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Indoor Wayfinding for an Electric Wheelchair Based on Wi-Fi Fingerprinting Localization

Jose Victorio Salazar Luces, Kengkij Promsutipong and Yasuhisa Hirata

Abstract— **Currently, society is experiencing a shift in the median age known as population aging. The number of people aged 60 years or over is at its highest, and it's expected to double by 2050. With age, people frequently experience difficulties in mobility, requiring them to use assistive technology, from wearable devices to mobile devices such as wheelchairs or walkers. Recently, power-assisted versions of these systems have been developed to further enhance the provided assistance, such as electric wheelchairs and power-assisted walkers. In scenarios such as shopping malls or airports, people often need to walk long distances to reach their destination, so these power-assisted systems can help them move without difficulties. However, these systems are still quite expensive, and having one device per user might prove difficult. To overcome this, these facilities could have a reduced number of devices and allow users to share them upon request. However, it's not desirable to have each user move toward the assistive device due to their limited mobility. Instead, in this research we propose a method to enable the device to navigate toward the user upon request by using onboard sensors and the existing Wi-Fi infrastructure. Specifically, we create a map with the Received Signal Strength Indicator (RSSI) of existing Wi-Fi access points (using a method called Fingerprinting). When a user requests an assistive device, the RSSI values at the user's position are sent to it, and the device determines the rough position of the user using a KNN algorithm. However, typical Fingerprinting methods are affected by infrastructural changes which alter the profile of RSSI values at each location. Therefore, we propose that the map is constantly updated while the device moves in order to avoid errors due to changes in the infrastructure. Through experiments we confirmed that the device could locate the position where the request originated with an error of 2.612 m, and it was able to navigate towards it.**

I. INTRODUCTION

In recent years, society has experienced a shift in the median age, particularly in developed countries, due to reasons such as an increase in life expectancy along with declining fertility rates. According to the United Nations' report on World Population Ageing [1], the global population aged 60 years or over numbered 962 million in 2017, and it is expected to double by 2050. With age, people usually experience a decline in their mobility [2], including cases where the person requires assistive devices such as wearable devices [3], wheelchairs [4] or walkers [5] in order to move around.

Thanks to recent technological advances, power-assisted versions of these devices such as electric wheelchairs have been proposed and commercialized. However, these devices are quite expensive. When we consider places such as hospitals or rehabilitation facilities, having one device per user is prohibitive, both economically and spatially. Furthermore, in places like shopping malls or airports, these devices could be used to help mobility-impaired people to move around, but the same problem arises. To address this issue, the concept of sharing devices has been proposed. A wheelchair company called WHILL [4] proposed a shared wheelchair system to be implemented in different public places in the future.

However, in these scenarios, having each user moving toward the device in order to use it is not desirable, given their reduced mobility. Instead, we can make the device locate and navigate towards the user upon request. To achieve this, in this paper we proposed a wayfinding system for an electric-powered wheelchair by using information from the existing Wi-Fi infrastructure.

J. Salazar, K. Promsutipong and Y. Hirata are with Department of Robotics, Tohoku University, 6-6-01 Aramaki-Aoba, Aobaku, Sendai 980-8579, JAPAN j.salazar, k.promsutipong, hirata@srd.mech.tohoku.ac.jp

II. CONCEPT OF THE SYSTEM

The concept of this wayfinding system is depicted in Fig. 1 We use the Wi-Fi fingerprinting method which creates a map with the Received Signal Strength Indicator (RSSI) of existing Wi-Fi access points. When a user requests an assistive device, the RSSI values at the user's position are sent to it, and the device determines the rough position of the user using KNN algorithm. The map is constantly updated while the device moves in order to avoid errors due to changes in the infrastructure.

We used the WHILL electric wheelchair to implement a proof of concept of this system. The WHILL wheelchair is a non-holonomic system with two motored rear wheels and two omni-wheels in the front. In order to allow the wheelchair to locate the user and move towards the user's position without colliding into obstacles, both a navigation system and a localization technique are required.

Regarding the navigation system, we used a laser rangefinder to detect obstacles and create a map in advance for path planning using Simultaneous Location and Mapping (SLAM).

