The 2009 IEEE/RSJ International Conference on
Intelligent Robots and Systems
October 11-15, 2009 St. Louis, USA

A Fuzzy Logic Approach to Passive RFID for Mobile Robot Applications

Annalisa Milella, Donato Di Paola, Grazia Cicirelli, and Arcangelo Distante

Abstract— **Passive Radio Frequency Identification (RFID) is being increasingly used in mobile robotics applications, as it provides inexpensive and effective solutions to data association issues in basic navigation tasks. Nonetheless, problems related to sensitivity of the signal to interference and reflections, and missing tag range and bearing information are open. In this paper, we propose a novel approach to passive RFID, which tackles those issues using fuzzy reasoning. Specifically, first, we present a fuzzy antenna model. Then, based on this model, we describe two fuzzy logic methods for tag localization. One allows us to accurately localize passive tags in the environment and to generate what we call an *RFID-augmented* map; the other is suited for estimating the bearing of a tag relative to the robot. The general use of both methods is in object localization, map building, environment monitoring, and robot pose estimation. Results of experimental tests demonstrate that fuzzy logic is appropriate to operate under uncertainty in RFID systems, and allows for accurate tag localization.**

I. Introduction

In the last years, Radio Frequency Identification (RFID) has received great attention, since it supplies an inexpensive and effective technology for object identification and tracking with a wide range of applications. Examples include inventory management, industry automation, ID badges and access control, equipment and personnel tracking.

RFID systems typically consist of radio frequency (RF) tags, a reader with one or more antennas, and a software to process the tag readings. The reader interrogates the tags, receiving their ID code and other information stored in their memory. Compared to conventional identification systems, such as barcodes, RFID tags offer several advantages, since they do not require direct line-of-sight; moreover, multiple tags can be detected simultaneously [1].

Recently, RFID has appeared on the scene of mobile robotics, promising to contribute solutions to data association problems in navigation tasks, such as localization and mapping [2], [3]. Nevertheless, in order for RFID sensors to be effectively used in mobile robotics applications, some 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 [4], [5]. These issues may be partially solved using active RFID [6]-[8]; however, active transponders are more costly than passive ones, and have a limited lifetime.

Methods to localize passive RFID tags and integrate them in mobile robotics systems have been developed by a few authors. For instance, in [9] Hähnel et al. 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 [4], [10], [11]. In [4], 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 [9]. 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 [10], 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 [11], 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 paper, we propose an alternative approach to passive RFID. As in [9], we use a mobile robot equipped with an RFID device, and refer to a model of the antenna reading range for tag localization. However, our approach is unique in that it uses fuzzy reasoning to both learn a model of the RFID system and localize the tags. Specifically we present two fuzzy logic-based tag localization approaches. The general use of both methods is in object identification and localization, map building, environment monitoring, and robot pose estimation.

The first one, named Fuzzy Tag Localization (FTL), aims at localizing accurately passive tags in the environment, in order to generate what we refer to as an *RFID-augmented*

Manuscript received March 1, 2009.

A. Milella, D. Di Paola, G. Cicirelli, and A. Distante are with the Institute of Intelligent Systems for Automation, Italian National Research Council, via G. Amendola 122/D, 70126, Bari, Italy. Corresponding author: Annalisa Milella; e-mail: milella@ba.issia.cnr.it; tel.: +39 080 5929447.

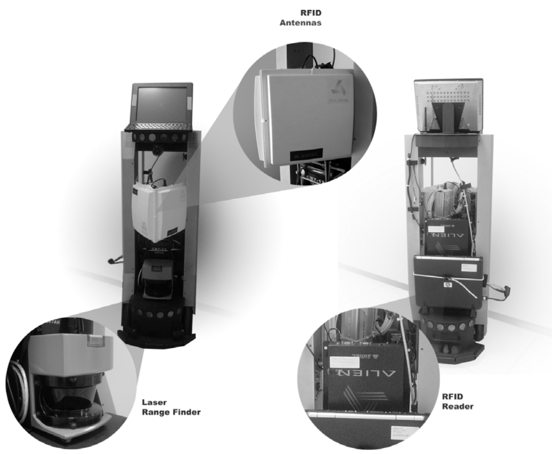


Fig. 1. The mobile robotic platform equipped with RFID reader and antennas, and a laser rangefinder.

