Demo Abstract: Real-Time 3D Indoor Localization with Multi-Dimensional RSSI on Mobile Robot

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ABSTRACT

Indoor localization technology based on the Received Signal Strength Indicator (RSSI) holds significant practical promise for mobile robots. However, accuracy is directly diminished due to the challenge of precisely establishing correlations among 3D positional data (buildings, floors, and coordinates) from RSSI, as well as RSSI fluctuations caused by numerous signal interferences. This demonstration proposes MMLoc, a 3D indoor localization system for mobile robots. To enhance positional features, MMLoc reshapes one-dimensional RSSI data into images and jointly utilizes them as inputs to a prediction model. To further optimize the model's performance, the building prediction task works as a prerequisite for floor and coordinate prediction tasks, followed by staged feature extraction and multidimensional data fusion. Experimental results on a JetBot demonstrate that MMLoc has achieved high-precision 3D indoor localization.

KEYWORDS

3D Indoor Localization, Mobile Robot, RSSI

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1 INTRODUCTION

RSSI-based indoor localization technology for mobile robots is widely applied due to its cost-effectiveness and ease of deployment. However, factors such as pedestrian movement and object obstructions result in significant variations in RSSI signals, further complicating the extraction of location features. To address this issue, Sadhukhan *et al.* proposed a clustering strategy based on weighted fusion [1]. Nevertheless, this approach focuses on extracting features from one-dimensional information, ignoring the spatial positioning relationships of wireless transmitters. Considering the performance benefits of two-dimensional convolutional kernels, Ye *et al.* transformed one-dimensional RSSI fingerprints into two-dimensional images, enhancing localization performance by establishing a multi-step data flow [3]. But such method only implements plane positioning and disregards factors such as buildings and floors, which is unable to meet the requirement of 3D indoor localization.

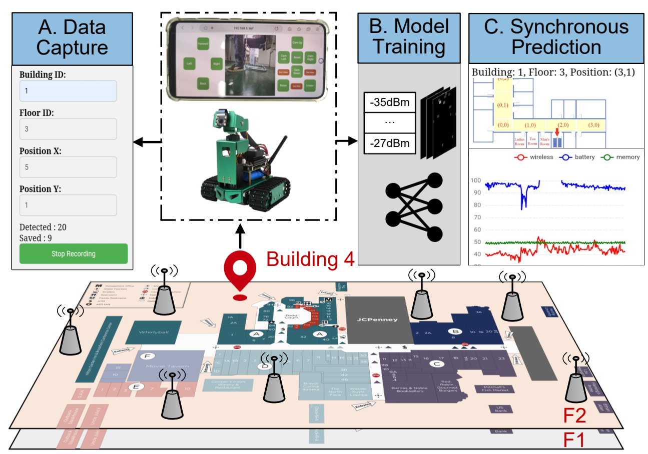

Figure 1: An overview of MMLoc.

To achieve high-precision 3D indoor localization, the primary motivations behind this work are: (1) In order to reduce the multiple interferences caused by complex indoor environments and enhance the position features in RSSI signals, this work attempts to design a mechanism involving multi-dimensional reshaping and data augmentation of RSSI to enhance the position features and achieve effective extraction of position features. (2) Features such as buildings, floors, and coordinates can be extracted from RSSI data is critical for 3D indoor localization task. Based on this thinking, this work attempts to analyze multi-dimensional RSSI data and improve the accuracy of 3D positioning by identifying the correlation among these features.

This demonstration presents MMLoc as a 3D indoor localization system designed for mobile robots and relies on multidimensional RSSI. Firstly, MMLoc performs data reshaping and augmentation

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on the RSSI. Then, separate feature extraction and fusion processes are carried out to obtain accurate position information related to 3D position data and finally achieve high-precision 3D indoor localization.