As for the localization, there are several categorization of various localization methods existing. Depending on the precision, localization methods can be separated into coarse or fine localization. So far there are no borderlines explicitly defined to describe whether the localization method is either coarse or fine since it depends on the situation where the localization is being used. For example, in our case, the localization method capable of exactly locating the user with very small errors could be called a fine localization while coarser localization is unable to exactly locate the user, but precise enough to locate the area where the user locates in. In the current stage, we first focus on moving close enough so that the user is visible to the visual localization method such as camera since the location and pose of user will be once more investigated by a fine visual localization method. In other words, at the current stage, we intend to develop a coarse localization method to locate the user's position in the map. There are various methods for roughly finding the position of the user like GPS or Bluetooth. However, while the former performs inefficiently within an indoor environment, the latter has a limited operating range. Instead, we propose using the existing Wi-Fi infrastructure, as most places nowadays have multiple wireless networks available. By utilizing the strength of the

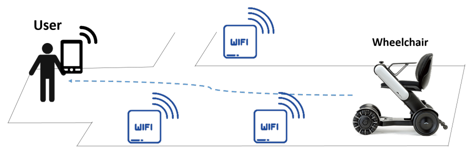


Fig. 1: Concept of the proposed system

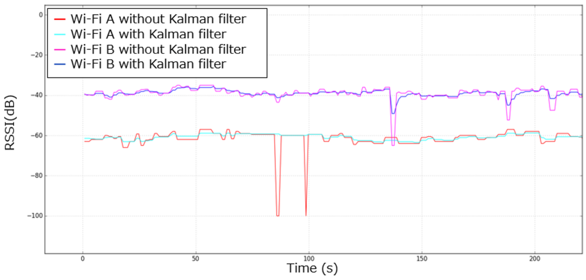


Fig. 2: Noise reduction using a Kalman filter

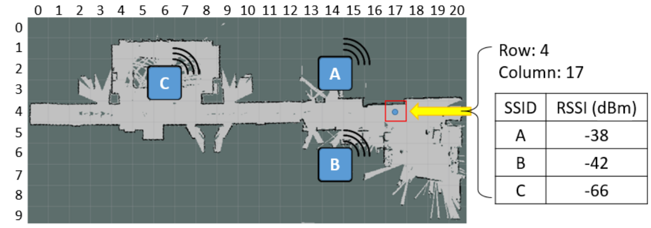


Fig. 3: Gridmap with a Wi-Fi database example

existing Wi-Fi signals as a data source, no additional infrastructure is required, which reduces the implementation costs.

In the past, multiple localization methods using Wi-Fi have been proposed, such as triangulation based on RSSI [8], time of arrival [9] or angle of arrival [10]. While this method works robustly in an ideal situation, it requires additional information such as the exact position of the access points and a line of sight between the access points and the receiver to perform efficiently. To overcome this, a method known as fingerprinting, which relies on recording the signal strength and corresponding coordinates for posterior comparison, has been used in the past to allow a robotic system to estimate its position [6], [7].

In this paper, we propose using Wi-Fi fingerprinting to estimate the position of a user requesting the system, which is conveyed to the wheelchair, enabling it to autonomously navigate toward the user. Different to traditional fingerprinting, the system records the signal strength of multiple Wi-Fi sources while creating the map using SLAM, and updates this data constantly in order to compensate for changes in the environment. Based on the strength of the multiple signals at the user's position, we use the K Nearest Neighbors Algorithm (KNN) to select the most suitable candidates. Through experiments, we evaluated the accuracy of the user's position estimation, and confirmed that the wheelchair was able to reach the user's position in most cases.

III. PROPOSED METHOD

A. Wi-Fi data processing

To obtain the strength of the Wi-Fi signals, we used a Unix network traffic analyzer (tcpdump), which provides the SSID (Service Set Identifier) or name of the access point, and RSSI, which is measured in dBm. Data acquisition is performed on a Raspberry Pi running ROS (Robot Operating System) with a dedicated Wi-Fi antenna for scanning. Due to the noisy nature and the variability of the signal, we processed the data in two steps:

- RSSI Average
  The traffic analyzer runs for 1 s, gathering multiple measurements for each SSID. The average of these measurements is published as a ROS message
- RSSI Filtering
  We use a simplified Kalman filter to remove the noise from the averaged RSSI value which is easily affected by environmental conditions such as signal interference. An example of the filtered data can be seen in Fig. 2.