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 [12], [13], or when an approximate knowledge of the tag location is sufficient.

Experimental verification of the proposed techniques has been performed in the ISSIA CNR Mobile Robotics Laboratory, using the multisensor platform shown in Fig. 1. It consists of a commercial mobile robot, which we equipped with two RF antennas and an RF reader. The platform is also provided with a laser rangefinder that was used to construct a metric map of the environment in which RFID tag locations were estimated using the FTL approach. In addition, a theodolite station was employed to get ground-truth basis about tag positions in the environment. The obtained results show that the proposed methods are efficient in tag localization, with the additional advantage of relying on fuzzy rules, easily understandable by humans for direct examination and modification.

The remainder of the paper is organized as follows. Section II presents the fuzzy antenna model and the two tag localization methods. Experimental results are reported in Section III. Conclusions are drawn in Section IV.

II. 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 [4].

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 a trivial task. 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 [9], [14].

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 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 [4], [9], [10].

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.

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. Our work shows

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

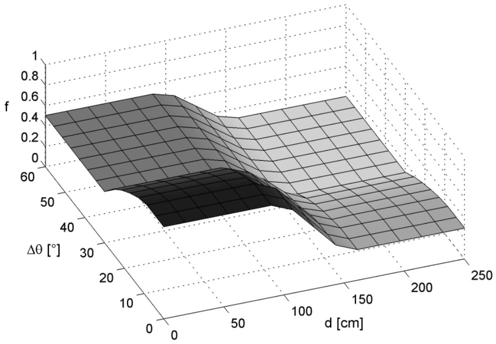


Fig. 3. Input-output surface of the fuzzy antenna model (see Table I for the fuzzy rules): darker grey denotes higher frequency of detection.

that fuzzy logic is appropriate to deal with uncertainty in RFID systems.

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

A. Fuzzy Antenna Modeling

As a first step for RFID modeling, similarly to [9], 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 for our system (see Section III for specifications) the coverage map of each antenna has approximately the shape of a sector with a radius of about 2.5*m* 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.

This result can be easily expressed by using fuzzy logic. Specifically, we employ a zero-order Sugeno fuzzy inference system [15] 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, labeled *Low* and *High*, respectively. The output, instead, 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 output f is given by the weighted average of all rule outputs. The *if-then* rules for fuzzy inference are reported in Table I. They consist of heuristic rules, such as

IF *Range (d)* IS "Low" AND *Bearing (Δθ)* IS "Low" THEN *Frequency (f)* IS "High"

The input-output surface of the fuzzy logic system, using the rules in Table I, is shown in Fig. 3, with darker grey representing higher frequencies of detection.

B. Fuzzy Tag Localization (FTL)

In this section, we describe our approach to localize passive tags relative to the robot and also in a map of the environment.

TABLE I
FUZZY RULES FOR MODELLING THE RFID READING RANGE.

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

The main idea underlying the proposed method is that of estimating the position of a tag as the 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 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, 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 II.

Eventually, to reduce the set of potential tag locations, each point P_j is 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 progressively remove, 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

