2025 International Conference on Intelligent Computing
July 26-29, Ningbo, China
https://www.ic-icc.cn/2025/index.php

An Indoor Terminal Positioning Algorithm for Mobile Communication Management and Control Scenarios

Jingwen Fu[1,2], Hang Zhang[1,✉], Liqi Zhuang[1,2], Xing Gao[2] and Meng Zhang[1,2]

[1] Institute of Information Engineering, Chinese Academy of Sciences, Beijing 100085, China
[2] School of Cyberspace Security, University of Chinese Academy of Sciences, Beijing 100049, China
[3] Beijing Zhongke Chuangjia H.R.Consulting Co., Ltd., Beijing, China
zhanghang1996@iie.ac.cn

Abstract. The popularity of mobile terminals has brought convenience to people's lives, but in some important areas and critical places, the illegal use of mobile terminals will introduce the problem of sensitive information leakage, for the security and confidentiality risk of such scenes. This paper proposes an indoor mobile terminal high-precision grid positioning algorithm based on the Received Signal Strength Indicator (RSSI). Firstly, by mining the uplink signal protocol characteristics of mobile communication, the correlation of the demodulation reference signal (Demodulation Reference) is used to accurately extract the target user data, and the interference from non-target radiation sources is effectively excluded. Secondly, an efficient grid positioning strategy is proposed, which divides the complex indoor environment into multiple fine grids and constructs a probabilistic model based on RSSI data to achieve the target location estimation. Finally, an indoor mobile terminal positioning prototype system for mobile communication control scenarios is built based on the self-developed receiver board. Experiments show that the method in this paper is an effective and feasible solution for indoor mobile terminal positioning in mobile communication control scenarios and improves the ability to protect electromagnetic security in confidential and critical areas.

Keywords: Indoor location, Received signal strength indicator, Demodulation reference signal, Terminal management and control.

1 Introduction

With the large-scale deployment of mobile communication technologies, network and information security face increasingly serious risks and challenges [1]. In critical infrastructures and sensitive areas, unauthorized terminal access has become a major source of information leakage, posing significant hidden dangers to information security protection. Therefore, strengthening mobile terminals' security management and location monitoring has become a core requirement for building a network security protection system.

Currently, technologies for locating mobile terminals based on wireless signals include range-based [2] and range-free [3] methods, each with its own advantages and limitations. The RSSI positioning algorithm based on ranging is a common indoor positioning technology that calculates the distance between the transmitting and receiving nodes according to the attenuation characteristics of the signal during indoor propagation, thus achieving localization [4]. However, due to the openness of wireless channels, they are susceptible to environmental factors such as multipath effects and obstacle occlusion, which impose high demands on the accurate measurement of wireless signal strength. Range-based positioning algorithms, such as Time of Arrival (TOA) and Time Difference of Arrival (TDOA) [5], calculate the distance between the transmitting node and the receiving node by utilizing the propagation time of signals indoors [6]. Although these methods theoretically offer higher positioning accuracy, they require devices with high-precision timing capabilities, which are difficult to achieve in indoor environments. Another range-based algorithm, the Angle of Arrival (AOA) [7], determines location by measuring the direction of signal propagation. However, this method requires hardware equipment capable of measuring angles, resulting in higher costs. The range-free fingerprint-matching localization algorithm achieves positioning by building a wireless signal fingerprint database and leveraging the characteristic matching of signals at different locations. When the quality of signals is stable, fingerprint-matching localization technology can provide more consistent and reliable positioning results compared to other methods. However, constructing a fingerprint database requires extensive preliminary work, including collecting, storing, and processing data for each location point. This process not only consumes significant time and cost, but also demands specialized equipment and technical support. Additionally, fingerprint-matching localization technology is highly sensitive to environmental changes, such as alterations in furniture arrangement or human movement, which can lead to significant variations in fingerprint data and impact positioning accuracy. Moreover, due to differences in hardware performance and signal reception capabilities between various brands and models, introducing heterogeneity in positioning devices, it is challenging to achieve high-precision indoor localization. Given the specific requirements of mobile communication control scenarios, there is an urgent need for an indoor mobile terminal positioning solution that is simple to implement, cost-effective, and highly compatible. This paper utilizes RSSI ranging technology, which is straightforward to implement and involves relatively low complexity in setting up RSSI reception and measurement systems.

