MU-PDR: A Method of Fingerprint Passive Positioning for WiFi6 Based on MU-RTS/CTS

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Abstract. With the rapid development of wireless communication technology and mobile Internet, requirements for accuracy and efficiency of location services are on the increase. In recent years, WiFi fingerprint passive positioning technology has received more and more attention from the academic community. RSS fingerprint is usually adopted in this field, but it has some inherent defects in real-time positioning due to its unstable acquisition timing. Packet Delivery Rate (PDR) fingerprint has been proposed in recent years, which has great advantages over RSS fingerprint in passive positioning scenario. However, it still has the problems of low positioning efficiency and huge resource consumption. Therefore, this paper proposes an improved positioning method named MU-PDR (Multi User Packet Delivery Rate), which utilizes the newly introduced MU-RTS/CTS feature in WiFi6. The corresponding MU-PDR fingerprint acquisition and positioning methods are proposed to optimize the performance of PDR-like fingerprint in multi-target scenes. Finally, simulation result shows that MU-PDR has higher efficiency than traditional PDR in multi-target scenario, which is illustrated by the significant reduction of channel resource occupation under the same accuracy requirements.

Keywords: Fingerprint positioning · Passive positioning · WiFi6

1 Introduction

With the popularity of WiFi devices, WiFi based positioning technology [1] shows significant advantages of low cost and easy deployment, which has excellent development potential. WiFi-based fingerprint positioning technology realizes the positioning and tracking of user terminals through different signal characteristics and matching algorithms [2]. This technology usually does not need additional hardware support and can be completely based on common WiFi devices. It is commonly realized through received

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signal strength (RSS) [3]. The advantage of location fingerprint technology is that it can handle the difference of signal characteristics in different locations without signal resolution. It is not affected by non-line-of-sight propagation (NLOS) errors and has excellent stability and robustness.

According to which side the signal is acquired and the fingerprint is generated, the fingerprint positioning can be divided into active method and passive method [4]. Active positioning covers most of the current fingerprint positioning technologies [5], that is, collecting data sent by AP on the positioning target side, generating location fingerprints and matching the fingerprints of the server-side fingerprint database. In contrast, passive fingerprint technology collects the wireless signal sent by the target on the AP side, generates a fingerprint and uploads it to the local server for matching and estimating the location of the signal source. Its characteristic is that the AP side has the initiative of positioning, and the user usually does not need to install software and hardware or proceed with something else on the mobile device. The positioning process is semi-independent from the user's participation.

At present, passive fingerprint positioning [6] mostly adopts RSS as the fingerprint, and mainly acquires RSS data through probe request frame and data frame. Due to the long transmission interval of the probe request frame, the frequency of RSS obtained by the positioning system is low, and vacuum period is prone to occur. Moreover, the data frame also has problems such as unstable sending frequency and loss of key information. The AP must capture the data frame sent by the target to parse the RSS data contained in it. In practice, it is rare for the target to actively send packets, and the frequency with which the target sends packets is unpredictable, especially when the target is not associated with any AP. In this case, the positioning system can not get RSS of a specific device at any time, and the real-time requirement can not be satisfied.

For such problems, Duan et al. [7] proposed a positioning technology solution based on the Packet Delivery Rate (PDR), where the AP actively sends a request to send (RTS) frame to solicit the target device to reply to a clear to send clear to send (CTS) frame to calculate the PDR, and use this instead of RSS as the fingerprint. While satisfying the real-time requirement of passive positioning, they solve the device dependence problem by specifying modulation mode and power. Since the PDR positioning technology adopts the RTS/CTS mechanism, a group of APs in the positioning system can only locate a single target in a same period. The high-frequency and mass-transmitted positioning frames will inevitably lead to waste of channel resources in the multi-target scenario. As a result, the cost in real scenarios is worth paying attention to. In general, under the previous protocol, the one-to-one mechanism of RTS/CTS is the most important bottleneck limiting this positioning technology.

