

RFID Technology for Mobile Robot Surveillance

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1. Introduction

The increasing need for automated surveillance systems in indoor environments such as airports, warehouses, production plants, etc. has stimulated the development of intelligent systems based on mobile sensors. Differently from traditional non-mobile surveillance systems, those based on mobile robots are still in their initial stage of development, and many issues are currently open for investigation (Everett, 2003; Dehual et al., 2007).

The use of robots significantly expands the potential of surveillance systems, which can evolve from the traditional passive role in which the system can only detect events and trigger alarms, to active surveillance in which a robot can be used to interact with the environment, with humans or with other robots for more complex cooperative actions (Burgard et al., 2000; Vig & Adams, 2007).

A major challenge in surveillance tasks using mobile robots is that of providing the robot with a suitable knowledge of the environment to both navigate safely and perform inspection tasks. Furthermore, in order to effectively exploit mobility and multi-functionality, it is important to develop integrated control systems, capable of addressing simultaneously a number of problems, such as task planning, dynamic task sequencing, resolution of conflicts for shared resources, event-based feedback control.

These issues are part of our current research concerning the development of a multi-sensor Surveillance Mobile Robot (SMR). The SMR consists of a commercial mobile robot (see Fig. 1), which is equipped with various sensors including a laser rangefinder and a Radio Frequency IDentification (RFID) device, and takes advantage of a hybrid control architecture to implement both high-level functions, like mission execution monitoring, and low-level reactive control. So far, several behaviours and tasks have been implemented and experimented. In this chapter, we focus on environment mapping and exploration using 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. 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, instead, are powered by an on-board battery (Finkenzeller, 2003). 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 advantages, since they do not require

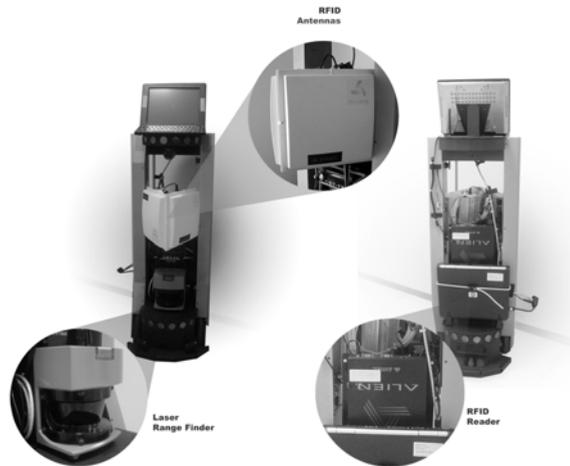


Fig. 1. The SMR equipped with RFID antennas and reader, and a laser rangefinder.

direct line-of-sight and multiple tags can be detected simultaneously. Owing to these properties, RFID has recently found its way in the mobile robotics field, promising to contribute new solutions to data association problems in basic navigation tasks, such as localization, mapping, goal reaching, and item detection (Kubitz et al., 1997; Tsukiyama, 2005; Schneegans et al., 2007; Milella et al. 2007). Nevertheless, in order for RFID sensors to be effectively used in mobile robotics applications, various issues have to be tackled. First, due to low cost and low power constraints, RFID devices are sensitive to interference and reflections from other objects. Therefore, RFID readings are generally affected by high uncertainty. Moreover, at least in the case of passive tags, an RFID reader can only determine whether a tag is present or not in its reading range, while it is not able to provide information about the position of the tag (Liu et al. 2006). These issues may be partially solved using active RFID (Kim & Chong, 2007; Chae & Han, 2005; Zhou et al., 2007). However, active transponders are more costly than passive ones and have a limited lifetime. Methods to localize passive tags, mostly based on probabilistic schemes, have been also developed by a few authors (Hähnel et al., 2004; Liu et al., 2006; Jia et al. 2006).

In this chapter, we present an alternative approach to passive RFID using fuzzy logic. Specifically, we present a fuzzy model of the RFID system, which describes the detection range of an antenna, as its distance and orientation relative to the tags vary. Based on this model, we develop two algorithms that allow a mobile robot equipped with RFID reader and antennas to localize passive tags deployed in the environment. The first one, named Fuzzy Tag Localization (FTL), aims at localizing accurately passive tags in the environment, generating what we refer to as an *RFID-augmented* map, i.e. a map of the environment enriched with RFID tags. Such a map can serve as a support for a variety of service robot tasks, like detecting items, obtaining information about the robot position, getting instructions to reach a given goal. The second method is called Fuzzy Tag Bearing

Estimation (FTBE). It allows one to estimate the bearing of a tag with respect to the mobile robot. The approach is suited when only the tag bearing relative to the robot is needed, like in some landmark-based self-localization algorithms (Stella & Distanto, 1995; Milella et al., 2008), or when an approximate knowledge of the tag location is sufficient. The general use of both methods is in object identification and localization, map building, environment monitoring, and robot pose estimation.