In practical applications, the complex and dynamic nature of indoor environments often results in data being sourced from multiple origins. This multiplicity and complexity of data impose more stringent demands on the stability and accuracy of positioning algorithms. To address the aforementioned challenges, this paper delves into the New Radio (NR) mobile communication protocol and proposes a power measurement optimization method based on demodulation reference signals in the control scenarios, to accurately acquire data from target mobile terminals. We use the dedicated network base station to induce mobile terminals to reselect the desinged cell and use the monitoring station to detect terminal signals and measure uplink signal power. Ultimately, terminal location estimation is achieved through distributed multi-station positioning technology. To validate the effectiveness of the positioning technology and algorithm proposed in this paper, a positioning prototype system was constructed and tested. This system meets the practical requirements of mobile communication control scenarios and achieves a significant breakthrough in addressing the challenge of high-precision positioning in complex indoor environments. The main contributions of this paper are as follows:

- We propose a power measurement optimization method based on NR demodulation reference signals for control scenarios, achieving precise capture of data from target mobile terminals.
- We develop an RSSI-based grid positioning algorithm characterized by low complexity, strong environmental adaptability, and robust anti-interference capabilities, meeting real-time processing requirements. Additionally, the self-built positioning system is cost-effective and easy to deploy.

2 System Model

This paper focuses on mobile communication control scenarios and accomplishes power measurement of target terminals with the assistance of dedicated network base stations. The system comprises the following components: 1) Dedicated network base station. It is used to induce intelligent terminals to transmit specific uplink signals. 2) User equipment (UE). The target UE is to be located. 3) Monitoring nodes. These are receiving nodes for uplink signals. These nodes are typically distributed in numbers no fewer than three. 4) Server. The server aggregates data from distributed nodes and performs positioning calculations. The system model is showed in Fig. 1.

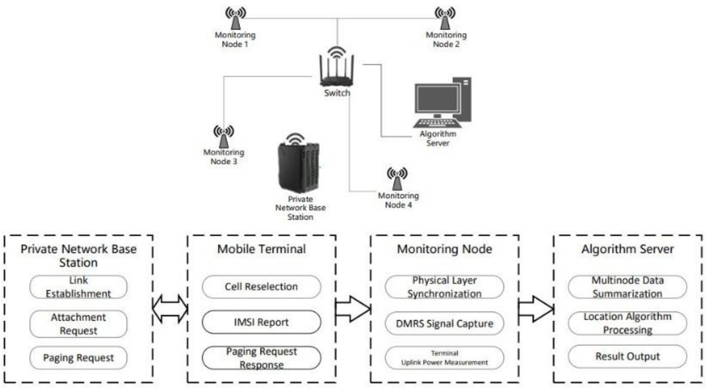

Fig. 1. System Design Flow Chart.

2.1 Target User Data Extraction Based on Demodulation Reference Signals

First, according to the NR cell reselection mechanism, we utilize the dedicated network base station to guide the UE to access the designed cell. Specifically, the dedicated network base station broadcasts downlink signals, typically with communication quality significantly higher than that of the currently serving operator cell. This triggers the UE to perform cell reselection [8] and automatically connect to the dedicated network base station, entering the control mode.

