP algorithm, the weights and thresholds can be updated by:

$$\begin{cases} \omega_{l-1,l}^{(i,j)} = \omega_{l-1,l}^{(i,j)} + \alpha\delta_l^{(j)} y_{l-1}^{(j)} \\ \theta_l^{(j)} = \theta_l^{(j)} - \beta\delta_l^{(j)} \\ \delta_l^{(j)} = \begin{cases} \sum\limits_{m=1}^{2} \delta_{l+1}^{(m)} \omega_{l,l+1}^{(i,m)} g'\left(u_l^{(j)}\right), l = 2 \\ \left(e^{(j)} - y_l^{(j)}\right) g'\left(u_l^{(j)}\right), l = 3 \end{cases} \\ \begin{cases} i = 1, 2; j = 1, 2, \cdots, H, l = 2 \\ i = 1, 2, \cdots, H; j = 1,2, l = 3 \end{cases} \end{cases}, \tag{17}$$

where $e^{(j)}$ is the expected output and α and β are learning rates. The learning rates can be adjusted adaptively to balance stability and training time of the ANN.

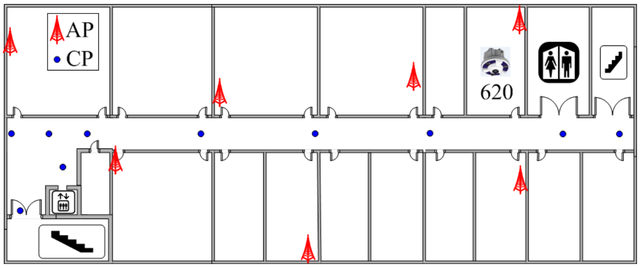

FIGURE 6. Experimental floor plan.

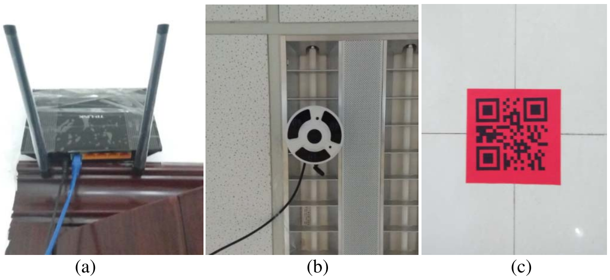

FIGURE 7. (a) TP-LINK TL-WR845N AP, (b) 28mm CMOS panoramic camera, (c) 2-D code sticker on the ground.

IV. EXPERIMENTAL RESULTS AND ANALYSES

A. EXPERIMENTAL SETUP

In this paper, all the experimental data are collected in a real indoor environment. The experimental environment consists of office rooms and a corridor that are two kinds of typical experimental scenarios for indoor localization. As shown in Fig. 6, the experimental environment is an office floor with dimensions of 51.6m×20.4m×2.7m. A total of 7 TP-LINK TL-WR845N APs were deployed with a height of 2.2m for communications coverage. One of them was shown in Fig. 7(a). We used a 28mm CMOS panoramic camera shown in Fig. 7(b) for localization. A surveillance video recorded by the camera was divided into 530 images and these images were used as our testing data. The images recorded a user's trajectory along the selected testing points (TPs) in Room 620. We also took extra 300 observed images as training data to train the ANN for coordinate mapping. Meanwhile, all the RSS samples were collected with a Meizu smartphone that was laid on a tripod with a height of 1.2m. The smartphone was installed with an RSS collection software that was developed by our own. The sampling rate of the software was 1 RSS sample per second.

As shown in Fig. 6, we selected 10 CPs on the floor for crowdsourcing participants to collect RSS data. Because office rooms were not allowed to enter sometime, all the CPs were marked with red stickers in the corridor and some of them were near the entrances, washroom and elevator, where it was convenient for crowdsourcing participants to collect data. The location information of CPs could be obtained through scanning the 2-D codes printed on the red stickers as shown in Fig. 7(c). Because the time for collecting data by each crowdsourcing participant should be less than one minute for fear that they might feel bored [30], 60 RSS samples were collected at each CP. For performance comparison, fingerprinting method was also performed in the same experimental area. A total of 116 reference points (RPs) were selected in the corridor and Room 620 and 120 RSS samples were measured at each RP for radio-map establishment. In the corridor and Room 620, a total of 5400 RSS testing samples were collected.

TABLE 1. Mean errors of propagation model localization with different parameters.

