RFID-based Object Localisation with a Mobile Robot to Assist the Elderly with Mild Cognitive Impairments

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Abstract. Mild Cognitive Impairments (MCI) disrupt the quality of life and reduce the independence of many elderly people at home. Those suffering with MCI can become increasingly forgetful, hence solutions to help them finding lost objects are useful. This paper presents a framework for mobile robots to localise objects in a domestic environment using Radio Frequency Identification (RFID) technology. In particular, it describes the development of a new open-source library for interacting with RFID readers, readily available for the Robot Operating System, and introduces some methods for its application to RFID-based object localisation with a single antenna. The framework adopts occupancy grids to create a probabilistic representations of tag locations in the environment. A robot traversing the environment could then make use of this framework to keep an internal record of where objects were last spotted, and where they are most likely to be at any given point in time. This information could be communicated directly to the elderly person or used by the assistive robot for activity monitoring. Some preliminary results are presented, together with directions for future research.

Keywords. RFID, object localisation, assistive robotics, MCI

1. Introduction

Mild Cognitive Impairments (MCI) affect a significant number of people. MCI is often related to age-associated cognitive decline, which progressively has an increasing effect on the elderly [1]. MCI can lead to diseases such as Alzheimers, which affects approximately 10% of the population at some point in their lives [2]. The result of reduced cognition, particularly in the aged, is huge not only financially, but in terms of the impact it has on those affected and their loved ones. Approximately 40% of these end up in full time care. The effect of an ageing population is likely to make this problem worse in years to come [3]. Research has

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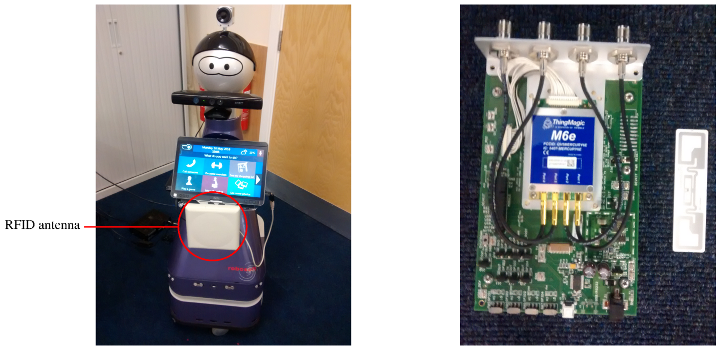

Figure 1. Left: ENRICHME assistive robot for the elderly with MCI, provided with various sensors, including RFID antenna for object localisation. Right: ThingMagic M6e Development Kit including RFID reader and tag sample.

shown that one of the best preventive strategies for those at risk is to maintain an independent life style, although this can prove difficult for those living alone [4].

Assistive robotics looks at how the lives of the elderly can be improved, particularly in maintaining their independence, by providing support with people's daily activities. The main problem with this technology is that it is still very difficult for robots to perceive and make sense of the world around them, which makes solving practical problems, such as finding a set of keys, a challenging task. This paper looks at the use of modern RFID technology as a solution to this problem. The emergence of this technology gives mobile robots an extra dimension with which to sense their surroundings. Combined with the relatively low cost of fitting a home with RFID tags, a mobile assistive robot can be made aware of objects within a domestic environment, and therefore where they were last seen, and where they are most likely to be in the future given past experiences.

The major contributions of this paper are the design and technical description of a new software library[2] for a mobile robot equipped with an RFID reader and a single antenna, which is readily available within the Robot Operating System (ROS) framework, and its application to the problem of indoor object localisation. The research is also part of the European project ENRICHME[3], one of the tasks of which is to provide an assistive robot (see Figure 1) with the capability of finding objects at home for the elderly with MCI.

The remainder of the paper is as follows: Sec. 2 covers relevant work in this research area; Sec. 3 describes the framework and some innovative technical solutions adopted in the proposed software library; Sec. 4 presents preliminary results towards the implementation of RFID-based object localisation; finally, Sec. 5 concludes the paper with insights into current achievements and future work.

[2] LibMercuryRFID – `http://github.com/broughtong/LibMercuryRFID`

[3] ENRICHME: ENabling Robot and assisted living environment for the Independent Care and Health Monitoring of the Elderly – `http://www.enrichme.eu`

2. Related Work

Combining mobile robots with RFID technology is an interesting and well known area of research, although it still poses many challenging problems. The ability to remotely detect small passive tags, which are easily embeddable within an environment, has appealed to many, with uses ranging from self localisation, to object detection and recognition [5,6]. However, the associated difficulty with using RFID in these contexts stems from the noisy data received, particularly as the radio waves emitted have a tendency to reflect in indoor environments, creating multipath signals which can confuse most localisation models [7,8].

