RFID-Assisted Mobile Robot System for Mapping and Surveillance of Indoor Environments

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Purpose – Investigates the use of passive RFID technology for environment mapping and surveillance by an autonomous mobile robot.

Methodology – Proposes a fuzzy inference method to localize RFID tags in the environment.

Findings – Demonstrates that RFID technology can be successfully integrated in mobile robot systems to support navigation and provide the robot with mapping and surveillance capabilities.

Originality – Use of fuzzy reasoning to learn the model of the RFID device and localize the tags, enhancing the capability of the system to recognize and monitor the environment.

Abstract

Mobile robots are increasingly being used to provide automated mapping and surveillance systems. A concurrent trend is the growing interest in Radio Frequency Identification (RFID) technology for access control and object tracking, with a wide range of applications. In this paper, we examine whether low-cost, passive RFID tags can be used for mobile security system development. First, we propose a fuzzy inference method to accurately localize RFID tags in a geometric map of the environment, by a mobile robot equipped with an RFID device and a laser rangefinder. Afterwards, we present experiments showing that, using a map augmented with RFID information, the robot is able to navigate in indoor environments and successfully perform inspection tasks.

Paper Type

Research paper

Keywords

RFID, mobile robotics, mapping, surveillance

1. Introduction

In these last years, automated mapping and surveillance systems using mobile robots are being widely investigated. Equipped with sensors, such as cameras, sonar and laser rangefinders, mobile robots are able to gain information useful for constructing a map of the environment; they also provide reliable inspection and monitoring systems for anywhere conventional manned or Closed-Circuit Television (CCTV) surveillance is inefficient, expensive, or even unfeasible. As a result, several worldwide projects have attempted to develop mobile security platforms (Saitoh et al., 1995; Osipov et al. 1996; Everett and Gage, 1999; Birk and Kenn, 2001; Capezio et al., 2005).

For instance, the Mobile Detection Assessment and Response System (MDARS) (Everett and Gage, 1999) provides automated inspection capability in warehouses and storage sites, by simultaneous control of multiple robots, able to identify anomalous situations, such as flooding and fire, detect intruders, and determine the status of inventoried objects using specialized RF transponders. In the RoboGuard project (Birk and Kenn, 2001), a semi-autonomous mobile security device is proposed that uses a behaviour-oriented architecture for navigation, while sending video streams to human watchguards. The Airport Night Surveillance Expert Robot (ANSER) (Capezio et al., 2005) consists of an Unmanned Ground Vehicle (UGV) using non-differential GPS unit for night patrols in civilian airports and similar wide areas, interacting with a fixed supervision station under control of a human operator.

A concurrent trend in the domain of object identification and tracking for inspection purposes is the growing interest in the use of Radio Frequency Identification (RFID) technology. An RFID device typically consists of radio frequency (RF) tags, a reader with one or more antennas, and software to process the tag readings (Finkenzeller, 2003). The reader interrogates the tags, receiving their ID code and other information stored in their memory. Tags can be either passive or active. Passive tags are activated by the electromagnetic field generated by the RFID antenna. Active tags powered by an on-board battery may also be used, but are expensive and have limited operational lifetime.

Applications of RFID include inventory management, industry automation, ID badges and access control, equipment and personnel tracking. Compared to conventional identification systems, such as barcodes, RFID tags offer several

Figure 1 PeopleBot, equipped with a laser range finder and an RFID system.

advantages, since they do not require direct line-of-sight and multiple tags can be detected simultaneously.

Recently, RFID technology has been introduced in the field of mobile robotics. Attached to walls, machines, or other specific places in the environment, RFID tags enable the robot to detect items, obtain information about its position, and even get instructions to reach goals. Tags can store information about the objects they are attached to. Alternatively, the returned tag ID can be employed to recall information from an external database. Although infrastructure preparations are needed, these are simple, and RFID tags can be placed almost anywhere a landmark is required. Hence, these devices potentially constitute an effective support to navigation of autonomous vehicles (Kubitz et al., 1997; Tsukiyama, 2005).

This work investigates the use of passive RFID technology for mapping and surveillance of indoor environments by a mobile robot. The robotic platform employed to carry out this research is shown in Figure 1. It consists of a PeopleBot mobile robot, equipped with a laser range finder, two RF antennas, and an RF reader. The antennas are mounted on the top of the robot with an angular aperture with respect to each other of about 60°.

A model of the RFID system is, first, learnt, which describes the detection range by the robot as its distance and orientation relative to the tags vary, using fuzzy inference. Then, based on this model, a fuzzy logic frame is developed that allows position estimation of tags deployed in the environment.

Tag locations are referred to a map of the environment, previously built with laser data, using a Simultaneous Localization and Mapping (SLAM) algorithm (Gutmann and konolige, 1999). Once the map augmented with RFID tags has been constructed, the robot can use it to keep track of its pose in the environment, plan its trajectory toward given goals, and inspect the surroundings searching for either new or missing tags.

Experimental results from tests performed in the ISSIA-CNR Mobile Robotics Laboratory of Bari, Italy, suggest that the proposed approach is accurate in localizing RFID tags and can be effectively integrated with autonomous navigation and mapping systems for inspection tasks.

The remainder of the paper is organized as follows. After discussing related work in

Section 2, the tag localization method is described in Section 3. Section 4 illustrates the RFID-assisted mobile robot navigation and the RFID-based environment surveillance approach. Experimental evidences are provided in Section 5. Conclusions are drawn in Section 6.

2. Related Work

Recent advances in the field of radio frequency technology have contributed to a large diffusion of RFID-based systems. Currently, low-cost, passive tags that can be detected in the range of several metres are commercially available. That makes RFID suitable for mobile robotics tasks, such as localization and mapping.

