[1]Toward Hazard Aware Spaces: Localization using Passive RFID Technology

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Abstract

In this technical report, we investigate the use of passive RFID technology for object localization and tracking. This work is motivated by the desire to design, and build, robust smart spaces (pervasive spaces), and in particular their application in the area of hazard aware spaces. In particular we are interested in building spaces that can detect hazards and autonomously take action to gain more information about the hazard and alert the users of the space. To enable a robot to operate in such a space, accurate localization and tracking must be carried out, allowing the robot to then sense and detect hazards and alert humans about when, where, and what hazards occur. We evaluate the strengths and weaknesses of passive RFID technology as a solution to this problem. In addition, we present a methodology for building a sensor model which is required for accurate localization, and we discuss one specific method of performing probabilistic localization. Finally, we present experimental results illustrating the successful global localization of a robot using these methods.

We address the problem of building hazard aware spaces (HAS) to alert innocent people. We propose building a prototype HAS system for detecting fire, vision impairing light, earthquake, extreme sonic waves and dangerous gases. Our long term goal is to sense and detect indoor hazards and then alert humans with information about where, when and what hazards occur. In this project, we focus on incorporating passive radio frequency identification (RFID) technology to our existing prototype HAS system in order to improve localization of hazards, objects in a building and deployed wireless sensors.

1 Introduction

The problem we are focusing on in this technical report is that of global localization using passive RFID tags, in order to increase the performance and reliability of previous HAS system concepts. Such a system must be accurate, robust, rugged, and fault-tolerant. While meeting these performance requirements, the system must also satisfy many constraints. There must be a minimal cost for hardware, setup, maintenance, data transmission, and computational processing. The system also has to accommodate limited

human access, implying remote deployment and sensing. Possible applications for such a system are (a) safety hazard detection (fire, nuclear, etc), (b) smart spaces supporting elderly and disabled citizens, (c) part detection or tracking in automobile industry assembly lines, (d) merchandise tracking and business process intelligence, (e) monitoring maintenance and operational activities of buildings or plants.

In order to design a system that can meet all of these requirements and constraints, an approach is taken that evaluates the strengths and weaknesses of many technologies, and investigates solutions by intelligently fusing those technologies together into a robust and efficient system.
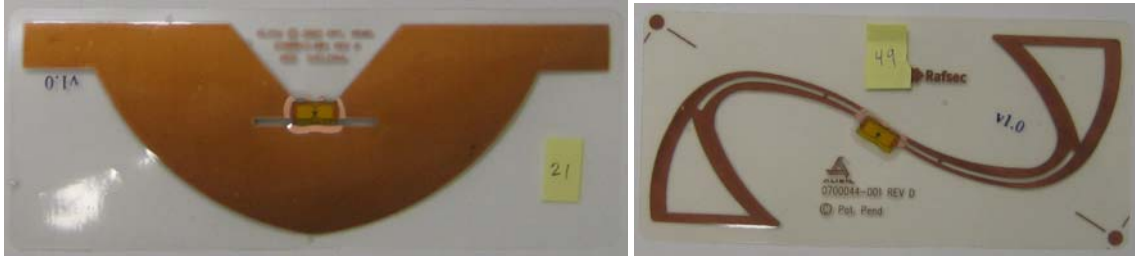

Figure 1. Tag types used in our experimental analysis.

In order to evaluate passive RFID technology, we pose the following specific problem:

A robot (or person) is moving in a space containing RFID tags, and has a priori knowledge of the passive RFID tag locations. The sensor is an antenna (Alien Reader) that detects tags, and obtains their ID and possibly other information, like temperature, position, etc. The types of RFID tags we used are shown in Figure 1. Our current goal is to use the RFID Reader to detect tags and, given a previously determined map locations of tags, globally localize itself in the space. Furthermore, our long term goal is to deploy MICA active sensors using the robot. The location of each MICA sensor will be determined by the robot and transmitted to the MICA, and hazard sensing will be activated. Thus, future signals transmitted by the MICA sensors will be tagged with the location of that sensor. Additional RFID tags on objects in the room will then be used for robot collision avoidance and for hazard material understanding. The main elements to incorporating passive RFID tags into the system become (a) building a sensor model for passive RFID tag detection, and (b) creating a suitable localization algorithm.