The presence or absence of RFID tags in an environment can be used to give mobile robots hints about their environment for self-localisation and environment mapping. However, information about tags is not limited to a simple binary detection, but also provides information about the tag's identity. Each tag has its own alpha-numeric serial number encoded into it, which is modulated into the signal returned to the reader. RFID readers can then be used, for example, in indoor positioning systems [9], by including this technology as part of a sensor fusion model to help robots estimate their location using strategically positioned "landmark" tags at known points [10,5].

One of the most commonly used approaches to determine the proximity of RFID tags is based on the Received Signal Strength Indication (RSSI). Some approaches work by searching for robot locations and orientations with the highest RSSI, and use this to calculate the most likely location of the tag [11]. Other approaches involve predicting how the signal will behave within a given setting, then comparing the prediction to actual tag data [12].

Most of the RFID localisation algorithms tend to use multiple readings, taken from different antennas at several robot locations and orientations. The problem can then be solved as a results of an optimisation process, or using some form of Bayesian estimation (e.g. Adaptive Monte Carlo Localisation) to find the most probable location of the tag [11,12]. Locating objects from a mobile robot with a single antenna, however, is still an open problem.

One of the most sophisticated approaches to locating tags involved the use of the returned signal's phase information to identify very small movements of the tag. This approach looks at how the signal phase is tied to the distance of the tag, and how this could be used with prior knowledge of range to detect very minor changes in distance [13]. The approach has been used for robot localisation, where odometry and other sensor information can be fused to reduce the estimation error, but its application to objects localisation is still mostly unexplored.

3. System Framework

To maximise compatibility with existing robotics systems, a requirement of the proposed framework is that it must be compatible with the Robot Operating System[4] (ROS). This benefits both the current research, in terms of being able to readily access existing robotic infrastructure, and also the general robotics community, which will be able to take advantage of the RFID localisation framework

[4]Robot Operating System – `http://www.ros.org`

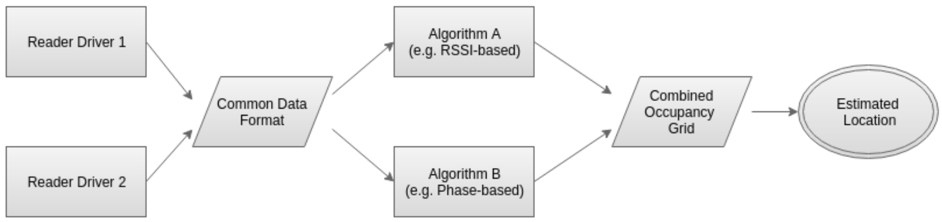

Figure 2. Modular framework design. To work with a new reader, a developer would need only to add a node to output its data in the correct format. Alternative localisation algorithms (e.g. RSSI- or Phase-based) can be added to make use of this data and provide additional information for the occupancy grid, which is then used to determine the most likely position of tags.

and the respective software library for other uses. The systems should also be able to concurrently track multiple tags, and handle multipath errors. The latter are usually caused by reflections in the environment, where several different paths can be taken by the radio waves between the tag and the reader, with performance-degrading effects on the algorithms estimating distance or direction. Finally, the framework should be compatible with the many different use-cases in the robotics community. This means, for example, a software design that is independent from the specific RFID readers, and which allows future updates, improvements or porting across different platforms with ease. The modular design illustrated in Figure 2 addresses these issues.

Algorithmically, the framework consists of ROS nodes listening for the RFID information provided by the reader driver. These nodes then use such information to detect and localise tags in the environment. Based on this, they update a global occupancy grid, i.e. a discrete map representation of the environment. Many of these algorithms could be run in parallel, and the respective results combined using the most appropriate approach. As an example, if algorithm A performed better when the system had just started, it could receive a higher weighting, whereas if algorithm B performed better once it had refined the data over several tag reads, its weighting could be gradually increased. Other approaches such as probabilistic sensor fusion, e.g. Kalman-based [14], could also be adopted, although the topic is currently outside the scope of this paper. From the global occupancy grid, where the output of the framework algorithms is collated, the most likely tag position can be inferred and used for the specific application.