Experimental verification of the proposed techniques has been performed in the ISSIA CNR Mobile Robotics Laboratory. The results suggest that both approaches are accurate in localizing RFID tags and can be effectively integrated with robotic mapping and surveillance systems.

The remainder of the chapter is organized as follows. After discussing related work in Section 2, the tag localization algorithms are detailed in Section 3. Section 4 provides a description of our SMR. Section 5 illustrates experimental results. Conclusions are drawn in Section 6.

2. Related Work

In the last decade, several worldwide projects have attempted to develop mobile surveillance platforms. A notable example is the Mobile Detection Assessment and Response System (MDARS) (Everett & Gage, 1999). The aim of this project was that of developing a multi-robot system able to inspect warehouses and storage sites, identifying 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 & Kenn, 2001), a semi-autonomous mobile security device uses a behaviour-oriented architecture for navigation, while sending video streams to human watch-guards. 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 Robotic Security Guard (Duckett et al., 2004) for remote surveillance of indoor environments has been also the focus of a research project at the AASS Learning Systems Laboratory, Örebro University, Sweden. The objective of this project was that of developing a mobile robot platform able to patrol a given environment, acquire and update maps, keep watch over valuable objects, recognise known persons, discriminate intruders from known persons, and provide remote human operators with a detailed sensory analysis. Another example of security robot is the one developed at the University of Waikato, Hamilton, New Zealand (Carnegie et al., 2004). It is named MARVIN (Mobile Autonomous Robotic Vehicle for Indoor Navigation) and has been designed to act as a security agent in indoor environments. In order for the robot to interact with humans, it is provided with speech recognition and speech synthesis software as well as with the ability to convey emotional states, verbally and non-verbally.

A current trend in the field of automated security is the growing use of RFID technology for object identification and tracking. Recently, several authors have shown RFID tags to be also effective in mobile robot navigation tasks, such as localization and mapping. For instance, the use of RFID as landmarks in topological maps for mobile robot navigation is proposed in (Tsukiyama, 2005). In (Kulyukin et al. 2004), passive RFID tags are manually attached to objects in an indoor environment to trigger local navigation behaviours of a mobile robot for

visually impaired assistance. Robot localization methods using particular tag arrangement on the floor are described in (Jing & Yang, 2007) and (Lim et al., 2006).

Although these methods are all effective in supporting mobile robot navigation, they 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. Moreover, tagged objects could be displaced, causing the necessity to recalculate their position. Hence, methods for localizing automatically RFID tags in the environment are generally desirable.

One of the first works dealing with the automatic localization of passive tags is the one in (Hähnel et al., 2004). The authors suggest a particle filtering method for localizing passive tags in a previously built map of the environment, using a mobile robot equipped with an RFID device and a laser rangefinder. Specifically, while the robot moves in the environment, the location of a tag is estimated starting from a set of particles, whose weights are updated at each successful detection of the tag, using the Bayes rule and a probabilistic model of the antenna. Bayesian solutions for tag localization are also adopted in (Liu et al., 2006; Jia et al. 2006; Alippi et al. 2006). In (Liu et al., 2006), two RFID tag-positioning algorithms are developed, namely an online approach and an offline approach. The offline method is equivalent to the one proposed in (Hähnel et al., 2004). The online algorithm is based on a simplified antenna model that defines a high probability region, instead of describing the probability at each location, in order to achieve computational efficiency. In (Jia 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 (Alippi et al. 2006), 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 this chapter, we introduce two novel methods for localizing passive tags. The algorithms are integrated in our surveillance mobile platform. As in (Hähnel et al., 2004), we refer to a model of the antenna reading range for estimating tag locations from a mobile robot. However, our approach is unique in that it uses fuzzy reasoning to both learn a model of the RFID system and localize the tags. Fuzzy logic has been widely recognized for its effectiveness and for the simplicity to define and understand the knowledge representation. It is especially useful when the process under analysis is complex, when the available source of information is inexact or uncertain, or for intelligent sensor integration and fusion (Mahajan et al., 2001). Our work shows that fuzzy logic is appropriate to deal with uncertainty in RFID systems.

