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Reliable and Cooperative Target Tracking Based on WSN and WiFi in Indoor Wireless Networks

JUAN LUO[1], (Member, IEEE), ZHENYAN ZHANG[1], CHANG LIU[1], AND HAIBO LUO[2]
[1]College of Computer Science and Electronic Engineering, Hunan University, Changsha 410082, China
[2]College of Physics and Information Engineering, Fuzhou University, Fuzhou 350108, China

Corresponding author: Juan Luo (juanluo@hnu.edu.cn)

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ABSTRACT Indoor localization and tracking have attracted growing attention because of its widely application for indoor location-based services (LBSs). However, for indoor localization, only with single positioning technology, the positioning accuracy, and localizability are difficult to satisfy the requirement due to the complex and crowed indoor environment. An indoor cooperative localization and tracking algorithm (CLTA) based on grid is developed to solve above problems. The CLTA is divided into offline phase and online phase. In the offline phase, a cooperative localization fingerprint database is established based on reliable nodes. In the online phase, a region overlapping mechanism is used to narrow location area in multi-network surroundings at first. Then, we use a prediction mechanism to predict the mobile target position in order to further narrow the location area. At last, a cross grid strategy is used to update the data in fingerprint database if possible, aiming at improving the accuracy of localization. Simulation and experiment results show that the proposed algorithm is better than single network localization algorithm on localization and tracking performance.

INDEX TERMS Indoor localization, reliable, target tracking, wireless network.

I. INTRODUCTION

A. MOTIVATION

With the maturity and popularity of Internet of Things (IoT) [1]–[3], the application deployment of mobile environment has become a hot discussion topic in academic and industry [4]–[7], and the requirements for localization accuracy in various fields are also increasing. In many practical applications of IoT, it is a basic function for tracking moving targets (As shown in Fig. 1), such as localization and tracking firemen in a burning building, localization and tracking patients in a hospital, localization and tracking police dogs for some urgent tasks, etc. If the localization accuracy is not high enough, it is hard to ensure that personnel are rescued in the first instance in case of emergency.

At the present time, there are Global Positioning System (GPS) [8], Wireless Local Area Network (WLAN) [9], [10] and Wireless Sensor Network (WSN) [11], [12], which can provide mobile target localization. Indoor wireless localization has attracted increasing research interests and many techniques have been widely applied in every walk of life, such as WiFi [13], [14], Bluetooth [15], [16], Ultra-Wide Band (UWB) [17], [18], radio frequency identification (RFID) [19]–[21] tags etc. But their positioning technologies have various advantages and disadvantages in aspects of application scenario, positioning error, positioning delay, energy consumption and so on. Different positioning technology, however, has different overlapping range and different network characteristic, wherever in indoor or outdoor environment, it is difficult to achieve a higher positioning accuracy and range requirements only relying on a certain kind of mobile positioning technology. If several anchor nodes (ANs) are captured because of the complex indoor environment, the accurate positioning of unknown nodes would be affected and the location error of the system would also increase. It is a challenge on how to cooperate localization and tracking based on a reliable mechanism in an indoor environment with more than one network.

B. CONTRIBUTIONS

There is often more than one type network in an indoor environment, such as WiFi, WSN, Bluetooth and so on, they are common in our daily life. In the indoor hybrid-network environment, in order to improve the utilization rate of network signal and increasing positioning accuracy and

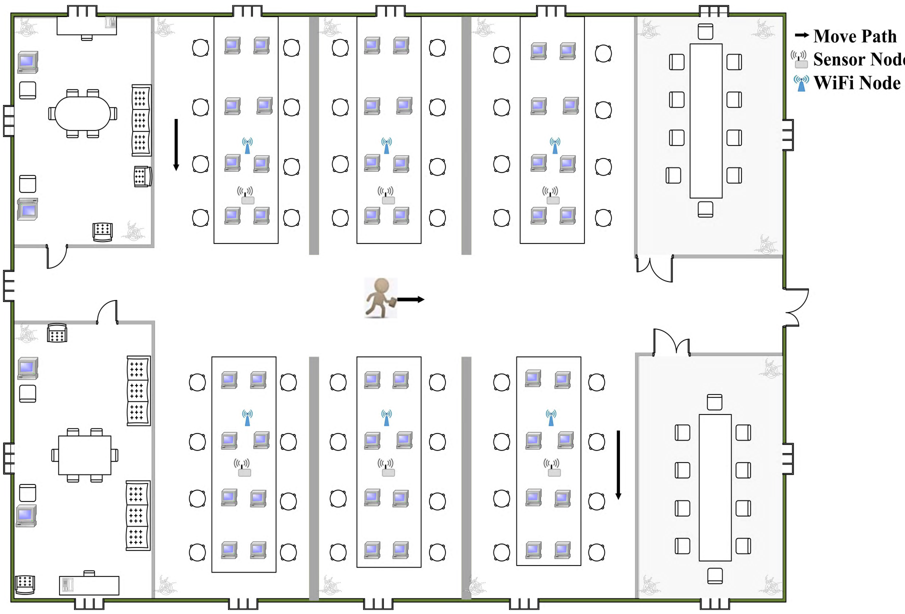

FIGURE 1. Indoor scene.

localizability of positioning area, a CLTA based on indoor wireless networks for target tracking is proposed in this paper. The main contributions of this paper are listed as follows:

1) A cooperative target localization and tracking algorithm (CLTA) in indoor wireless networks by analyzing the characteristics of different networks in order to improve localizability and positioning accuracy.
2) Unknown nodes are located by CLTA, which can reduce positioning error with cooperative technology that combines with the region overlapping mechanism, the prediction mechanism and the cross grid strategy.
3) The strategy of reliable nodes selection that based on RSS to get the relationship of distance between nodes is used to further decrease the location error.