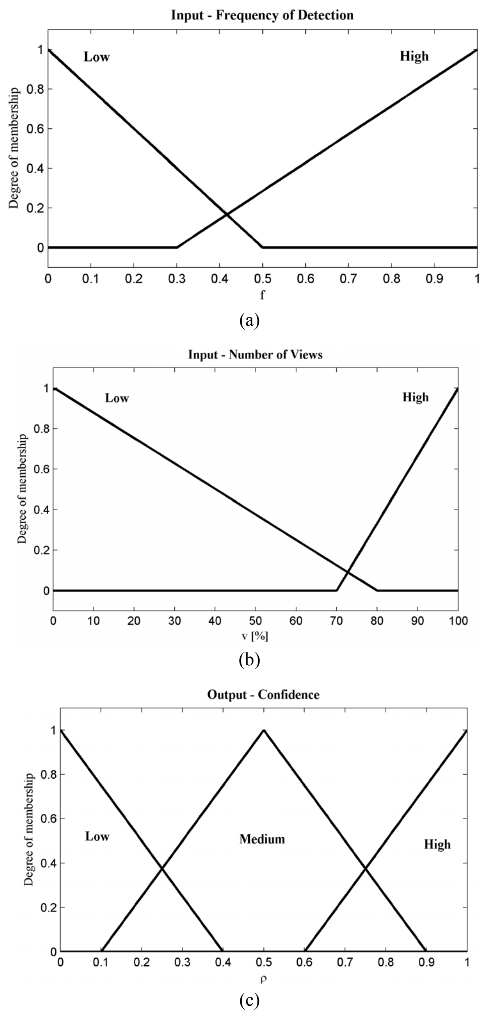


Fig. 4. Fuzzy inference system for tag localization: (a)-(b) membership functions for input variables, i.e. frequency of detection and number of views; (c) membership functions for the output variable, i.e. confidence.

objects and regions, or to support mobile robot navigation tasks [16].

C. 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.

TABLE II
FUZZY LOGIC RULES FOR TAG LOCALIZATION

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

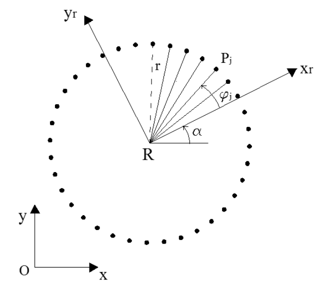


Fig. 5. Potential directions φ_j for estimating the bearing of a tag with respect to the robot reference frame (R, Xr, Yr).

With reference to the notation of Fig. 5, let us indicate with P_j, for $j = 1, 2,\ldots, M$, 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 (or the antenna) 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 f_j^i is computed, based on the antenna model. 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

$$[f_j^1 \quad f_j^2 \quad \ldots \quad f_j^i \ldots \quad f_j^{N_j}] \tag{1}$$

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

$$\bar{f}_j = \frac{1}{N_j}\sum_{i=1}^{N_j} f_j^i \tag{2}$$

Furthermore, we can compute a parameter v_j

$$v_j = N_j / N \tag{3}$$

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 from the chosen radius r, we normalize the average frequencies with respect to their maximum value $\bar{f}_j^{\max}$. Then, we compute the inputs to the fuzzy inference system for a point P_j which are $\bar{f}_j / \bar{f}_j^{\max}$ 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 II, 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 chosen as the tag bearing measure.

III. Experimental Results

The described methods were implemented and tested on a PeopleBot mobile robot by MobileRobots Inc., 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 Fig. 1).

The RFID device is a UHF system working at 866MHz with passive Alien's Class 1 Gen 1 128-bit NanoBlock tags. They consist of rectangular targets with long side of about 10*cm*, 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.

Two processing units are employed: the robot embedded PC, and an additional laptop for RFID data acquisition and storage and application control. The connection between the laptop and the RFID reader is via RS232 serial cable. ARNL C++ libraries by MobileRobots Inc. are used for laser mapping. The Java libraries provided by Alien Technology are employed for RFID data acquisition and storage.

Experiments were performed in the ISSIA CNR Mobile Robotics Laboratory of Bari, Italy.

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.

A. 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 40*m* and an average width of about 2*m*. 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. At the end of the acquisition phase, for each tag, a set of robot poses was available for tag location estimate using the FTL approach. Note that information concerning different tags could be kept separate since a tag is univocally identified by its own code. Measurements of the tag positions were also performed with a theodolite station and were regarded as the ground truth.