There are a few works in literature that investigate the use of passive RFID in mobile robotics. In (Kubitz et al., 1997), radio frequency identification tags are employed as artificial landmarks for mobile robot navigation, based on topological map. In (Tsukiyama, 2005), the robot follows paths using ultrasonic rangefinders until an RFID tag is found and then executes the next movement according to a topological map. In (Kulyukin et al., 2004), an RFID-based robotic system for visually impaired assistance is developed. It uses passive RFID tags manually attached to objects in an indoor environment to trigger local navigation behaviours of a mobile robot.

Although effective in supporting mobile robot navigation, most of existing approaches either assume the location of the tags to be known a priori or require the tags to be installed to form specific patterns. This is reasonable in some industrial applications, while in office or home environments it is generally difficult to measure tag positions, and arrangement of multiple tags could turn into a difficult task, requiring complex infrastructure preparations. In addition, tagged objects could be displaced, causing the necessity to recalculate their position. Hence, methods for localizing automatically the tags in the environment are generally desirable.

However, localizing passive tags is not straightforward. Due to low cost and low power constraints, RFID systems are usually sensitive to interference and reflections from other objects. The position of the tag relative to the receivers also influences the result of the detection process, since the absorbed energy varies accordingly and may become too low to power the chip inside the tag, causing the tag to not respond. These undesirable effects produce a number of false negative and false positive readings that lead to an incorrect belief about the tag location and, eventually, could compromise the performance of the overall system (Brusey et. al., 2003; Hähnel et al., 2004).

Solutions to the problem of passive tag localization based on probabilistic frameworks have been proposed in (Hähnel et al., 2004; Alippi et al., 2006; Liu et al., 2006; Jia et al., 2006). In (Hähnel et al., 2004), a mobile robot equipped with RFID sensors and a laser range finder is used to localize passive tags based on a Bayesian scheme. RFID technology and laser range scanner are also combined for robot global localization. In (Alippi et al., 2006), a Bayesian approach is developed, where the tag localization algorithm is formalized as a non-linear stochastic inversion problem. Several readers, equipped with rotating antennas, take observations. The reading units are connected in a local network with a server, which gathers the data and executes the localization task. In (Liu et al., 2006), two RFID tag positioning algorithms are developed, namely an online approach and an offline approach. The offline method is based on a criterion equivalent to the one proposed in (Hähnel et al., 2004). The online algorithm defines a high probability region of the antenna detection range, instead of describing the probability at each location, in order to achieve computational efficiency. The tag position is estimated by successive intersections of the detection ranges in multiple readings. The method is implemented on a mobile platform named Ferret, which is equipped with an RFID device and a camera. The location of tagged objects is displayed on the video captured by the camera. In (Ja et al., 2006), RFID tags are used for obstacle detection and avoidance. The Bayes rule is applied to estimate tag positions. Tags are also used as landmarks for robot localization based on visual input from a stereovision device.

In (Kleiner et al., 2006), an RFID-based SLAM approach is described. It uses the method by Lu and Milios (Lu and Milios, 1997) for calculating globally consistent maps from detected tags, which are automatically distributed in the environment. In (Wilson et al., 2007), a tag count procedure is proposed that allows to estimate the distance of a passive tag relative to the reader by matching tag count percentages under various signal attenuations to a database of tag count percentages, attenuation levels, and distances from the reader.

This work describes an alternative approach to tag localization and RFID-assisted navigation. The general use of the method is for mapping and surveillance of indoor environments. As in (Hähnel et al., 2004), we employ a mobile robot equipped with an RFID system and a laser range finder, and refer to a model of the antenna reading range for passive tag location estimate. Our approach, however, is different in that it uses fuzzy reasoning for both learning a model of the RFID system and locating the tags.

Tag positions are referred to a map of the environment, constructed using laser data. Tags can be placed anywhere in the environment. No specific tag arrangement is needed. The only assumption is that the robot knows its position and orientation in the map using some global localization method and is able to detect each tag from multiple poses.

Fuzzy logic is useful in situations that are not suited to be modelled through mathematical approaches. We show that fuzzy logic is a proper framework to operate under uncertainty in RFID systems.

We also demonstrate that a mobile robot can effectively use the map augmented with RFID tags to perform navigation tasks. During navigation, displaced or missing tags can be easily identified. That makes the proposed approach particularly suitable for integration with mobile robotic surveillance systems.

3. Mapping passive RFID Tags

Passive RFID tags are smaller and less expensive than active devices. They provide nearly unlimited operational lifetime, and can be, therefore, easily embedded in the environment and used as landmarks in mobile robotics applications (Tsukiyama, 2005). However, passive tags are not able to directly provide their location relative to the reader or a distance measure. Only positive or negative responses are generated, depending on the presence or absence of a tag in the antenna detection field.

Nevertheless, positive readings can be used to estimate the tag position. A positive response reduces, in fact, the potential locations of the tag to those that lie in the reading region of the device. A further improvement in tag position estimate can be achieved by considering that, whenever a tag is present in the reading range, the reader will detect it with a certain probability. Specifically, as will be shown in the next section, a tag closer to the centroid of the read range is most likely to be detected than a tag located at the boundary. In summary, each positive reading provides a region that is likely to contain the tag and also allows associating a probability to each point of the region (Liu et al., 2006).