The rest of this paper is organized as follows. In section II, we describe the relevant research of indoor localization and tracking. An indoor cooperative localization and tracking algorithm is proposed in section III. In section IV shows the experiments and analyses. Finally, we conclude our algorithm in section V.

II. RELATED WORKS

Cooperation technology, to a certain extent, eliminates the time and space constraints. Various kinds of cooperation technologies and platforms have developed in the computer network, such as Habanero [22]: Java distributed cooperative environment that developed by NCSA software development team. It can share data and events on all participating computers through the internet.

In recent years, with the increasing attention on cooperative technology in wireless communication, some other cooperative technologies are emerged, such as cooperative

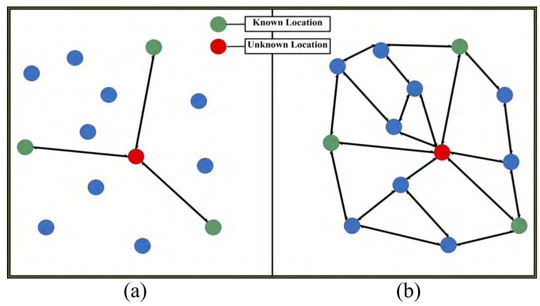

FIGURE 2. Traditional and cooperative localization.

positioning [23], [24], cooperative diversity technology [25]. Cooperation localization is a technique, which accompanies with the development of computer network technology and expands on wireless localization technology. A simple comparison of conventional and cooperative localization is depicted in Fig. 2: Traditional multilateration (a) uses only measurements between an unknown location node and multiple known location nodes. Cooperative localization (b) allows measurements between any pairs of nodes to aid in the location estimate to find its position.

Janapati et al. [26] investigated indoor localization of cooperative WSN where nodes exchange information through Ultra Wide Band (UWB) signal. UWB offers wide bandwidth and high resolution which is prefer for ranging measurement. Information exchange between heterogeneous nodes under cooperative environment brings great challenges to the selection and rejection of information. Yang and Shao [14] proposed mechanisms to a WiFi system where exists one AP or more APs with multiple antennas as nearby anchors. The paper applied a hybrid AoA/ToA system to locate the target's positioning. The position performance can reach

TABLE 1. Key symbol and term description.

Key Symbol	Description
N	The number ID of grid
N_{grid}	The number of grids
N_{net}	The network name
N_{order}	The calculation order in cooperate localization
A_x	The weight of network x in the grid
$Region_x$	The overlapping shadow area of the network x
r	The communication radius of network
γ	The location error
d	The distance between two reference nodes
v	The move speed of the unknown node
T	The current localization time point
t	The minimum time unit of target movement
Term	Description
RSS	Received signal strength
AN	Anchor node (The geographic coordinate is known)
RN	Reference node (The geographic coordinate is unknown)

2.2m with one WiFi AP and 0.5m with multiple APs respectively. The performance is affected by WiFi AP hardware conditions. Adewumi et al. [27] researched the correlation between distance and RSSI in WSNs. A RSSI model estimated the distance between sensor nodes in WSNs. The performance both in indoor and in outdoor environment were evaluated and analyzed. But it did not verify in a real environment.

Klingbeil and Wark [28] developed a real-time positioning and tracking algorithm for indoor environment, which based on Monte Carlo Location (MCL). In the algorithm, first to process the monitoring data of moving target, then to locate the position through the ANs. Zhong et al. [29] proposed a robust tracking framework using node sequences, the monitor area is divided into lots of small regions, the trace of the mobile target can be estimated by processing a series of detection sequences. The challenge in this system is that node sequences are unreliable due to outside factors. Their approaches are only applicable to a particular sensor network for positioning and tracking.

Bargshady et al. [30] used Particle Filter (PF) to integrate WiFi and UWB RF signaling for cooperative localization in indoor environment. In the paper, PF, Received Signal Strength (RSS) of WiFi and the Time Of Arrival (TOA) of UWB RF signal are used for improving cooperative localization precise in indoor environment. Chen et al. [31] proposed a cooperative localization method to combine the fingerprint-based algorithm and the physical constraint of pairwise distances to refine the localization estimates for multiple users simultaneous. The number of peers and peers selection have a strong impact on accuracy performance.

Most of previous work were based on WiFi because of it's widely deployed in indoor environment. Our approach makes use of both WiFi and WSN technologies to achieve a high accuracy for indoor positioning and improve the localizability. Besides, we also adopt the reliable nodes selection strategy to ensure the effectiveness and reliability of nodes. We will introduce our method in detail in the following.

III. INDOOR COOPERATIVE LOCALIZATION AND TRACKING ALGORITHM

With the development of indoor infrastructure, the needs for accurate tracking and positioning in various fields are getting increasing. In the indoor multi-network environment, this paper proposes a cooperative localization and tracking algorithm by analyzing the characteristics of network signals (WSN and WiFi) and predicting the dynamic trajectory of the moving target. WSN is composed of some sensor nodes which are in the monitoring area for building a multi-hop Ad-hoc network system by wireless communication. The purpose of the system is to sense cooperatively, collect and process the information of the sensed objects in the network coverage area and send it to the observer. WiFi is one of the most widely used wireless network transmission technologies today. Its transmission speed can reach 54Mbps which can meet personal and social information needs. The important symbols and corresponding descriptions are listed in Table 1.