Then, we utilize NR Demodulation Reference Signals (DMRS) to achieve uplink signal power measurement for the UE. DMRS is transmitted in the Physical Uplink Shared Channel (PUSCH) and the Physical Uplink Control Channel (PUCCH). PUSCH and PUCCH together support the normal uplink communication and serve as critical channels for uplink and downlink communication between the UE and the base station. The base station can accurately estimate the channel state of the UE via DMRS to achieve correct demodulation of data. DMRS is designed specifically for individual UEs, meaning each UE has its own dedicated DMRS. This design helps distinguish between different UEs, facilitating multi-user simultaneous communication. DMRS is transmitted in fixed sequences along with uplink data within the Radio Block (RB). Typically, one RB occupies one-time slot, which contains 7 OFDM symbols in the time domain and 12 consecutive subcarriers in the frequency domain.

In the system built in this paper, the time domain positions of DMRS have a specific regularity and are transmitted at designated symbol positions within each time slot. In the PUSCH, DMRS is located at the fourth symbol from the end of each time slot. Within each time slot occupied by the PUSCH, in addition to the symbols used for data transmission, one symbol is reserved for sending DMRS. This fixed position enables the receiver to anticipate and accurately detect the DMRS signal, facilitating subsequent channel estimation and signal demodulation operations.

However, during the actual data acquisition process, the uplink data may face interference from co-frequency signals transmitted by other devices. Therefore, this paper leverages the characteristics of DMRS signals to acquire target user data, thereby reducing the impact of co-frequency interference on data acquisition. In mobile communication control scenarios, DMRS signals from different UEs are transmitted in a time-division manner. This strategy relies on the operating mode of the dedicated network base station. the base station will sequentially lock a specific UE and page it on the paging channel. Subsequently, the paged UE transmits control information and service data containing DMRS signals in designated time slots. During this process, monitoring nodes utilize known DMRS parameters to construct local DMRS sequences and perform correlation calculations with the collected signals. The correlation results are then used as the energy of the UE's uplink signal. Due to the time-division transmission strategy of DMRS signals, the results only include data from the target user, thereby completing the uplink power measurement for a single mobile terminal. This method effectively reduces the mixed transmit signals from non-target devices in the collected data and realizes the optimization of the power measurement of uplink signals.

The sequence generation for NR DMRS requires invoking corresponding functions or algorithms [9]. The generation function is determined according to the NR standard and uses input parameters to calculate the DMRS sequence. The generation function for the DMRS sequence can be expressed as Eq. 1.

$$r(m \cdot M_{sc}^{RS} + n) = w(m) r_{\{u,v\}(n)}^{\alpha}, m = \{0,1,2,3\}, n = 0,1,\ldots,M_{sc}^{RS} - 1 \tag{1}$$

In Eq. 1, M_{sc}^{RS} represents the frequency-domain bandwidth occupied by the DMRS sequence, expressed in terms of subcarriers. $R_{\{u,v\}(n)}^{\alpha}$ denotes the reference signal sub-sequence, which is generated by cyclically shifting the base sequence $r_{\{u,v\}(0)}$, where α is the cyclic shift factor.$r_{\{u,v\}(0)}$ can be expressed as Eq. 2, where $\alpha = 2\pi \frac{n_{cs}}{12}$ represents the cyclic phase.

$$r_{\{u,v\}(n)}^{\alpha} = e^{j\alpha n}\overline{\{r_{\{u,v\}}\}(n)}, 0 \le n \le M_{sc}^{RS} \tag{2}$$

A commonly used basic sequence is the ZC sequence, which has a constant amplitude and possesses zero autocorrelation properties. This characteristic makes it easier to detect and synchronize signals and can be represented by Eq. 3.

$$\overline{r_{\{u,v\}}(n)} = x_q(n \, mod \, N_{zc}^{\mathrm{RS}}), 0 \le n \le M_{\mathrm{sc}}^{RS} \tag{3}$$

where $x_{q(m)}$ is the zc sequence with root index q and length N_{ZC}^{RS}, which is shown in Eq. 4. $N_{\{ZC\}}^{\{RS\}}$ is the largest prime number not exceeding M_{sc}^{RS}.