3. Tag localization using fuzzy logic

Passive tags are not able to directly provide their location relative to the antenna or a distance measure. Only positive or negative responses whether a tag is present or not in the reading range are generated. Yet, positive readings can be used to estimate the tag position. As a matter of fact, a positive response reduces the potential locations of the tag to those that lie in the reading region of the device. 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 likelihood. Specifically, it has been shown that a tag closer to the centroid of the reading range is detected more frequently than a tag located at the boundary

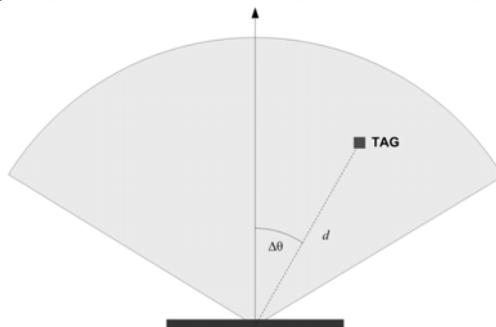


Fig. 2. Representation of bearing and range of a tag relative to the antenna.

(Liu et al., 2006). In summary, a successful detection provides a region that is likely to contain the tag and also allows the association of a detection rate to each point of the region. This region is usually referred to as the coverage map of the RFID device, and constitutes the observation or sensor model in probabilistic approaches.

Constructing an observation model for passive RFID systems is not trivial. RFID are sensitive to interference and reflections from the surroundings. The position of the tag relative to the receiver 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 idea about the tag location and, eventually, could compromise the overall performance of the system (Hähnel et al., 2004; Brusey et al., 2003). It is not feasible to explicitly account for all these factors, separately. Instead, a widely used approach to generate a model of the RFID device is that of manually mapping the probability of detecting a tag at different offsets from the reader by counting the detection frequencies over a 2D or a 3D grid of the environment. That leads to the construction of likelihood histograms, which are, then, typically, conservatively approximated with discrete models, consisting of two or, at most, three likelihood regions (Liu et al., 2006; Hähnel et al., 2004; Jia et al. 2006).

In this work, we propose a fuzzy logic solution to build a better approximation of the antenna detection field, though preserving computational simplicity. Then, based on this model, we develop two algorithms for estimating the position of passive tags using fuzzy reasoning: the Fuzzy Tag Localization (FTL) algorithm and the Fuzzy Tag Bearing Estimation (FTBE) algorithm.

In the rest of this section, first, we describe the fuzzy antenna model, then, we introduce the FTL and the FTBE methods.

3.1 Fuzzy Antenna Modeling

As a first step for RFID modelling, we generated a statistic histogram for our RFID system. Specifically, we rotated the robot in front of a tag, at different distances, several times, and we counted the number of successful detections for each pose in a discrete 2D grid. It was found that the coverage map of each antenna has approximately the shape of a sector with a

radius of about 2.5m and an angular aperture of about 120°. Moreover, it was observed that detection rates tend to decrease smoothly at the boundaries of the coverage map.

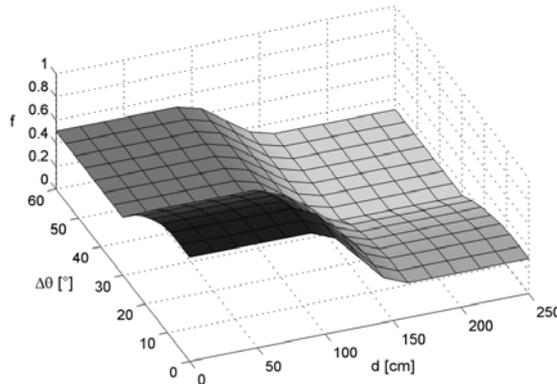


Fig. 3. Input-output surface of the fuzzy antenna model (see Table 1 for the fuzzy rules): darker grey denotes higher frequency of detection.

Such a result can be easily expressed using fuzzy logic. Specifically, we employ a zero-order Sugeno fuzzy inference system (Sugeno & Yasukawa, 1993) with two inputs and one output. With reference to the notation of Fig. 2, the inputs are the range d and the bearing $\Delta\theta$ of the tag relative to the antenna. The output f is an index defined in $[0, 1]$ expressing the expected occurrence of detection, which we refer to as the frequency of detection of the tag. Two functions are defined for each input, labelled *Low* and *High*, respectively. The output, instead, consists of four constant values, labelled *Very Low* (VL), *Low* (L), *Medium* (M), and *High* (H). The parameters for these functions were tuned based on experimental data. The output f is given by the weighted average of all rule outputs. The *if-then* rules for fuzzy inference are reported in Table 1. They consist of heuristic rules, such as

IF Range (d) IS “Low” AND Bearing (Δθ) IS “Low” THEN Frequency (f) IS “High”

A representation of the input-output surface of the fuzzy logic system is shown in Fig. 3, with darker grey representing higher frequencies of detection.

