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Research Article

Platform Design of Passive Target Perception and Localization Based on Sensor Networks

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With the rapid development, extensive knowledge, and diverse application scenarios of target perception and positioning technology in sensor networks, a passive target perception and localization platform based on Wireless Sensor Networks (WSN) has been designed. The platform is mainly applied for the teaching of electronic information, communication, and Internet of Things (IoT) engineering. The platform follows the teaching concept of "developing students' ability to solve complex engineering problems" in the emerging engineering discipline and combines experimental simulation with real-world testing, as well as integrating scientific research and teaching. It encompasses technical elements such as perception and localization theory, sparse representation classification modeling, solving underdetermined equations, data analysis, and sparse coding, as well as nontechnical aspects such as team collaboration and cost budgeting. The platform boasts high fidelity and scalability, providing students with the opportunity to develop comprehensive practical and innovative skills in solving complex engineering problems.

1. Introduction

With the rapid development of the digital economy, there is an increasing demand for new, innovative technology talents in society [1]. In 2017, a new engineering construction plan [2] was introduced with the goal of cultivating comprehensive practical abilities and the ability to solve complex engineering problems in engineering students. While the existing experimental teaching equipment, such as the virtual simulation experimental platform [3–5], has helped to overcome time and space limitations, allowing students to conduct experiments anytime and anywhere, it is still not fully effective in cultivating practical abilities in electronic information majors when facing complex engineering problems.

In recent years, information and communication technology (ICT) has played an increasingly important role in both industrial and social fields. Because of the excellent performance in speech signal processing and image processing, machine learning methods, particularly deep learning, have been widely applied in various areas such as signal feature extraction [6], recognition and classification [7, 8], and information security [9] for wireless communication networks [10]. Liu et al. [6] presented the SA2SEI method, which effectively extracts discriminative radio frequency fingerprinting features and achieves higher identification performance. In a similar vein, the authors [7], developed a novel framework called contour stellar image (CSI) to transform signal waveforms into images. This approach allows for the use of deep learning methods and provides a new solution for signal recognition. In addition, a multistream convolutional neural network (MS-CNN) was proposed in [8] to handle multiview pearl images and achieved better accuracies. In [9], the authors explored the attack methods on modulation recognition and evaluated the effectiveness of adversarial attacks on signals. They also assessed the reliabilities of convolutional neural networks (CNNs). To reduce the computing's memory consumption of delay tolerant networks based on wireless networks, Zheng et al. [10] proposed an algorithm called Galliot. This algorithm aims to minimize the on-board memory consumption.

The sixth generation (6G) has been the focus of extensive research in wireless communication in recent years. One key technology in the sixth-generation mobile communication (6G) is target perception and localization, which is essential for integrated sensing and communications (ISAC) [11].

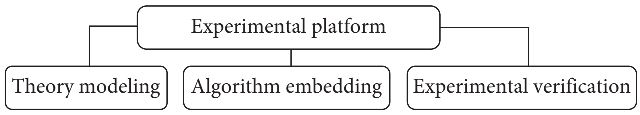

Figure 1: Design scheme of the experimental platform.

This technology will play an increasingly important role in future scenarios such as intelligent transportation, smart home, and healthcare. However, traditional localization techniques typically require the target to be attached with electronic devices, which may not be suitable for specific application scenarios such as emergency rescue and intrusion detection. In contrast, passive target perception and localization technology [12–14] does not require the target to carry any electronic device or tag, and does not require the target to actively participate in the localization process. By deploying a number of radio frequency (RF) sensors around the monitoring environment, target localization can be achieved. This technology is suitable as an innovative experimental project due to its typical characteristics of complex engineering problems, which involve interdisciplinary knowledge such as mathematical modeling, algorithm design, protocol analysis, and image processing, as well as nontechnical factors such as team collaboration, task allocation, and engineering budgeting.