$$x_{q(m)} = e^{-j\frac{\pi q m(m+1)}{N_{ZC}^{RS}}}, 0 \le m \le N_{ZC}^{RS} - 1 \tag{4}$$

The root index q is given by Eq. 5 and Eq. 6, where u is the base sequence group number, and v is the base sequence number within the group.

$$q = \left| \overline{q} + \frac{1}{2} \right| + v \cdot (-1)^{\{|2\overline{q}|\}}, v = 0,1 \tag{5}$$

$$\overline{q} = N_{ZC}^{RS} \cdot \frac{(u+1)}{31}, u = 0,1,\cdots,29 \tag{6}$$

When the DMRS length is less than 36, a CQ sequence generated by the computer is used as the base sequence. The CQ sequence exhibits characteristics similar to the ZQ sequence and can be expressed as:

$$\overline{r_{\{u,v\}}(n)} = e^{\frac{j\varphi(n)\pi}{4}}, 0 \le n \le M_{sc}^{RS} - 1 \tag{7}$$

where $\varphi(n)$ is generate by the computer and related to the sequence group u, which is defined by Eq. 8. In Eq. 8, f_{ss} represents the sequence frequency shift mode, and f_{gh} represents the group hopping mode. The current slot number is n_s.

$$u = \left(f_{gh}(n_s) + f_{ss}\right) mod \, 30 \tag{8}$$

The generated DMRS sequence $r(\cdot)$ is a series of complex values representing signal samples in the time or frequency domain. When the DMRS signal is transmitted, the sequence undergoes amplitude conversion and is mapped to resource elements (k, l) according to NR rules, where k represents the subcarrier index and l represents the OFDM symbol within the time slot. Using the locally generated DMRS sequence, the next step of data extraction for the target mobile terminal can be performed.

Due to the complexity and variability of indoor positioning scenarios [10], such as the movement of scatterers, the signal will encounter various scatterers during propagation, resulting in phenomena like scattering, reflection, and refraction, thus altering the signal's propagation path and phase. When scatterers move, they introduce dynamic changes to the signal, including fluctuations in signal strength, variations in phase, and jitter in propagation delay. To mitigate measurement errors caused by scatterer movement, this paper employs Kalman filtering to process the collected energy. The overall process of uplink power measurement at the monitoring nodes is summarized in Fig. 2:

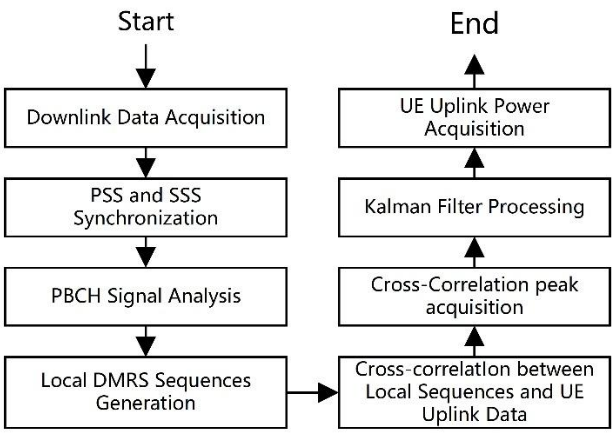

Fig. 2. Flowchart of Uplink Power Measurement.

Traditional power optimization schemes typically involve frequency domain filtering to filter out noise and interference signals, while there is a lack of simple and effective means of solving the co-frequency interference, especially in the context of more complex resource scheduling strategies for mobile terminals in the mobile communication. Compared to traditional approaches, this paper proposes a novel approach in the context of mobile communication control scenarios. The dedicated network base station locks the target mobile terminal by acquiring its International Mobile Subscriber Identity (IMSI). During each locking process, the dedicated network base station schedules resources for the target terminal according to a fixed strategy.