3.2 Fuzzy Tag Localization (FTL)

In this section, we describe our approach to localize passive tags in the environment. The main idea underlying the proposed method is that of estimating the position of a tag as the

Rule #	Input 1: Tag Range (d)	Input 2: Tag Bearing (Δθ)	Output: Frequency of Det. (f)
1	High	High	Very Low
2	High	Low	Low
3	Low	High	Medium
4	Low	Low	High

Table 1. Fuzzy logic rules for modelling the RFID reading range.

most likely location among a set of potential locations. Specifically, as a tag is detected, a set of points P_j , for $j = 1, 2, \dots, M$, is generated in a circular area around the current robot

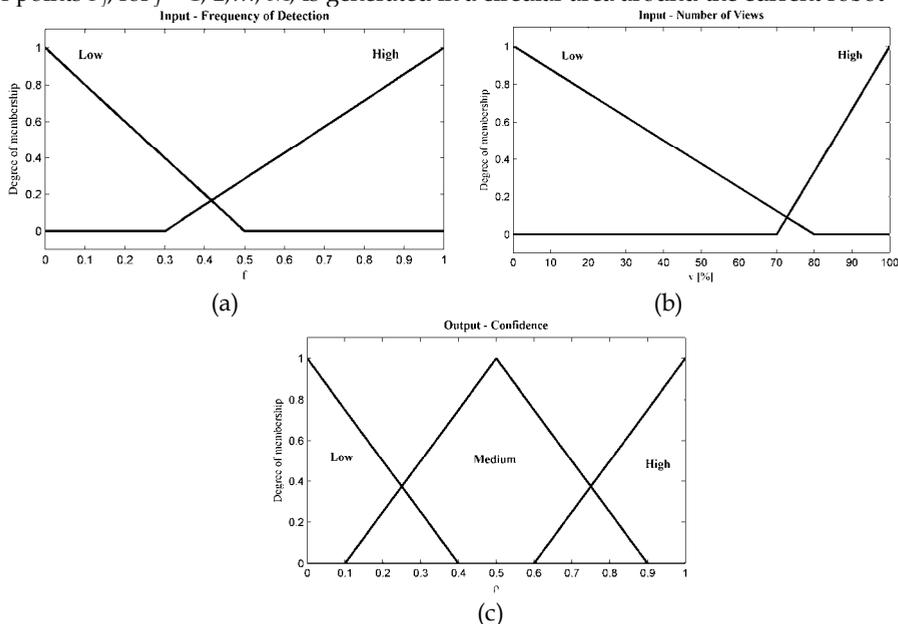


Fig. 4. Fuzzy inference system for tag localization: (a)-(b) membership functions for input variables, i.e. frequency of detection and number of views; (c) membership functions for the output variable, i.e. confidence.

position. The robot, then, moves around, performing multiple tag detections from different positions. It is assumed that the robot displacement from one position to another is known. At each new detection, a confidence value is assigned to every point P_j , expressing the likelihood that P_j corresponds to the actual tag location.

Our hypothesis in confidence estimation is that the higher is the detection frequency associated to a point according to the fuzzy antenna model, the higher is the possibility for that point of being the actual tag position. Furthermore, we assume that a point is more likely to correspond to the actual tag location if it belongs to the intersection region of the coverage maps drawn for the various robot poses during the localization procedure.

In order to express these hypotheses, we adopt fuzzy logic. The triangular membership functions used are shown in Fig. 4 (a)-(b) and Fig. 4 (c), for input and output variables,

Rule #	Input 1: Frequency (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.

respectively. The inputs are the detection frequency f_j^i associated to the point P_j at the i -th detection, which depends on the position of the point relative to the antenna, and the parameter v_j^i , expressing the number of times the point has been found to lie in the antenna detection area. The output is the confidence level ρ_j^i associated to the point P_j at the i -th iteration. The *if-then* rules for fuzzy inference are reported in Table 2.

To reduce the set of potential tag locations, each point P_j is finally assigned an average confidence level. This 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 value is greater than a threshold are retained. This process allows us to remove progressively, from the set of potential tag locations, those points which have low possibility of being the actual tag position, thus refining the estimate.

It is worth to note that if a map of the environment is available and the robot pose in the map is known from some global positioning system, then the described procedure allows us to localize the tags in the map. That leads to what we call an *RFID-augmented* map. Such a map may provide useful information about the environment in a simple form, since RFID tags can store data either to describe interest objects and regions, or to support mobile robot navigation tasks. In Section 5.1, we will show that such a map can improve the robot capability of performing environment monitoring tasks.

3.2 Fuzzy Tag Bearing Estimation (FTBE)

As a variation of the FTL method, we propose an algorithm to estimate only the bearing of a tag relative to the mobile robot, disregarding the range. This method is referred to as Fuzzy Tag Bearing Estimation (FTBE).