We summarized the main contributions of the article as follows: (1) we design a scheme for passive target perception and localization platform; (2) a set of RF sensor network equipment in three scenarios is constructed; and (3) with numerical experiments, we validate the feasibility of the platform that can not only fulfill the requirements for experimental verification and scientific research measurement, but also foster students' professional knowledge and practical innovation abilities in advanced theory, platform construction, algorithm design, and data analysis methods for target perception and localization.

The remainder of the article is organized as follows. Section 2 introduces the design scheme of the platform. In Section 3, the theory modeling is described. Followed by algorithm embedding in Section 4 and Section 5 elaborates on the experimental verification. In Section 6, conclusions are drawn.

2. Design of Platform System

The platform consists of three modules: theory modeling, algorithm embedding, and experimental verification, as illustrated in Figure 1. The first module, theoretical modeling, involves the modeling and analysis of passive target perception and localization. This includes a description of target localization problems, the impact of wireless signal shadowing, channel fading models, sparse signal representation, received signal strength (RSS) measurement, and unconstrained optimization problems. In the second module, algorithm embedding, the mechanism of positioning algorithms is studied and the algorithm is designed and improved. Finally, the experimental verification module tests and verifies the performance of the localization algorithms using the platform. Through the process, students can learn to design experimental plans that are tailored to specific scenarios, build a sensor network platform, collect experimental data, and analyze the performance.

3. Theory Modeling

Theoretical modeling involves analyzing radio frequency signal propagation and wireless channel features, as well as utilizing sparse signal representation and reconstruction methods. Wireless channels are characterized by variability and multipath propagation, and the communication link is susceptible to factors such as limited sensor node energy and multipath signal interference. In addition, spatial obstacles, such as humans, can block the propagation of wireless links, resulting in significant fluctuations in the RSS measurements of the nodes, which is known as the shadowing effect. By leveraging the shadowing effect, radio frequency sensing networks have the potential to accurately detect the target location, making it possible to design a passive target localization platform.

Sparse representation methods are commonly utilized in various digital signal processing fields, including compressed sensing [15], pattern recognition, and image processing [16]. This approach involves representing natural signals through linear combinations of a small number of atoms from a standard orthogonal basis. An overcomplete dictionary [17] is the one in which the number of columns in the dictionary matrix, known as atoms, greatly exceeds the number of rows. A key aspect of sparse representation is dictionary learning, which can be achieved through two main methods. The first method involves using a predefined dictionary, such as discrete cosine transform and wavelet, as orthogonal basis functions. The second approach is adaptive dictionary learning, which involves learning from training data [18].

The area is divided into square grids, with the target assumed to be at the center of the grid (reference point or RP). As the number of targets is significantly smaller than the number of grids, the problem of target location estimation can be transformed into a sparse representation classification (SRC) task [19]. This approach utilizes signal reconstruction to achieve accurate target location estimation.

The Orthogonal Matching Pursuit (OMP) algorithm is known for its high-computational efficiency and is often utilized [20] in signal reconstruction. However, its use of the least-squares method for each iteration and selection of only one effective atom can result in worse accuracy in signal reconstruction. To address this issue, researchers have proposed the iterative soft thresholding algorithm (ISTA) algorithm [21], which utilizes the gradient method of convex optimization to solve the optimal solution of the objective function based on sparse constraints, thereby improving the accuracy of signal reconstruction.

The issue of passive target perception and localization in sparse scenes involves various theoretical challenges which are not typically covered in traditional localization theory and practical teaching. Therefore, teachers must persist in the latest scientific research and students must engage in thorough analysis and self-learning of theories.