B. Wi-Fi fingerprinting

Since this research focuses on indoor localization, ordinary outdoor localization techniques such as GPS are not suitable since the signals are attenuated and scattered as it tries to move through the building. There are some methods for indoor localization like RFID or Bluetooth Low Energy, but they have a comparatively short range. To overcome this problem, in this paper we propose using the existing Wi-Fi infrastructure as a data source to localize the user in space. As Wi-Fi technology has become commonplace, most indoor scenarios are expected to be covered by Wi-Fi signals which can be used for this purpose. In this research we propose using a technique called Wi-Fi fingerprinting, which consists of recording the RSSI values on determined positions for posterior comparison. Fingerprinting is less susceptible to no-line-of-sight problem [11], and the measurements are expected to be stable if the infrastructure remains the same. To estimate the position corresponding to a set of SSIDs and RSSI values, it compares them to stored values and finds the closest match. Usually, fingerprinting is done in two phases: offline phase and online phase.

In the offline phase, the signal strength from the different available access points in range is stored in a database along with the known coordinates of this measurement. In this paper, we carry out the offline phase simultaneously with the SLAM based map creation, and the measurements are stored using SQLite. We divide the space into a grid of 2 x 2 m^2 cells (Fig. 3), and store up to 16 measurements for each existing cell to avoid long processing times. Each measurement, also denoted fingerprint, is defined as

$$F = [R\,C\,(\mathbf{SSID}, \overline{\mathbf{RSSI}})] \tag{1}$$

where, R and C are the row and column in the gridmap corresponding to the fingerprint. ($\mathbf{SSID}$,$\overline{\mathbf{RSSI}}$) represents a vector with tuples consisting of access point's identifier and mean RSSI value.

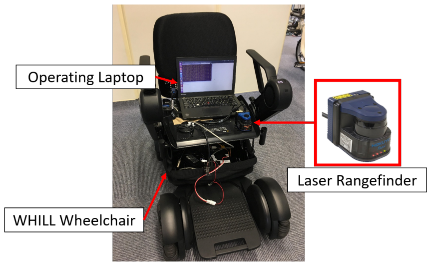
In the online phase, the SSID-RSSI tuples measured at the place we want to localize are compared with each fingerprint stored in the database. The algorithm used for determining the closest match is the K-Nearest Neighbors (KNN) with a few modifications for this specific use case.

As mentioned earlier, the fingerprints should remain the same given that there are no changes in the infrastructure. However, slight changes in the environment such as changing the position of an access point or disconnecting it can greatly affect the performance of the localization. In this case, the ordinary approach is to conduct an offline phase exploration again to update the database. However, in this paper we constantly update the database while the system is moving in space during the online phase. This will keep our database updated and make the system robust to changes in the environment.

The algorithms of traditional online phase and proposed online phase are as described in Algorithm 1 and 2 respectively.

C. K-Nearest Neighbors Algorithm

KNN Algorithm is an easy-to-implement non-parametric classification method. Given some labeled data points, this algorithm is capable of classifying a new data point by considering the labels of the K most similar data points existing in the database. We use



(a) Electric wheelchair

(b) RaspberryPi

Fig. 4: System Setup

Algorithm 1: Traditional Online Phase

```
Load database;
Read real time RSSI data from the user's device;
for Each row of the map do
    for Each column of the map do
        Compare RSSI data for each cell in the database
          with the real time data;
Find cells containing the N datapoints which are most
  similar from the real time data;
Calculate the mode of these cells;
```

Algorithm 2: Proposed Online Phase

```
Updating Module;
Load database;
Read real time RSSI data from the robot and acquire robot;
if Not Localizing then
    Lock the system from localizing ;
    Update the database;
    Unlock the system;
Localizing Module;
Load database;
if Not Updating then
    Lock the system from updating;
    Read data from the database;
    Read real time RSSI data from the user's device;
    for Each row of the map do
        for Each column of the map do
            Compare RSSI data for each cell in the database
              with the real time data;
    Find cells containing the N datapoints which are most
      similar from the real time data;
    Calculate the mode of these cells, let goal = mode;
    Send the wheelchair to the goal;
    Unlock the system;
```

the fingerprints stored in the database where each cell is treated as a distinct class, and the distance between data points is measured using the difference between RSSI values.