In our investigation, there are two phases for cooperative localization and tracking technique which are widely used for indoor positioning: Offline phase and online phase. The system architecture and the main ideas of CLTA are shown in Fig. 3. The main operations are as follows.

(1) **In the offline phase**, first to divide the grid and save ANs location. Then to establish a complete cooperative location fingerprint database on the basis of reliable ANs' RSS values, and to get the corresponding network weights in each grid.

(2) **In the online phase**, the grid-based indoor cooperative localization algorithm which contains the region overlapping mechanism, the prediction mechanism and the cross-grid strategy are used to track and locate the trajectory of target node.

In cooperative localization and tracking, the co-located fingerprint database is established in offline phase and the cooperative localization and tracking is used between the networks in online phase to obtain a higher precision of localization and tracking.

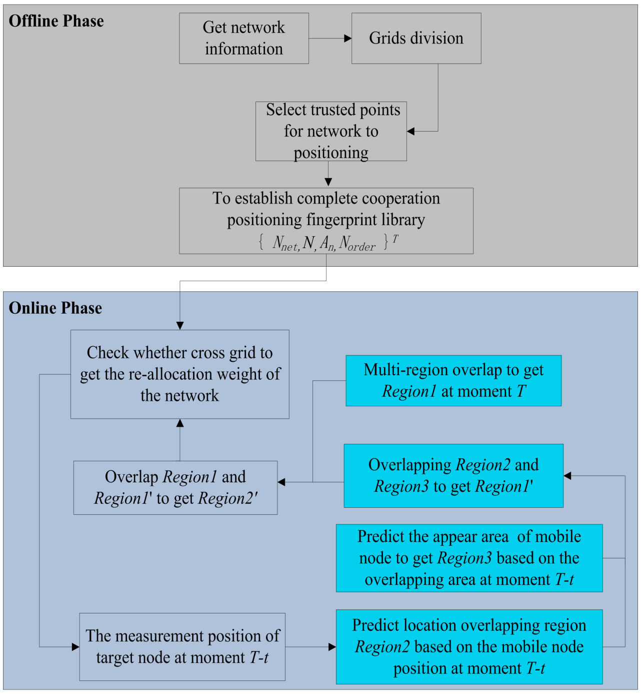

FIGURE 3. System architecture.

A. OFFLINE PHASE

In the offline phase, we need to set up a cooperative positioning fingerprint database that includes the network name, the grid ID, the corresponding weight and the calculation sequence. It is represented in a form of an array $[N_{net}, N, A_x, N_{order}]^T$. Among them, N_{net} is network name, such as GPS, GSM, WSN, WiFi, etc., it also can be expanded according to the actual situation.

We first to determine the network name N_{net} according to the type of network, then analyze the communication range of all networks as a basis for dividing the grid size. After that, the network RSS signals in each grid is collected, according to the network positioning error to determine the network x weight A_x which in the grid, and the online phase calculation order N_{order} of cooperative positioning is confirmed. Finally, a complete cooperative positioning fingerprint database is established.

Main methods for establishing fingerprint database are explained below.

1) GRIDS DIVISION

In this paper, the target location area is divided into a number of equal size regions, the location area is divided into a finite number of disjoint rectangular areas which are called grids.

In this section, the relationship between the number of grids and the radius of network communication in a single network environment is acquired according to [32], then the relationship between them in multi-network and the relationship between the edge length and radius of network communication are obtained.

Theorem 1 [32]: In a certain rectangular area, if the communication radius of the network node is r, there is a limit on the number of grids N_{grid} in this area.

$$(2S_{region}/r^2) \leq N_{grid} \leq [S_{region}/(10^{(\lg(I_{\min})-\wedge)/\alpha})]. \quad (1)$$

Where S_{region} is the area of rectangle, I_{min} is the smallest interference loss, $\wedge$ is a constant of $\lg(P_r/[P_tG_tG_r(h_th_r)^2])$ (P_t and P_r are transmit power and receive power of nodes respectively. G_t and G_r are antenna gains of sending and receiving nodes respectively. h_t and h_r are antenna heights of sending and receiving nodes respectively).

Theorem 2 [32]: In a rectangular area, if there are M kinds of network signals, in this area, the network with the smallest radius r_{min} of communication determines the number of grids N_{grid}.

From **THEOREM 2**, the network with the smallest communication radius among all network signals determines the edge length of the grid. According to simulation results, the paper suggests half of the minimum communication radius (the length of the grid) of all the network signals should be used as the base for the grid partition of the localization area.

2) GRID POSITIONING ERROR

Assume that the actual position coordinates of a point in a grid is (x_0, y_0). A localization algorithm is used in a network to get the measurement value (x_k, y_k) of the node to be localized which calls k, using the Euclidean principle to specify the location error of the point γ_k as:

$$\gamma_k = \sqrt{(x_0 - x_k)^2 + (y_0 - y_k)^2}. \quad (2)$$

Select reliable ten points for network i to positioning. We select reliable ANs (WSN nodes or WiFi nodes) by using RSS value to calculate the distance with different two RNs in the grid. As shown in Fig. 4, we give the flow chart to demonstrate the selection process. First to select two RNs in the grid, the distance of them is d. Then to select the AN to get the RSS values of these two RNs. Based on the RSS values to calculate the distance $d1$, $d2$ with them respectively. At last to check the relationship of d, $d1$ and $d2$ (The detail description shown as Fig. 5). If $d > |d1 - d2|$, keep the two RNs positions. According to the flow to get ten reliable positions and filter out inaccurate or malicious data. The positioning errors of them are $\gamma_1, \gamma_2, \ldots, \gamma_{10}$. So the average positioning error γ_i of network i is:

$$\gamma_i = (\gamma_1 + \gamma_2 + \ldots + \gamma_{10})/10. \quad (3)$$

If in most cases $d < |d1 - d2|$ (If there are more people or obstacles between AN and $RN1$ than AN and $RN2$, the RSS of RN_1 is relatively weaker than normal situation, the calculate distance between AN and $RN1$ will be less than $d1$, so the case $d < |d1 - d2|$ maybe happen), we will filter out the AN and re-select another AN for positioning.