Based on these considerations, we developed a fuzzy inference system for mapping RFID tags in the environment with a mobile robot. Our approach consists of two main steps: first, the reading range of the RFID device is determined, based on experimental data and a fuzzy antenna model is generated; then, a fuzzy logic inference system is

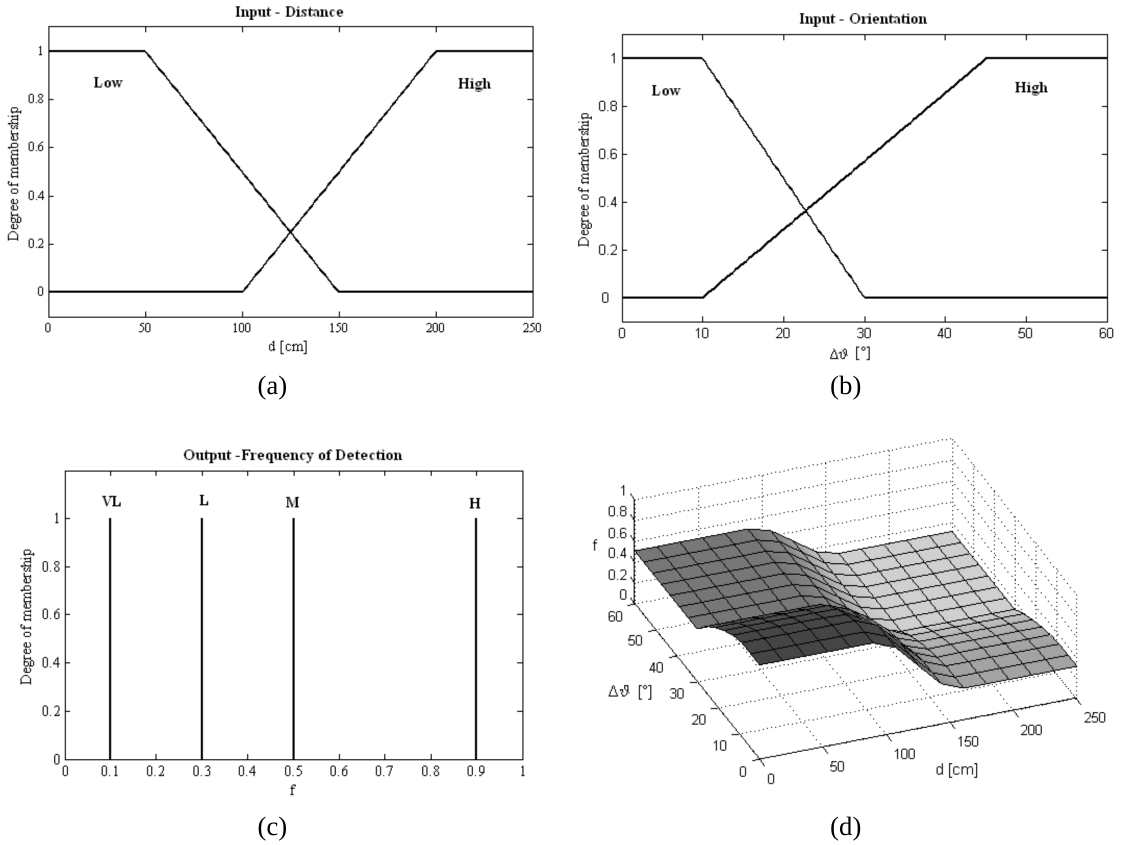


Figure 2 Fuzzy model of the RFID antenna: a)-b) membership functions for input variables, i.e. distance and orientation of the tag relative to the antenna; c) levels for the output variable, i.e. frequency of detection; d) input-output surface, with darker grey denoting higher frequency of detection.

proposed to estimate the position of each tag in the environment. Both steps are described in detail in the rest of this section.

3.1. Learning a fuzzy antenna model

A detection statistics was generated using a procedure similar to the one proposed in (Hähnel et al., 2004). Specifically, we rotated the robot in front of a tag, at different distances ranging from 0.5m to 2.5m, at a fixed angular resolution of 3°, and we counted, for every pose, the frequency of detections. It was found that the coverage map of each antenna can be conservatively approximated by a sector with a radius of 2.5m and an angular aperture of about 120°.

Rule #	Input 1: Distance (d)	Input 2: Orientation (Δq)	Output: Frequ. of Det. (f)
1	High	High	Very Low
2	High	Low	Low
3	Low	High	Medium
4	Low	Low	High

Table 1 Fuzzy rules for modelling the RFID reading range.

Based on these results, a fuzzy logic model of the RFID detection range was constructed. This model consists of a zero-order Sugeno's fuzzy inference system (Sugeno and Yasukawa, 1993) with two inputs and one output. The inputs are the distance d and the orientation Δq of the tag relative to the antenna. The orientation Δq is measured with respect to the direction normal to the antenna. The output is the expected frequency of detection f, which also expresses the likelihood that the antenna will detect a tag located at a certain position relative to itself.

The membership functions for input variables are shown in Figure 2.a and 2.b. Two functions are defined for each input, labeled *Low* and *High*, respectively. The output, instead, is shown in Figure 2.c. It consists of four constant values, labeled *Very Low* (VL), *Low* (L), *Medium* (M), and *High* (H). The parameters for such functions were tuned based on experimental data. The *if-then* rules for fuzzy inference are reported in Table 1. The output f is given by the weighted average of all rule outputs and is represented as a surface in Figure 2.d.

3.2. Localizing RFID Tags

In order to localize RFID tags in a geometric map of the environment, we propose a method that integrates RFID information with laser data. First, the robot is guided throughout the environment, where several tags are placed. In this phase, both laser and