To estimate the cell corresponding to a set of measured SSID-RSSI pair, we calculate the Euclidean distance between each fingerprint and the measured values. The Euclidean distance [12] is calculated as follows:

$$d = \sqrt{\sum_{i=1}^{N_m} \frac{(\overline{RSSI}_{i,m} - \overline{RSSI}_{i,db})^2}{N_m}} \tag{2}$$

where N_m is the number of available access points for measurement m, $\overline{RSSI}_{i,m}$ represents the average RSSI value corresponding to the i^{th} access point in measurement m, and $\overline{RSSI}_{i,db}$ is the average RSSI value stored in the database for the same access point. In case an access point present in the measurement does not exist in a stored fingerprint, the $\overline{RSSI}_{i,db}$ will be replaced by the minimum RSSI value detectable by the hardware, which is -100 dBm.

The algorithm then sorts all fingerprints by their corresponding Euclidean distance in ascending order, and the predicted class (i.e., the corresponding cell) is calculated using:

$$(\hat{R},\hat{C}) = mode((\hat{R},\hat{C})_i) \quad \text{where } i = 1,2,3,...,K \tag{3}$$

where $(\hat{R},\hat{C})$ represents the predicted cell and $(\hat{R},\hat{C})_i$ is the i^{th} fingerprint from the ordered list.

According to S.Thirumuruganathan [13], “the choice of K is very critical - A small value of K means that noise will have a higher influence on the result. A large value makes it computationally expensive and contradicts the basic philosophy of KNN (that points that are near might have similar densities or classes) since higher K means that the farther, less similar data points are also taken into account”. According to the result from pre-existing researches on Wi-Fi fingerprinting [14], a K value of 5 is adequate for this purpose.

IV. SYSTEM STRUCTURE

In order to measure the RSSI values, both wheelchair system and user should be equipped with a Wi-Fi enabled device. To achieve autonomous navigation, the wheelchair is equipped with a Laser Range Finder and a scanning-dedicated Wi-Fi interface. Ideally, we could use devices such as smartphones to measure the RSSI of the available access points. However, for simplicity we used a single-board computer RaspberryPi with a scanning-dedicated Wi-Fi interface. The dedicated interfaces are put into monitor mode for scanning, and the built-in Wi-Fi interface is used for communication between devices using ROS. Currently, both devices communicate through an access point which covers the whole map area. In the future, we are planning on using MQTT network protocol over 4G to communicate between devices when the devices are far apart enough that they cannot connect to the same access point. A representation of the devices is shown in Fig. 4

In the offline phase, the wheelchair is manually operated around the area while performing two tasks: 1. SLAM based mapping 2. populating fingerprints in database. Then, in the online phase, when the user performs a request, the message will be sent via ROS to the wheelchair along with the RSSI measurements. After data processing the aforementioned KNN algorithm estimates the cell where the measurement likely belongs to. The wheelchair is then ordered to move to this cell, hereinafter goal cell, through the navigation stack. To prevent the database from being outdated, the data scanned at the wheelchair is always updated to the database in the online phase. A depiction of the system is shown in Fig. 5. When the wheelchair reaches the estimated cell, the estimation is performed again using the RSSI measured at the user's position. If the newly estimated cell coincides with the wheelchair's position, then it has reached its destination. In cases where the estimation is different (possibly due to updated fingerprints in the database caused by changes in the environment), the wheelchair then proceeds to move to the newly estimated cell.