3.1. RFID Library Implementation

The current system has been implemented on a ThingMagic M6e (see Figure 1). The manufacturer, one of the largest producers of RFID readers worldwide, since 2009 does not allow direct serial communication to their devices. By preventing this protocol from being used, they in effect made many of the existing libraries and previous ROS interfaces incompatible with their readers. These packages include the `hrl_rfid` library for ROS, which was deployed on robots such as PR2 [11]. Because `hrl_rfid` communicated via the low level serial protocol, it cannot be used on any new versions of the ThingMagic devices. Instead, a dedicated Application Programming Interface, the Mercury API, has been provided, so that programs using this API should work with any of their readers (from

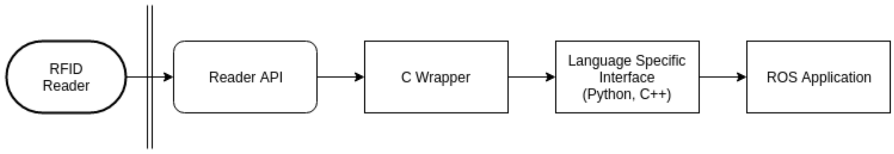

Figure 3. RFID library pipeline. The C wrapper provides a middleware to handle the communication between the RFID reader API and the ROS application interface.

M4 onwards, mandatory from M6), including future models. One of the benefits of using this particular model is the large read range, which has been tested to exceed 6m in a noisy environment. The reader is also able to distinguish between up to 200 tags simulatenously. Each RFID tag has an associated alpha-numeric identification key. This key is then modulated into the return signal, which allows it to be uniquely identified when multiple tags are present. RFID standards also make use of anti-collision algorithms which allow the reader to effectively read multiple tags simulatenously. As such, cluttering an environment with many tags has relatively little impact on the ability of the system to track an individual tag.

Unfortunately the Mercury API is available in C only and it is not directly accessible by many other programming languages. Normally, a workaround is provided by other simple library commands. In Python, for example (which together with C++ is the standard language for ROS), this functionality can be obtained by using modules such as CTypes[5]. Unfortunately, this means that Python would have to create and handle complex C data structures designed for the API, which is infeasible. These problems motivated the development of a more robust and flexible RFID software library, compatible with the above system framework.

The solution adopted in the current software library includes an extra C middleware, which is able to create instances of the reader's API classes without worrying about reimplementing its complex data structures. As a result, a C library was written to abstract the difficulties of interfacing with the API. This greatly simplified the task of managing memory across different languages, focusing only on useful information rather than data structures. The library works on a per iteration basis, so it is not a problem for the same library to communicate with several different readers and antennas on the same machine. Each of these can then track hundreds of tags independently.

A limitation of cross-language communication, like the one here presented, is the lack of protection from code incompatibilities (otherwise provided by a compiler able to check both code bases). As a result, incorrect parameters passed from Python to C, such as wrong number of arguments, could generate critical errors and segmentation faults. To avoid the risk, the library is designed with lightweight language-specific interfaces (see Figure 3). This has the advantage of allowing the library to be available to Python applications (and therefore to ROS), rather than being accessible via complex CTypes. Furthermore, the library includes an additional C++ interface to ease the development of applications in this language. Finally, an important feature of the library is that the drivers for other models of RFID readers can be plugged in and, with an appropriate wrapper, benefit from the same Python/C++ interfaces.

[5] A foreign function library for Python – `http://docs.python.org/2.7/library/ctypes.html`

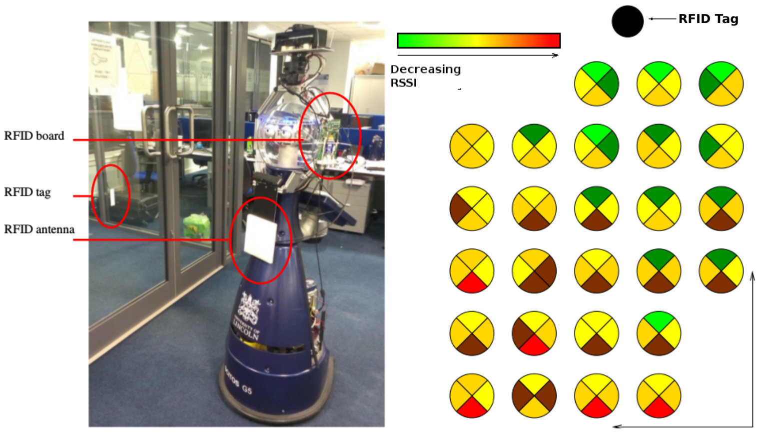

Figure 4. Left: Experimental platform with the RFID reader equipment and the RFID tag. Right: RSSI map with cardinal readings from set positions - tag position is in black, colour slices denote relative RSSI intensities. Readings are taken in a grid with 1m spacing.