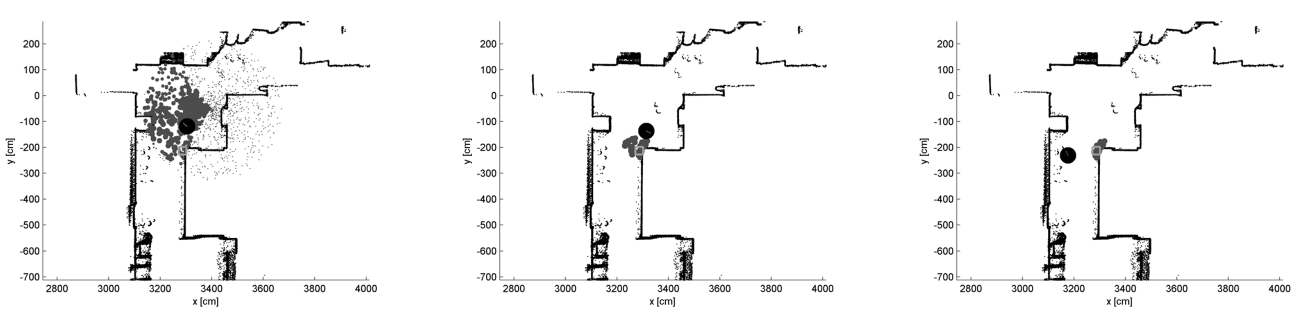
Fig. 6 shows the localization procedure using the FTL method for one of the tags. Whenever the tag is detected for the first time, a set of potential locations is generated in a circular area around the current robot position. As a new observation occurs, only those points whose confidence is greater 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.

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 and was run several times. The average discrepancy between the tag positions estimated by the FTL algorithm and those measured using the theodolite was less than 35*cm*, and it was less than 50*cm* for the worst-case measurement.

These results show 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.

B. Fuzzy Tag Bearing Estimation

In order to verify the accuracy of the FTBE approach, an experimental session was carried out attaching a tag to a



(a) (b) (c)

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 whose radius is proportional to confidence levels.

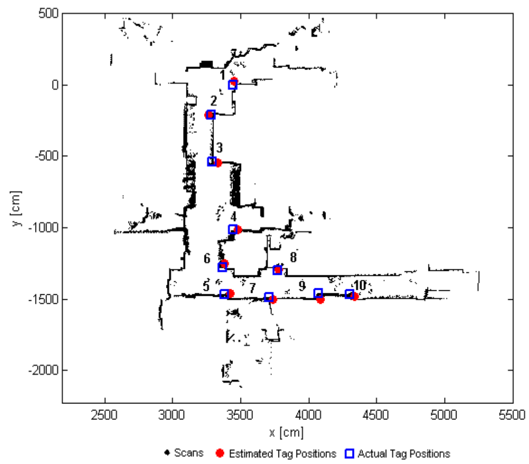


Fig. 7. Map of the environment with the tag locations estimated using the FTL module and those measured by a theodolite station.

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÷170cm and -90°÷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. 8 reports a graph of the bearing error e_b computed as the absolute difference between actual φ_a and estimated φ_e tag bearing, i.e.

$$e_b = |\varphi_a - \varphi_e| \quad (4)$$

The average error is of 5.4°. An error less than 13.0° was computed 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.

IV. Conclusion

We introduced two novel methods to estimate the location of passive RFID tags using a mobile robot equipped with RF reader and antennas. 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 sufficient, or only the bearing information is required, such as in some robot localization methods.

Experimental results performed in a real indoor environment were presented to demonstrate the accuracy of both approaches. It was shown that fuzzy logic is appropriate in knowledge representation under uncertainty in RFID systems for mobile robotics applications.