4. Algorithm Embedding

4.1. Sparse Coding. Sparse coding is the process of finding sparse solutions from underdetermined equations using overcomplete dictionaries, sparse coefficients, and observation matrices. It is known for its simple decision rules, high-positioning accuracy, and computational efficiency. The OMP algorithm, used for sparse encoding, employs L_0 norm constrained objective function minimization to determine the optimal sparse solution for Equation (1). In Equation (1), the first term represents the error function, whereas the second term is the regularization term. Y is the observation vector, A is the learning dictionary, X is the sparse coefficient vector, and τ is the regularization parameter.

$$X^* = \arg \min_{\mathbf{x}} \frac{1}{2} \|Y - \mathbf{A}X\|_2^2 + \tau \|X\|_0. \tag{1}$$

However, solving Equation (1) and finding the smallest subset that can represent the signal become more difficult to solve because it requires enumerating subsets of dictionaries and leads to an exponential increase in computational complexity as the number of dictionary columns increases. Furthermore, due to the nondifferentiability and nonconvexity of the L_0 norm, the processing speed is slowed down when dealing with high-dimensional data.

In contrast, the ISTA algorithm utilizes the L_1 norm minimization to achieve the optimal sparse solution. Recent research [22] has shown that sparse coding via the iterative shrinkage thresholding algorithm (SC-ISTA) offers several advantages, including improved localization accuracy, robustness and reduced time cost, when compared to using L_0 as a penalty. Accordingly, the objective function is represented as

$$X^* = \arg \min_{\mathbf{x}} \frac{1}{2} \|Y - \mathbf{A}X\|_2^2 + \tau \|X\|_1. \tag{2}$$

In the teaching process of embedding algorithms, it is important to supplement relevant literature, such as solving inverse problems of underdetermined equations and unconstrained optimization problems, understanding orthogonal basis and norm representation, and other basic concepts. In addition, the research content can be further expanded by comparing the performance of other algorithms proposed in recent literature [23], which demonstrates the effectiveness of the platform being used. Through the learning process, students will have a solid foundation to conduct innovative experiments.

4.2. The Embedded Algorithm Based on ISTA. In this section, we will provide an overview of the passive target perception and localization algorithm based on the ISTA algorithm.

The ISTA algorithm utilizes a soft thresholding operator to iteratively compute the sparse coefficient vector in Equation (1), as depicted in Figure 2, in which Y is the input signal, $W = \frac{1}{C}A^T$, $R = I - \frac{1}{C}A^T A$. The soft thresholding operator $h_\theta(\cdot)$ is defined as

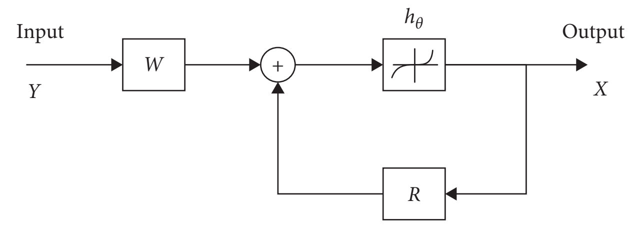

Figure 2: Flowchart of the ISTA algorithm.

$$h_\theta(x_i) = (|x_i| - \theta)_+ \operatorname{sign}(x_i), i = 1, 2, \cdots, n. \tag{3}$$

Among which, θ represents the thresholding constant. The soft threshold iteration operation in Figure 3 is represented as follows:

$$x_{i+1} = h_\theta\left(\frac{1}{C}A^T Y + \left(I - \frac{1}{C}A^T A\right)x_i\right). \tag{4}$$

The iterative operation process stops when certain conditions are met, and the output is represented by $X^* = \{x_1^*, \cdots, x_p^*, \cdots, x_K^*\}$, in which p represents the position of the grid center point and K represents the number of grids. Here, the term "certain conditions" refers to either reaching to the maximum number of iterations or having a residual that is lower than the empirical threshold value. The index of the target location is denoted by φ, which corresponds to the maximum element value in the solution as

$$\varphi = \arg \max\left\{x_1^*, \cdots, x_p^*, \cdots, x_K^*\right\}. \tag{5}$$

To this end, the experimental platform has successfully completed single target perception and localization. The theoretical analysis can help students understand the mechanism, clarify the design ideas, and lay the foundation for algorithm implementation and subsequent experimental verification. To achieve the goal, the teaching design requires teachers to concretize algorithm principles into algorithm implementation processes, encourage students to engage in immersive thinking, cultivate students' research-oriented learning [24], and adopt appropriate modeling methods and innovative practical abilities to represent different scenarios and changes in data with models.

