Autonomous RF Surveying Robot for Indoor Localization and Tracking

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***Abstract*—RF fingerprinting is an interesting solution for indoor localization and tracking because it uses existing devices and infrastructure and involves minimal intervention to ongoing activities. The method involves constructing a database of signal strengths at different locations in an indoor space. Real-time measurements are compared to the database to retrieve the best-matching location. The process of constructing the signal strength maps often involves lengthy labor, which causes difficulties in practical deployment. Furthermore, the maps need to be periodically updated for potential changes. To address these challenges, we describe the design and working of a robotic platform that can construct RF signal maps with minimal human intervention. Using a new method of multi-sensor integration for Simultaneous Localization & Mapping (SLAM), our robotic platform can autonomously navigate inside a building while localizing its position and gathering RF signal strength data.**

Keywords: Indoor Mapping Robot; SLAM; RSSI; RF fingerprinting; WLAN

I. INTRODUCTION

Technologies for tracking people within buildings are important enablers for many public safety applications and commercial services. The need has not been met by conventional navigation aids such as GPS and inertial systems. There have been many approaches to solve this problem such as using pseudolites, highly sensitive Inertial Measurement Units (IMUs), RF based systems using techniques like Received Signal Strength Indicator (RSSI), Time Difference of Arrival (TDOA) or Time of Flight (TOF) on different spectral bands and standards [1], [2], [3], [4], and hybrid methods using sensor fusion. Some solutions require special devices such as ultrasonic or RFID tags and readers, or are constrained by requiring line of sight such as in the use of video cameras. The most desirable are systems that cause minimal intervention to ongoing activities, use existing device and infrastructures, and are cheap to deploy and maintain.

Over the years our team of researchers has worked on several components of a WLAN-based tracking technology that are ready to be refined and integrated into an operational solution. These include (1) a simulator for predicting radio propagation using path-loss models and ray-tracing computation; (2) a set of statistical algorithms for interpolating RSSI maps from manually collected, irregularly spaced raw data; and (3) algorithms for using the refined signal maps to determine positions in real time. But a practical solution still requires the elimination of the painstaking process of creating a signal map manually by walking/driving through the space and collecting signal strength measurements along with precise position information. Furthermore, it is necessary to be able to repeat the signal map construction periodically to adapt to potential changes in the radio environment. Motivated by these needs, we have recently developed a robotic test-bed that can carry multiple sensors and navigate within buildings autonomously while gathering signal strength data at various frequencies of interest. A robotic platform that can perform such tasks with minimal human intervention is a highly promising solution to bridge the gap between laboratory trials and practical deployments in large scale.

This paper describes the design and working of our robotic platform. The robot is capable of conducting repeated surveying of an indoor environment to update the signal maps as frequently as required. Also the robot serves as a test-bed to collect data in controlled conditions such as under uniform motion and with accurate positioning. As it moves autonomously in the indoor environment, it uses a new method of multi-sensor integration for Simultaneous Localization & Mapping (SLAM) to construct the spatial model and infer its own location. In this way, the construction of the spatial map of RF signal strength can be fully automated. The robot can carry different receivers and systematically compare the effectiveness of different localization methods. Currently we experiment with WLAN fingerprinting techniques. We expect that the robot can support similar experiments on other RF signals of interest, including GSM, CDMA and LTE.

II. INDOOR MAPPING ROBOT

A. Hardware Configuration

This section describes the hardware of the Indoor Mapping Robotic (IMR) test-bed vehicle which is used to survey and construct radio signal maps within buildings quickly and as frequently as needed. Since the robotic platform is primarily intended for indoor application we chose a vehicle that was easily maneuverable through narrow corridors and doorways. Our choice was a Jazzy Jet 3 wheelchair with two motors, two 12 V rechargeable batteries and a maximum operating time of 4 hours. The chair and chair mount was replaced by a custom built aluminum base that hosted all our sensor, electronics and hardware.Fig. 1 shows the hardware layout of the robotic platform and Fig. 2 the platform itself.