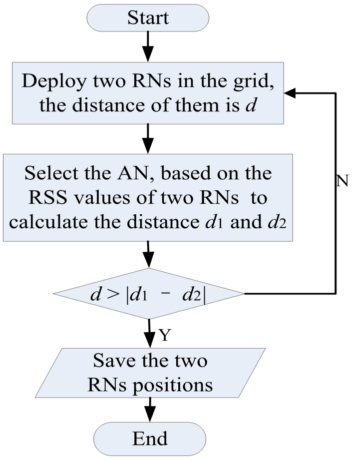

FIGURE 4. Flow chart of selecting reliable nodes.

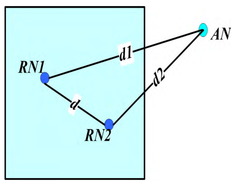

FIGURE 5. Distance of RNs and AN.

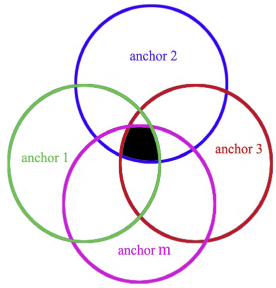

FIGURE 6. Single network overlay mechanism.

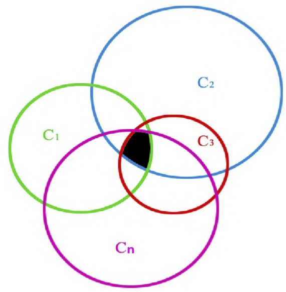

FIGURE 7. Multi-network overlay mechanism.

3) WEIGHT ALLOCATION

Assume there are two kinds of network which are network x and y, and the average positioning error of network x and y are γ_x and γ_y in grid. In the grid, let the weight A_x of network x is:

$$A_x = 1 - \frac{\gamma_x}{(\gamma_x + \gamma_y)} = \frac{\gamma_y}{(\gamma_x + \gamma_y)}. \quad (4)$$

So the weight of A_y of network y is:

$$A_y = 1 - \frac{\gamma_y}{(\gamma_x + \gamma_y)} = \frac{\gamma_x}{(\gamma_x + \gamma_y)}. \quad (5)$$

Based on above methods, the cooperative positioning fingerprint database can be established.

B. ONLINE PHASE

In online phase, first to calculate a rough position of unknown node based on single network. According to the rough position to judge the grid number of it, then query from fingerprint database to obtain the weight and calculation order. At last based on below three main mechanisms to improve positioning accuracy and get a final positioning result.

The grid-based indoor cooperative localization algorithm, the region overlapping mechanism, the prediction mechanism and the cross-grid strategy are used to track and locate the trajectory of the moving target in the online phase. The following is a detailed description about three main mechanisms.

1) THE REGION OVERLAPPING MECHANISM

Region overlapping mechanism is to obtain the overlapping region by overlapping the communication area of the ANs within the communication range of a node to be localized. In multi-network environment, the region overlapping mechanism can obtain the overlapping region of the ANs with different communication ranges. Assume that the node communication radius in network x is r_x. If node a is within the communication range of node b, and node b is also within the communication range of node a. So, if node a can receive the message sent by node b, then the distance between two nodes is less than r_x. As shown in Fig. 6, if the anchor node 1, anchor node 2, ..., anchor node m can receive the message from moving target, the communication area of the m ANs must be intersecting.

There are m ANs from anchor 1 to anchor m. According to the region overlapping mechanism, the moving target node must be in the overlapped shadow area of m ANs. The overlapping shadow area defined in network x is $Region_x$, and the overlapping symbols are indicated by $\cap$. Then in the network x, the communication area overlapping can be written as $Region_x = r_1 \cap r_2 \cap \cdots \cap r_k$, in which the communication area of the anchor node k is represented as r_k. We assume that the communication radius of network 1, network 2, ..., and network n are $r_1, r_2, \ldots, r_n$ respectively, node a in network A is within the communication range of node b in network B, vice verse. So, if node a can receive the message sent by node b, then the distance between the two nodes is less than the communication range. As shown in Fig. 7, $C_1, C_2, \ldots, C_n$ are circles of different radius, representing network 1, network 2, ..., network n respectively. If the ANs in the network 1, the network 2, ..., the network n can receive the moving target message, then the communication area of the ANs in the n networks must be intersecting.

In the network 1, the network 2, ..., the network n, according to the regional overlapping mechanism, the moving target node must be in the overlapping shadow area of n networks. Define the $Region_x$ as the overlapping shadow area of the network x, and in a multi-network environment, the overlapping communication area can be recorded as $Region1 = Region_1 \cap Region_2 \cap \cdots \cap Region_x \cap \cdots \cap Region_n$. $Region_x$ represents the shadow area of the network x.

2) THE PREDICTION MECHANISM

The prediction mechanism can predict the possible position of node to be located at the next time point according to the moving speed v and the minimum unit time of movement t.