5. Experimental Verifications

After completing the theoretical modeling and algorithm embedding, the next step is to enter the experimental verification stage. The stage is divided into three parts: experimental scenario construction, data collection and preprocessing, and algorithm programming and analysis, as illustrated in Figure 3.

5.1. Experimental Scenario Construction. The scenario consists of three distinct areas: an unobstructed square indoor corridor, a rectangular indoor scene with mess, and an obstructed square outdoor scene, as shown in Figure 2. The outdoor scene serves as the testing environment for

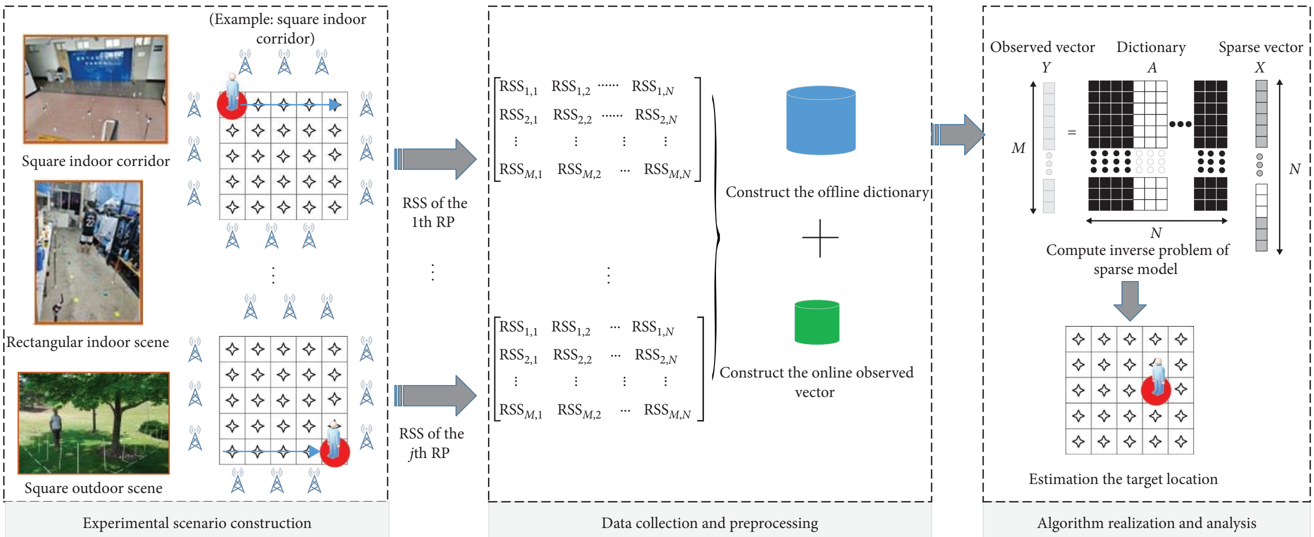

Figure 3: Diagram of the experimental verification.

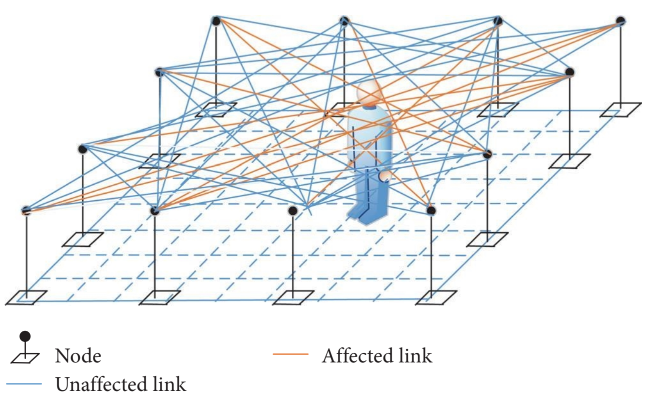

Figure 4: Experimental scenario diagram.