4. Experiments

In order to test the functionality of the RFID library and its application to object detection, two mobile robots were alternatively equipped with the ThingMagic M6e RFID reader depicted in Figure 1, and their ability to detect RFID tags in an indoor environment evaluated. To this end, a platform based on the MetraLabs SCITOS-G5 mobile robot (see Figure 4) was initially used. The robot was equipped with a precise self-localisation system based on an on-board laser rangefinder and an Adaptive Monte Carlo Localisation software [15], which provided position and orientation with 5cm / 5° accuracy.

In the first experiment, the dependence of the RSSI response on the direction of the RFID tag (with respect to the robot) was measured. In the second one, a probabilistic estimate of the RFID tag position was obtained by first creating a coarse model of the antenna's radiation pattern, and then using the latter in a Bayesian filtering scheme to map the tag's position on a uniformly-spaced grid while the robot rotates. Finally, an experiment with the Robosoft KOMPAÏ platform (see Figure 1), having hardware and software configurations similar to the previous one, was performed to simulate a simple object detection scenario.

4.1. Cardinal Points

In this experiment, an initial data set was created to analyse how the RSSI of a single tag varies while the robot moves around the environment. and take RSSI measurements. RSSI combined with the robot's position and orientation was used to establish how the signal varied around a real environment.

In order to do that, the robot was moved in a two-dimensional grid of equally spaced navigation points; at each point, a series of readings was taken for each cardinal direction (i.e. North, East, South, West). The median values of these readings were then used to create the RSSI map on the right part of Figure 4, where each circle represents one of the navigation points, and the four colour slices within it represent the signal strength in the respective cardinal directions.

As expected, the results of this experiment confirmed that most of the signal strength concentrated in directions facing the tag, and quickly dropped as the robot's orientation moved away from the tag's bearing.

4.2. Grid-based Position Estimation

In order to implement the following object localisation method, a sensor model for the antenna needs to be created. This sensor model is the basis from which tag position is derived, so its accuracy directly influences that of the final results. Ideally, such sensor model should contain the unique propagation distortions caused by the robot and the rest of the environment interfering with the RFID signal. Any change to the layout of the robot or the state of the environment can influence the signal propagation and negatively affect the estimation process.

For the current experiment, therefore, an initial approximation of the antenna's radiation pattern, provided by the manufacturer, was refined by using real data collected with the RFID reader. This was done by spinning the robot on the spot, with a tag at a fixed distance from the centre of rotation. As the robot rotated, the RSSI values were recorded together with the robot's actual orientation (from its self-localisation). The approach was sufficient to yield a coarse approximation of the sensor model, which was then used to implement the following probabilistic occupancy grid. The above sensor model was used to determine the likelihood of a particular RSSI reading, given that the position of the tag relative to the robot is known. This allows the implementation of a simple Bayesian update to compute the probability of the tag being at a particular location whenever a new RSSI reading is available. The approach adopted next is analogous to the practice of building occupancy grid models from noisy sensors in mobile robotics [16,17]. A uniform, 1000×1000 grid was created, with a 8mm resolution, representing the probability of the tag's location in the robot environment. Each cell contained a value that indicates the probability of the tag being at that particular cell location. Whenever a reading was received, the grid's cells were updated using the aforementioned Bayesian approach, which allowed for continuous integration of the sensor readings during the robot's movement.

To test the approach, the robot was rotated on a set location while continuously gathering new RSSI readings. The robot localisation system provided a precise position estimate in the global reference frame. The grid-based position estimation of the tag, in the same global reference frame, was then refined during the rotation.

Figure 5 illustrates the evolution of the tag's likely position as the robot rotates. The upper-left picture of Figure 5 shows the grid after the 360 degrees: note that the robot is oriented towards the bottom left of the grid and the most probable locations of the tag's locations lie on an curve that correspond approximately to an isoline of the sensor model. This is expected, as a single measurement cannot provide the position of the tag, but it can at least constrain the tag's possible location around an isoline that corresponds to the strength of the RSSI reading. However, integration of the RSSI measurements during the robot rotation into the probabilistic grid results in an improved estimate of the tag's location. The figure indeed shows how the probability distribution of the tag's position evolves as more and more measurements are integrated in the grid – the individual images