The key experimental elements to be evaluated during testing can be summarized as follows: (a) Reader and tag geometric configuration, (b) tag detection behavior during occlusion, (c) Reader and tag relative speed, (d) tag density, (e) tag type, (f) and Reader type. Our experimental results show that accurate modeling of the RFID Tag and Reader configuration is the key for Tag detection performance for a given type of Reader and Tag, but once this is done, robust global localization can be achieved. Our results also show that occlusion material between the Reader and Tag is not a very large issue unless that material is metallic, in which case tag detection does not occur, or is severely perturbed.

The process of detecting an RFID tag depends on many factors: antenna footprint, the distance between the antenna and tag, and the relative orientation between the antenna and tag. We have identified so far the robustness of RFID tag detection to be dependent on the following main attributes: (1) geometry of RFID tag versus reader configuration,

(2) relative motion of RFID tag versus reader and (3) media properties between RFID tag and its reader (e.g., occlusion material). These dependencies introduce the possibility of false-negative and false-positive RFID tag readings. We have ignored in our RFID tag detection model the non-zero likelihood of RFID tag or reader failure and it could be incorporated after a basic probabilistic RFID tag detection model is developed. For now, we assume that the RFID tag type is not a major contributor to the robustness of RFID tag detection.

The remainder of this technical report is organized as follows: After discussing related work, we outline our preliminary experiments to determine RFID tag detection robustness and behavior. Then, in Section 4, we discuss building a sensor model, and its importance in the performance of the system. In Section 5 we describe how we use Bayesian methods to perform global localization, which were straightforward to implement, but computationally expensive. Finally, in Section 6 we discuss experimental results.

2 Related Work

There is much ongoing and active research in the area of smart spaces. There are many different technologies that can contribute to a smart space. A technology that performs a similar function to the localization task that we wish to accomplish is floor-based sensor systems [5]. Using floor-based sensors such as pressure sensors can be quite useful, but they obviously limit use to an environment with an accessible floor. Also, in order to be low-cost, it is likely that floor-based sensing will only be able to provide 2-D tracking, and not orientation tracking, due to the difficulty of attempting to detect in which direction a person or robot is pointing. Other costs of floor-based sensing involve power usage, wiring, installation of electronics, etc. Also, there are interesting developments in the use of smart sensor technology combined with computer vision for the purpose of tracking objects in a space [4]. The use of passive RFID technology has potential to make simple and robust contributions to such problems, especially when the object being localized is a robot.

Our theoretical framework follows the work of Philipose et al., [7]. The probabilistic sensor model for the RFID antenna was derived for the same technology components (a Pioneer robot and Alien reader/RFID tags) but the geometrical configuration of readers, the number of readers, and the elevation and orientation of RFID tags were different from our experiments (compare Figure 4 and Figure 2). Figure 2 (right) illustrates the angular and range dependency of the RFID tag detection reported in Philipose et al [7]. Also, while Philipose et al. presented an analysis of the use of augmenting a laser rangefinder with RFID tags during mapping and localization, our objective is to evaluate the strengths and weaknesses of using passive RFID tags as the sole sensor during localization.
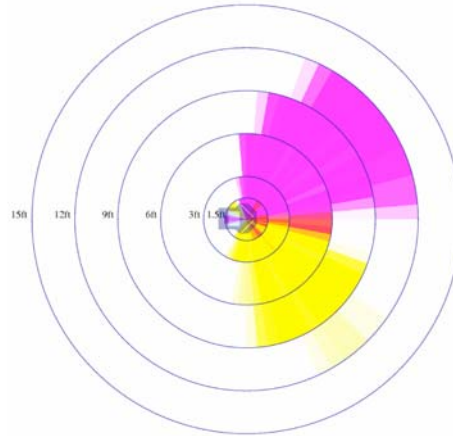
Figure 2. This figure, adopted from Philipose et. al. [7], illustrates the experimental setup and learning a probabilistic sensor model for the RFID antenna.