The heart of the electronic system is a low-power 1.66 GHz Mini-ITX computer motherboard that handles all the operations of the robot including navigation and signal strength data

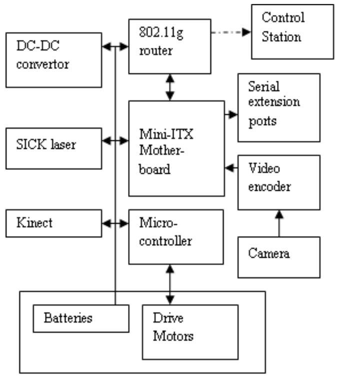


Fig. 1. Hardware configuration of indoor mapping robot.

collection. The robot is controlled through a microcontroller that sends serial PWM signals to the motor controllers for navigation. Data from different on-board sensor such as the sonar, inertial sensors, Microsoft Kinect and video cameras are streamed through an on-board 802.11g link to a control station for post processing and analysis. The robot autonomously navigates the indoor environment using collision detection algorithms. The main sensor used for this feature is the Microsoft Kinect® RGB-D sensor developed by PrimeSense Inc, which can simultaneously acquire depth and color images. An open-source software driver (available at http://openkinect.org) enables to grab both depth and RGB images at 30Hz and 640x480 pixel resolution, and respectively as 11-bit depth and 8-bit color definitions [5].

B. Autonomous Robot Navigation

Autonomous robot navigation is currently implemented as a collision avoidance strategy using the Kinect and other sensors including sonar and contact sensors. The collision detector primarily relies on the output from the Kinect RGB-D sensor. After sub-sampling the depth image to an 80x30 pixel size and converting depth information to metric distances, a simple threshold-based algorithm makes decisions to turn if there are obstacles within 1m on the right or left of the field of depth vision. Another threshold is used for stairs detection, by scanning the bottom five lines of the depth image. The robot moves forward if no collisions or falls are perceived. If the kinect does not detect small obstacles such as a pillar or trash cans which are not in the field-of-view of the Kinect camera the sonar sensors serve as additional backup sensors for obstacle avoidance.

III. DATA COLLECTION EXPERIMENTS

The robot can support many designs of controlled experiments to compare the effects of various factors that may impact the quality of an RF signal map. Examples include differences between alternative data collection software, and independent effects of spatial and temporal variations.

A. Software for Gathering Signal Strength Data

In order to build our radio signal map we have considered two methods for gathering WLAN received signal strength data (RSS); active probing and passive sniffing technique.

Fig. 2. Indoor mapping robot.

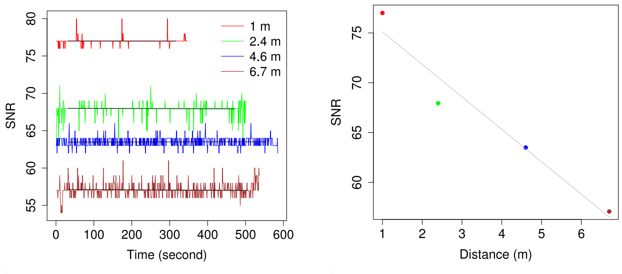
In the active probing technique the probing software such as NetStumbler [6] sends out an active probe request and the surrounding access points respond with data such as SNR, channel information and other relevant information. In passive sniffing technique the software such as Kismet [7] passively scans the networks by gathering data packets and analyzing their contents. Early experiments show that an active scanning technique produces more reliable signal strength measurements.

B. Experiments with Controlled Variability

Ad hoc measurements of signal strengths often include a combination of many effects, such as spatial signatures as determined by multi-path propagation, disturbances due to objects moving in the environment, and transient presences of interfering signals. For example, from test runs measuring signal strengths from various access points at specific locations inside the building over long periods of time, and also when moving at a constant speed at a sampling rate of 1 sample per second, we found that there was more than 10 dB variation in the signal levels even over short distances. These variations could be either due to multi-path effects in the indoor environment or device related or a combination of both. In order to identify and isolate these variations, we designed a set of experiments to measure WLAN signal strength with different effects in control.