X	N	Mean Error (m)
28	30	20.85
28	38.70	18.66
19.20	30	20.75
20.84	37.18	14.89
$\bar{\hat{X}}^{(j)}_{\text{Tab}}$	$\bar{\hat{N}}^{(j)}_{\text{Tab}}$	5.79

B. RESULTS OF OPTIMIZED PROPAGATION MODEL LOCALIZATION

In our localization system, although the crowdsourcing-based PM method is proposed for corridor scenarios, we perform the PM method in the whole experimental environment, so that the experimental results can be more persuasive. With the crowdsourcing data of CPs, we first optimize one parameter that is parameter X or N using a single-variable optimization algorithm that combines golden section search and parabolic interpolation. However, as listed in Table I, the mean errors of PM method with the optimized parameters mentioned above decrease just a little. Then we optimize parameters X and N at the same time with Nelder-Mead simplex algorithm. First, we computed the mean values $\bar{\hat{X}}_{\text{All}} = 20.84$ and $\bar{\hat{N}}_{\text{All}} = 37.18$ of all the optimized parameters, respectively. The mean error of PM method with parameters $\bar{\hat{X}}_{\text{All}}$ and $\bar{\hat{N}}_{\text{All}}$ is reduced from 20.85m to 14.89m as shown in Table I, which is still not satisfactory. Therefore, we calculate the mean values $\bar{\hat{X}}^{(j)}_{\text{Tab}}$ and $\bar{\hat{N}}^{(j)}_{\text{Tab}}$ of each CP and establish a data table consists of optimized PM parameters and location coordinates of each CP. We assume that when a user walks by a CP, the user will scan the 2-D code and obtain the location coordinates of the CP. Then corresponding PM parameters in the data table can be found and used for trilateration localization. With this method, the localization performance is improved greatly and the mean error decreases to 5.79m.

C. COORDINATE CORRECTION WITH RESTRICTIVE DISTANCE

Because all crowdsourcing data are available to users, after a user scans a 2-D code sticker, a restrictive distance between the user and CP can be estimated. If the localization coordinates deviate from the real location greatly, then the restrictive distance is used to correct the localization coordinates.

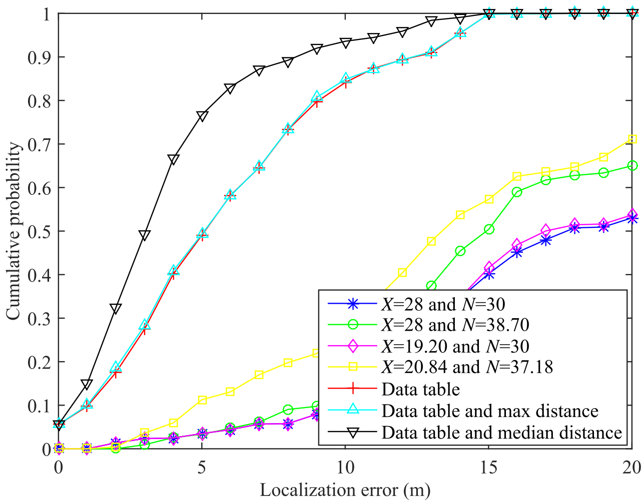

FIGURE 8. **Cumulative probabilities of PM-based localization methods.**

According to (9) and (10), the estimated restrictive distance $d_{\text{Res}}^{(i,j)}$ should be equal to the maximum value of all the distance differences $\left|d^{(k,i)} - d^{(k,j)}\right|, k \in \{1, 2, \cdots, K\}$. However, in practical application, radio propagation may vary considerably in indoor environments, which causes the maximum estimated distance to be too large to correct localization coordinates. Thus, in this paper, we eliminate distance outliers and take the median distance to correct localization coordinates [31].

As mentioned above, we test the methods with all the RSS testing samples collected in the corridor and room scenarios. The mean errors of localization results with maximum and median restrictive distances for coordinate correction are 5.74m and 3.75m, respectively. These experimental results verify our analysis above. Although the localization performance of our proposed method with the data table is much better than PM method with other optimized parameters, the performance is still limited as shown in Fig. 8. The cumulative probability of the method using the data table is only 40.1% within localization error of 4m. After coordinate correction with the median distance, the cumulative probability increases to 66.6% within localization error of 4m.