When uplink signal collection is performed in a dedicated network base station scenario, if the collected signals include co-frequency uplink signals from terminals connected to operator base stations, this paper utilizes known DMRS sequences to perform sliding correlation calculations with the received signals. By locating the time-domain position of the target user, data extraction can be effectively performed, resolving the issue of mixed data from multiple user terminals. The method of using DMRS for power optimization is also applicable in commercial base station networks. However, operator base stations typically schedule resources for a large number of users, resulting in more complex system configuration strategies. Additionally, for third parties, the base station configuration strategies are unknown and require operator cooperation to obtain.

2.2 RSSI-Based Indoor Mobile Terminal Grid Positioning Algorithm.

This paper proposes an indoor positioning algorithm based on probability estimation. The positioning results measure the received power differences among monitoring nodes. By deploying at least three monitoring nodes in the target area, the algorithm estimates the probability of the target terminal's presence at each grid point within the area based on the path loss model [11], thereby estimating the terminal's location.

We distributively deploy k signal collection nodes, divide the positioning area into a grid of $n \times n$ and establish a coordinate system. The actual collected uplink signal power of the terminal at each node is denoted as PR. Assuming the target terminal is at any estimated point (x_i, y_i) within the area, the path loss PL can be used to calculate k estimated transmission power values for each estimated point based on the positions of the receiving nodes and the RSSI values. The transmission power is denoted as Eq. 9.

$$PT = PL + PR \tag{9}$$

The differences among the k estimated transmission power values are measured. Theoretically, when the estimated point coincides with the true location of the target terminal, the differences among all estimated values are minimized. By converting the degree of transmission power differences at each estimated point into the probability of the target terminal's presence at that point, an indoor positioning algorithm based on probability estimation using received power differences can be achieved. The overall flow of the algorithm is illustrated in Fig. 3.

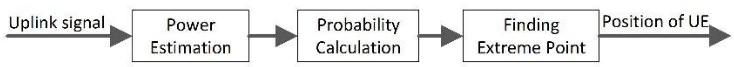

Fig. 3. The implementation process of localization algorithms.

After processing the collected uplink signals using power measurement optimisation techniques to obtain target user data, the algorithm proceeds with power estimation based on grid points, probability calculation, and finging extreme point, ultimately completing the target location estimation.

Node Deployment and Data Collection Processing. Using an $n \times n$ grid, Fig. 4 illustrates an example with four receiving nodes $P1(x_1, y_1)$, $P2(x_2, y_2)$, $P3(x_3, y_3)$, and $P4(x_4, y_4)$. The position of each receiving node (x_k, y_k) is known, and the terminal's uplink signal strength is synchronously collected. The received power at each node is denoted as PR_k. The received signals are processed to obtain the target user's power.

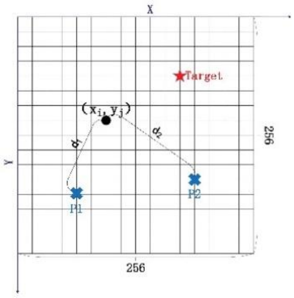

Fig. 4. The schematic diagram of positioning calculation.

Power Estimation Based on Grid Points. We assume the target's position in the grid is $(x_i, y_j)_{\{i,j\,=\,1,2,\ldots,n\}}$, and the distance between the point (x_i, y_j) in the grid and monitoring node can be calculated as Eq. 10.

$$d_{\{<i,j>,k\}} = \sqrt{\left\{(x_i - x_k)^2 + \left(y_j - y_k\right)^2\right\}} \tag{10}$$

According to received power and the path loss model, the k estimated transmission power values $\widehat{PT}_{\{<i,j>,k\}}$ for the target at position (x_i, y_i) can be calculated as Eq. 11, where $pathloss\left(d_{\{<i,j>,k\}}\right)$ is the path loss between the point (x_i, y_j) and node k.

$$\widehat{PT}_{\{<i,j>,k\}} = PR_k + pathloss\left(d_{\{<i,j>,k\}}\right) \tag{11}$$

Probability Calculation Based on Grid Points. Theoretically, the grid point where the target mobile terminal is actually located will have the smallest differences among the k estimated transmission power values. The standard deviation $D\left(\widehat{PT}_{\{<i,j>,k\}}\right)$ is used to measure the degree of differences among the estimated transmission power values at (x_i, y_j).