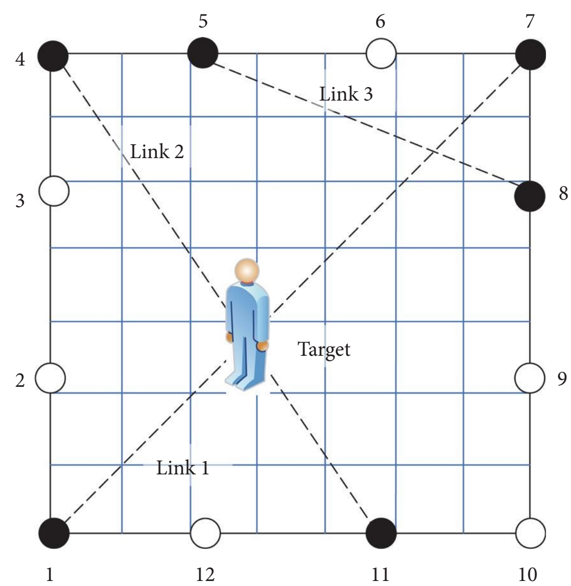

Figure 5: Plan diagram.

the signal processing and network (SPAN) laboratory [25]. To ensure consistency in the testing, the parameters for each scenario, such as sensor node spacing and node height from the ground, are kept consistent with those of the public dataset. For example, in the indoor square scene, 12 ZigBee sensor nodes are deployed around the area with a size of 4 m × 4 m. The nodes are spaced 1.3 m apart and are positioned 0.9 m above the ground. The area is divided into 25 square grids, which serve as RPs (represented by a quadrangle in Figure 2). The ZigBee nodes use a CC2530 chip and operate in the 2.4 GHz frequency band, communicating through the IEEE 802.12.4 protocol. Each node collects data and sends it to the coordinator, which then transmits it to the computer for processing through a serial port.

5.2. Feasibility Verification. The experiment aims to detect the presence of a target in a monitoring area by observing the attenuation of wireless links caused by the obstruction of the target (such as humans, animals, or objects). The experiment is shown in Figure 4, for which the target's position is inferred using the shadowing effect.

Taking the indoor square scene shown in Figures 4 and 5 as an example, the 12 sensor nodes in the monitoring area are sequentially numbered as modules 1–12. These nodes were tested in both unmanned and manned scenarios. With the target occupied, the coordinates of the target location are recorded. For instance, Modules 1 and 7 form link 1, whereas Modules 4 and 11 form link 2. Both links are obstructed by targets, but there is no obstruction between link 3, formed by Modules 5 and 8. To illustrate, Figure 6(a) shows the measured value of link 1 undergoing significant attenuation under target occlusion, while the signal attenuation of link 3 in Figure 6(b) remains almost unchanged. According to [25], the average RSS difference between the outdoor link with obstruction link and the link without obstruction is about 8 dBm. However, the difference is nearly