After getting $Region1$ according to the region overlapping mechanism, the localization area of the mobile node can be predicted. According to the prediction mechanism, the possible position area at T moment can be predicted at the moment $T-t$. Setting it as $Region1'$. $Region1'$ consists of two sets of overlapping areas(The detail as below description).

a: PREDICTION LOCALIZATION REGION AT $T-t$ MOMENT

According to the positioning step, we can get the position coordinates of the target node at $T-t$ moment. Using the moving speed v and the unit time t of the target node, the position coordinate region of target node at the time point T is obtained, i.e., the region whose circle center is target node coordinate at $T-t$ moment and the radius is $v \times t$. This region is defined as $Region2$ (Shown in Fig. 8).

b: PREDICTION OVERLAP REGION AT $T-t$ MOMENT

At the $T-t$ moment, we can get the overlapping region based on overlapping mechanism. The target node at the moment T must appear in the next prediction region of $T-t$ moment overlapping region. We use the centroid weighting algorithm to get the center of a circle. With the moving speed v and the unit time t to predict the moment T prediction region $Region3$ (Shown in Fig. 8).

By overlapping these two regions can get a more accurate range ($Region1' = Region2 \cap Region3$) of region where target node may appear.

We use region overlapping mechanism under multi-network to get $Region1$ and the prediction mechanism to get $Region1'$. Overlapping these two regions to obtain a more accurate target region $Region2'$ (Shown in Fig. 8). Therefore, at the T moment, the target node is most likely to appear in the region $Region2'$ ($Region2' = Region1 \cap Region2 \cap Region3$).

3) CROSS-GRID STRATEGY

The signal strength of different network in the grid is different. So the network positioning error is different. That is, the weights of same network in different grids are different, and the weights of different networks in the same grid are different. Based on this, if the trajectory of the mobile node cross-grid, there is a problem of re-allocation the weight to improve the positioning accuracy.

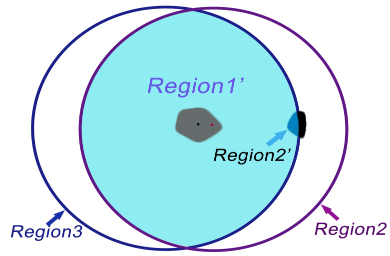

FIGURE 8. The prediction and overlapping region.

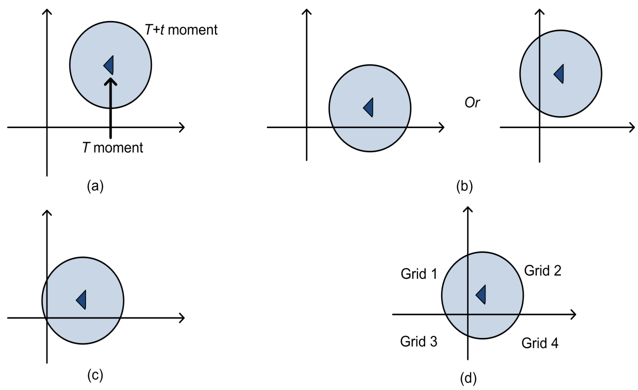

FIGURE 9. Cross-grid problem analysis. (a) Not cross the grid. (b) Cross one grid. (c) Cross two grids. (d) Cross three grids.

A complete cooperative fingerprint database $[N_{net}, N, A_x, N_{order}]^T$ was established in offline phase. By querying the fingerprint database, we can get the network name N_{net} and the weight A_x of each network in each grid.

After period t, there are four kinds of situation as shown in **FIGURE 9**. Here we use T moment overlapping area as example to check at $T+t$ moment the target node whether cross-grid. Assume that there are four grids, the coordinate of the intersections of grid nodes numbered 1, 2, 3 and 4 is (x_0, y_0). N_{net} is network 1, network 2, ..., network n. Mobile target node at number 2 grid at T moment and coordinate is (x_1, y_1). The moving speed is v and the moving unit time is t. Assume that the weights of network 1, network 2, ..., network n are $A_1, A_2, \ldots, A_n$ respectively in the grid 1. The weights are $A_1', A_2', \ldots, A_n'$ respectively in the grid 2, the weights are $A_1'', A_2'', \ldots, A_n''$ respectively in the grid 3 and the weights are $A_1''', A_2''', \ldots, A_n'''$ respectively in the grid 4.

The relationship between $(x_1 + v \times t, y_1 + v \times t)$ and (x_0, y_0) is discussed as follows:

a: DOES NOT CROSS THE GRID

$$\begin{cases} x_1 + v \times t > x_0 \\ y_1 + v \times t > y_0 \end{cases}$$

FIGURE 9(a) shows the mobile node does not cross the gird, the weight for the cooperative positioning keep same as offline phase.

b: CROSS ONE GRID

$$\begin{cases} x_1 + v \times t > x_0 \\ y_1 + v \times t \le y_0 \end{cases} \quad \text{or} \quad \begin{cases} x_1 + v \times t \le x_0 \\ y_1 + v \times t > y_0. \end{cases}$$

Show as **FIGURE 9(b)**: A mobile node may cross from grid 2 to grid 4 or from grid 2 to grid 1. At time $T + t$, the weight of network i is $\tilde{A}_i$:

$$\tilde{A}_i = \frac{v \times t + (y_1 - y_0)}{2v \times t} A_i{}' + \frac{v \times t - (y_1 - y_0)}{2v \times t} A_i{}''', \tag{6}$$

or

$$\tilde{A}_i = \frac{v \times t + (x_1 - x_0)}{2v \times t} A_i{}' + \frac{v \times t - (x_1 - x_0)}{2v \times t} A_i{}'''. \tag{7}$$

c: CROSS TWO GRIDS

$$\begin{cases} x_1 + v \times t \le x_0 \\ y_1 + v \times t \le y_0 \end{cases}$$

and $(x_1 + v \times t)^2 + (y_1 + v \times t)^2 \le {x_0}^2 + {y_0}^2$.