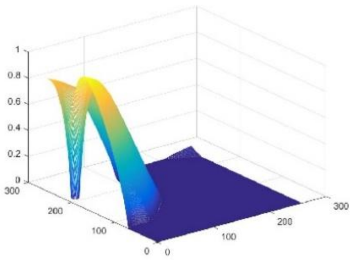

Fig. 5. The degree of variance in estimated transmission power at different points.

Among the $n \times n$ grid points, the point with the smallest standard deviation $\widehat{PT}_{\{<i,j>\}}$ is identified as the target location. The standard deviation values for each grid point are illustrated in Fig. 5.

We convert the final result calculation process into probability estimation. In this process, we need to normalize the calculated standard deviations and ultimately yielding the probability estimation values $p_{<i,j>}$ for each point in the grid.

Target Mobile Terminal Location Search. When performing indoor multi-node positioning, we constrain the target location of the mobile terminal to the indoor area. This paper specifies that during maximum probability search, the target search area is the largest matrix formed by the horizontal and vertical coordinates of the nodes. The point with the maximum probability value within the target area is identified, and the final search result is the estimated location of the target mobile terminal.

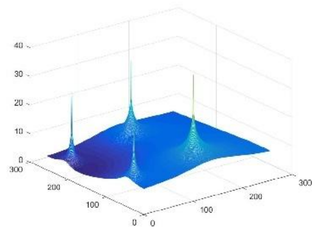

Fig. 6. Probability estimation of target terminal position.

3 Experiment Setup and Evaluation

This paper constructs an indoor mobile terminal positioning system for mobile communication control scenarios, including a dedicated network base station, nodes, an algorithm server, and target terminals. The system integrates wireless signal collection, data analysis and processing, real-time mobile terminal positioning, and dynamic display of positioning results. The test scenario is illustrated in Fig. 7, taking the deployment of four nodes as an example.

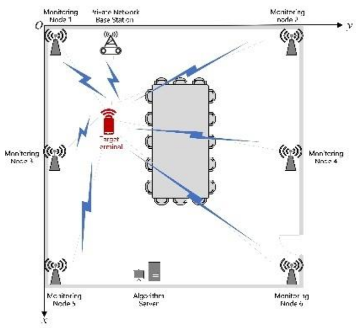

Fig. 7. The design of the prototype system.

3.1 UE Uplink Power Collection

With the assistance of the dedicated base station, uplink signal collection from the mobile terminal in the controlled state is completed. The actual collected time-frequency waterfall diagram of the UE uplink signal is shown in Fig. 8. In this scenario, the time-frequency resources occupied by the UE are allocated by the dedicated base station, and the mobile terminal transmits uplink signals on fixed time-frequency resources. The time-frequency characteristics of the uplink signal in the control scenario can be utilized for target user data extraction.

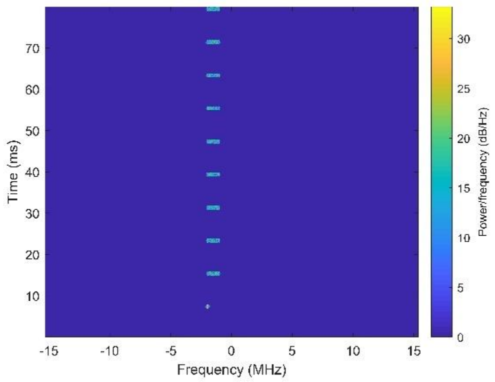

Fig. 8. Time-frequency Waterfall Diagram of UE Uplink Signals.