The strategy adopted is similar to the one used in the FTL approach. The main difference is that, since only the bearing of the tag has to be estimated, the points P_j representing the potential locations of the tag can be generated at a unique radial distance from the robot, arbitrarily chosen inside the antenna detection field, rather than in a predefined area around the vehicle. That leads to higher computational efficiency, making it more feasible an on line implementation of the approach. In addition, once the tag has been detected for the first time, the robot is not required to move around to perform multiple detections of the tag, but it has just to turn in place. Alternatively, a rotating antenna may be used.

With reference to the notation of Fig. 5, let us indicate with P_j , for $j = 1, 2, \dots, M$, the points generated at the first detection of the tag, distributed at regular angular intervals and fixed radial distance r from the current robot position. Each point allows us to define a vector RP_j whose angle φ_j relative to the X_r - axis of a reference frame (R, X_r, Y_r) attached to the robot, represents a potential value for the tag bearing.

Once the point set has been generated, the robot starts to turn in place, while the reader continues to interrogate the tag. Every time a positive response is received, for each point P_j that falls in the antenna detection area, a frequency value is computed, based on the antenna model. If we approximate the centre of the antenna detection field with the centre of rotation of the vehicle, the inputs to the fuzzy antenna model for every point P_j at the i -th reading are

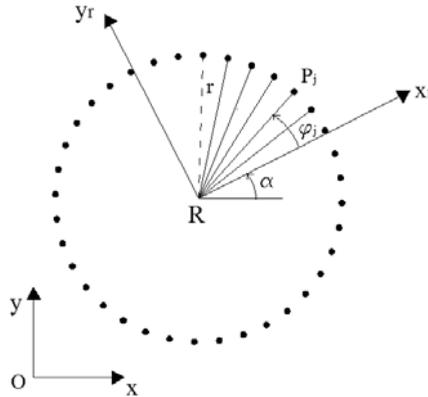


Fig. 5. Potential directions φ_j for estimating the bearing of a tag with respect to the robot reference frame (R, X_r, Y_r) .

$$d_j^i = r \tag{1}$$

$$\Delta\theta_j^i = \varphi_j + \delta^i \tag{2}$$

where δ^i depends on the known orientation of the antenna relative to the vehicle (60° in our case) and on the robot rotation angle a . The output is the frequency of detection f_j^i . Since we only have to manage a limited number of points (e.g. 180 points for a set of points generated at angular interval of 2°), we do not need to discard points at each novel reading. Instead, frequency values f_j^i are stored in a vector

$$[f_j^1 \ f_j^2 \ \dots \ f_j^i \ \dots \ f_j^{N_j}] \tag{3}$$

so that, at the end of the acquisition phase, for each point, we can calculate an average detection frequency value

$$\bar{f}_j = \frac{1}{N_j} \sum_{i=1}^{N_j} f_j^i \tag{4}$$

Furthermore, we can compute a parameter v_j

$$v_j = N_j / N \tag{5}$$

where we have denoted with N_j the dimension of the frequency vector for RP_j , which also represents the number of times the point P_j has fallen inside the antenna detection field, and with N the total number of detections. Then, similarly to what is done in the FTL module, fuzzy reasoning is used for confidence level computation. A two inputs-one output fuzzy inference system is employed. In order to eliminate the dependency of the frequency values on the chosen radius r , we normalize the average frequencies with respect to their maximum

value f_j^{max} . Then, we compute the inputs to the fuzzy inference system for a point P_j which are $\tilde{f}_j / \tilde{f}_j^{max}$ and v_j . The output is the confidence level ρ_j . The membership functions and the *if-then* rules are formally similar to those shown for the FTL module in Fig. 4 and Table 2, respectively. Only the bearing values with an associated confidence level higher than a threshold are retained. Finally, the median of these values is calculated and is assumed as the bearing measure.

It is worth to note that if the tag bearing estimate is performed from at least two different robot positions and the displacement of the robot from one position to the other is known, also the range of the tag relative to the robot can be computed by triangulation. Alternatively, if the tag position in the environment is known, the knowledge of the tag bearing relative to the robot may be exploited to get robot position information.

4. The mobile robot surveillance platform

To prove the feasibility of the proposed methods, we developed an RFID managing and processing system integrated in our Surveillance Mobile Robot (SMR) (see Fig. 1).