D. RESULTS OF PANORAMIC CAMERA-BASED LOCALIZATION

After a user enters Room 620 from the corridor and observed by our mounted panoramic camera, localization coordinates are computed by the proposed panoramic camera-based localization method. We take one of the testing images as an example. The image of real scene, background image, detected foreground object, and localization coordinates on the room map are all shown in Fig. 9. More specifically, in the object detection phase, the observed image after resizing and rotation processing is shown in Fig. 9(a). As shown in Fig. 9(b), the background image of the scene is modeled using (12). Then pixel difference values between the observed

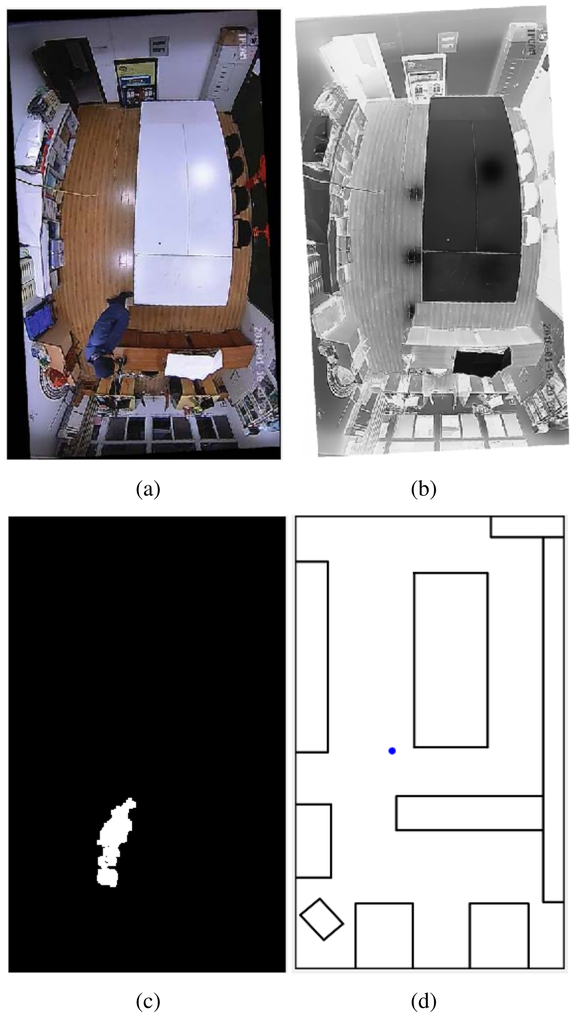

FIGURE 9. **(a) Resized and rotated image, (b) Background image, (c) Detected foreground object, (d)Localization result on the map.**

image and background image are computed. In this paper, the threshold T that is used to determine whether a pixel belongs to the foreground object or not is set to be 32. So the foreground object can be detected as shown in Fig. 9(c). In the coordinate calculation phase, the foreground pixel location that is nearest to the camera is first searched using (14) and then the location is mapped to a corresponding pixel location on the map using (15). As shown in Fig. 9(d), the localization result is marked with a blue point on the room map.

In Room 620, we also perform fingerprinting and PM localization methods for performance comparison. We only use RPs in Room 620 for fingerprinting localization, The mean errors of fingerprinting algorithms K-nearest neighbors (KNN), weighted KNN (WKNN) and ANN are 1.70m, 1.65m and 1.81m, respectively. With the RSS data collected at the RPs in Room 620, the PM parameters are optimized. The mean error of PM method is 2.33m. These experimental results are shown in Table II. By contrast, the mean error of our proposed panoramic camera-based localization is 0.84m and the cumulative probability within localization error of

TABLE 2. Performance comparison of various methods in room 620.

Method	Mean Error (m)	Cumulative Probability (%) Within 1m error	Within 2m error
KNN	1.70	33.6	63.3
WKNN	1.65	38.0	62.6
ANN	1.81	26.1	59.2
PM	2.33	17.1	53.6
Camera	0.84	70.1	86.3

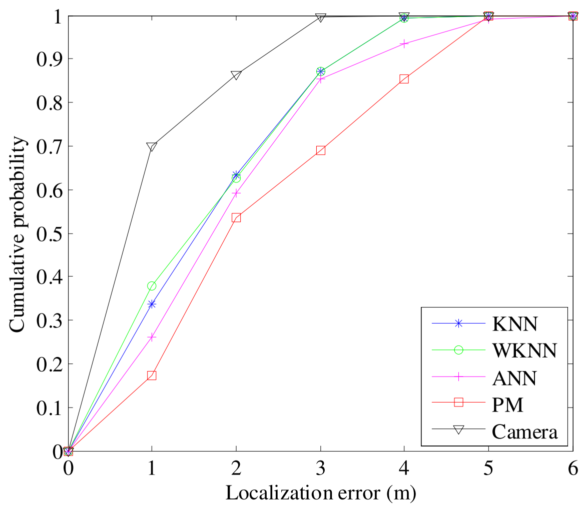

FIGURE 10. Cumulative probabilities of various methods in room 620.