3   RFID Tag Detection Robustness

After preliminary studies of passive RFID technology, we realized that a key factor to designing a robust system is the understanding of the behavior of RFID tag detection under various conditions, both nominal and off-nominal.   Only by examining tag detection behavior will one be able to match the capabilities and limitations of passive RFID technology with their specific application.   In our preliminary experiments, we analyzed four main areas: (a) tag detection under varying Tag/Reader geometric configurations, (b) tag detection under varying tag speeds, (c) tag detection during tag occlusion, and (d) tag detection under various tag spatial densities.

An example of the recorded RFID tag detections is shown below in Table 1, where the order of entries corresponds to tag ID, time stamp, reader description, reader ID.

Table 1. Examples of RFID tag detections.

Tag ID			Time stamp	Reader description	Reader ID
8000	8004	2565 8145	1139348415894	Alien RFID Reader	0
8000	8004	2565 8145	1139348416084	Alien RFID Reader	0
8000	8004	2565 8079	1139348416084	Alien RFID Reader	0
8000	8004	2565 8145	1139348416375	Alien RFID Reader	0
8000	8004	2565 8079	1139348416375	Alien RFID Reader	0
8000	8004	2565 8145	1139348416705	Alien RFID Reader	0
8000	8004	2565	1139348416715	Alien RFID Reader	0

8079			

Testing tag detection under varying tag/Reader configurations: In this area, we performed a variety of simple experiments, which are summarized below.

- **Measurement:** lay tag on floor and find average detection range.
  - **Result:** we found that the average detection range is less than 25 inches.
- **Measurement:** suspend tag in the air and find average detection range.
  - **Result:** we found that the average detection range is on the order of 7 feet.
- **Measurement:** lay tag on floor and find maximum detection range for various angles of the tag with respect to the reader.
  - **Result:** We found that the maximum detection range varies by approximately 15% depending on the orientation of the tag. This is consistent with the observation that the physical tag is not built with rotational symmetry (i.e. the tag's antenna does have a preferred orientation with respect to the Reader).

Testing tag detection under varying tag speeds: For tag positions in the main detection range of the reader, we found that the Reader detects tag's moving at all practical indoor speeds, with virtually no change in detection rate. We tested this by physically waiving tags, running by the reader, etc.
> **Result:** The reader always detected the tag promptly.

Testing tag detection during tag occlusion: We performed simple occlusion experiments which involved completely covering the RFID tag with various materials. We performed these experiments with plastic, wood/paper, and metal.
> **Result:** We found that plastic, wood, and paper (up to approximately 2-4 inches thick) have virtually no effect on the nominal detection range, whereas any metal (tinfoil, aluminum sheet metal were specifically tested) covering the tag will completely prevent detection.

Testing Tag Detection with spatially dense tag distribution: Measurement: put roughly 15 tags in the main detection area of the Reader, and see if there is a processing bottle-neck.
> **Result:** We found that when approximately 10 - 15 tags are simultaneously detected, there is a bottle-neck in the Alien Reader processing, and delays of up to 5 seconds occur between reported tag detections (vs 5-10 ms between reported tag detections when only a few tags are being detected).

To summarize these observations: The dependencies noted above introduce the possibility of both false-negative measurements, in which case a tag is in the expected nominal detection range, but does not get detected, and false-positive RFID tag measurements, in which case the tag is outside the expected nominal detection range, yet still gets detected. In addition to this, it is also noted that depending on the specific tag/Reader configuration, extremely different tag detection behavior can occur. Thus, the tag/Reader configuration is probably the most important factor during the detection

process (for a given type of RFID Tag). This complex behavior requires one to spend much effort in building an accurate sensor model, which is discussed in the next section.