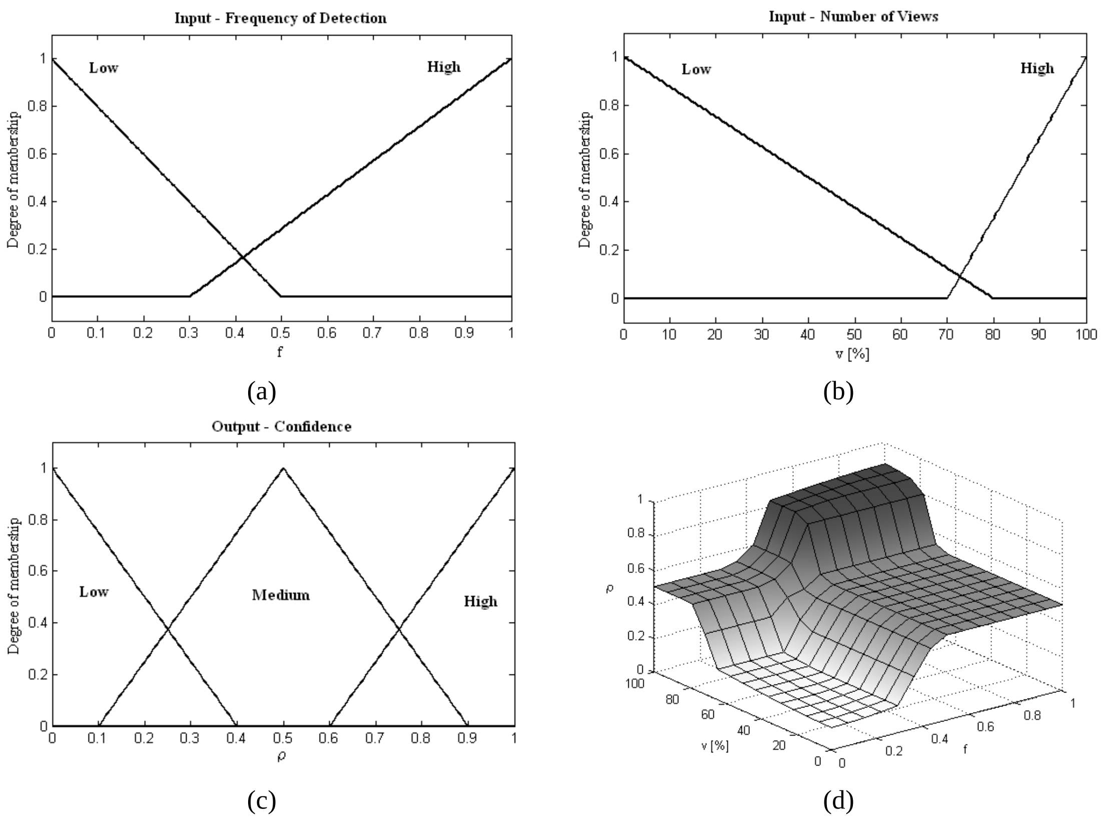


Figure 3 Fuzzy inference system for tag localization: a)-b) membership functions for input variables, i.e. frequency of detection and number of views; c) membership functions for the output variable, i.e. confidence; d) representation of the input-output surface, with darker grey denoting higher confidence level.

Rule #	Input 1: Frequ. of Det. (f)	Input 2: Num. of Views (v)	Output: Confidence (ρ)
1	High	High	High
2	High	Low	Medium
3	Low	High	Medium
4	Low	Low	Low

Table 2 Fuzzy logic rules for tag localization.

RFID data are stored. Upon completion of data storage, a SLAM algorithm is used to learn a geometric map of the environment and estimate the path of the robot. Successively, tag localization is started.

The main idea underlying this process is that of estimating the pose of each tag as the most likely location among a set of potential locations. To represent the belief about the position of a tag, we consider a set of M points P_j, for $j = 1, 2,\ldots, M$, uniformly distributed in a circular area around the current robot pose. This set is generated as soon as the tag is detected for the first time.

A confidence value ρ_j is then assigned to each point P_j, expressing the likelihood that P_j corresponds to the actual tag location. Our hypothesis in estimating the confidence level for each position is that the higher is the frequency of detection f_j associated to the point according to the fuzzy antenna model and the higher is the percentage number of robot poses v_j from which the point is detected within the antenna coverage map, the higher is the likelihood for the point of being the actual tag position.

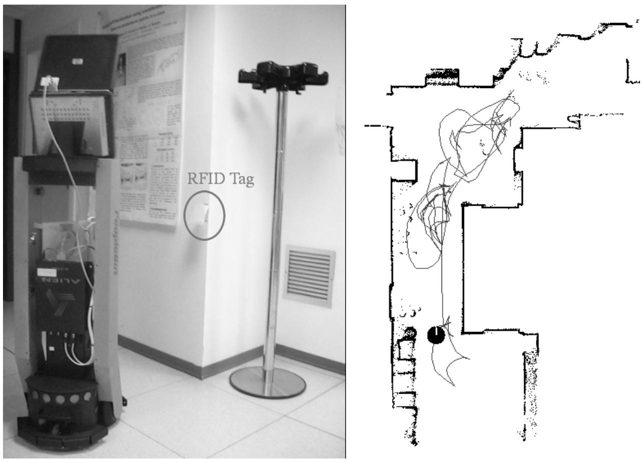
In order to express this hypothesis, we adopt fuzzy logic. The inputs to the fuzzy inference system are f_j and v_j. The output is the confidence ρ_j associated to the point P_j. The triangular membership functions are shown in Figure 3.a, 3.b, and 3.c. A plot of the output surface is illustrated in Figure 3.d. The *if–then* rules for fuzzy inference are reported in Table 2.

Whenever a positive reading is taken, each point is assigned an average confidence level, which is computed as the mean value of the confidence levels calculated for the same point in all the previous steps. Only the points whose average confidence is greater than a threshold are retained. As will be shown in Section 5, this process allows reducing progressively the possible tag locations, thus refining the tag position estimate.

It is worth noticing that tag localization must be performed offline only if no map of the environment is already available. Instead, once this map is learnt, online processing may be carried out in order to localize new or displaced tags.

4. RFID-Assisted Robot Navigation and Environment Monitoring

The robot can use the map augmented with RFID information, for navigation and environment monitoring. Navigation tasks mainly include localization and path



(a) (b)

Figure 4 Data acquisition: a) snapshot of the robot approaching a tag; b) portion of the map generated by SLAM. The light grey line represents the robot trajectory. The robot is shown as a black circle.

planning. Specifically, in order to localize the vehicle in the mapped environment the Monte Carlo localization method (Dellaert et al., 1999) using laser data is employed. RFID information can also be integrated for approximate robot location estimate or to solve ambiguities and reduce the number of samples required for global localization (Hähnel, 2004). The path planning algorithm, instead, uses a grid-based approach to plan the shortest and safest path for the robot to navigate from the current location to a given goal. Local re-planning is also performed to avoid unmapped obstacles, detected by laser and sonar sensors during navigation.

