Indoor Localization: Automatically Constructing Today's Radio Map by iRobot and RFIDs

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***Abstract*—For outdoor localization, GPS already provides a satisfactory solution. For indoor localization, however, a globally usable solution is still missing. One promising direction that is proposed recently is the fingerprinting-based solution. It involves a training phase to collect the *radio signal strength (RSS)* patterns in fields where localization is needed into a database (called *radio map*). The radio signal could be from WiFi access points, GSM base stations, or other RF-based networks. Then, during the positioning phase, an object which is interested in its own location can collect its current RSS pattern and compare it against the radio map established in the training phase to identify its possible location. We present an interesting system based a robot and numerous cheap RFID tags deployed on the ground to automate the training process and, more importantly, to frequently update radio maps to reflect the current RSS patterns. This not only significantly reduces human labors but also improves positioning accuracy.**

***Index Terms*—indoor positioning, localization, pervasive computing, RFID, robot**

I. Introduction

Recently, *location-based services* are regarded as one of the killer applications in mobile networks. A key factor in location-based services is the location estimation accuracy. For outdoor localization, GPS already provides a satisfactory solution. For indoor localization, however, a globally usable solution is still missing. Many indoor localization technologies have been proposed, such as infrared-based [1], ultrasonic-based [2], and RF-based [3] systems. Generally, localization models can be classified as AoA-based [4], ToA-based [5], TDoA-based [6], and fingerprint-based [3][7][8].

In this work, we are interested in fingerprint-based localization systems, such as RADAR [3]. This method does not rely on calculating signal fading in an environment. Instead, it relies on a *training phase* to collect the *radio signal strength (RSS)* patterns at a set of training locations from pre-deployed beacons in a sensing field into a database (called *radio map*). These beacons can be existing infrastructures, such as IEEE 802.11 access points, GSM base stations, or other RF-based networks. Then, during the *positioning phase*, an object to be localized can collect its current RSS pattern and compare it against the radio map established in the training phase to identify its possible location.

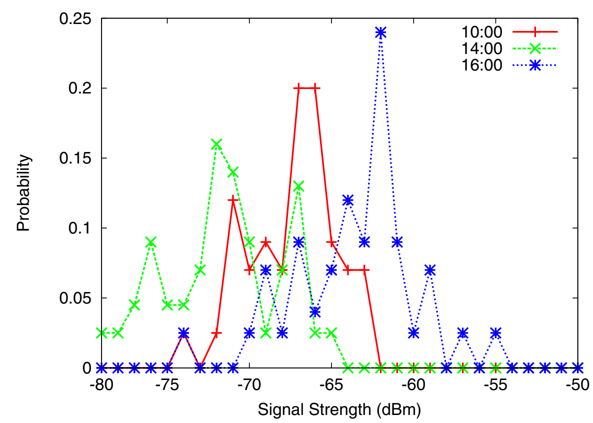

Fig. 1. RSS patterns of an AP measured at different times.

The major drawback of the fingerprinting approach is its labor-intensive training process, especially in a large-scale field. Further, since the RF signal is inherently unstable, the radio map collected earlier may deviate significantly from the current one. Manually calibrating radio maps is error-prone. Besides, environment may change, furniture may be moved, and beacons may be reconfigured or upgraded anytime [9]. Fig. 1 shows the RSS distribution of an AP collected at different times in one day, which shows significant variation. This may result in non-negligible errors when positioning objects.

The above observation motivates us to design a *self-guided* robot to collect RSS patterns automatically. Our system contains some WLAN APs and a large number of RFID tags placed on the ground. The self-guided robot does a two-level positioning to identify its location. In the first level, a location server based on WiFi fingerprinting helps position it at meter-level precision. The WiFi network can also provide the robot a local map containing the deployment of RFID tags in the field. In the second level, the robot searches the field and, if any RFID is scanned, its location is at the centimeter-level . With its accurate position, the robot can move around to automate

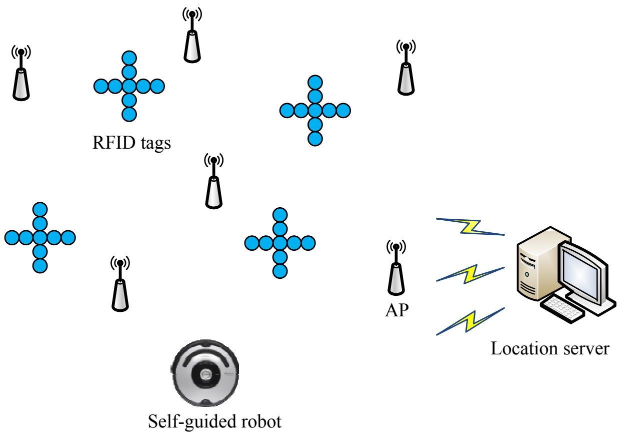

Fig. 2. System architecture of our work.

the training process and, more importantly, to frequently update radio maps to reflect the current RSS patterns. This not only significantly reduces human labors but also improves positioning accuracy. We implement our system on iRobot Create [10], on which a WiFi interface and a RFID reader are attached.