4 Building a Sensor Model

As will be discussed further later, it is common during probabilistic localization to make use of a sensor model which specifies a likelihood of a sensor measurement given the position of the robot (or person). In this section we present a methodology for developing such a sensor model for use during localization with passive RFID technology. As noted above in discussion regarding tag detection under varying Tag/Reader configurations, it is necessary to build a sensor model which is specifically appropriate for the Tag/Reader geometries and configurations that will occur during deployment of the tracking/localization system. This is because the tag detection behavior changes drastically between different Reader/tag configurations. A simple model will not be sufficient if one's actual implementation differs in any number of fundamental ways, some of which are extremely difficult to foresee before the actual implementation. For example, in our experiments, we mainly worked with RFID Tags distributed in a grid on a carpeted floor, which leads to a very different sensor model than that obtained in [7]. (Compare Figure 2 and Figure 3.) When laid out on a carpeted floor, the maximum read range was roughly 90 cm. In contrast, when tags are held in the air in front of the Reader, the maximum read range is on the order of 200 cm.

This behavior led us to develop the following methodology for building a sensor model. First, one must determine the possible Reader/tag configurations and geometries that will arise in their given implementation. Next, one must fix the Reader's location, and distribute a spatially dense array of tags in the very configurations and geometries that are expected. This array of tags is then used to determine the ``footprint'' of the Reader, and more specifically, the likelihood of a tag detection given the relative position of the tag and Reader. The sensor model then becomes a manifold of detection likelihoods, which can be used directly in the localization algorithm described below.

In our experimental analysis, we followed this procedure with great success. We distributed tags in front of the Reader (Figure 3 left), and collected statistics on tag detection while varying the angle of the Reader. We then used that information to derive the manifold of detection likelihoods over the space of possible geometries.

Once we collect the data represented in Figure 3, we can then build a mathematical model which specifies the likelihood of a detection given a relative position of a Tag with respect to the Reader.
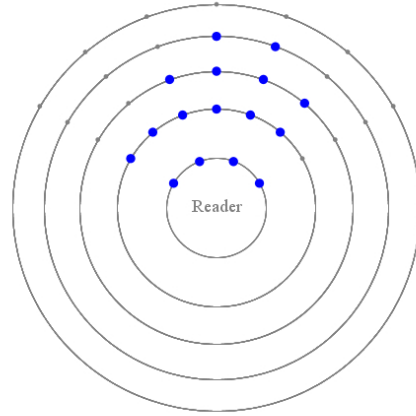
Figure 3. Left: documentation of setup used to build the sensor model. Right: Image showing nominal detection range when Tags are distributed on the floor and the Reader is mounted on the robot and tilted forward 60 degrees. The 4th "row" has a radius of roughly 90 cm.

5 Probabilistic Localization

There are many methods available to perform localization and tracking. We present one probabilistic localization method here, in order to quickly evaluate the accuracy and robustness of using RFID technology as the sole sensing capability during localization. The algorithm we used to perform probabilistic localization, derived from Choset et al [2], is very simple, but also very computationally expensive. The problem of localization is to estimate the state $x \in X$ of the robot, where X is a discretized state space consisting of possible 2-D positions and orientations. So, for each time step k, we estimate the *posterior probability* P(x(k) | u(0:k-1),y(1:k)) over all possible states, where y(1:k) represents the sensor measurements obtained at times $1,…,k$ and u(0:k-1) represents motions taken at times $1,…,$k-1. Note that during a given time step, k, it is possible to detect multiple RFID tags, where the likelihood of a tag_m detection is independent of whether or not tag_n was detected (for all m, n such that $m \neq n$). Also note that as background knowledge throughout this analysis, we have a given map of RFID tags.