In order to monitor the environment, the robot follows a sequence of goal stations, each one fixed in the vicinity of a tag. Three inspection tasks are implemented:

- verifying the presence of mapped tags: each time the robot reaches a goal station, if the expected tag is not found an alarm signal is produced;
- identifying new tags: if, while navigating throughout the environment, the robot detects an unmapped tag, then either an alarm signal is sent or the tag localization procedure is activated;
- detecting displaced tags: if, while navigating throughout the environment, the robot detects a known tag whose location has changed, i.e. the object holding the tag has been displaced, either an alarm signal is produced or the tag localization procedure is activated.

5. Experimental Results

The described approach was implemented and tested on a PeopleBot mobile robot by ActivMedia Robotics, equipped with a SICK LMS 200 laser range finder and an Alien Technology’s ALR-8780 reader with two external circularly polarized ALR 8610-C antennas (see Figure 1). The laser scanner is mounted on the robot at a height of about 35cm. It is able to sense objects at a distance of up to 80m with a resolution of

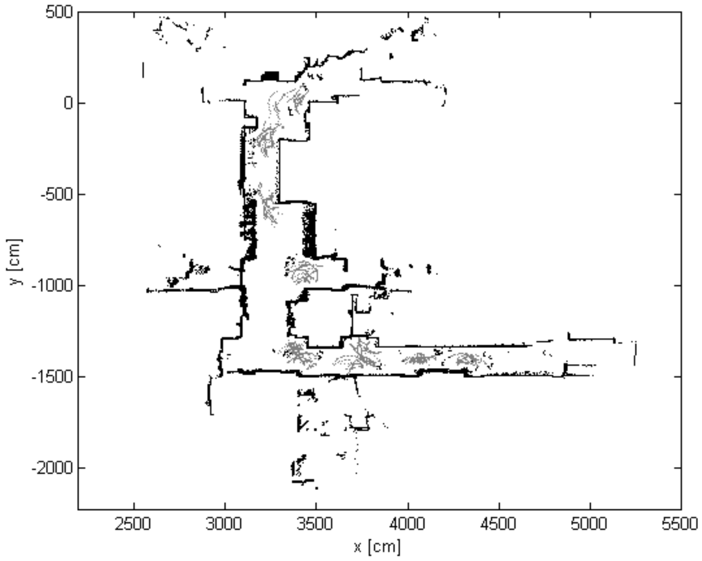


Figure 5 Result of SLAM: map of the environment, with superimposed the robot positions (light grey markers) from which RFID tags were detected.

0.5°. The RFID system works at 866MHz. Passive Alien's Class 1 128-bit NanoBlock tags are employed. They consist of rectangular targets with long side of about 10cm, containing, internally, an antenna for communication with the reader, and a microchip, which stores the ID code. Communication between the reader and the tags is performed through backscatter modulation. The platform is also equipped with front and rear sonar rings, which are used for obstacle avoidance tasks.

Two processing units are employed: the robot embedded PC and an additional laptop, i.e. a Pentium M @ 1.6 Ghz mounted on board the robot for RFID data acquisition and storage, and application control. The connection between the laptop and the RFID reader is via RS232 serial cable.

ARIA and ARNL C++ libraries by ActivMedia Robotics were used for communication between sensors and the robot controller, for laser mapping, and for the development of the navigation modules. The MobileEyes software by ActivMedia Robotics was employed as a graphical interface. The libraries provided by Alien Technology were used to develop a C++ code for RFID data acquisition and storage.

Experiments were carried out in the ISSIA-CNR Mobile Robotics Laboratory, Bari, Italy. Ten tags were manually placed in the environment, distributed along an L-shaped corridor with a total length of about 40m and an average width of about 2m.

The robot was guided on a tour of the environment, acquiring laser and RFID data. Then, both the geometric map of the environment and the robot trajectory were reconstructed using the laser-based SLAM routine. Figure 4.a shows a picture of the robot approaching a tag during the acquisition phase. Figure 4.b displays, instead, a portion of the map and of the robot trajectory reconstructed by SLAM. The entire map is reported in Figure 5. This figure also shows, as light grey markers, the robot positions from which the RFID tags were detected.

Note that information concerning different tags can always be kept separated since a tag is univocally identified by its own code. Hence, at the end of the acquisition phase, for each tag, a set of robot poses is available to be used for tag location estimate.

In the rest of this section, first, we show the result of tag localization, then, we present an application of the constructed map as a support to mobile robot navigation for environment inspection.

5.1. Tag localization

The robot poses estimated by SLAM were employed to map all the tags distributed in the environment, using the described method. Measurements of the tag positions were also performed with a theodolite station. These measurements were regarded as the ground truth in our experiments.

Figure 6 shows the localization procedure for one of the tags. Whenever the tag is detected for the first time, a set of 1500 potential locations is generated as a uniform