Show as **FIGURE 9(c)**: The mobile node may be in the grid 1, 2, 4 at $T + t$ time point, at this time, the weight of the network i is $\tilde{A}_i$:

$$\tilde{A}_i = \frac{v \times t - (x_1 - x_0)}{2v \times t} A_i + \frac{v \times t + (x_1 - x_0) + (y_1 - y_0)}{2v \times t} A_i{}' + \frac{v \times t - (y_1 - y_0)}{2v \times t} A_i{}'''. \tag{8}$$

d: CROSS THREE GRIDS

$$\begin{cases} x_1 + v \times t \le x_0 \\ y_1 + v \times t \le y_0 \end{cases}$$

and $(x_1 + v \times t)^2 + (y_1 + v \times t)^2 > {x_0}^2 + {y_0}^2$.

Show as **FIGURE 9(d)**: The mobile node may be in the grid $1, 2, 3, 4$ at $T + t$ time point, and the weight of the network i is $\tilde{A}_i$:

$$\begin{aligned} \tilde{A}_i = &\frac{(v \times t - (x_1 - x_0))(v \times t + (y_1 - y_0))}{4v^2t^2} A_i \\ &+ \frac{(v \times t + (x_1 - x_0))(v \times t + (y_1 - y_0))}{4v^2t^2} A_i{}' \\ &+ \frac{(v \times t - (x_1 - x_0))(v \times t - (y_1 - y_0))}{4v^2t^2} A_i{}'' \\ &+ \frac{(v \times t + (x_1 - x_0))(v \times t - (y_1 - y_0))}{4v^2t^2} A_i{}'''. \end{aligned} \tag{9}$$

By using cross-grid strategy, at $T - t$ moment, the weights of different network at T moment can be re-allocated.

The real measurement coordinate of the target node is:

$$(x, y) = \tilde{A}_1 \times (x_1, y_1) + \tilde{A}_2 \times (x_2, y_2). \tag{10}$$

Among it, (x_1, y_1) is the coordinate measured by network 1. (x_2, y_2) is the coordinate measured by network 2. $\tilde{A}_1$ and $\tilde{A}_2$ are corresponding re-allocation weights of network 1 and network 2 in the grid.

TABLE 2. Comparison of average localization ability and error.

Positioning method	WSN	WiFi	WSN+WiFi
Positioning ability	64	68	87
Average positioning error/m	0.5196	0.5088	0.4354

IV. SIMULATION EXPERIMENT AND ANALYSIS

A. SIMULATION SETUP

For verifying the efficiency of our methods, our simulation environment with 30 WiFi ANs and 30 wireless sensor nodes randomly deployed in indoor environment within the area of $100m \times 100m$ (In reality, the nodes should be evenly distribution relatively). The communication radius of WiFi and WSN is 20m. According to [32, Th. 2], the grid length is 10m, so each grid size is $10m \times 10m$, total 100 (10×10) grids. The transmission power of AN is 20dBm. Simulations are carried out using MATLAB.

First, we applied 30 unknown nodes randomly in the area to check the localizability and positioning accuracy of CLTA compare with the single network. Then we adopted a mobile node in the area moving with uniform and accelerated motion separately under different moving steps. After 30 times of the experiment, the average accuracy and final results is concluded.

B. RESULTS ANALYSIS

In this paper, we use improved centroid weighting algorithm to locate unknown nodes in a single network. Each positioning, according to the RSS values to select the three nearest ANs which near the unknown nodes as positioning ANs. If the positioning area can only receive one kind of network signal, the region degenerates into a single network localization region. If there is no network signal in the area, the area can not be located. In the simulation experiment, the average error of the experiment is calculated according to Euclidean principle.

First, we evaluated the localizability and positioning accuracy of our proposed cooperative target tracking mechanism. Total 30 unknown nodes randomly distributed in the $100m \times 100m$ area. Fig. 10(a) shows one positioning ability (The percent of successful positioning points in the total positioning points. Such as 100 points, how many points we can positioning) result of 30 times experiments. Fig. 10(b) shows each positioning error result of 30 times. Table 2 indicates the average result of 30 times experiments.

As shown in Table 2, we observed that the cooperative method can increase localization ability as well as improve the accuracy performance.

Second, the localization tracking accuracy of the algorithm under different moving steps is compared with the localization tracking accuracy in single network environment, as shown in Fig. 11. In the experiment, tracking nodes were tracked and positioned with 15 steps, 30 steps and 60 steps separately (In this paper, the moving speed v equals 1.5 m/s). Table 3 shows the experiment of the average localization tracking error at different moving steps.