The key to this probabilistic localization scheme is the recursive Bayesian filtering equation, which specifies how to use the last estimate (the *prior*), in conjunction with current sensor measurements and assumptions about current motions, to calculate a current estimate of the robot's state (the *posterior*):

$$P(x(k) \mid u(0{:}k{-}1),y(1{:}k)) =$$
$$= \eta(k)P(y(k)|x(k)$$
$$\sum_{x(k{-}1) \in X} P(x(k)|u(k{-}1),x(k{-}1)) \; P(x(k-1) \mid u(0{:}k-2)\,y(1{:}k-1))$$

Above, $P(x(k-1) \mid u(0:k-2),y(1:k-1))$ represents the prior, or the probability that the robot is at location $x(k-1)$ before motions or sensor measurements are taken into consideration. The term $P(y(k) \mid x(k))$ is called the *sensor model*, which represents the likelihood of the measurement $y(k)$ given the robot (or person) is at location $x(k)$; and the term $P(x(k) \mid u(0:k-1),x(1:k-1))$ is called the *motion model*. In our application, we used a Gaussian distribution centered on $x(k-1)$ as the motion model, and the sensor model is determined as according to the procedures described in the previous section. The value $\eta(k)$ is normalization constant to ensure that $P(x(k) \mid u(0:k-1),y(1:k))$ sums up to one over all $x(k)$ [2]. We adopted an algorithm from Choset et al [2], pg 313, which we used to compute the above posterior at each time step. We initialized the prior to be a uniform distribution across all possible states, which allows us to perform a global localization.

Note that, because we are representing possible states using a discrete grid, the above algorithm leads to $O(N^2)$ computational complexity, where N is the number of points in the grid [2]. In the near future, we would like to update the algorithm to improve efficiency to allow larger state spaces and finer time discretization. This can be done by using particle filters and Monte Carlo localization techniques [2], [3].

6 Experimental Results

Figure 4. Experimental setup. The Alien Reader was mounted on the platform of a robot (left). The RFID tags were placed on the floor in a regular grid pattern (right).

We implemented the approach described above using one Alien Technology RFID Reader and tags of the type shown in Figure 1. We arranged a grid of RFID tags as shown in Figure 6, loaded the Pioneer robot's platform with the RFID Reader, and moved it in a pre-defined path. Note that in this configuration, the maximum detection range is approximately 90 cm. Ground truth measurements were acquired throughout the experiments by keeping track of the times at which the robot passed certain pre-determined positions. Note that these ground truth measurements include relatively large errors of up to 13 cm. The experimental variables are (1) RFID tag types (97 passive

sensors with 4 different RFID tag designs), (2) RFID grid spacing, (3) RFID reader orientation on the robot's platform, and (4) velocity of the robot.

Our short term goal was to detect at least one RFID every 100 ms while moving the robot through the grid of tags. We found that using a tag spacing of approximately 40 cm allowed us to maintain this detection rate. Figure 5 show an example of the experimental data, and the resulting localization performance. Our localization algorithm quickly arrived at the robots position, and was able to track the movement of the robot very well. Figure 6 shows the localization error throughout one experiment. We believe that much of the variability in the error is due to inaccuracies during ground truth observations. Despite this, we were able to quickly achieve and maintain a fairly smooth position estimate over time to within an average of roughly 20 cm of the actual position.
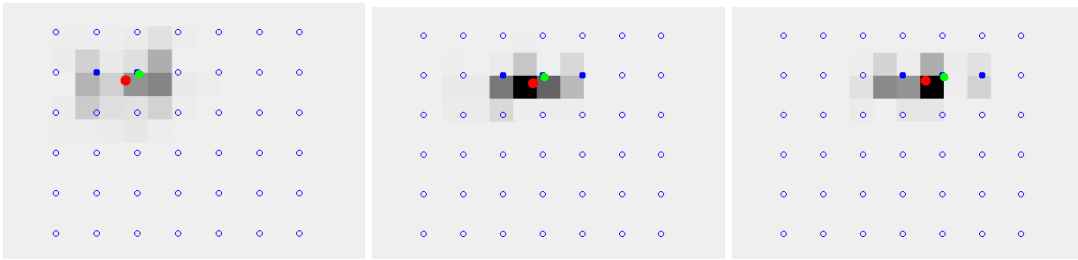

Figure 5. These images show three time steps in the middle of an experimental run. Open circles represent undetected tags. Filled blue circles represent detected tags. The red circle represents the average robot location, and a green circle represents a ground truth measurement.