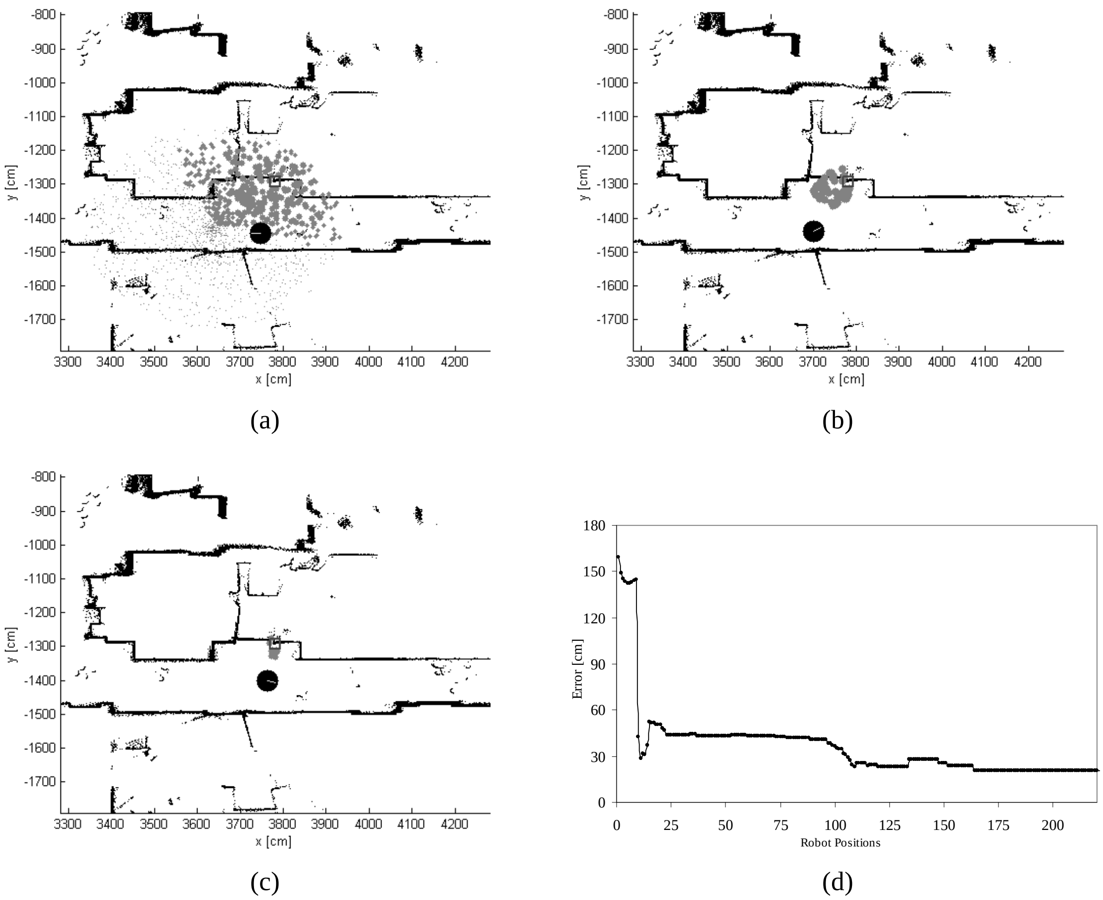


Figure 6 Tag localization after (a) 10, (b) 50, and (c) 200 iterations; (d) evolution of the tag localization error. In (a), (b), (c): a black circle represents the robot pose in the map; the actual tag position is indicated by a dark grey square; potential tag locations are shown as light grey circles whose width is proportional to the average confidence levels.

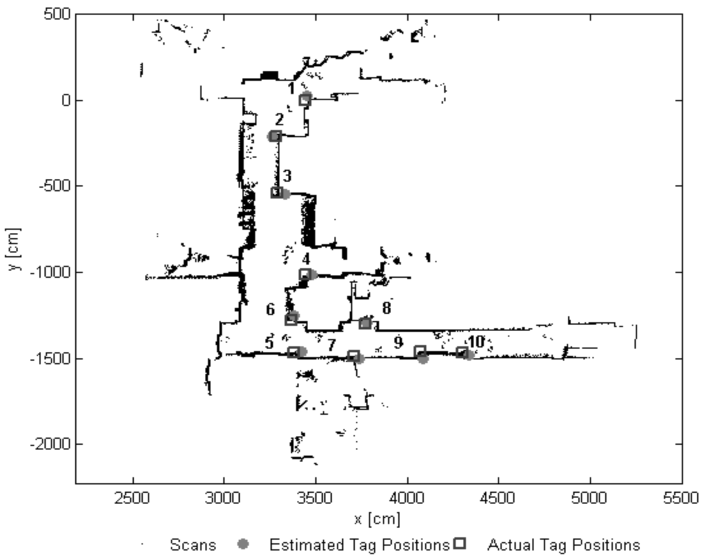


Figure 7 Map of the environment with estimated and actual tag locations.

distribution of points around the current robot position. As new observations occur, only those points whose confidence is greater than a threshold are retained. Then, at each step, the tag position is estimated as the weighted average of the residual points. Note that at least ten robot poses are considered for the computation of average confidence levels before points are discarded for the first time.

Figure 6.a shows the sample set after 10 detections, while Figure 6.b and Figure 6.c display the distribution of the possible locations after 50 and 200 detections, respectively, showing how the belief converges toward the actual tag position. The corresponding evolution of the localization error is illustrated in Figure 6.d. It can be observed that, after 200 detections, the error is of 20.6cm.

Similar results were obtained for all the tags. Figure 7 illustrates the map of the environment with the tag locations estimated using, for each tag, an initial set of 1500 points and 200 observations. Actual tag positions obtained from theodolite measurements are also displayed. In order to evaluate the accuracy of the method, for every tag k with $k= 1, 2,\dots, N$ ($N=10$), the algorithm was run several times; then, the average absolute error E_k for the k-th tag was computed as

$$E_k = \frac{1}{n}\sum_{i=1}^{n}\left\| p_a - p_e^i \right\| \qquad (1)$$

where n is the number of runs, while $p_a=[x_a, y_a]$ and $p_e^i=[x_e^i, y_e^i]$ denote, respectively, the actual tag position and the position of the tag estimated at the i-th run. In Figure 8, the average errors E_k are reported for all the tags along with the indication of the statistical spread. It can be

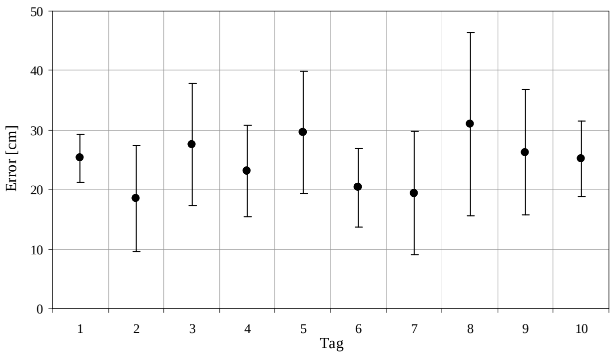


Figure 8 Tag localization errors: mean values with statistical spreads.

observed that the average error was always within 35cm and for the worst-case measurement it was less than 50cm.

