Line Tracking Delivery Robot Using Wi-Fi-based Indoor Positioning

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***Abstract*—This paper presents a line tracking delivery robot using Wi-Fi fingerprint as an indoor positioning technology. The YOLOv5 model was used to detect people, such as medical workers and hospital patients, for this proposed line tracking robot. In addition, an Android app was developed to order the delivery and manage its status and movement.**

Keywords—AI, Wi-Fi Fingerprinting, WKNN, People Detection, Line Tracking

I. Introduction

The recent outbreak of COVID-19 has highlighted the need for additional personnel to care for patients due to the shortage of healthcare workers. The issue of nursing staff shortages and excessive workloads have been a persistent concern even before the emergence of COVID-19. However, it has become more pronounced during the pandemic, significantly increasing workforce shortages [1]. In such circumstances, robots can play a crucial role in addressing hospital workforce shortages and ensuring efficient care delivery. By deploying robots, hospitals can decrease the burden on nurses, reduce their workload, and improve working conditions. As a result, it not only helps mitigate the shortage of healthcare professionals but also enhances the effectiveness of healthcare delivery.

In implementing the delivery robot, which is the subject of this study, indoor measurement using Wi-Fi in the hospital is used. By implementing YOLOv5 only detecting people, the robot increases the security and convenience of the delivery service [2]. Complex architectures and paths inside buildings to deliver medical charts and materials could exist. Thus, to identify the robot's path, line tracking, and Wi-Fi positioning are used in this paper. Our robot stops when it detects a human and resumes its operation only when the human is no longer in sight. Wi-Fi, commonly available in public facilities, provides a convenient way of determining the robot's position, even though its fingerprinting shows some positioning errors.

II. Related Works

There are multiple options available for indoor positionings, including Bluetooth Low Energy (BLE) and Wi-Fi fingerprinting. BLE and Wi-Fi are predominantly utilized to facilitate communication between low-power mobile devices. Radio Frequency (RF) positionings are frequently employed for indoor localization close. The Wi-Fi fingerprinting recognition used in this paper is an indoor positioning technique that utilizes the fact that the received signal strength (RSS) of the Wi-Fi signal varies depending on the location and RF channel environment. Using Wi-Fi RSS information requires no additional devices to estimate the current location [3, 4]. However, if the location is determined only by the existing Wi-Fi fingerprinting, a positioning error range of about 5 to 10 meters may occur. This paper introduces the advantage of combining Wi-Fi fingerprinting and line tracking methods to reduce positioning errors compared to using Wi-Fi fingerprinting alone.

Wi-Fi-based indoor positioning can provide robot positions without concern for patient privacy. Hospitals are places where many patients and caregivers exist, necessitating increased care and security. Whereas camera-based indoor positioning can lead to privacy concerns, Wi-Fi leverages the existing infrastructure within the ward, eliminating the need to consider this particular issue.

III. Proposed Methodology

A. Line Tracking

This paper describes a line tracking robot that follows a given line. The robot was built with a Raspberry Pi 4B 8GB and an Arduino Mega. To facilitate the movement of the line tracking robot, a track was constructed using a black line with a width of 19mm. In order to detect the black line, infrared line sensors were utilized. The sensors emit infrared light from the emitter and receive the infrared light reflected from the floor through the receiver. In this work, the values from the infrared sensors were normalized to a range of 0 to 100 for further processing and analysis.

Additionally, an L298N motor driver was used to control the DC motors. The robot was powered by a series connection of three 18650 3.7V lithium batteries, providing a voltage of 11.1V. Fig. 1 shows the picture of the robot and the roadway implemented for the actual test. Additionally, Fig. 2 shows the operation procedure of the proposed hospital delivery robot.