1m and 2m are 70.1% and 86.3%, respectively, which are much higher than those of fingerprinting and PM methods. As shown in Fig. 10, the cumulative probability curves of these methods also validate that the proposed camera-based localization method outperforms the other localization methods.

E. RESULTS OF PROPOSED LOCALIZATION SYSTEM USING MULTI-SOURCE HETEROGENEOUS DATA

Our proposed localization system employs RSS samples in the corridor scenario as well as surveillance images and room map information in the room scenario, which not only saves time and labor cost for system construction, but also achieves better performance than the fingerprinting and PM-based localization systems. We combine the proposed localization methods in the corridor and room scenarios and perform the proposed localization system on the whole experimental environment. This means that the RSS testing samples in the corridor and testing images in Room 620 are exploited for localization. Once a user enters Room 620 from the corridor, the location coordinates of the user are estimated with the panoramic camera and room map information. Fingerprinting localization is also performed in the experimental environment for performance comparison. As shown in Table III, the mean errors of KNN, WKNN, ANN, and proposed PM are 4.20m, 4.19m, 4.37m, and 3.75m, respectively. The mean error of our localization system using heterogeneous data is 3.15m. As shown in Fig. 11, the proposed system outperforms the others within localization error of 8m. The reason is that the localization errors that are larger than 8m are computed by

TABLE 3. Performance comparison of various methods in corridor and room 620.

Method	Mean Error (m)	Cumulative Probability (%) Within 2m error	Within 3m error
KNN	4.20	37.4	54.4
WKNN	4.19	37.9	54.2
ANN	4.37	20.0	37.1
PM	3.75	32.4	49.3
Proposed	3.15	43.9	62.5

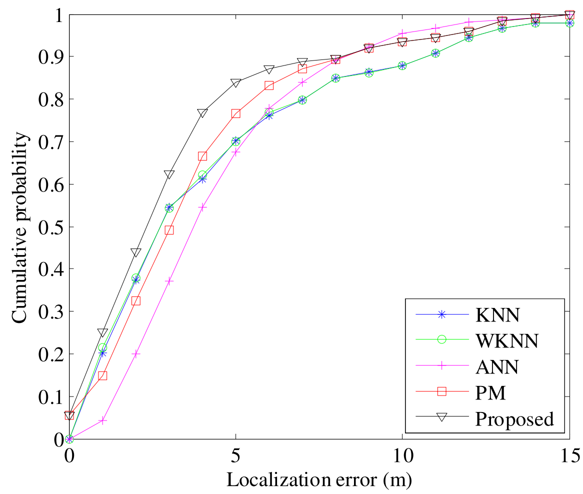

FIGURE 11. Cumulative probabilities of various methods in corridor and room 620.

the proposed PM method in the corridor scenario. Compared with KNN, WKNN, ANN, and proposed PM, the cumulative probabilities of our proposed localization system within localization errors of 2m and 3m can reach to 43.9% and 62.5%, respectively.

V. CONCLUSION AND FUTURE WORK

In this paper, a human localization system using multi-source heterogeneous data is proposed. The proposed system can be easily implemented without extensive labor and time cost and also it outperforms the localization systems using fingerprinting and PM methods. In corridor scenarios, localization performance of PM method is improved by using a data table that consists of optimized parameters and location coordinates of each CP and localization results are also corrected with a restrictive distance estimated with crowdsourcing data. In room scenarios, a panoramic camera is used to detect a human object and then locate the object through location mapping with room map information. This method is suitable for human localization in room scenarios and is able to achieve much better performance than fingerprinting and PM localization methods. The experimental results demonstrate that our proposed localization system not only achieves a comparable localization performance, but also offers a valuable reference for human localization using multi-source heterogeneous data in indoor environments.

In the future, we will concentrate on a deep integration of multi-source heterogeneous data for indoor localization. In addition, other PMs and map filtering might be tried.

Privacy protection of crowdsourcing participants and multi-user localization with a panoramic camera and room map will also be investigated.

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