In this paper, we propose a passive positioning method of MU-PDR (Multi User Packet Delivery Rate) fingerprint integrated with the MU-RTS/CTS [8] features newly introduced in 802.11ax [9, 10], based on the passive positioning technology of PDR fingerprints. This method integrates the more flexible channel resource allocation mechanism in 802.11ax into the PDR fingerprint positioning technology, and replaces the traditional RTS with MU-RTS, so that the target can perform parallel CTS responses, which greatly improves the condition of the same transmission data rate. It improves the efficiency of fingerprint collection and construction, thus expanding the potential of PDR fingerprint positioning technology in multi-target scenarios. Through simulation experiments, this paper verifies the effectiveness of the method from two aspects: positioning accuracy and the number of positioning frames. The results show that the positioning accuracy of MU-PDR method for multiple targets is basically the same as that of traditional PDR method for single target, but the overall positioning cost of the former is significantly reduced.

2 MU-PDR Fingerprint Positioning Frame

The MU-PDR fingerprint acquisition method is based on the MU-RTS/CTS mechanism in WiFi6. The parallel PDR data calculation is realized through the CTS replied in parallel in multiple RU. The allocation mode of positioning RU adapts to the general 802.11ax protocol. MU-PDR positioning method is a multi-AP collaborative positioning process. Therefore, it is necessary to plan the transmission time of positioning frames reasonably, in order to avoid the waste of resources and accuracy loss caused by the collision of high-frequency positioning frames from different Aps (Fig. 1).

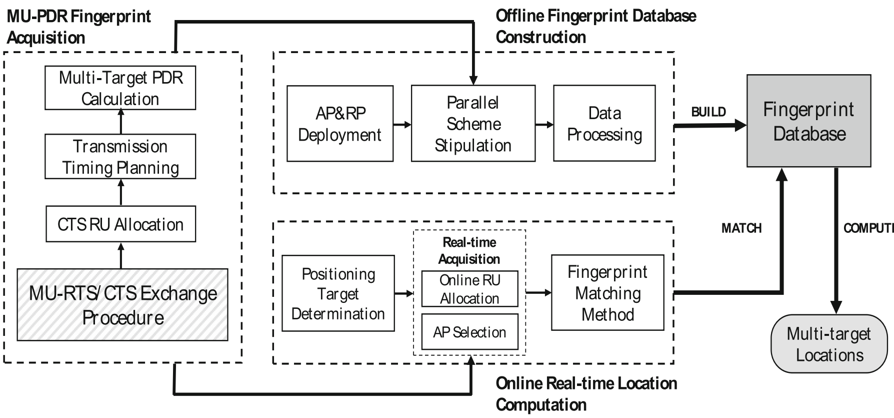

Fig. 1. The PDR involved in the online and offline phase is obtained by calculating the MU-RTS frame sent by the AP and the CTS frame replied by multiple targets in parallel.

The construction method of offline MU-PDR fingerprint database is similar to the general one of fingerprint database. The positioning range is planned according to the AP coverage, and some location points in the indoor space are preselected as reference points (RP). Based on the MU-PDR fingerprint acquisition method, the multi-target PDR fingerprint of an RP is collected in parallel to form the complete MU-PDR fingerprint as the location feature of the RP. After data processing, the MU-PDR fingerprints data of multiple APs are stored in the local server to build an offline fingerprint database.

In the section of online real-time location computation, it is first necessary to collect real-time MU-PDR fingerprints, in a multi-AP and multi-target scenario, which involves the determination of targets before positioning, the positioning RU planning of each target, and the specific enabled APs in this positioning, so as to ensure the positioning efficiency and reduce the occupation of channel resources. Finally, the MU-PDR fingerprint collected in real time is matched with the fingerprint database to obtain the positioning results. Different matching algorithms have some impact on the accuracy.

3 MU-PDR Fingerprint Acquisition Method

The behavior of different types of WiFi terminals is uncertain. Thus, it is difficult to ensure the accuracy and timeliness of information acquisition by using the probe request frames and data frames from the terminals. One way to solve this problem is to install corresponding programs on the WiFi terminal device to cooperate with fingerprint collection on the side of the positioning system, but this way obviously violates the original intention of passive positioning. Therefore, a more reasonable way is to make the AP solicit the terminal to a certain extent within the scope of the protocol.

3.1 MU-RTS/CTS Mechanism

MU-RTS is a new trigger frame in the 802.11ax. The trigger frame requests and allocates resources for one or more HE-TB-PPDU (High Efficient Trigger-based Physical Layer Protocol Data Unit) transmissions, and carries other information required by the responding STA to send the HE-TB PPDU.