The rest of this paper is organized as follows. Section II describes some related works. Section III presents our design methodology. Section IV demonstrates our prototype. Section V concludes this work.

II. Related Works

Our goal is to automate the training phase via robots. To do so, a critical thing is to precisely navigate robots to visit each training point. In the past, indoor robot navigation systems can be divided into three categories: (1) laser guiding system [11], (2) magnetic tape guiding system [12], and (3) vision-based system [13]. Laser and magnetic tape guiding systems are more accurate but allow only limited routes. Vision-based systems are more flexible, but they require high computing cost and expensive equipments.

Recently, RFID techniques have also been applied to robot navigation [14][15][16]. In [14][16], an array of short range passive RFID tags are deployed on the entire field. Each tag represents a unique location. On scanning these tags, the robot can calculate its location. Grid deployment is discussed in [14], while triangular deployment is discussed in [16]. As can be seen, both [14] and [16] will need a large number of RFID tags. The work [15] uses a rotatable RFID reader to guide a robot to a stationary target, which has an active tag as a location transponder. An AoA-like model is adopted to guide the robot. This solution is more costly and it is mainly for one single target. Our work uses passive tags and it takes advantage of existing WiFi networks for meter-level positioning.

III. Methodology

Fig. 2 shows our system architecture, which contains four components.

- **WiFi network**: The network contains a number of APs, which periodically transmit beacons. By collecting signal strengths of these beacons, a device can estimate its current location.
- **Location server**: The location server runs a fingerprinting algorithm for positioning purpose. It also keeps some maps and those locations on the maps where RFID tags are deployed. The fingerprinting algorithm provides meter-level localization.
- **RFID tags**: RFID tags serve as landmarks, each identifying a unique location for centimeter-level localization. These tags are divided into groups, and each group is deployed in a cross shape as shown in Fig. 2. On scanning a tag, the robot can query the location server to get a local map as well as its location in the map.
- **Self-guided robot**: The self-guided robot has a WiFi interface and a RFID reader. It decides its location in two phases. Through collected RSS patterns, it can determine its rough location on a map. According to the map, it can further search for RFID tags. Once a tag is found, it knows its precise location.

Fig. 3 shows the working flow of the self-guided robot. At first, the robot gets a *tour*, which contains a sequence of entries, from the location server. These entries can be divided into two types: *training point* and *RFID target*. If the next entry is a training point, the robot moves toward it, collects the RSS patterns at that point, and reports to the location server for constructing the current radio map. Otherwise, the robot moves to the predicted location of the next RFID target. If no RFID tag is scanned (due to error), it searches in a spiral manner.

IV. Prototype

Fig. 4 shows the hardware components of the self-guided robot. We adopt iRobot Create [10] as the mobile platform and attach to it a RFID reader, an electronic compass, and a notebook with a WiFi interface. Fig. 5 shows some searching scenarios of the robot. Fig. 6 shows our testing environment, which contains eight WiFi APs and six RFID tag groups. Our experiments show that 5 to 10 seconds are needed for the robot to visit each tag group and totally 3 to 5 minutes to construct a new radio map in this environment.

V. Conclusions

Major drawbacks of the fingerprint-based position approach are its training cost and the signal deviation problem between the training phase and the positioning phase. We have developed a self-guided robot to conquer these problems. The two-phase position algorithm helps the self-guided robot to position itself. In particular, RFID tags serve as landmarks to accurately position the robot at centimeter-level precision. With accurate locations, the robot can automate the training phase and, more importantly, frequently reconstruct the current radio map to improve the precision of the fingerprinting algorithm.