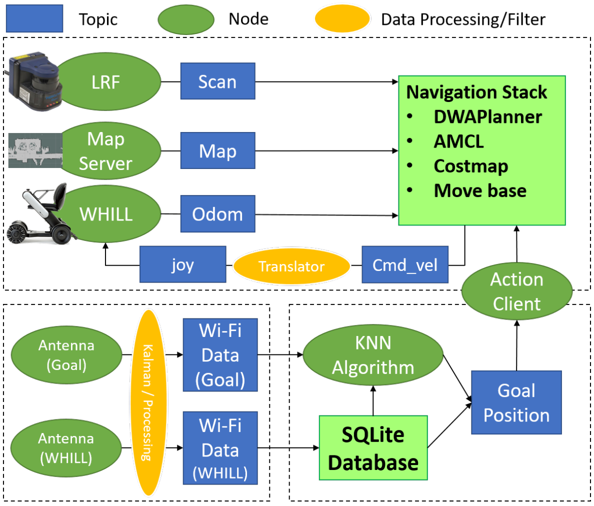
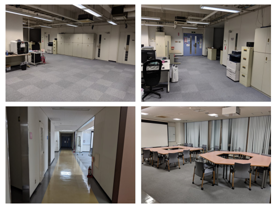
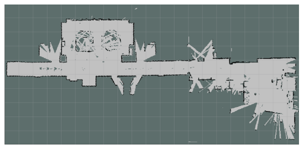


Fig. 5: Overall Workflow in a ROS environment



(a) Pictures of 5F M.A.E. Building



(b) Map of 5F M.A.E. Building

Fig. 6: Experiment Area

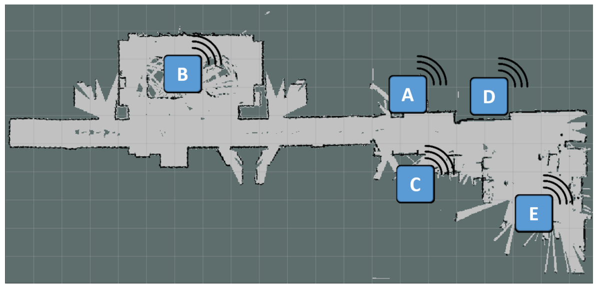


Fig. 7: Location of access points

A. Electric Wheelchair Control

The electric wheelchair used in this system is a WHILL model C equipped with a Hokuyo UBG-04LX-F01 Laser Range Finder (LRF), which has a FOV of 270°. However, we limited the FOV to 180°. The wheelchair is connected to a computer running Ubuntu 16.04 through a USB cable, and controlled using ROS Kinetic Kame. The WHILL API enables users to control the wheelchair using messages of type Joy, corresponding to a joystick input, which is proportionally mapped to the wheelchair's velocity. To determine the wheelchair's pose (position and orientation), we used the following inverse kinematics model for differential drive system:

$$x(t) = \frac{1}{2}\int_0^t [v_r(t) + v_l(t)]\cos[\theta(t)]dt \tag{4}$$

$$y(t) = \frac{1}{2}\int_0^t [v_r(t) + v_l(t)]\sin[\theta(t)]dt \tag{5}$$

$$\theta(t) = \frac{1}{l}\int_0^t [v_r(t) - v_l(t)]dt \tag{6}$$

where t is time, v_r and v_l are velocity of right and left wheel respectively, and l is the distance between the center of the two wheels.

B. Navigation System

We use the ROS 2D navigation stack in order to control and command the wheelchair around space, as well as to perform SLAM. Navigation stack processes the robot's odometry, sensor data, and goal as an input and processes it to plan the path and outputs the corresponding velocity to the robot. In this research we utilize Adaptive Monte Carlo Localization (AMCL) [15] approach for localizing the robot in the map, costmap and Dynamic Window Approach (DWA) [16] planner for deciding the path with the lowest cost based on Djikstra's theorem. The cost is determined by obstacles on the path and the distance of the path.

V. EXPERIMENTS

The experiments are conducted in order to verify the validity of the method as well as evaluate the performance of the proposed system. The operating area is the fifth floor of M.A.E. building, Aobayama campus of Tohoku University (Fig. 6a). The map of the area is made using LRF-based SLAM mapping package gmapping as shown in Fig. 6b. The map size is $840 \times 400\ pixel^2$ which is equivalent to $42 \times 20\ m^2$. We place 3 access points in additional to 2 existing access points in the experimental area as shown in Fig. 7. However, in the future, we aim to utilize the system with unknown location of access points.