802.11ax APs firstly need to initiate a TXOP transmission time through competition (CSMA/CA). During this TXOP period, the channel is occupied by this AP. Then, this AP reserves the channel by sending MU-RTS to terminals and avoids some issues such as "hidden terminal".

When receiving an MU-RTS, the terminal should feed back the CTS to the AP for confirmation. The MU-RTS frame contains a list of RU assignments for each 802.11ax client and helps coordinate the multiuser frame exchange. The 802.11ax clients send clear-to-send (CTS) responses in parallel using their assigned RUs, thereby enabling parallel transmission of CTS frames from multiple terminals. By setting the NAV timers of all other nodes, all terminals are in a passive receiving state and will not actively compete for channels within the reservation time. The time value set by the NAV timer is used for OFDMA data frame exchange procedure (Fig. 2).

Compared with the traditional RTS/CTS mechanism, MU-RTS/CTS mechanism provides more flexible resource allocation and channel reservation ability, which logically changes from one-to-one to one-to-many. It can greatly improve the measurement efficiency of PDR in multi-target scenario.

3.2 MU-PDR Acquisition Method

MU-PDR fingerprints essentially differentiate locations by differences in the success rate of MU-RTS/CTS exchanges at different physical locations. PDRs from multiple APs are combined to form MU-PDR fingerprints with positioning capabilities. Furthermore, the APs need to specify lower CTS reception power in the corresponding field of MU-RTS to ensure the location discrimination and the equal CTS transmission power between different terminals.

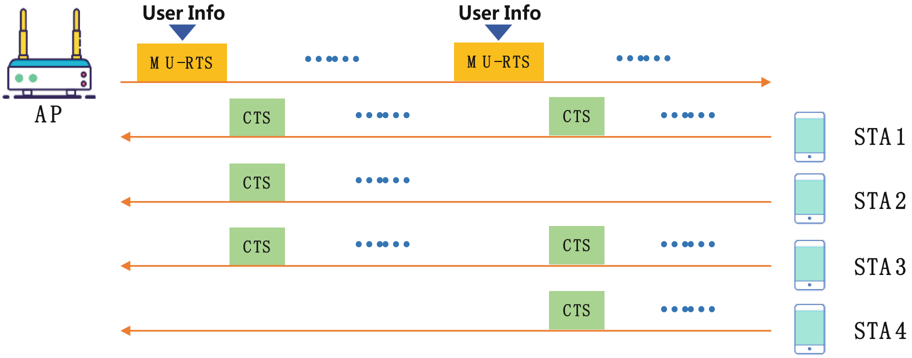

Fig. 2. MU-RTS transmits on the entire channel, which can be received by both 802.11ax nodes and traditional 802.11 nodes.

The process of a single MU-PDR fingerprint collection is that the AP sends the MU-RTS frame to the target at the specified sampling rate in the specified time window, and receives the parallel CTS of each target.

Define the sampling window size T as the time used for one fingerprint collection, and the data rate s as the MU-RTS sampling rate of a single AP within the window period, then the number of MU-RTS frames sent by a single AP for a single acquisition of a single target can be calculated as:

$$r = T \times s \tag{1}$$

Assuming that the number of CTS frames replied by this target received by the AP after the end of the sampling window is c ($c \leq r$), the PDR can be calculated as:

$$PDR = \frac{c}{r} \tag{2}$$

Consider a fingerprint collection of m targets by n APs. After the window period ends, the PDR of each target is calculated separately and combined as:

$$\begin{bmatrix} PDR_1^1 & PDR_1^2 & \cdots & PDR_1^n \\ PDR_2^1 & \cdots & \cdots & \vdots \\ \vdots & \cdots & \cdots & \vdots \\ PDR_m^1 & \cdots & \cdots & PDR_m^n \end{bmatrix} \tag{3}$$

where PDR_j^i is the PDR collected from the AP_i to the $Target_j$. If m is greater than the maximum number of parallels in the scheme, it is ensured that each target has the same positioning resources by increasing the data rate.