First we minimized the environmental interference by setting up experiments in an anechoic chamber to measure the signal strength at various distances. We noticed that the signal strength received from a particular access point was relatively stable over long periods of time. Fig. 3(a) shows the constant WLAN signal strength seen in the anechoic chamber and Fig. 3(b) the mean of the values. This led us to conclude that most of the variation in the signal strength is due to the indoor propagation environment which could be people and objects moving in the vicinity of the robot and the access points.

We then collected data at various locations in the building to characterize and map the signal strength values. We gathered the data using the robot by moving to a specific location, collecting signal strength data for a fixed time interval and then



(a) WLAN RSS in anechoic chamber

(b) Mean of WLAN RSS

Fig. 3. WLAN RSS measurements in anechoic chamber

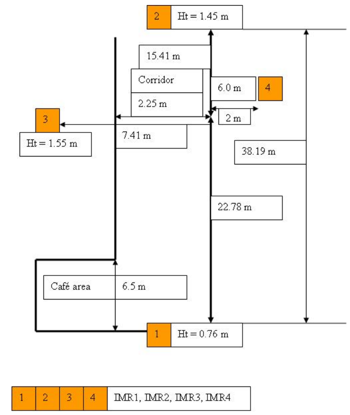


Fig. 4. Experimental setup in the building.

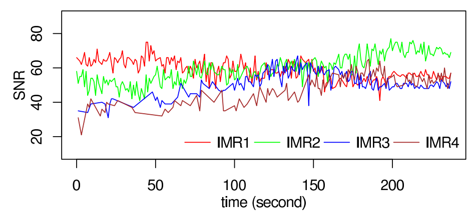


Fig. 5. WLAN signal strength data for run 1.

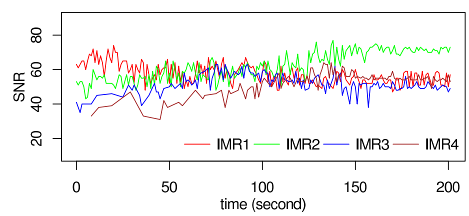


Fig. 6. WLAN signal strength data for run 2.

moving to the next location at uniform speed. Fig. 4 shows the in-building experimental setup and the location of the access points. We installed four WLAN access points in a corridor of the building and measured their signal strength using the robot. Two access points were in line-of-sight of the robot (IMR1, IMR2) while two were placed inside cubicles along the corridor (IMR3, IMR4). The scheme was to understand the WLAN signal propagation characteristics in varying multi-path conditions. We gathered WLAN data during constant continuous motion of the robot along a specific route and repeated this path at different times of the day. Fig. 5 and Fig. 6 show WLAN signal strength values from data gathered along the same path and locations at two different times of the day. It can be observed that the signal values vary due to the temporal variation of multi-path effects in the indoor environment. This phenomenon illustrates the need for repeated data collection to accurately characterize the spatial and temporal variation of the RF signal. Such needs highlight the advantage of our robotic platform in its capability for conducting these measurements systematically, and repeating as often as necessary.

In our next set of experiments the robot was set to traverse along a straight line down the corridor with stops at specific locations for fixed time intervals. Fig. 7 shows the varying signal strength from the four access points as the robot moves along a specified path in the experimental setup shown in Fig. 4. The x-axis shows the time of motion and the y-axis the SNR values measured from the 4 access points. The stopped times are shown by the dashed lines on plot. By modifying our WLAN fingerprinting algorithms to take into account the full distribution of the RSSI [8], and using the RSSI from Fig. 7 as training data, we were able to achieve a median accuracy of 1m (2m accuracy at the 90% quantile) on subsequent runs along that corridor [13].

IV. SIMULTANEOUS LOCALIZATION AND MAPPING

A critical need in constructing a spatial map of RF signals is to accurately record the location of the receiver at the time when the signal strength is measured. In addition, the location needs to be registered to the building layout for use in applications and services, even if no detailed blueprints are available for the building of interest. On the robotic platform, these can be accomplished using a SLAM (Simultaneous Localization And Mapping) algorithm.