As the wheelchair has a comparatively large footprint, enough space in each cell is required to allow the system to navigate through it. To asses this, we measure the Cell Occupancy, which is defined by

$$CO = \frac{\sum PO}{N_{pi}} \times 100\% \tag{7}$$

where N_{pi} is the number of pixels within the cell and PO is the Pixel Occupancy which can be calculated as following equation.

$$PO = \begin{cases} 1, & \text{for an occupied pixel} \\ 0, & \text{for a free pixel} \\ -1, & \text{for an unknown pixel} \end{cases} \tag{8}$$

Through preliminary experiments, we set the threshold for CO at 20% in order to guarantee the safe navigation of the wheelchair.

According to this criterion, the operating area is limited to 29 cells or about 116 m^2. After creating the fingerprint database, we obtained a total of 29 different classes. Additionally, we assumed the following conditions to be true:

- At least one offline phase has been performed required for mapping and fingerprint database population.
- Wi-Fi access points are available and their signals cover the operating area.

A. Prediction Test

We performed a preliminary experiment to evaluate the quality of the prediction obtained using the proposed method. We randomly placed the RSSI measuring device in an accessible cell (i.e., CO < 20%). The measurements are processed and sent to the wheelchair system. Then, the estimated cell is calculated using the proposed method. To evaluate the estimation, we used the averaged cell error which is defined as

$$\overline{CE} = \frac{\sum\sqrt{(R-\hat{R})^2 + (C-\hat{C})^2}}{N_{pr}} \tag{9}$$

TABLE I: Prediction Test Result

Actual Goal Cell	Averaged Predicted Goal Cell	Averaged Cell Error
(3,6)	(4,7)	1.414
(4,3)	(4,4)	1
(4,4)	(4,4)	0
(4,7)	(3.9,2.5)	4.6
(4,13)	(4,13.8)	0.8
(4,14)	(4,13.4)	0.6
(4,17)	(4.6,18.6)	2.032
(5,18)	(4.9,17.8)	1.614
(6,19)	(7,19)	1
(7,19)	(7,19)	0

where $\hat{R}$ and $\hat{C}$ represent the predicted cell's row and column, R and C represent those of the actual goal cell, and N_{pr} is the number of predictions made. We took 10 measurements per position, and evaluated the 10 different predictions. The results are presented in the following table. The predictions had an average cell error of 1.306 cells, which is equivalent to 2.612 m. We think these results are reasonable for the intended scenarios.

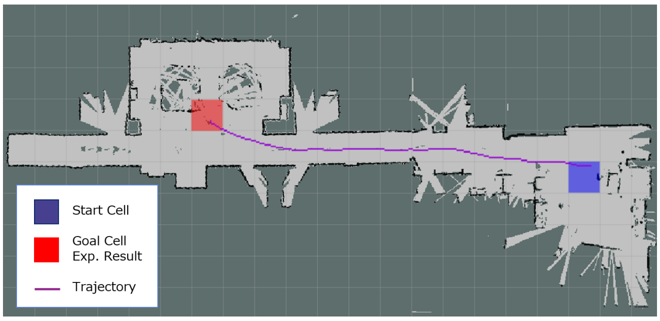
B. *Wayfinding Test*

In order to verify the validity of the proposed concept, we tested it in the actual system. We set 20 different situations with different distances between the start cell and the user's position. The start and goal cells are both random and must be accessible cells. The length of the paths varied from less than 10 m to 40 m. The wheelchair, initially located at the start cell, uses the measurements at the goal cell and estimates where the user should be, subsequently navigating toward it. As mentioned earlier, after reaching the initially predicted cell, the system estimates the user's position again. If the new estimation is different from the cell where it's currently at, it navigates toward the newly estimated position. If this occurs more than three times, this is considered as a failure. We chose 3 cases with different lengths (short: <10 m, medium: 10 m - 20 m, long: >20 m) to discuss the results. The actual path traveled by the wheelchair can be seen in Fig. 8