Since MU-PDR fingerprint collection requires high-frequency MU-RTS/CTS exchange procedure. In a positioning process with dense APs, it is necessary to reduce the interference between positioning frames sent by different APs as much as possible, which will occupy time resources and even have some impact on the positioning accuracy. When used for positioning, a MU-RTS/CTS exchange procedure does not initiate an uplink transmission of the terminal at the end, but defaults to relinquishing the channel and competing for the next transmission opportunity.

Next, Consider the time consumed for a single MU-RTS/CTS exchange:

a. If the AP sends MU-RTS and successfully receives CTS frames addressed by MU-RTS trigger frame:

$$T_{success} = MU\_RTS\_TIME + CTS\_TIME + aSIFSTime \tag{4}$$

b. The 802.11ax protocol states that the AP should wait for a CTSTimeout interval after sending MU-RTS:

$$CTSTimeout = aSIFSTime + aSlotTime + aRxPHYStartDelay \tag{5}$$

The interval starts with the PHYTXEND.confirm primitive of the MU-RTS trigger frame sent by the MAC. If the MAC does not receive the PHY-RXSTART.indication primitive during the CTSTimeout interval, the AP should determine that the transmission of MU-RTS trigger frames failed.

Therefore, this paper stipulates that MU-RTS should set a very low NAV(TXOP_DURATION) for other APs and terminals in the same channel, just enough to protect this exchange.

In the MU-PDR positioning method proposed in this paper, due to the high frequency of positioning frames, the failed exchange caused by other positioning frames at the same time should be avoided, and the PDR obtained in the online phase should not be affected by the number of enabled APS.

This method preliminarily optimizes this process by separating the MU-RTS transmission timing of each AP. Assuming a fingerprint acquisition initiated by N APs, the transmission window is divided into $B \times N$ blocks. Each block is allocated to each AP in order, and each AP only performs MU-RTS/CTS procedure for positioning purpose in the allocated time block (Fig. 3).

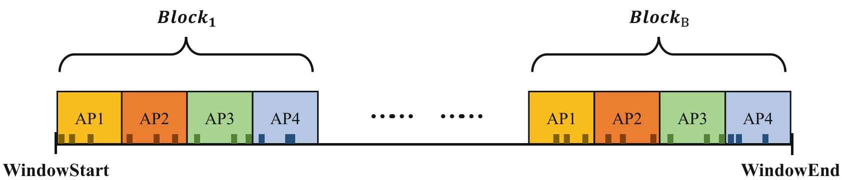

Fig. 3. In this way, the acquisition process of MU-PDR fingerprint becomes more fine-grained, and it is possible to further optimize according to the PDR data of each reduced window.

Then the specific sampling window of AP_i is defined as:

$$\left[\frac{bn+i-1}{Bn} \cdot T,\ \frac{bn+i}{Bn} \cdot T\right],\ b = 0, \cdots, B-1 \tag{6}$$

The sampling rate in a single reduced time window is $n \cdot s$.

By splitting multiple blocks, the MU-RTS/CTS exchange of each AP is independent of each other, and the independent transmission window is evenly distributed in each part of the total window. The simulation part of this paper will verify the improvement of this scheme in time domain resource occupation.

The above MU-PDR fingerprint construction method is carried out within the scope of 802.11ax protocol, without pre-operation of terminal equipment, and has good applicability to 802.11ax terminals in general scenes, with low deployment difficulty.

4 MU-PDR Fingerprint Positioning Method

4.1 Offline Fingerprint Database Construction Method

In the offline phase, the indoor area should be divided firstly. Based on the actual situation, the area is divided into RPs separated by a certain distance. The granularity and distinction of RPs need to be considered simultaneously. Usually the distance between adjacent RPs is about 1 m, and the final positioning results are indirectly from the locations of these RPs.

For convenience, the following discussion defaults to a 20 MHz channel. Four bandwidth sizes of RUs are defined in 20 MHz channels: 2 MHz (RU_a), 4 MHz (RU_b), 8 MHz (RU_c), and 20 MHz (RU_d). The impact of different RU is reflected not only in throughput, but also in packet delivery rate. Therefore, RUs with different bandwidth sizes should be attributed to different fingerprint dimensions and have corresponding location discrimination capabilities.