These results suggest that the proposed method is accurate in localizing tags deployed at generic locations of an indoor environment.

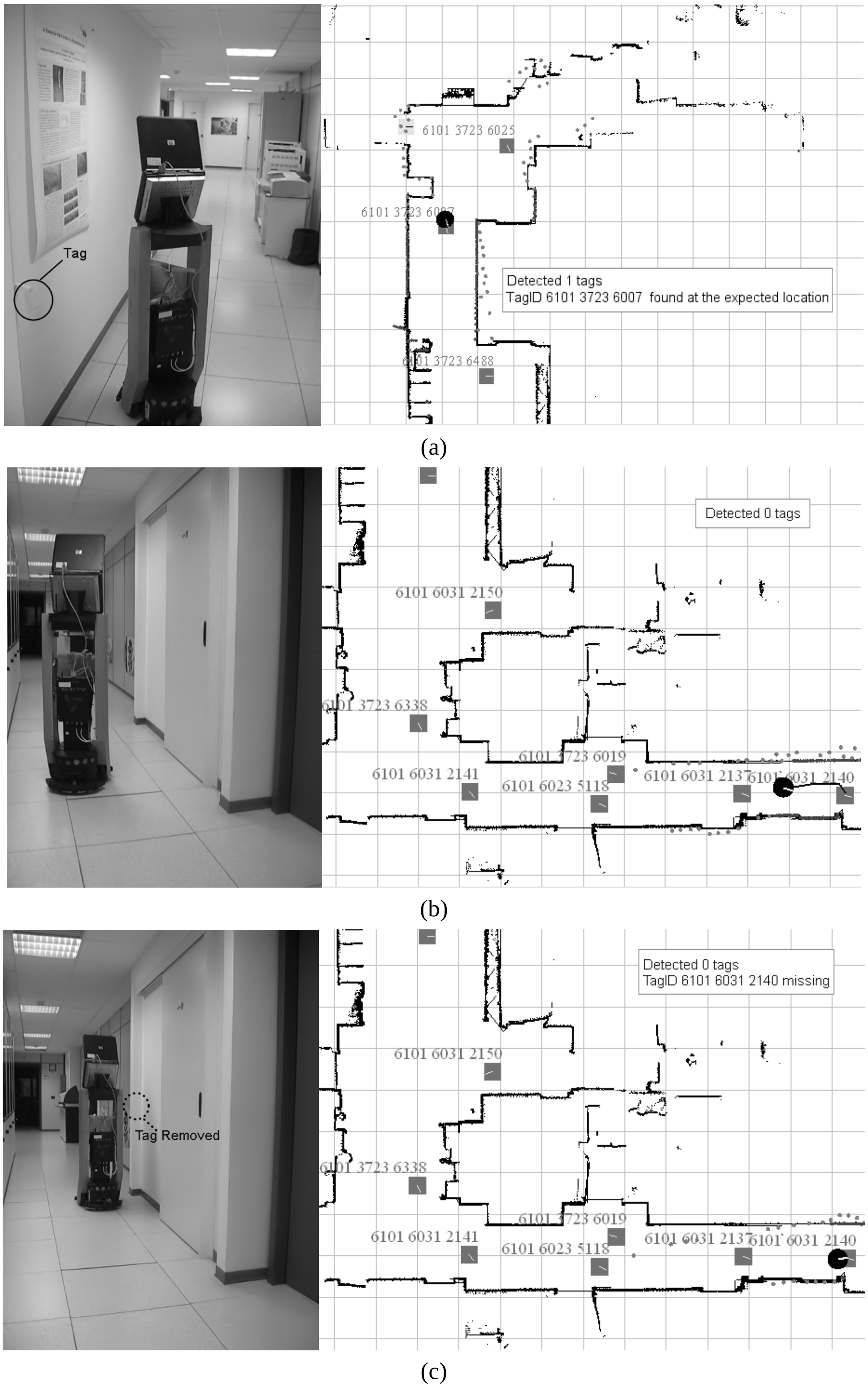


Figure 9 RFID-based environment monitoring: a) the robot detecting a tag; b) the robot following the planned trajectory toward a goal; c) the robot warning of a missing tag removed from its original location.

5.2. RFID-assisted navigation and environment monitoring

The map augmented with RFID information can be used to support robot navigation and environment surveillance tasks. For instance, based on RFID, a mobile robot can acquire information about its pose in the environment. Vice versa, known its pose from other sensors, it can use RFID information for inspection purposes.

Here, we describe an experiment in which the robot was programmed to move in the environment using the constructed map, in order to perform a typical surveillance task, based on the concept of goal points.

A goal point is a location of the environment from which the robot observes the scene. Goal points were fixed in proximity of the tags and the robot was programmed to reach each goal and verify the presence or absence of the expected tag.

Figure 9 shows different scenarios encountered during the experimental session. The pictures on the left portray the robot in the test environment. On the right, the output of the navigation module is shown with overlaid the output of the RFID module. Small squares are used to represent the goal stations in the map. ID codes of the tags located nearby the stations are also reported. Specifically, in Figure 9.a, the robot is shown while approaching a goal and detecting the expected tag. In Figure 9.b, the robot is moving from one station to the next one. A black line indicates the planned path. Finally, in Figure 9.c, the system properly warns that a tag has been removed from its original location.