Below are some experimental results. We used a discrete grid spacing of 25cm, and discretized the time into 1 second time steps. We chose the RFID grid spacing to be 1.5 feet in our preliminary experiments.
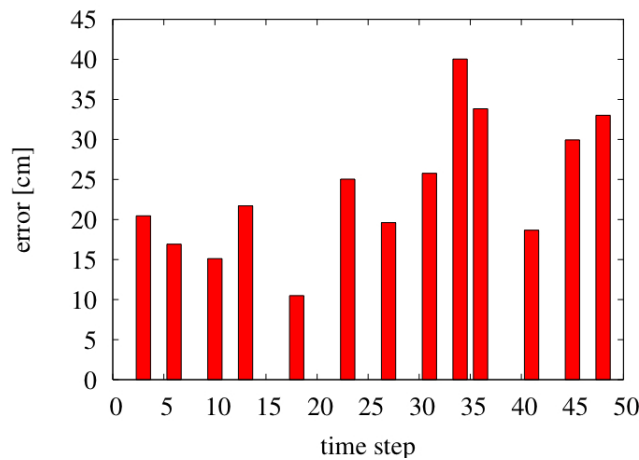
number of measurements	13
mean error [cm]	23.8
std dev [cm]	8.42

Figure 6. Plot of 2-D position error over the course of an experiment with the summary results. Note that our ground truth measurement was extremely noisy, having an accuracy of only +/- 13 cm.

7 Conclusions and Future Work

In this technical report, we explored the effectiveness of using passive RFID technology for robotic localization. We analyzed what elements most effected RFID tag detection robustness, such as Reader/tag relative geometry and occlusion material between the Reader and tag. Additionally, we presented a methodology for building a sensor model, which we found to be one of the most important elements necessary for accurate localization. We then presented one method for performing probabilistic localization, which efficiently handles sensing uncertainties, motion uncertainties, and an unknown initial state. Finally, we showed experimental results, where an Alien Technology RFID Reader was mounted on a Pioneer robot, and global localization and tracking was achieved with an accuracy of roughly 20 cm.

Despite our preliminary successes in localization and tracking, there are many possibilities for future work. We can explore more advanced algorithms which would lead to more accurate real time tracking accuracy. Also, augmenting the RFID system with other types of sensors, such as cameras, has great potential for achieving even faster and more robust results.

8 Acknowledgments

References:

[1] Alien Technology. Nanoscanner Reader RFID Primer, 2003.

[2] Choset, H., Lynch, K., Hutchinson, S., Kantor, G., Burgard, W., Kavraki, L., and Thrun, S. Principles of Robotic Motion: Theory, Algorithms and Implementations. MIT Press, 2005.

[3] Dellaert, F., Fox, D., Burgard, W., and Thrun, S. Monte Carlo localization for mobile robots. In Proc. of the IEEE International Conference on Robotics and Automation (1999).

[4] El-Zabadani, H., Helal, S., Mann, W., and Schmaltz, M. PerVision: An integrated pervasive computing/computer vision approach to tracking objects in a self-sensing space. In Proc. of the 4th IEEE International Conference on Pervasive Computing and Communicationcs (PerCom) (2006). Submitted.

[5] Kaddoura, Y., King, J., and Helal, S. Cost-precision tradeoffs in unencumbered floor-based indoor location tracking. In Proc. of the ICOST 3rd International Conference on Smart Homes and Health Telematics (2005).

[6] Lavalle, S. M. Planning Algorithms. Cambridge University Press, 2006.

[7] Philipose, M., Fishkin, K. P., Fox, D., Hahnel, D., and Burgard, W. Mapping and localization with RFID technology. Tech. Rep. IRS-TR-03-014, Intel Corporation, 2003.