Given a positioning system consisting of N AP. Within the coverage of this positioning system, for each RP point, the AP measures the combined PDR of the point by multiple MU-RTS/CTS exchanges, as shown in Eq. (3). In this phase, the set of targets is in the same location, thus obtaining PDR data of each size of RU from an AP at that RP.

$$PDR_{(AP_i,RP_j)} = \left[PDR_{RU_a}, PDR_{RU_b}, PDR_{RU_c}, PDR_{RU_d}\right] \tag{7}$$

Then combine all AP data to get the MU-PDR fingerprint of the RP.

$$MU - PDR_{RP_j}^{Offline} = \begin{bmatrix} PDR_{(AP_1,RP_j)} \\ PDR_{(AP_2,RP_j)} \\ \cdots \\ PDR_{(AP_N,RP_j)} \end{bmatrix} \tag{8}$$

For this RP_j, PDR_x^y represents the PDR measurement value of the x_{th} AP in RU_y. The MU-PDR fingerprint serves as the complete location feature for this RP_j.

The MU-PDR fingerprints and their coordinates for all RPs construct a fingerprint database that is stored on the local server for invocation during the online phase. Considering the complexity of the indoor environment, a more representative MU-PDR fingerprint is usually measured multiple times at each RP.

4.2 Online Real-Time Location Computation Method

Online Fingerprint Obtaining and Matching
In the online phase, a scene with multiple positioning targets is given. After determining multiple targets to locate by positioning requests from the upper application, this positioning system will perform the RU pre-allocation process of OFDMA according to the MU-PDR acquisition method described above, assigning a specific band to each locating target (Fig. 4).

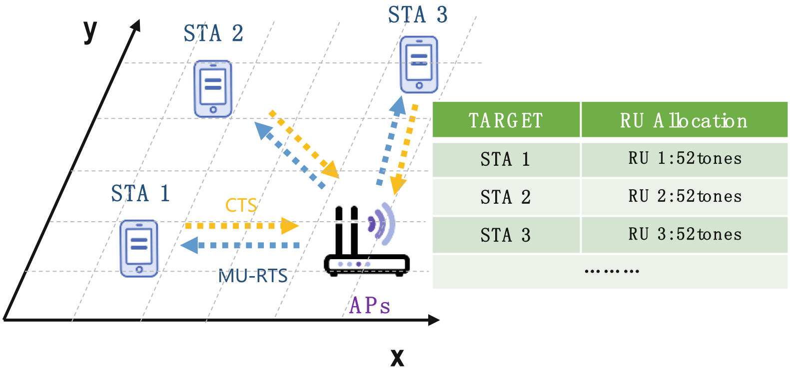

Fig. 4. An exchange process involving three STAs at a time.

Next, the system selects the appropriate sampling window and sampling rate based on the actual situation. Within a certain range, the higher the MU-RTS sampling rate is, the more stable the PDR data will be, and the more channel resources will be occupied.

Consider a single localization initiated by $n(n \leq N)$ APs to m targets. When the sampling window is over, MU-PDR fingerprints are calculated based on the total number of MU-CTS sent and the number of CTS received by each allocation channel:

$$MU - PDR^{Online} = \begin{bmatrix} PDR^{Online}_{AP_1} \\ PDR^{Online}_{AP_2} \\ \cdots \\ PDR^{Online}_{AP_n} \end{bmatrix} \tag{9}$$

$$PDR^{Online}_{AP_i} = \left[pdr^{RU_1}_{Tgt_1}, pdr^{RU_2}_{Tgt_2}, \cdots, pdr^{RU_m}_{Tgt_m} \right] \tag{10}$$

where pdr_{Tgt_j} represents the PDR of the target Tgt_j over an allocated RU by AP_i.

Then, using the computed MU-PDR fingerprint and the MU-PDR fingerprint database constructed in the offline phase, the positioning system performs a matching algorithm to calculate the results. The specific matching algorithm will have a slight impact on the positioning accuracy. As an example, the KNN algorithm is adopted in this paper, by selecting the K most similar locations and average their coordinates (Fig. 5).