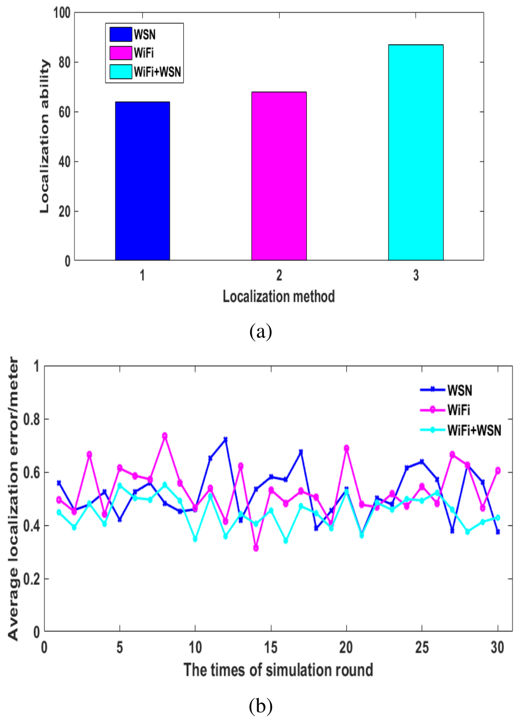

FIGURE 10. **Localization ability and error. (a) Localization ability. (b) Positioning error.**

TABLE 3. **Comparison of average tracking error.**

Number of steps	15	30	30(Noise)	60(Noise)
WSN error/m	0.2649	0.3341	0.4387	0.4885
WiFi error/m	0.2604	0.3361	0.3208	0.2871
CLTA error/m	0.2013	0.2373	0.2080	0.2427

As shown in Fig. 11(a), (b), the tracking node moved 15 steps and 30 steps at speed $v = 1.5$ m/s with uniform velocity. We can know, from the simulation result, the CLTA localization error is less than single network WiFi or WSN.

When the numbers of tracking steps are 30 and 60, the Gaussian noise is added to the experiment (i.e., the starting speed $v = 1.5$ m/s and with a certain acceleration). The results are shown in Fig. 11(c), (d). Due to the influence of Gaussian noise, the cooperative localization and tracking between networks has a great influence on the localization results of localization and tracking, which leads to the localization error of cooperative tracking and positioning between networks is increased but it is acceptable. Furthermore, under different moving steps, the average tracking error with the proposed algorithm is less than the average tracking error in the single network environment. The average localization and tracking error shown in Table 3.

The simulation shows the proposed algorithm can predict dynamic trajectory of target node with superior accuracy and localizability than single-network localization and tracking. With the increase of the number of moving steps, CLTA improves the positioning accuracy of tracking by using the overlapping mechanism, the prediction mechanism and the cross-grid strategy for trajectory localization and tracking of the target node in the online phase.

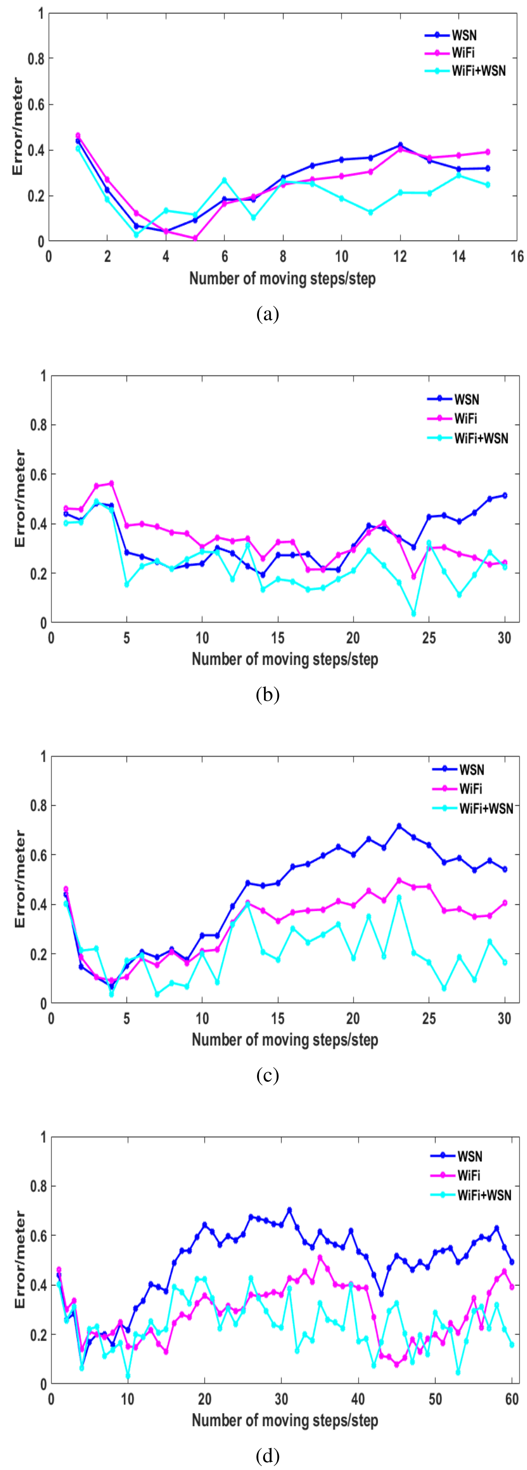

FIGURE 11. **Localization and tracking under different moving steps. (a) 15 steps without Gaussian noise. (b) 30 steps without Gaussian noise. (c) 30 steps with Gaussian noise. (d) 60 steps with Gaussian noise.**

C. REAL EXPERIMENT SETUP

Our experiments were conducted on a laboratory of our university which covering a $25m \times 30m$ area, there were

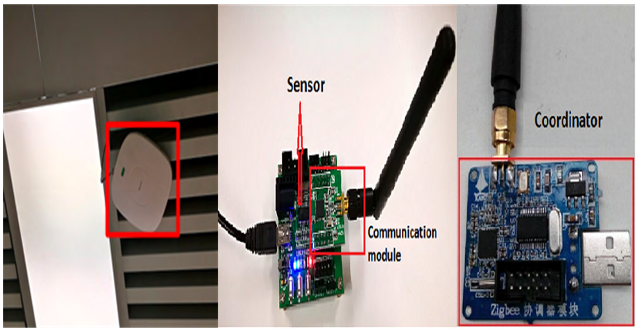

FIGURE 12. The experiment devices.