Based on the allocation method of DMRS in the radio resource block, the interval between two DMRS sequences is 0.5 ms. Based on this feature, the locally generated DMRS sequence and the uplink signal are correlated, and the calculation results are shown in Fig. 9.

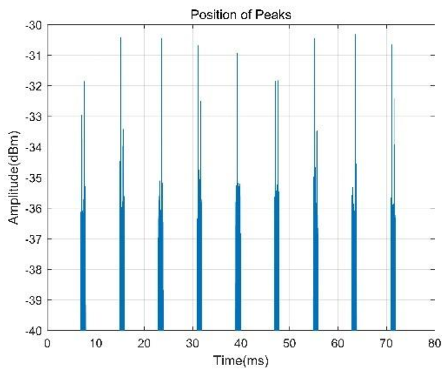

Fig. 9. Peak detection results.

By using a peak detection algorithm for local maxima, significant peaks can be effectively identified, and the location of the target user data can be determined. The located peak points are shown in Fig. 10.

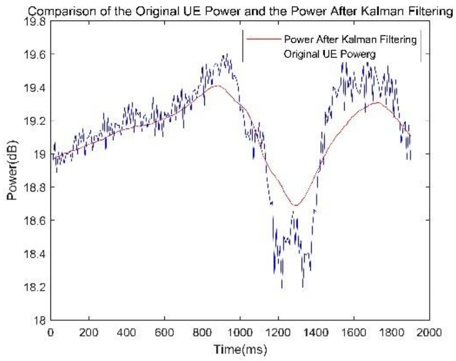

Fig. 10. Extracted target UE data.

The positions of the peak points reflect the physical resource allocation rules of the target user. By indexing the peak point positions in the time-domain data, the uplink data information of the target user is extracted from the raw data in Fig. 8, and the final result is shown in Fig. 10.

3.2 Node Deployment Test

In the field of indoor positioning technology, the accuracy and reliability of positioning functions are the core requirements of a positioning system. Indoor positioning systems aim to provide users with precise location information to meet the needs of various application scenarios. Therefore, positioning accuracy is a key metric for evaluating the performance of wireless indoor positioning technologies, directly impacting whether the system can function effectively in practical applications and influencing the user experience. This paper explores the positioning accuracy of the proposed algorithm in practical deployment through designed experiments. The relevant experimental parameter configurations are as Table 1.

Table 1. Parameters of the node deployment experiment.

Experiment Parameter	Value
Target Region	$8.23m \times 4.15m$
The Number of the Grid	256×256
The Number of UE	1
The Number of Collection Node	3-6
Path Loss Exponent γ	1.8
Path Loss Exponent Standard Deviation σ	0.41

From Fig. 11, it can be observed that when the CDF = 50% and the number of nodes is 3, the positioning error is the largest, at 0.94 meters; when the CDF =90% and the number of nodes is 3, the positioning error is the largest, at 2.3 meters.

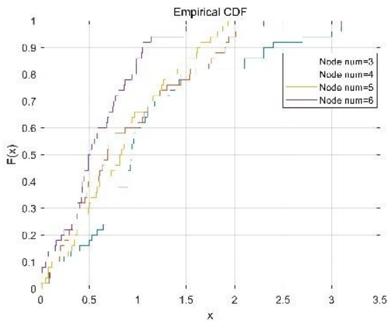

Fig. 11. Average positioning error.

From the cumulative error distribution results of positioning, it is evident that, in general, the more positioning nodes there are, the higher the positioning accuracy. However, when the positioning area is not large, increasing the number of nodes requires more communication and computational resources, reducing the convenience of device deployment.

This section primarily introduces the positioning algorithm and tests the positioning errors under different node deployment schemes. The RSSI-based grid positioning algorithm adopted in this paper centers on dividing the target area into a fine grid structure and estimating the probability of the target being at each grid point based on the signal propagation model. Experiments demonstrate that this algorithm achieves high positioning accuracy and effectively addresses the issue of varying transmission power due to device heterogeneity, which can affect positioning precision. Additionally, the preliminary power optimization scheme endows the algorithm with robust anti-interference capabilities.