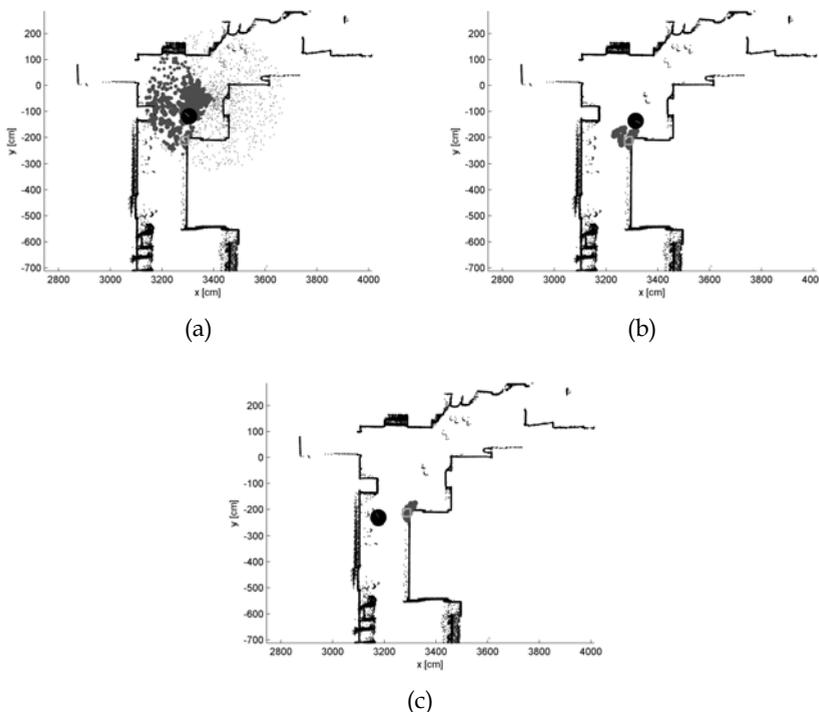


Fig. 6. Tag localization after (a) 5, (b) 15, and (c) 50 iterations using the FTL approach. In (a), (b), (c): a black circle represents the robot pose in the map; the actual tag position is indicated by a square; potential tag locations are shown as small circles with a radius proportional to the average confidence levels.

The latter consists of a commercial platform, i.e. PeopleBot by MobileRobots Inc., equipped with sonar and infrared sensors, a SICK LMS-200 laser range finder, an AVT Marlin IEEE 1394 FireWire monocular camera, and an Alien Technology's ALR-8780 reader with two external circularly polarized ALR 8610-C antennas. 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 system has two processing units: the robot embedded PC and an additional laptop for RFID data acquisition and storage, vision processing, and application control. The software is based on an open source robotic development framework, named MARIE (Côté et al., 2006). The Java libraries provided by Alien Technology are employed for RFID data acquisition and storage.

The SMR is designed to perform active environment surveillance operations, taking advantage of an extremely modular software architecture that allows several sensor processing modules to be easily integrated. The robot is able to execute various missions. Each mission consists of a predetermined set of atomic tasks, which may be subject to precedence constraints (the end of one task may be a necessary prerequisite for the start of some other ones). Specifically, to control the robot and manage the surveillance tasks, we use a Matrix-based Discrete Event Control (M-DEC) approach (Tacconi & Lewis 1997). M-DEC is an integrated modelling and control framework based on Boolean matrices and vectors, which is intuitive (it can be interpreted using simple *if-then* rules), inherently modular (models of large systems can be obtained by assembling submodels of smaller size) and versatile. More details concerning the control system of the platform can be found in (Di Paola et al. 2009).

5. Experimental results

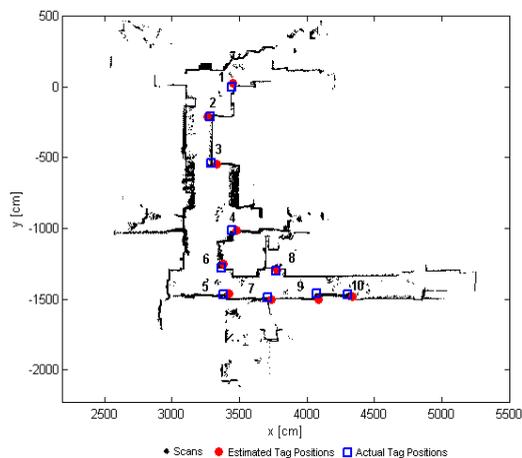


Fig. 7. Map of the environment with the tag locations estimated using the FTL module and those measured by a theodolite station.