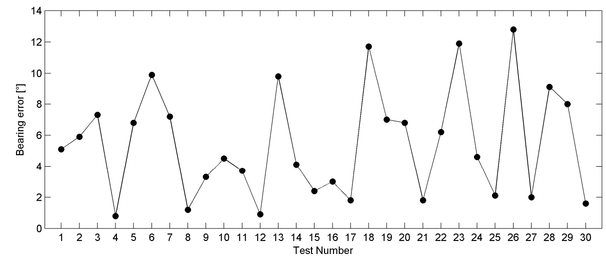


Fig. 8. Tag bearing error, estimated starting from 30 different robot poses around a tag.

References

[1] K. Finkenzeller, *RFID Handbook: Fundamentals and Applications in Contactless Smart Cards and Identification*, 2nd Edition, Wiley, 2003.

[2] O. Kubitz, M. Berger, M. Perlick, and R. Dumoulin, "Application of Radio Frequency Identification Devices to Support Navigation of Autonomous Mobile Robots," *Proceedings of IEEE 47th Vehicular Technology Conference*, Phoenix, Arizona, USA, May 4-7, 1997.

[3] T. Tsukiyama, "World Map Based on RFID Tags for Indoor Mobile Robots," *Proceedings of the SPIE*, vol. 6006, pp. 412-419, 2005.

[4] X. Liu, M.D. Corner, and P. Shenoy, "Ferret: RFID Localization for Pervasive Multimedia," *Proceedings of the 8th Ubicomp Conf.*, Orange County, USA, September 2006.

[5] S. Schneegans, P. Vorst, and A. Zell, "Using RFID Snapshots for Mobile Robot Self-Localization", *Proceedings of the 3rd European Conference on Mobile Robots (ECMR 2007)*, Freiburg, Germany, pp. 241-246, September 19-21, 2007.

[6] M. Kim and N. Young Chong, "RFID-based mobile robot guidance to a stationary target," *Mechatronics*, vol. 17, no. 4-5, pp. 217-229, 2007.

[7] H. Chae and K. Han, "Combination of RFID and Vision for Mobile Robot Localization," *Proceedings of the 2005 International Conference on Intelligent Sensors, Sensor Networks and Information*, Melbourne, Australia, pp. 75- 80, 2005.

[8] Y. Zhou, W. Liu, and P. Huang, "Laser-activated RFID-based Indoor Localization System for Mobile Robots," *IEEE ICRA*, Roma, Italy, pp. 4600 – 4605, 2007.

[9] D. Hähnel, W. Burgard, D. Fox, K. Fishkin, and M. Philipose, "Mapping and Localization with RFID Technology," *Proceedings of the IEEE International Conference on Robotics and Automation*, New Orleans, LA, USA, April 26- May 1, 2004.

[10] S. Jia, E. Shang, T. Abe, and K. Takase, "Localization of Mobile Robot with RFID Technology and Stereo Vision," *Proceedings of the IEEE International Conference on Mechatronics and Automation*, Luoyang, China, June 2006.

[11] C. Alippi, D. Cogliati, and G. Vanini, "A statistical Approach to Localize Passive Tags," *Proceedings IEEE International Symposium on Circuits and Systems (ISCAS)*, Island of Kos, Greece, May 2006.

[12] E. Stella and A. Distante, "Self-Location of a mobile robot by estimation of camera parameters," *Robotics and Autonomous Systems* vol. 15, pp. 179-187, 1995.

[13] A. Milella, D. Di Paola, G. Cicirelli, and T. D'Orazio, "RFID Tag Bearing Estimation for Mobile Robot Localization," *Proceedings of IEEE ICAR 2009*, Munich, Germany, June 2009.

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

[15] M. Sugeno and T. Yasukawa, "A fuzzy-logic-based approach to qualitative modeling," *IEEE Transactions on Fuzzy Systems*, vol. 1, no. 1, pp. 7-31, 1993.

[16] A. Milella, G. Cicirelli, and A. Distante, "RFID-Assisted Mobile Robot System for Mapping and Surveillance of Indoor Environments," *Industrial Robot: An International Journal*, vol. 35, no. 2, 2008, pp. 143-152.