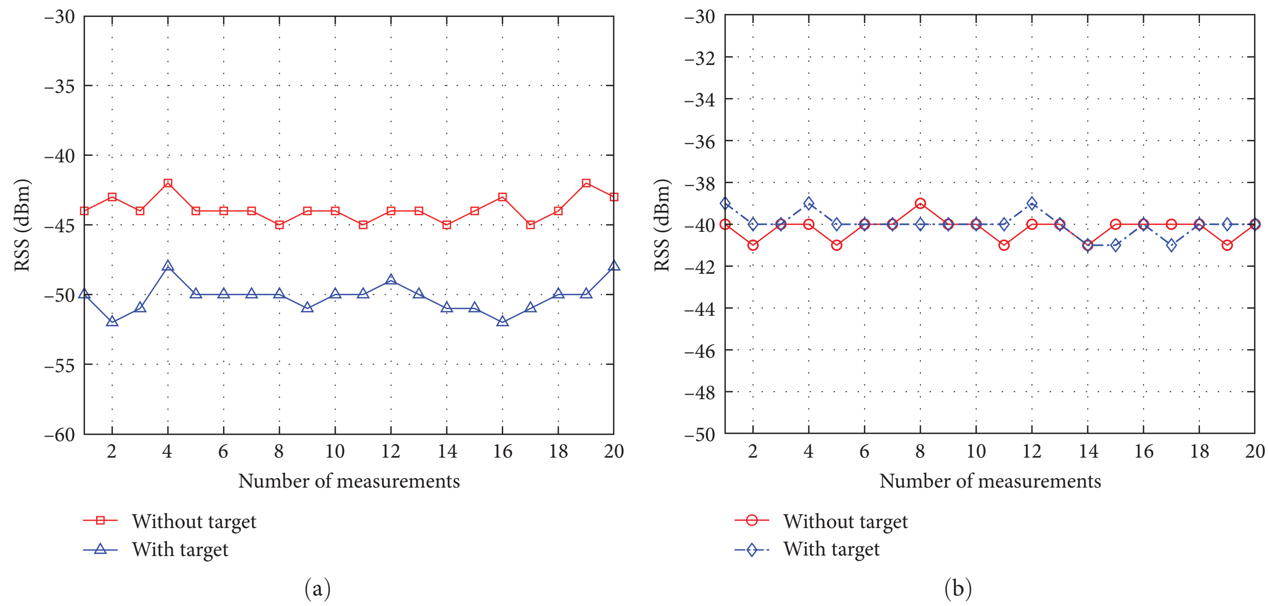

Figure 6: Results of the verification experiment. (a) Received RSS fluctuation of link 1. (b) Received RSS fluctuation of link 3.

zero between the two links without obstruction. The designed experimental results demonstrate that target occlusion can cause a significant decrease in wireless link signal strength, and that it is possible to use this effect to infer the target's position.

5.3. Data Collection and Preprocessing. The process has two stages: offline training and online matching, for which data are collected and preprocessed as depicted in the middle of Figure 2. During the offline training phase, the target traverses all grids and collects multiple received signal strength identifier (RSSI) measurements at each RP to form the dictionary matrix. Each element of the matrix is denoted as $RSS_{M\times N}$, representing the RSSI measurement received by the Mth access point (AP) from the Nth AP. Specifically, when the target is first located at the first RP, each sensor as AP takes turns collecting 12 measurements, which are repeated 20 times at each AP. This process is then repeated at the second RP and all remaining 25 RPs. To improve computational efficiency, the collected data are preprocessed. This involves selecting 15 out of 20 measurements to form an offline overcomplete dictionary with a size of 144×375. The dictionary has 144 rows, representing the atomic elements of the dictionary composed of 12 APs taking turns collecting RSS data from the other 12 APs (including this AP), and 375 columns, representing the atomic number composed of 15 RSS measurements and 25 RPs. In the online matching stage, the current RP's target RSS value is measured to form an online observation vector, and the objective function optimization method is used to calculate a sparse solution. To enhance the accuracy of our experiments, we can take measures such as increasing the number of APs and data dimensions. However, this may result in higher hardware costs and decreased computational efficiency.

The design of programming includes node programming, coordinator programming, and fingerprint database construction programming. Taking node program design as an example, first, we should initialize and apply for each node to join the coordinator to create a ZigBee network. After the node successfully joins the network, it enters a waiting state for data to be transmitted. After receiving the configuration information sent by the upper computer through the coordinator and completing the configuration, the coordinator sends a RSSI request. The working node then broadcasts the signal, which is received by the sampling node. The sampling node then receives the RSSI value and ID information sent by the working node. The sampling node packages the data into the corresponding format and sends it to the coordinator.