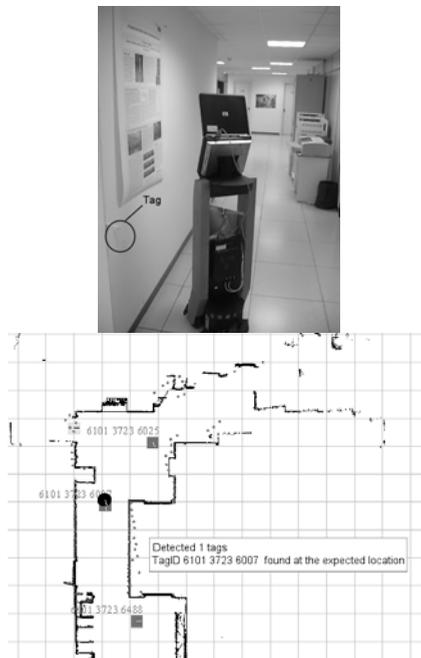
Experiments were performed in the ISSIA CNR Mobile Robotics Laboratory of Bari, Italy, using the mobile platform described in Section 4. In the rest of this section, first, we show the results of tests concerning the FTL approach and the related RFID-augmented mapping, then, we present the tests carried out to verify the accuracy of the FTBE approach.

5.1 Fuzzy Tag Localization for RFID-Augmented Mapping

Ten tags were distributed in the environment, along an L-shaped corridor with a total length of about 40m and an average width of about 2m. Then, the robot was guided on a tour of the environment, acquiring laser and RFID data.

Both the geometric map of the environment and the robot trajectory were reconstructed using a laser-based SLAM routine.

Note that information concerning different tags can always be kept separate 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 for tag location estimate. Measurements of the tag positions were also performed with a theodolite station and were regarded as the ground truth.



(a)

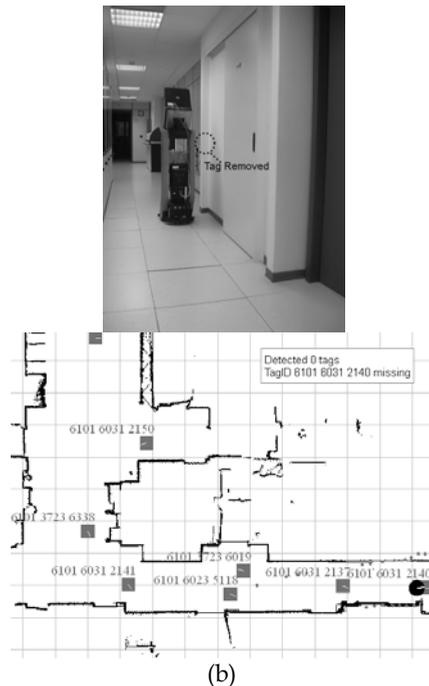


Fig. 8 RFID-based environment monitoring: (a) the robot detecting a tag; (b) the robot warning of a missing tag removed from its original location.

Fig. 6 shows the localization procedure using the FTL method for one of the tags. Whenever the tag is detected for the first time, a set of potential locations is generated in a circular area around the current robot position. As a new observation occurs, 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. In order to reduce the risk of eliminating valid points, at least ten robot poses are considered for the computation of average confidence levels before points are discarded for the first time. Fig. 6 (a) shows the sample set after 5 detections, while Fig. 6 (b) and Fig. 6 (c) display the distribution of the possible locations after 15 and 50 detections, respectively, showing how the estimate converges toward the actual tag position. In this test, after 200 detections, the error was of 10.0cm . Similar results were obtained for all the tags.

Fig. 7 shows the map of the environment reconstructed by SLAM with overlaid the locations of the tag estimated by the FTL method and those measured using the theodolite station. We used, for each tag, 200 detections. The algorithm was initialized with 1500 samples. The average discrepancy between the tag positions estimated by the FTL algorithm and those measured using the theodolite was less than 35cm and in the worst-case measurement the discrepancy was less than 50cm . These results demonstrate that the FTL method is accurate in localizing tags deployed at generic locations of an indoor environment, with the additional advantage of relying on simple fuzzy rules defined in the universe of discourse.

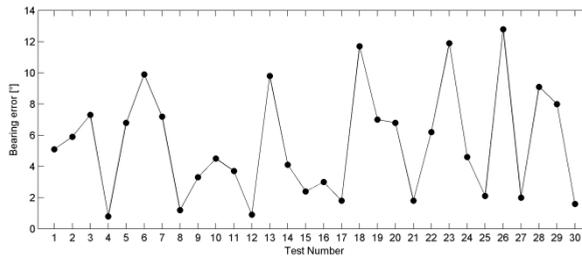


Fig. 9. Tag bearing error, estimated starting from 30 different robot poses around a tag, at distances ranging from 50cm to 170cm and orientations comprised between -90° to 90° .