Fig. 1. Illustration of delivery robot on the line

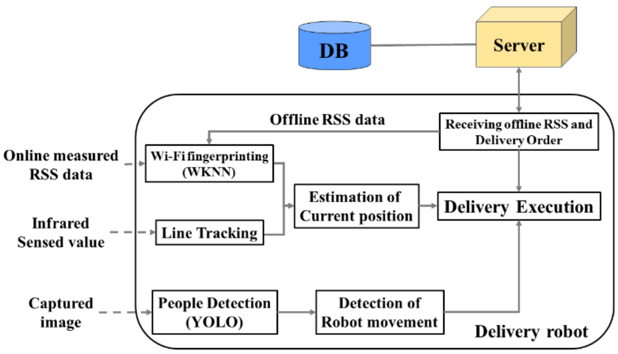

Fig. 2. Operation procedure of the proposed hospital delivery robot

B. Indoor Position Estimation

This paper utilizes Wi-Fi fingerprinting as the indoor localization method. The data used for Wi-Fi fingerprinting consists of online and offline data. The online data is Wi-Fi RSS information the robot captures as it moves to different locations. In contrast, the offline data contains pre-recorded Wi-Fi signal strength measured at specific reference locations. In the data preprocessing stage, a moving average filter is applied. The moving average filter calculates the average based on the past data within the specified buffer size at the current point. By using this filter, Wi-Fi RSS noise can be reduced. This can be seen with (1), where n indicates the buffer size. Specifically, a buffer size of 5 was selected. As a result, the RSS values of each reference point (RP) are smoothed out.

$$\boldsymbol{RSS_i(k) = \frac{RSS_i(k)+RSS_i(k-1)+\cdots RSS_i(k-n-1)}{n} \quad (k \geq 1)} \quad (1)$$

This paper utilized Weighted K-nearest neighbors (WKNN) for Wi-Fi fingerprinting. KNN is an algorithm that estimates the position by utilizing the average values held by the K nearest neighbors, while WKNN is a modified KNN that incorporates weights [5, 6, 7]. The weights used in WKNN are the inverses of the distances between the online Wi-Fi RSS data and the offline data of Wi-Fi fingerprints. We utilize the Euclidean distance shown in (2). D_i is the distance between the $RSS_{i_{online}}$ of a test location and the recorded fingerprint $RSS_{j_{offline}}$, where n is the number of APS. Thus, we can estimate the current location by performing the weighted average of the known locations of K nearest samples. Equation (3) and (4) represent the procedure for calculating the weights used in WKNN. By applying (4), a weighted average is used to determine each coordinate.

$$D_i = \sqrt{\sum_{j=1}^{n}(RSS_{i_{online}} - RSS_{j_{offline}})^2} \quad (2)$$

$$W_i = \frac{1}{D_i} \quad (3)$$

$$(x, y) = \frac{\sum_{i=1}^{k} w_i(x_i, y_i)}{\sum_{i=1}^{k} w_i} \quad (4)$$

In order to achieve more accurate indoor localization, we employed line tracking combined with Wi-Fi fingerprinting. For the position estimation of a robot moving on a straight line, we can take advantage of its linear trajectory. As shown in Fig. 3, when using line tracking together, the positioning error can permanently be reduced compared to not using it. D in Fig. 3 means Error Distance.

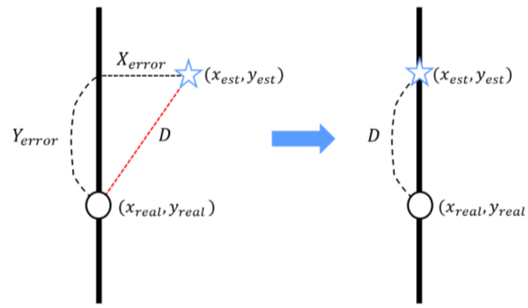

Fig. 3. Update of the estimated robot position using line tracking and fingerprinting

C. Robot Location Display App

It is required to know the robot's position in order to increase the operational effectiveness of the line tracking robot at the hospital. Using an Android app, a real-time map exhibiting the robot's position was created to address this issue. Because of the necessity of real-time position updates for the delivery robot, the position estimated through Wi-Fi fingerprinting was saved in the Firebase Real-time Database [8, 9]. The Android app retrieves these position values and uses them to move the robot icon on the map, allowing for easy tracking. It ensures efficient and reliable robot operation within the hospital.

D. Real-time People Detection

We implemented a real-time people detection system using a camera to halt the robot's movement when people are around the path. The system utilizes the Jetson Nano board to process real-time video and employs the YOLOv5 to detect people. The Jetson Nano board has a 128-core NVIDIA Maxwell GPU and a quad-core ARM Cortex-A57 MPCore processor CPU.

For this experiment, a custom dataset was created by capturing images of people in the environment where object detection would be performed. Images were collected using iPhone 12 PRO and Galaxy S22 models. Furthermore, Roboflow's Data Augmentation tool was used to do image augmentation, creating about 900 augmented images. The dataset was trained using the Google Colab GPU environment, with an image size of 416x416, a batch size of 16, and the miniature model of the existing YOLOv5.