5.4. Algorithm Realization and Analysis. According to the ISTA algorithm described in Section 4.2, high-level programming languages such as C, Python, and Matlab can be used to solve the optimal problem of the objective function in Equation (1). However, students may encounter difficulties during this process due to a lack of experience in parameter debugging. These difficulties may include setting an unreasonable maximum iteration time and using improper values for the threshold parameter. To overcome these challenges, students will need to consult a significant amount of information, engage in deep thinking, and continuously practice to gain experience.

Accuracy is commonly used as an evaluation metric for measuring localization performance. It is defined as the ratio of correctly estimated samples to the total number of samples. To account for environmental noise, the signal-to-noise ratio (SNR) is often used to assess signal quality under varying levels of noise. As shown in Figure 7, the algorithm's

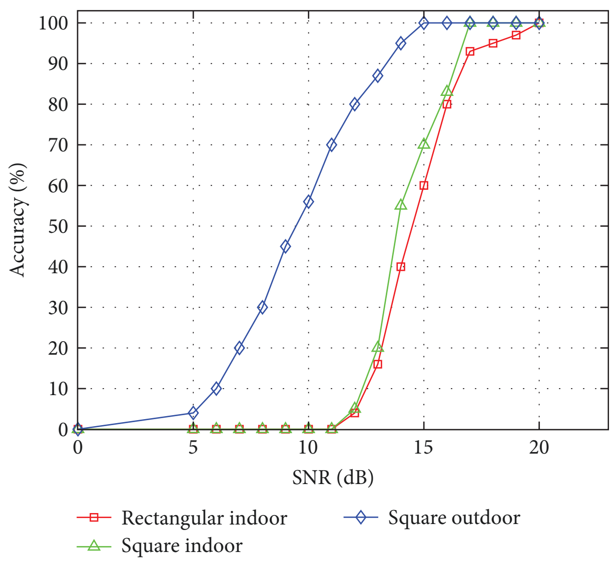

FIGURE 7: Accuracy comparison of ISTA algorithm for different scenarios.

positioning accuracy was compared in three different experimental scenarios, as depicted in Figure 2. The results indicate that the accuracy was higher in the square outdoor scene compared to the other two scenarios. This can be attributed to the presence of buildings and other structures in indoor environments, which can cause multipath interference and impact the accuracy of the algorithm. In addition, it is important for students to be guided in using other evaluation metrics and strategies to improve their performance. For instance, they can utilize localization error to evaluate the accuracy of their predictions. Providing students with specific examples and guidance is crucial in helping them improve their performance.

During the verification process, it is important to analyze the impact of multiple factors on positioning performance. For example, the factors that contribute to the higher positioning accuracy of outdoor compared to square indoor areas, the superior performance of the ISTA algorithm over the OMP algorithm, and the general principles of node deployment for different scenarios. It is also crucial to guide students in integrating project design and development processes, as well as engineering project management principles, into solving engineering problems. Because the real scenarios and localization requirements vary, the threshold parameters and data dimensions are not standardized. Therefore, scientific planning is necessary to reflect the complexity and creativity of engineering problems. It should be noted that while increasing the number of nodes can improve positioning accuracy, it also leads to higher storage costs and reduced computational efficiency. Through practical experience, students can effectively apply their knowledge of technical factors and nontechnical factors such as cost budgeting and project management.

6. Conclusion

A passive target perception and localization platform has been designed, utilizing radio frequency sensor networks. The platform incorporates both technical and nontechnical elements, including theory analysis, algorithm design, software development, hardware deployment, data collection, and project management. It aims to assist students in mastering the latest theoretical modeling, algorithm design, and experimental verification techniques for passive target perception and localization. The platform utilizes affordable off-the-shelf sensors, making it more closely aligned with real-world engineering practices. By fully utilizing existing scientific research and teaching resources, the platform provides students with authentic, innovative, and comprehensive engineering exploration capabilities, effectively enhancing their ability to solve complex engineering problems.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

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 article.

Acknowledgments

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