The constructed RFID-augmented map can be used to support robot navigation tasks. For instance, based on RFID, a mobile robot can acquire information about its pose in the environment. Vice versa, knowing its pose from other sensors, it can use RFID information for environment monitoring.

As an example, Fig. 8 shows a navigation test, in which the robot was programmed to move in the laboratory using the constructed RFID-augmented 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. The robot was programmed to reach each goal and verify the presence or absence of the tag at the expected location. The pictures on the left portray the robot navigating in the environment. On the right, the output of the navigation module is shown with overlaid the output of the RFID system. Goal stations are denoted with small squares. ID codes of the tags located nearby each station are also reported.

5.2 Fuzzy Tag Bearing Estimation

In order to verify the accuracy of the FTBE approach, a first experimental session was carried out attaching a tag to a wall of the laboratory and running the algorithm from 30 different robot configurations around the tag. Tag range and bearing relative to the robot were comprised between 50cm to 170cm and -90° to 90° , respectively. In all tests, an angular interval of 2° was used for both data acquisition and point set generation.

The results were compared with ground-truth measures obtained using a theodolite station. Fig. 9 reports a graph of the bearing error e_b (angle β in Fig. 10) computed as the absolute difference between actual φ_a and estimated φ_e tag bearing, i.e.

$$e_b = |\varphi_a - \varphi_e| \quad (6)$$

It shows that the error has an average value of 5.4° , and is less than 13.0° in the worst case. Similar results were obtained in successive tests, performed using other tags wherever located in the environment, thus proving the effectiveness of the proposed approach.

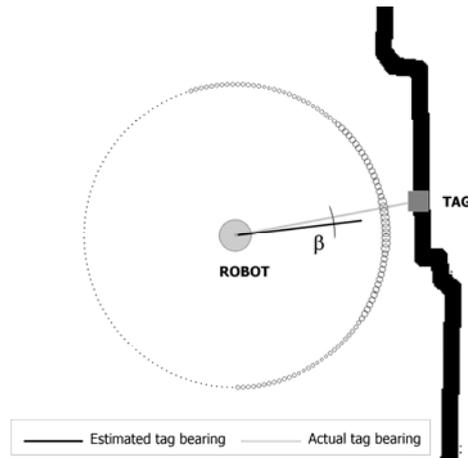


Fig. 10 Graphical representation of the tag bearing estimation process. The tag (light grey square) is attached on a wall of the environment (thick black line). Small circles located at $1m$ from the robot represent the points used for generating the potential tag bearings. The dimension of each circle is proportional to its confidence level.

6. Conclusion

We introduced two novel methods to estimate the location of passive RFID tags using a surveillance mobile robot equipped with RF reader and antennas, and a laser rangefinder. Both approaches are based on fuzzy logic and use a fuzzy model of the RFID system.

The first method, referred to as Fuzzy Tag Localization (FTL), allows us to accurately localize tags with respect to the robot. The positions of the tags in a map of the environment are also estimated, using a laser-based SLAM approach to globally localize the robot in the environment. That leads to what is called an RFID-augmented map. The second method, named Fuzzy Tag Bearing Estimation (FTBE), aims at estimating the bearing of a tag relative to the mobile robot. It can be used when an approximate knowledge about the tag location is needed, or only the bearing information is required, such as in some robot localization methods.

Experimental tests performed in a real indoor environment were presented to demonstrate the effectiveness of both methods. It was shown that fuzzy logic is appropriate in knowledge representation under uncertainty in RFID systems for mobile robotics applications like environment exploration and mapping.

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Mechatronic Systems Applications

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Mechatronics, the synergistic blend of mechanics, electronics, and computer science, has evolved over the past twenty five years, leading to a novel stage of engineering design. By integrating the best design practices with the most advanced technologies, mechatronics aims at realizing high-quality products, guaranteeing at the same time a substantial reduction of time and costs of manufacturing. Mechatronic systems are manifold and range from machine components, motion generators, and power producing machines to more complex devices, such as robotic systems and transportation vehicles. With its twenty chapters, which collect contributions from many researchers worldwide, this book provides an excellent survey of recent work in the field of mechatronics with applications in various fields, like robotics, medical and assistive technology, human-machine interaction, unmanned vehicles, manufacturing, and education. We would like to thank all the authors who have invested a great deal of time to write such interesting chapters, which we are sure will be valuable to the readers. Chapters 1 to 6 deal with applications of mechatronics for the development of robotic systems. Medical and assistive technologies and human-machine interaction systems are the topic of chapters 7 to 13. Chapters 14 and 15 concern mechatronic systems for autonomous vehicles. Chapters 16-19 deal with mechatronics in manufacturing contexts. Chapter 20 concludes the book, describing a method for the installation of mechatronics education in schools.

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