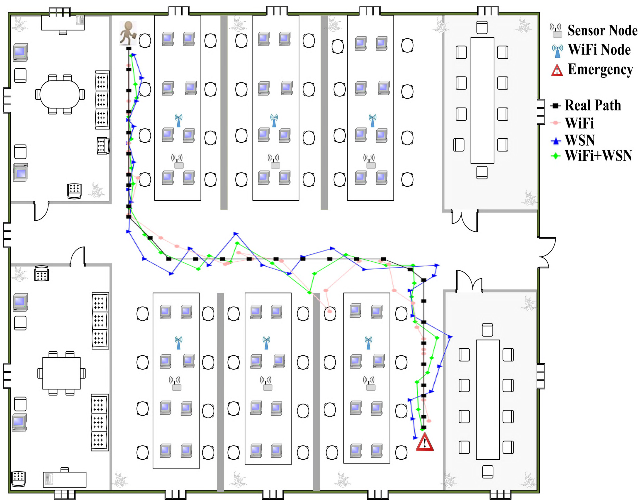

FIGURE 13. The target node moving tracking.

total 6 WiFi ANs and 6 WSN ANs uniformed distribution in the environment. WiFi ANs were deployed on the ceiling and WSN ANs were deployed on the table. The experiment devices shown in Fig. 12. In the offline phase, we used a smartphone with android system to collect the received WiFi signal strength and used a laptop to collect the received WSN signal strength of 42 positions in the corridor from ANs. The distance between two adjacent positions is around 1m. The target moving speed is around 1 m/s.

D. EXPERIMENT RESULTS ANALYSIS

The predicted and actual trajectory as depicted in Fig. 13. The real path of the target node is shown as a black full line. The pink and blue full lines represent the measurement paths of WiFi and WSN respectively. The green full line represents the measurement path by both WiFi and WSN with the proposed CLTA which is closer to the real path. There were more students and obstacles around the main road which is the middle of the corridor, so the error along the middle of the corridor is large than other two corridors. Table 4 provides the comparison regarding the localization and tracking errors. From the experiment results, we can know that the CLTA offers an improved accuracy in localization and tracking compare with single network WSN or WiFi. Table 5 provides the comparison with other algorithms. Combine Table 5 and Table 4, it shows only with WSN, CLTA (Localization error: 0.65m) has a higher accuracy then the method in [27] (Localization error: 0.9753m). It also shows CLTA performs better compared to other cooperative methods ([14] used hybrid AoA/ToA system and [26] proposed an indoor localization of cooperative WSN using PSO assisted AKF).

TABLE 4. Comparison of average localization and tracking error.

Localization method	WSN	WiFi	WSN+WiFi
Average Localization error/m	0.65	0.83	0.29

TABLE 5. CLTA compares with other localization methods.

Method	WSN	WiFi AOA/TOA	PSO-AKF	CLTA
Error/m	0.9753	0.5-2.2	0.85	0.29

V. CONCLUSIONS

In this paper, we proposed a cooperative tracking and localization algorithm (CLTA) which with three methods (the overlapping mechanism, the prediction mechanism and the cross-grid strategy) and the mechanism of selection reliable nodes for positioning. We demonstrate that networks cooperation can improve the positioning accuracy and localizability. The simulation results and real experiment results show that the proposed CLTA enhances the localization and tracking accuracy effectively compare with single network and it can achieve more precise positioning to meet higher demands.

For further investigation, we would like to mention several research points. First, WSN and WiFi techniques are used in this paper. Our study can be investigated or extended to more other position techniques. And we are testing and verifying the WiFi, WSN and Bluetooth these three kinds of networks with new algorithms. Second, outdoor environment is broader and changeable than indoor environment, it needs further effort to apply our study to actual outdoor application scenarios. Third, how to apply these position techniques to solve the problem of seamless integration between indoor and outdoor environment.

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JUAN LUO (M'10) received the bachelor's degree from the National University of Defense Technology, Hunan, China, in 1997, and the master's and Ph.D. degrees in communication and information system from Wuhan University, Hubei, China, in 2000 and 2005, respectively. She is currently a Professor and a Doctoral Supervisor with the College of Computer Science and Electronic Engineering, Hunan University, Changsha, China. From 2008 to 2009, she was a Visiting Scholar with the University of California at Irvine. She has published over 60 papers. Her research interests include wireless networks, cloud computing, and Internet of Things. She is a member of the SIGCOM and the ACM and a Senior Member of the CCF.

ZHENYAN ZHANG received the B.E. degree in computer science and technology from Chuzhou University, Chuzhou, China, in 2011. She is currently pursuing the M.E. degree with the College of Information Science and Engineering, Hunan University, Changsha, China. Her research interests include wireless networks.

CHANG LIU received the B.E. and M.E. degrees in biomedical engineering from the Changchun University of Science and Technology, Changchun, China, in 2009 and 2014, respectively. She is currently pursuing the Ph.D. degree with the College of Information Science and Engineering, Hunan University, Changsha, China. Her research interests include wireless networks.

HAIBO LUO received the B.E. degree in communication engineering from the Wuhan University of Technology, China, in 2006, and the M.E. degree in information and communication engineering from Hunan University, China, in 2009. He is currently pursuing the Ph.D. degree with the College of Physics and Information Engineering, Fuzhou University, Fuzhou, China. His research interests include Internet of Things, edge computing and mobile computing.