4 Conclusion

In the research on uplink signal power measurement optimization technology based on demodulation reference signals, this paper aims to address the challenges of power measurement in mixed multi-mobile terminal scenarios and the impact of interference signals on positioning accuracy. Leveraging the characteristics of mobile communication protocols, a novel power measurement scheme is proposed. This scheme enhances the accuracy and stability of uplink signal power measurement and reduces the impact of interference signals on positioning accuracy by performing sliding correlation between the demodulation reference signals and the uplink signals to measure the transmission power of the target mobile terminal. Compared to traditional filtering schemes, the proposed method effectively mitigates the influence of co-frequency signals. In the current mobile communication control scenarios, with the cooperation of a dedicated network base station, the power optimization scheme presented in this paper is relatively simple to implement.

This study has achieved certain results in power measurement in mixed multi-mobile terminal scenarios, analysis of the impact of indoor scatterer movement, high-precision positioning algorithms, and the construction of a positioning prototype system. However, continuous exploration and improvement are still needed in future research to advance and widely apply indoor positioning technology in mobile communication control scenarios.

Acknowledgments. This work was financially supported by the National Key Research and Development Program of China (Grant No.2023YFC3321403).

Disclosure of Interests. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Li, Z., Zhang, H., Che, H.: A new positioning method by two gnss satellites and relative position constraint. In: 2016 IEEE Chinese Guidance, Navigation and Control Conference (CGNCC). pp. 681–686 (2016).
2. ung, S., Kim, H., Jung, J.I.: Accurate indoor positioning for uwb-based personal devices using deep learning. IEEE Access 11.
3. Rahman, M.M., Moghtadaiee, V., Dempster, A.G.: Design of fingerprinting technique for indoor localization using am radio signals. In: 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN). pp. 1–7 (2017).
4. Cao, W., Huang, J., Zeng, M.: Rssi-based trajectory prediction for intelligent indoor localization. In: 2023 IEEE 23rd International Conference on Communication Technology (ICCT). pp. 445–450 (2023).
5. Chugunov, A., Petukhov, N., Kulikov, R.: Toa positioning algorithm for tdoa system architecture. In: 2020 International Russian Automation Conference (RusAutoCon). pp. 871–876 (2020).

6. Dabove, P., Di Pietra, V., Piras, M., Jabbar, A.A., Kazim, S.A.: Indoor positioning using ultra-wide band (uwb) technologies: Positioning accuracies and sensors'performances. In: 2018 IEEE/ION Position, Location and Navigation Symposium(PLANS). pp. 175–184 (2018).
7. An, D.J., Moon, C.M., Lee, J.H.: Derivation of an explicit expression of an approximate location estimate in aoa-based localization. In: 2017 7th IEEE International Symposium on Microwave, Antenna, Propagation, and EMC Technologies(MAPE). pp. 552–555 (2017).
8. Lin, P., Hu, C., Xie, W., Yu, J.: Interoperability research and experiments in 4g/5g netwok. In: 2022 4th International Conference on Communications, Information System and Computer Engineering (CISCE). pp. 275–279 (2022).
9. Li, X., Tong, C.: Dsp implementation of dmrs in pusch within the lte system. In: 2011 International Conference on Business Computing and Global Informatization. pp. 528–531 (2011).
10. Morelli, M., Moretti, M.: A robust maximum likelihood scheme for pss detection and integer frequency offset recovery in lte systems. IEEE Transactions on Wireless Communications 15(2), 1353–1363 (2016).
11. Chu, Y., Guo, W., You, K., Zhao, L., Peng, T., Wang, W.: Rss-based multiple sources localization with unknown log-normal shadow fading (2021).