IV. Performance Evaluation

A. YOLOv5

This work created a custom dataset, and the models were trained for 200 epochs. As a result, Model Small demonstrated the most suitable performance for the people detection at this delivery robot. Table I shows the performance of YOLOv5 by model. Mean Average Precision (mAP) is shown when Intersection Over Union (IOU) was applied from 0.5 to 0.95.

TABLE I. YOLOV5 PERFORMANCE BY MODEL

Model	***FPS***	***mAP***
Small	1.3	0.76
Medium	0.5	0.759
Large	0.3	0.758

B. *Wi-Fi Fingerprinting*

Wi-Fi RSS signals were collected at each RP during the offline data measurement time of Wi-Fi fingerprinting. Meanwhile, at the online data measurement time, Wi-Fi RSS was measured at the moving robot and compared with the offline data RSS stored in the database to estimate the current location. The Xiaomi Redmi Note 9S Android device was used for RSS collection for the experiment. During offline progress, Wi-Fi RSS was measured with 8-second intervals for 2 minutes and 30 seconds, resulting in observations of an average of 20 RSS. As depicted in Fig. 4, considering the variation in location error with the number of access points (APs), we utilized the 11 APs with the slightest error [10]. Figure 5 shows that 20 RPs (blue dots) are used, and the distance between the RPs is 2m. The red dot symbolizes the test area of the robot's position at the online stage. The tests were conducted in the laboratory of Chosun University's IT Convergence College in Korea.

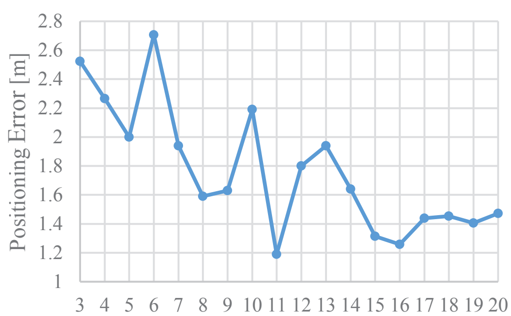

Fig. 4. Positioning error by Number of APs

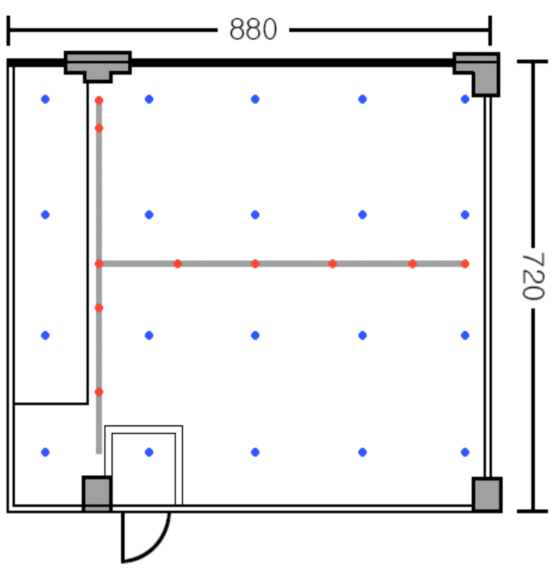

Fig. 5. Position of Reference Points at the experiment area (8.8 × 7.2 m)

In Fig. 6, the positioning errors are shown for the cases where Wi-Fi fingerprinting is used alone and when combined with line tracking. In the case of using Wi-Fi fingerprinting alone, the positioning error is 2.063m, while the positioning error is 1.189m when combined with line tracking. It shows a reduction in positioning error by approximately 0.874m.

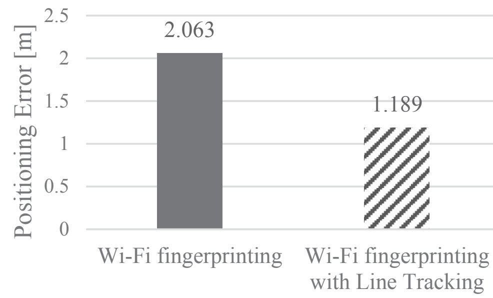

Fig. 6. Positioning error reduction when Wi-Fi fingerprinting is combined with line tracking

V. CONCLUSION

In the paper, we address the issue of hospital labor shortages and the expanding demand for robotic help. We use indoor positioning technology and line tracking to provide more stable and precise path tracking of the delivery robot. This paper shows that Wi-Fi fingerprinting performs better when combined with line tracking. The robot detects people on the path every 1 second and performs line tracking accordingly. We believe that the effectiveness of robots in medical facilities can be achieved by utilizing these frameworks and tools.

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