6. Conclusion

In this paper, the use of passive RFID technology for environment mapping and surveillance by an autonomous mobile robot was investigated.

First, a fuzzy model of the RFID reading range was constructed, based on experimental evidences. Then, a fuzzy logic inference system was introduced that allows a mobile robot, equipped with an RFID device and a laser rangefinder, to localize tags in a geometric map of the environment.

The method requires simple infrastructure preparations, as no specific tag arrangement is needed. The only assumption is that the robot knows its position and orientation in the map and is able to detect each tag from multiple poses.

Furthermore, it was shown how RFID tags can be used to identify interesting regions in the map in order to support mobile robot navigation and environment inspection tasks.

An experimental session was carried out using a PeopleBot mobile robot augmented with two RFID antennas and a reader. Ten tags were manually installed along an L-shaped a corridor with total length of about 40m and average width of about 2m, and were localized with the proposed tag localization method. The system was able to accurately localize all the tags with an average error less than 35cm.

Finally, an experiment of environment inspection was realized using the constructed map. It was shown that the integration of the proposed methods in multisensor robotic platforms can effectively contribute to the development of autonomous mobile security agents.

References

Alippi, C., Cogliati, D., and Vanini, G., (2006), "A statistical Approach to Localize Passive RFIDs," IEEE International Symposium on Circuits and Systems, Island of Kos, Greece.

Birk, A. and Kenn, H., (2001), "An Industrial Application of Behavior-Oriented Robotics," IEEE International Conference on Robotics and Automation, Vol. 1, pp. 749 – 754.

Brusey, J., Floerkemeier, C., Harrison, M., and Fletcher, M., (2003), "Reasoning about Uncertainty in Location Identification with RFID," Proceedings of IJCAI-03 Workshop on Reasoning with Uncertainty in Robotics, Acapulco, Mexico.

Capezio, F., Sgorbissa, A., and Zaccaria, R., (2005), "GPS-Based Localization for a Surveillance UGV in Outdoor Areas", Proceedings of the Fifth International Workshop on Robot Motion and Control (RoMoCo'05), Poland, pp. 157- 162.

Dellaert, F., Fox, D., Burgard, W., and Thrun, S., (1999), "Monte Carlo Localization for Mobile Robots", IEEE International Conference on Robotics and Automation, Detroit, Michigan, USA.

Everett, H.R. and Gage, D.W., (1999), "From Laboratory to Warehouse: Security Robots Meet the Real World," *International Journal of Robotics Research*, *Special Issue on Field and Service Robotics*, Vol. 18, No. 7, pp 760-768.

Finkenzeller, K., (2003), *RFID Handbook: Fundamentals and Applications in Contactless Smart Cards and Identification,* Second Edition, Wiley.

Gutmann, J.S. and Konolige, K., (1999), “Incremental mapping of large cyclic environments,” in IEEE International Symposium on Computational Intelligence in Robotics and Automation (CIRA-99), Monterey, CA.

Hähnel, D., Burgard, W., Fox, D., Fishkin, K., and Philipose, M., (2004), “Mapping and Localization with RFID Technology,” Proceedings of the IEEE International Conference on Robotics and Automation, New Orleans, LA, USA.

Jia, S., Shang, E., Abe, T., and Takase, K., (2006), “Localization of Mobile Robot with RFID Technology and Stereo Vision,” IEEE International Conference on Mechatronics and Automation, pp. 508-513.

Kleiner, A., Prediger, J., and Nebel, B., (2006), “RFID Technology-based Exploration and SLAM for Search and Rescue,” Proceedings of the IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS), Beijing, China.

Kubitz, O., Berger, M., Perlick, M., and Dumoulin, R., (1997), “Application of Radio Frequency Identification Devices to Support Navigation of Autonomous Mobile Robots,” IEEE 47th Vehicular Technology Conference, Phoenix, Arizona, USA, pp. 126-130.

Kulyukin, V., Gharpure, C., Nicholson, J., and Pavithran, S., (2004), “RFID in Robot-Assisted Indoor Navigation for the Visually Impaired,” IEEE/RSJ International Conference on Intelligent Robots and Systems 2004, Sendai, Japan, pp. 1979-1984.

Liu, X., Corner, M.D., and Shenoy, P., (2006), “Ferret: RFID Localization for Pervasive Multimedia,” 8th International Conference on Ubiquitous Computing, Orange County, CA, USA.

Lu, F. and Milios, E., (1997), “Globally Consistent Range Scan Alignment for Environment Mapping”, *Autonomous Robots*, vol. 4, No. 4, pp. 333-349.

Osipov, A., Kemurdjian, V., Safonov, B., (1996), “Mobile robots for security,” Proceedings of the 1996 Proceedings of Robotics for Challenging Environments, pp. 290-295, Albuquerque, NM.

Tsukiyama, T., (2005), “World Map Based on RFID Tags for Indoor Mobile Robots,” Proceedings of the SPIE, Vol. 6006, pp. 412-419.

Saitoh, M., Takahashi, Y., Sankaranarayanan, A., Ohmachi, H., and Marukawa, K., (1995), “Mobile Robot Testbed with Manipulator for Security Guard Application,” Proceedings of the IEEE International Conference on Robotics and Automation, vol. 3, pp. 2518-2523, Nagoya, Japan.

Sugeno, M. and Yasukawa, T., (1993), “A Fuzzy-Logic-Based Approach to Qualitative Modeling”, *IEEE Transactions on Fuzzy Systems*, Vol. 1, No. 1, pp. 7-31.

Wilson, P., Prashanth, D., Aghajan, H., (2007), “Utilizing RFID Signaling Scheme for Localization of Stationary Objects and Speed Estimation of Mobile Objects,” IEEE International Conference on RFID, Grapevine, Texas, USA, pp. 94-99.