Conventional 3D database modeling of indoor environment by mobile robots has involved the use of laser scanner and cameras [9]. The laser scanner is used to build a 3D point cloud map and the textures from the camera images are stitched to these point clouds to form the complete database. A recently published method succeeded in building precise 3D maps directly from the Kinect RGB-D images [10], taking advantage of the dense depth information, without relying on other sensors. It would estimate 3D point cloud transformations only between two consecutive RGB-D frames, and would resolve loop closures (going twice through the same location) using a maximum likelihood smoothing [11], but would be too computationally intensive for real-time application. Fig. 8 shows the RGB-D images and Fig. 9 shows a snapshot of the 3D map being constructed from the RGB-D sensors, using a simplified implementation of [10][1].

We also propose a modification of [10], that integrates 3D transformation matrices from RGB-D odometry with other measurements coming from wheel and inertial sensors on the robot. It relies on a nonlinear state-space model, where the hid-

[1]We used Kinect RGB Demo v0.4.0, available at http://nicolas.burrus.name

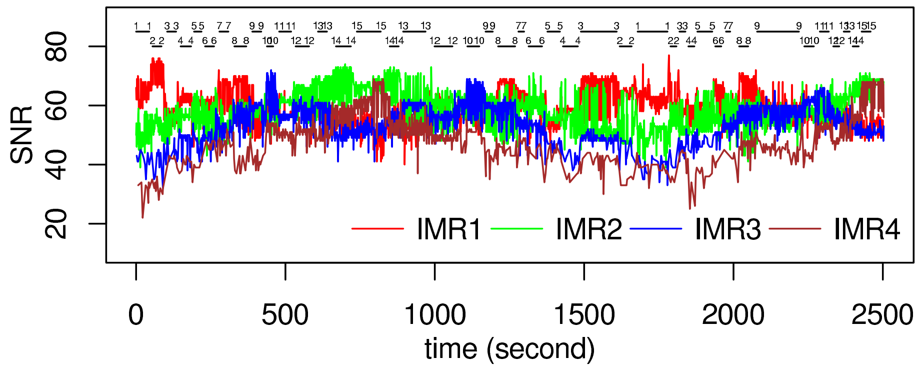


Fig. 7. WLAN signal strength data recorded along a corridor, with 15 locations spaced every 1m.

Fig. 8. View of the depth and RGB images from the robot Kinect® sensors.

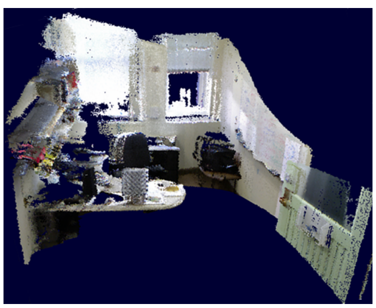


Fig. 9. Example of 3D office reconstruction from RGB-D-based odometry.

den/unknown state variable at time t is the vector of positions and orientations of the robot. However, instead of resorting to the conventional Kalman or particle filtering approach, we propose to do Maximum A Posteriori inference of the latent variables over longer sub-sequences (e.g. 1s-long), with both forward and backward message passing (smoothing) [12], and to handle 3D rotations like in [11].

V. ONGOING WORK

We are integrating additional sensing modalities on the robotic platform including sonar to improve the navigation and localization capabilities of the robot. Since the most of the robot hardware was built from commercial off the shelf hardware we plan to replicate this design for multiple robotic platforms which can be used to quickly cover large buildings in a coordinated manner. We are also exploring measuring signal data from other RF systems such as CDMA, GSM and 4G networks. The robotic platform is capable of supporting up to 100 kg of payload and thus integrating these additional signal receivers on the robotic platform will be a straightforward effort.

VI. CONCLUSION

The robot serves as a good experimental platform for obtaining results for a mixture of signals, particularly with a view to testing algorithms as well as the suitability of the signals per se. As we have stressed earlier the platform is well suited from performing repeated experiments with good matching between common factors such as location and motion.

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