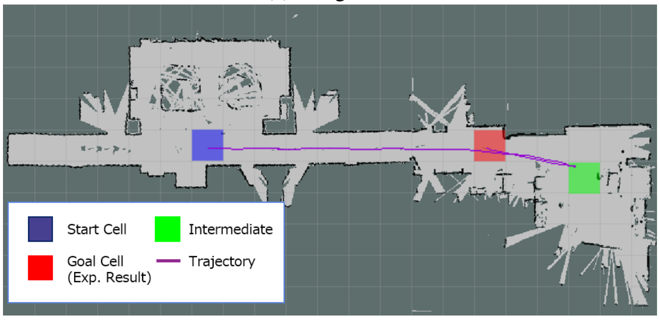
We classified the outcome of each trial in three different categories:

- Success: the wheelchair reaches the user's position on the first attempt (Fig. 8a)
- Success after recovery: the system initially went to the wrong position, but eventually succeeded in either the second or third attempt (Fig. 8b)
- Failure: after three attempts, the system could not reach the exact user's cell (Fig. 8c)

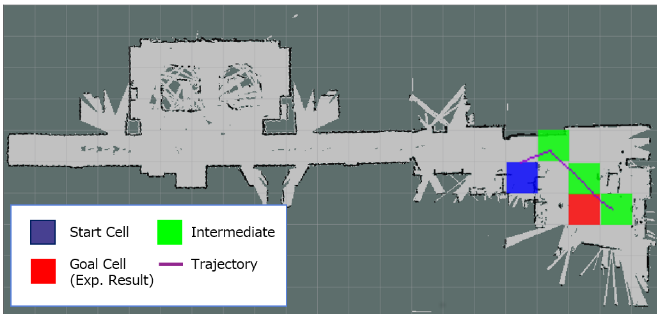
The outcome for the 20 trials is summarized in Table II. We observed that in most cases, the system was able to locate the user on the first attempt. In 4 cases, the system had a wrong prediction initially, but it managed to correctly predict it in a second or third attempt thanks to the update fingerprints in the database. In the case where the robot moves past the user (Fig. 8b) the robot did not stop because it is instructed to move until it reaches the predicted goal, then predict a new goal. In the future, introducing a fine localization method will enable the system to detect the user when it passes nearby, and head directly to his/her position. Even in the cases where the system failed (Fig. 8c) we can see that the system managed to reach the vicinity of the user's position. We think that our proposed method is suitable for roughly localizing the position of the user in a wide area, and combining it with fine localization



(a) Long Path



(b) Medium Path



(c) Short Path

Fig. 8: Actual Paths in the wayfinding test

TABLE II: Summary of Wayfinding Test

Times tested	20
Success	11
Success (Recovered)	4
Failure	5

methods such as cameras or RFID will guarantee that the wheelchair reaches the user.

One of the limitations of the current approach is that places that are not visited frequently have less chance to be updated in the database. This might make the system prone to make mistakes when locating the user in those cells. This might be addressed by scheduling periodic visits to these places.

VI. CONCLUSIONS

In this paper, we introduced an indoor wayfinding system that performs Wi-Fi signal strength based coarse localization in order to determine the user's position in a map. The system is designed for an electric wheelchair equipped with a Laser Range Finder and a Wi-Fi interface. The system creates a database using Wi-Fi based fingerprinting method, which is updated continuously with the RSSI measurements while the wheelchair navigates through the map. Using the KNN learning algorithm, the system estimates the user's location in the map by comparing the RSSI measurements at the user's location with those in the database. The estimations had an average position error of 2.612 m, which is reasonable for rough localization. We tested the integrated system, and the wheelchair managed to reach the exact cell of the user 75% of the times. Through these experiments we observed that the system was capable of recovery in cases the initial estimation was not correct, thanks to the constant updates to the fingerprints database to reflect changes in the environment.

The proposed method is intended to be used as a coarse localization method since its accuracy alone is not enough to exactly locate the user, thus, in future works, the system will be combined with a fine localization system which has a shorter range but higher precision such as visual localization using a camera or depth sensor [17]. Also, since wayfinding relies heavily on the performance of the navigation part of the system, improving the navigation method will likely improve the performance of the proposed system.

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