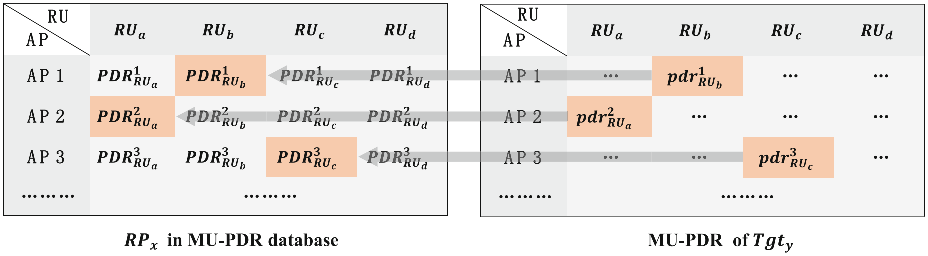

Fig. 5. The collected online fingerprint and the offline fingerprint at the corresponding RP.

About MU-PDR fingerprints involved in this phase, the column vectors represent each target's PDR fingerprint, and each dimension of the fingerprint can find the corresponding in the offline fingerprint database. Similarity is calculated from the Euclidean distance between the offline and online fingerprints:

$$SIM_{(RP_x, Tgt_y)} = \frac{1}{\sqrt{\sum_{i=1}^{n}\left(PDR^i_{RP_x} - pdr^i_{(Tgt_y, RU)}\right)^2} + \varepsilon} \tag{11}$$

Select the K RPs with the greatest similarity of the positioning target, and compute the location estimates of multiple targets at the same time. Therefore, the multi-target parallel positioning initiated by the positioning system is realized.

$$\begin{cases} (x_1, y_1) = \frac{\sum_{i=1}^{K}(x_1^i, y_1^i)}{K} \\ \quad \cdots\cdots \\ (x_m, y_m) = \frac{\sum_{i=1}^{K}(x_m^i, y_m^i)}{K} \end{cases} \tag{12}$$

Quantity Limit of Concurrent Enabled AP

The accuracy of MU-PDR fingerprints depends on the number of MU-RTS/CTS sent. However, a higher amount of transmission may result in higher channel time-frequency resource consumption and power consumption.

Set p as the number of CTS parallels on the target side and $p = 1$ as the case with traditional PDR schemes. It is easy to get the increase of time-frequency resource occupancy of MU-PDR scheme compared with traditional PDR scheme. For the same number of positioning frame exchanges, the MU-PDR scheme achieves p times the number of positioning targets compared with the traditional PDR scheme, while the time-frequency resource consumption is basically the same.

Furthermore, this paper analyses the power consumption from the point of view of the number of positioning frames. Considering the two parts of MU-RTS sent by AP and CTS sent by target, the total theoretical transmission of positioning frames in a sampling window is calculated as:

$$Frames = \underbrace{n \times T \times s \times \left\lceil \frac{m}{p} \right\rceil}_{MU-RTS} + \underbrace{n \times T \times s \times m}_{CTS} \tag{13}$$

where p is the maximum number of CTS parallel scheme. $p = 1$ represents the case with traditional PDR scheme.

$$Frames_{PDR} = 2 \times n \times T \times s \times m \tag{14}$$

Compared with traditional PDR, MU-PDR first significantly reduces the number of RTS frames sent for positioning in multi-target scenarios with the same sampling rate. It is easy to calculate that under the same other conditions, MU-PDR theoretically reduces the number of positioning frames by 25%–50%, depending on the specific parallel scheme.

When the target is within the scope of multiple APs ($N > 3$), the number of used AP needs to be limited. Although more AP means higher fingerprint dimensions, positioning accuracy can be slightly improved (with severe marginal effects). However, in dense scene of MU-PDR fingerprint positioning, it is easy to overflow the positioning frames in the channel, causing serious congestion.

To further optimize the cost of positioning frames, the number of AP used for fingerprint collection is limited. In an independent N AP positioning system, the number of AP per positioning is limited as:

$$AP_{adopt} = min\left(AP_{cover}, AP_{max}, \ \frac{N}{L+Q-1+\frac{N}{(N-3)\sqrt{p}}}^{\frac{1}{\sqrt{p}}} + AP_{min}\right) \tag{15}$$

where AP_{cover} is the number of AP around this target, AP_{max} is the maximum number of AP allowed, L is the number of targets already in the window, and Q is the number of targets of this positioning. When there are fewer targets in the positioning window, more APs are enabled for this positioning task. As the number of targets in the positioning window increases, the number of concurrently enabled AP quickly converges to the minimum fingerprint dimension requirement number AP_{min}.