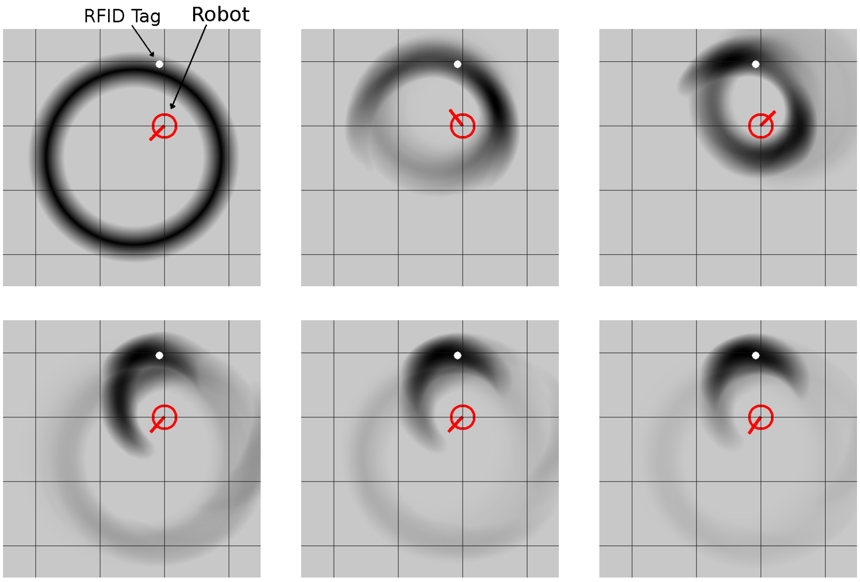

Figure 5. Probability distribution of the tag's estimated location during the grid experiment. Robot's position and orientation are in red; tag's real location is the white mark located almost directly above the robot. The black color corresponds to a higher likelihood of the tag being on the respective location. The top-left image reflects the situation after the first RSSI reading, and the following images represent the probabilistic update after the robot rotated by 90, 180, 360, 720, 1080 and 1440 degrees.

corresponds to the grid's states after the robot rotated 90, 180, 360, 720, 1080 and 1440 degrees respectively. After two rotations, the tag's position estimate is already good enough for many practical applications of the system.

4.3. Object Detection Scenario

A final test was performed by simulating a typical object detection tasks, with the KOMPAÏ robot moving in a domestic-like environment and identifying several tagged objects. These include a mug, a stapler, a remote control, a kitchen table and a coffee table. The approach used in this case was simpler than the one described before: the robot simply counted how many times every tag was detected within a specific interval of time. If the detections were more than an empirically determined threshold (50 in this case), then the system would consider the respective object as detected somewhere nearby the robot.

As illustrated in Figure 6, the robot was successful in locating the tagged objects. The readings obtained during this experiment are also consistent with the simpler one-tag scenario in Sec 4.1. A video of the whole test is also available online[6]. Although still relatively simple, the results validate the approach and show that the proposed RFID system is able to deliver reliable information about objects position.

[6]Object detection video – `http://goo.gl/QSNWk0`

Figure 6. Object detection. The three tagged objects (kitchen table, remote control, stapler) are shown on the top-left. The remaining figures show the moment in which the objects were correctly detected by the robot navigating in a simulated domestic environment. The name, RSSI and Phase of the objects are printed on the laptop screen at the bottom of each figure.

5. Conclusion

This paper presented the design and implementation of a library that integrates several software components, providing a seamless interface for the task of RFID localisation. The successful application of the library to detect RFID tags was demonstrated using an experimental set-up mounted on a mobile robot. Developers could benefit from using this library with its ease of access to RFID readers from various programming environments in order to manipulate and process RFID data. A ROS publisher is also included, allowing this information to be combined with other robotic sensor data for various sensor-fusion based applications. The experiments demonstrated the efficacy of the system for performing object localisation with a mobile robot. They showed that the system can potentially be used in real world applications, including domestic robotics scenarios. In terms of real-world potential, the system is not solely limited to the specific context, but could also be used in other scenarios, including those without a mobile robot.

From a technical point of view, the system could be extended further to take into account other approaches for RFID signal processing. These include exploiting techniques such as Minimum Required Transmission Power, which would look at reducing the power of the antenna to the point where a particular tag is only just being detected, and use this to discard locations where estimated drop in RSSI does not match that observed. Another technique involves making use of the signal phase information to enhance the accuracy of the system. Future work will look at whether the limitations of phased-based techniques can be overcome by integrating RSSI information as well. Furthermore, the sensor model used in this work represents only a coarse approximation of the antenna. A refined, higher resolution sensor model will enable more accurate estimations of the tags in the robot's surroundings. This preliminary work is part of a more advanced project, ENRICHME, to assist the elderly at home. One of the key tasks in this project is indeed to develop an RFID-based object localisation system that can help the user finding lost items. These solutions will be eventually validated in real homes of elderly with MCI, and evaluated in terms of technical performance as well as quality of life improvement.

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