2 DESIGN AND IMPLEMENTATION

MMLoc primarily comprises three processing stages, as illustrated in Figure 1. **A. Data Capture:** The one-dimensional RSSI fingerprint database is created by moving through the environment with JetBot. **B. Model Training:** The one-dimensional RSSI data undergoes two-dimensional feature reshaping and augmentation, followed by model-based feature extraction and fusion. **C. Synchronous Prediction:** The JetBot performs localization tasks while completing mobility, hardware control, device performance monitoring, and video stream acquisition.

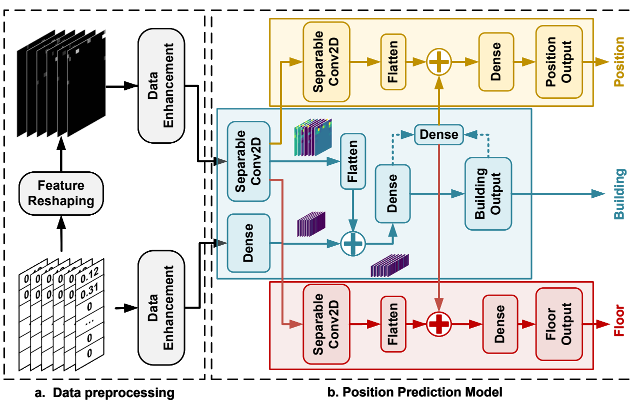

Figure 2: Data Flow for RSSI.

2.1 Data Preprocessing

As depicted in Figure 2a, MMLoc performs the following operations on the raw RSSI data. (1) Feature Reshaping: Using a one-dimensional sliding window to iterate through each fingerprint data, MMLoc obtains segments of the specified size and stacks them vertically to create two-dimensional RSSI images. (2) Data Enhancement: MMLoc introduces random interference noise to individual one-dimensional RSSI data points and incorporates multiple noise blocks into the two-dimensional image.

2.2 Position Prediction Model

As illustrated in Figure 2b, MMLoc has two flows in the model. (1) Image stream: MMLoc performs initial feature extraction to the inputs and employs convolutional layers for building-related feature extraction. After finishing the image flattened, feature alignment, and fusion, MMLoc extracts deeper features while computing the building's position results using Softmax. Notably, it merges the results again with the data from the previous layer, which serves as one-dimensional features guiding the completion of the floor and coordinate tasks. Regarding the two-dimensional feature inputs for the latter two tasks, MMLoc directly utilizes the building features that have not undergone flattening. (2) Data stream: The processing logic is fundamentally symmetrical to that of images, while dense layers replace the convolutional layers and flattened layers removed.

2.3 Operations Analysis

The operational demonstration displays the JetBot in its normal phase, during model training, and during the prediction phase, represented by A, B, and C, respectively, as shown in Figure 3. The results indicate that battery consumption and memory usage at any stage remain within manageable limits. Simultaneously, we validated the MMLoc's accuracy with the UJIIndoorLoc [2] dataset that training and testing data have a 4-month interval, which can demonstrate the system's generalization performance effectively. Table 1 shows that the proposed method achieves localization accuracy of 99.97% for buildings and 92.99% for floors on the test set. Additionally, the position error is 7.91m, and the prediction time for each data point is 18.93 ms, outperforming the current state-of-the-art methods.

Table 1: Accuracy on publicly available dataset UJI

Building (%)	Floor (%)	Position (m)	Detection Speed (ms)
99.97	92.99	7.91	18.93

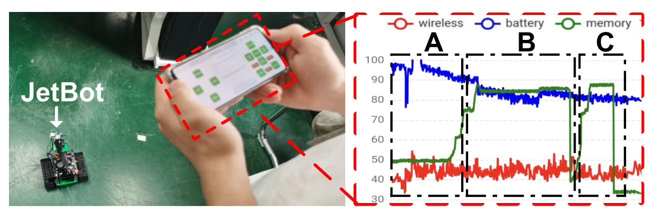

Figure 3: Demonstration of the MMLoc Operation.

3 DEMONSTRATION

As MMLoc is fully deployed on the JetBot, we will showcase all its functionalities through JetBot and record a demonstration video. In the video, all module functionalities will be accessible via a mobile web page, with a particular focus on the positioning model, as shown in Figure 1.

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