MU-PDR, as a fingerprint positioning method, also has the advantages of strong robustness and no need of signal computation. MU-PDR realizes real-time passive positioning through MU-RTS/CTS exchange procedures initiated on the side of the positioning system, independent of random data frames sent by the terminal device.

5 Simulation

In this chapter, the validity of the proposed method is verified through simulation experiments, based on MATLAB. The simulation mainly includes positioning accuracy and positioning cost.

The indoor WiFi signal propagation scene is built based on MATLAB simulation platform, in which the simulation network with multiple APs and nodes is built, and the exchange process of MU-RTS/CTS mechanism is simulated. The indoor propagation model is used to determine the path loss between nodes, with the parameters of indoor scenario and the distance between nodes as the main parameters. To simulate the real indoor environment, this simulation experiment adds random ambient noise interference to the signal, and simulates the fluctuation of indoor positioning while guaranteeing the distance difference.

5.1 Positioning Accuracy

This section aims to test the impact of one-to-many mechanism of MU-RTS/CTS on positioning accuracy in multi-target scenarios.

Set a 10 m * 10 m * 3 m indoor area and divide the X/Y plane into 100 reference points, 1 m apart. The positioning system is built with three APs, which are distributed indoors and triangulated to ensure unambiguous positioning results. All APs and targets separately use the constant transmission power during this simulation.

Three schemes are compared with the same sampling window of 1 s and sampling window of 500 per second:

a. Traditional RTS/CTS scheme. Locate only one single target at a time in the whole 20 MHz channel.
b. Traditional RTS/CTS scheme. Considering multi-target scenario with 4 targets, the window size is compressed to 1/4 of the original.
c. The MU-PDR scheme proposed in this paper, which uses 20 MHz channel for MU-RTS and 4 MHz RUs for each CTS.

The experiment simulates the offline and online phases and uses the following MU-PDR fingerprint acquisition methods: the positioning system sends MU-RTS or RTS frames to indoor targets to be located, then the targets reply CTS frames in the indicated RUs when the reception is successful. The channel environment does not change during one exchange procedure. Repeat this process in the sampling window at a given sampling rate.

During the positioning process, the target to be located is set to move with a random track in the indoor space with a constant height. After repeated positioning for many times, the average error is calculated by measuring and calculating the positioning results of each time. Finally, the positioning accuracy of each scheme under given conditions is obtained (Fig. 6).

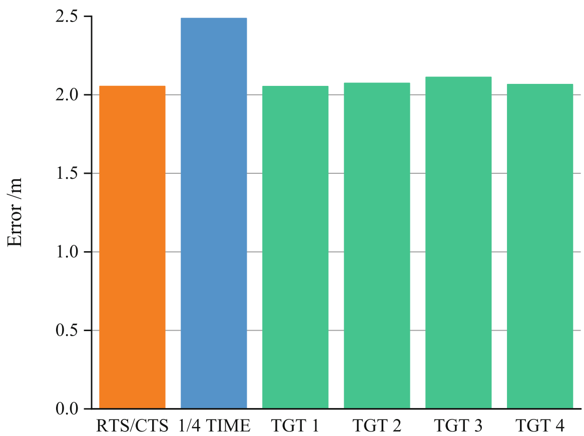

Fig. 6. Positioning accuracy simulation results.

As shown above, taking 4 MHz RU as an example, the accuracy of multi-target positioning using MU-RTS/RTS is basically the same as that of single-target RTS/CTS in this simulation environment. The results show that the CTS frames transmitted in parallel have no significant impact on the positioning accuracy. In the multi-target scenario, when the sampling window of the RTS/CTS scheme is shortened, the average error increases significantly. It can be inferred that in such PDR-like fingerprint positioning scheme, the discrimination of position is less sensitive to the transmission bandwidth of CTS than to the sampling window and the sampling rate. With similar positioning accuracy, more attention should be paid to the resources occupied in the positioning process.

5.2 Positioning Cost

This section considers a scenario where there are more APs and more targets on such region and simulates the positioning cost at the system level. Each target to be located randomly sends out a positioning request at some moments with a certain probability, and the location service is provided by some of these APs in the system. Set the same sampling window and sampling rate as the previous experiment, to simulate the number of positioning frames needed and the average time consumption of AP under different preset parameters. In order to more intuitively reflect the channel resource occupation, it is assumed that all nodes are in the same channel (Table 1 and Fig. 7).