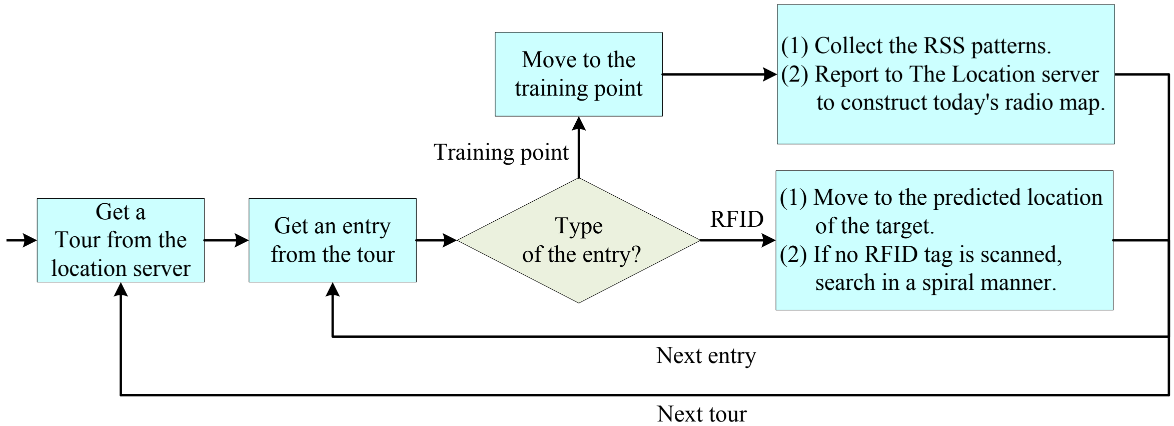

Fig. 3. Working flow of the self-guided robot.

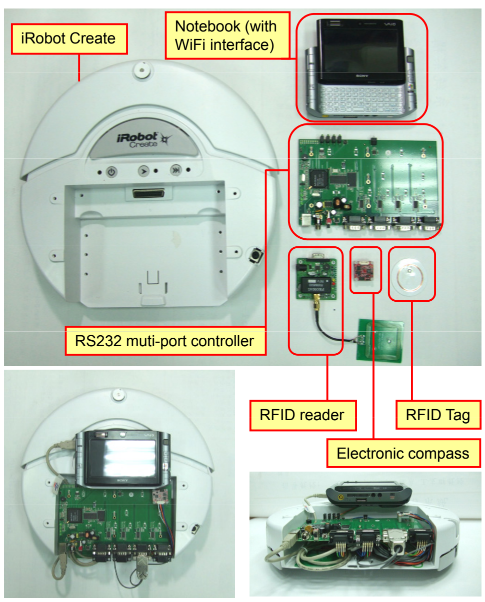

Fig. 4. Hardware components of the self-guided robot.

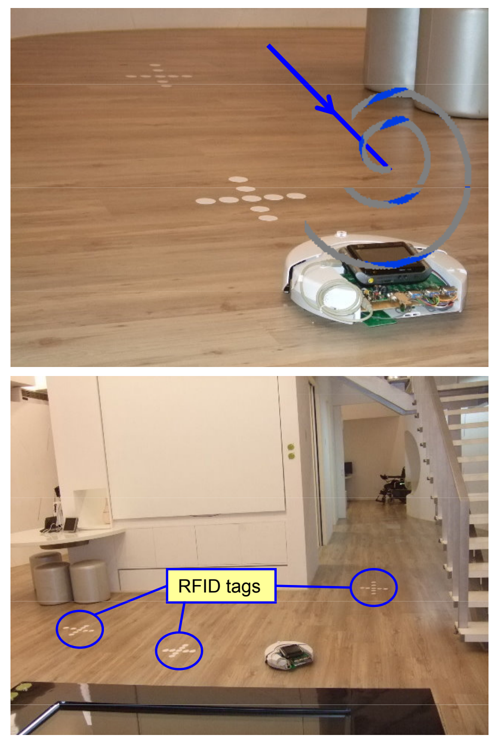

Fig. 5. Some searching scenarios.

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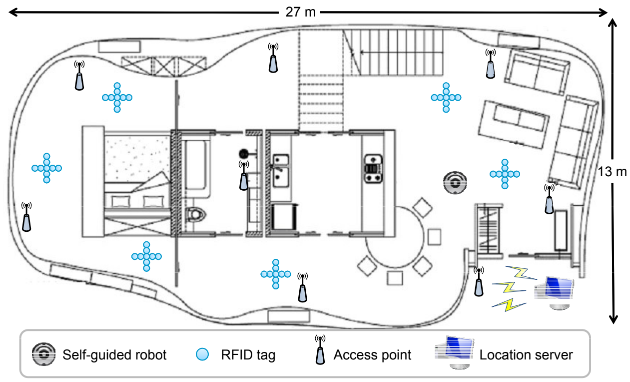

Fig. 6. Our experimental environment.

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