Table 1. Simulation parameters

Parameter	Value
Sampling window	1 s
Sampling rate	1000 frames/s
CTS parallels	4
Request rate	0.1
Block num	5
$T_{success}$	25 μs
$T_{timeout}$	59 μs

The positioning power consumption is weighed from the number of positioning frames sent. PDR and MU-PDR use the same AP selection scheme. The simulation results display the sum of RTS (MU-RTS) and CTS frames under ideal conditions, reflecting the combined costs of different positioning schemes from the side. The result shows that when the number of targets in the area is small, there is little difference between the number of theoretical frames used for PDR positioning and MU-PDR positioning. In the case of more dense targets, the parallel construction mechanism of MU-PDR has obvious advantages in power consumption, reducing the number of positioning frames by 33.7% (Fig. 8).

In terms of the time-frequency resource consumption, this experiment tests different strategies. Different numbers of APs compete to occupy channels during a given period.

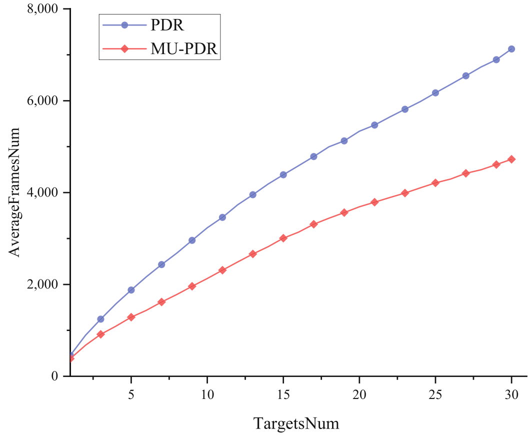

Fig. 7. Number of positioning frames simulation results.

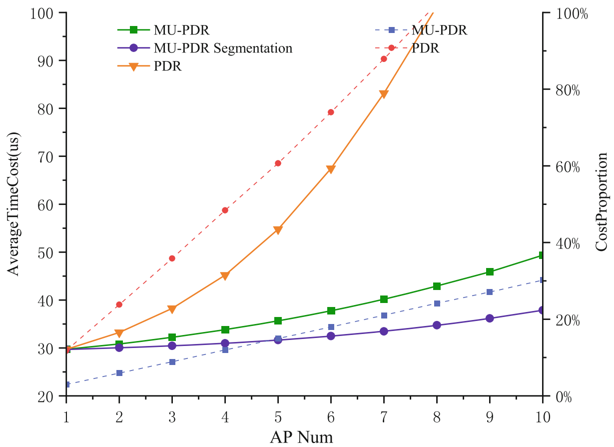

Fig. 8. Positioning time cost simulation results.

The period from waiting for transmission to exchange completion or timeout is recorded as the time consumed for one positioning procedure. In the traditional PDR scheme, the transmission success rate is low and the queuing time is long due to the excessive number of positioning frames sent and the overcrowded channel. As the number of positioning AP adopted increases, the average time consumption of a single RTS/CTS exchange will exceed 100 µs. In this case, the time-frequency resources are insufficient to meet the sampling rate requirements. By contrast, the MU-PDR scheme improves significantly in this field. The time consumption of a single exchange is limited to less than 50 µs. And in extreme cases, the channel occupancy is less than 30%, which is of more practical worth.

6 Conclusion

In this paper, we propose a MU-PDR fingerprint passive positioning method, which utilizes the new feature of MU-RTS/CTS in 802.11ax to increase the number of locatable targets in a single window. Compared with traditional PDR method, the positioning efficiency in multi-target scenes is improved while the positioning accuracy is guaranteed. The MU-PDR method is applicable to the general 802.11ax protocol, which does not require additional hardware support, and has the advantages of low cost and easy deployment.

Through simulation experiments, this paper verifies the validity of the scheme at the system level. The results show that the MU-PDR method proposed in this paper achieves simultaneous multi-target parallel positioning without sacrificing accuracy, and optimizes the limitation of traditional PDR fingerprint channel resource consumption, thereby greatly reducing the cost of positioning in multi-target scenes.

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