

# We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

6,900

Open access books available

186,000

International authors and editors

200M

Downloads

Our authors are among the

154

Countries delivered to

TOP 1%

most cited scientists

12.2%

Contributors from top 500 universities



WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index  
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?  
Contact [book.department@intechopen.com](mailto:book.department@intechopen.com)

Numbers displayed above are based on latest data collected.  
For more information visit [www.intechopen.com](http://www.intechopen.com)



## RFID Sensor Modeling by Using an Autonomous Mobile Robot

Grazia Cicirelli, Annalisa Milella and Donato Di Paola

*Institute of Autonomous Systems for Automation (National Research Council)*

*Italy*

### 1. Introduction

Radio Frequency Identification (RFID) technology has been available for more than fifty years. Nevertheless, only in the last decade, the ability of manufacturing the RFID devices and standardization in industries have given rise to a wide application of RFID technology in many areas, such as inventory management, security and access control, product labelling and tracking, supply chain management, ski lift access, and so on.

An RFID device consists of a number of RFID tags or transponders deployed in the environment, one or more antennas, a receiver or reader unit, and suitable software for data processing. The reader communicates with the tags through the scanning antenna that sends out radio-frequency waves. Tags contain a microchip and a small antenna. The reader decodes the signal provided by the tag, whereas the software interprets the information stored in the tag's memory, usually related to its unique ID, along with some additional information. Compared to conventional identification systems, such as barcodes, RFID tags offer several advantages, since they allow for contactless identification, cheapness, reading effectiveness (no need of line of sight between tags and reader). Furthermore, passive tags work without internal power supply and have, potentially, a long life run. Owing to these advantageous properties, RFID technology has recently attracted the interest of the mobile robotics community that has started to investigate its potential application in critical navigation tasks, such as localization and mapping. For instance, in (Kubitz et al., 1997) RFID tags are employed as artificial landmarks for mobile robot navigation, based on topological maps. 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 (Gueaieb & Miah, 2008), a novel navigation technique is described, but it is experimentally illustrated only through computer simulations. Tags are placed on the ceiling in unknown positions and are used to define the trajectory of the robot that navigates along the virtual line on the ground, linking the orthogonal projection points of the tags on the ground. In (Choi et al., 2011) a mobile robot localization technique is described, which bases on a sensor fusion that uses an RFID system and ultrasonic sensors. Passive RFID tags are arranged in a fixed pattern on the floor and absolute coordinate values are stored in each tag. The global position of the mobile robot is obtained by considering the tags located within the reader recognition area. Ultrasonic sensors are used to compensate for limitations and uncertainties in RFID system.

Although effective in supporting mobile robot navigation, most of the above approaches either assume the location of tags to be known a priori or require tags to be installed in order to form specific patterns in well-structured environments. Nevertheless, in real environments this is not always possible. In addition, due to the peculiarities of these approaches, no sensor model is presented, because they use only the identification event of RFID tags, without considering at what extent. On the other hand, modelling RFID sensors and localizing passive tags is not straightforward. 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. These undesirable effects produce a number of false negative and false positive readings that may 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).

Algorithms to model RFID system have been developed by a few authors. They use different approaches that varies depending on the type of sensor information used and the method applied to model this information. Earlier works model the sensor information considering only tag detection event. More recent ones, instead, consider also the received signal strength (RSSI) value. This difference is principally due to the evolution of new RFID devices. Nevertheless, in some cases the RSSI is simulated by means of the different power levels of the antenna (Alippi et al., 2006; Ni et al., 2003). (Alippi et al., 2006), for example, suggest a polar localization algorithm based on the scanning of the space with rotating antennas and several readers. At each angular value the antenna is provided with an increasing power by the reader. At the end of each interrogation campaign from each reader, the processing server obtains, for each tag, a packet containing the reader ID, the angular position, the tag ID and the minimum detection power.

One of the first works dealing with RFID sensor modeling is the one proposed in (Hähnel et al., 2004). The sensor model is based on a probabilistic approach and is learnt by generating a statistics by counting the frequency of detection given different relative position between antenna and tag. In (Liu et al., 2006) the authors present 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 (Vorst & Zell, 2008) the authors present a novel method of learning a probabilistic RFID sensor model in a semi-autonomous fashion.

A novel probabilistic sensor model is also proposed in (Joho et al., 2009). RSSI information and tag detection event are both considered to achieve a higher modelling accuracy. A method for bootstrapping the sensor model in a fully unsupervised manner is presented. Also, in (Milella et al., 2008) a sensor model is illustrated. The presented approach differs from the above in that they use fuzzy set theory instead of probabilistic approach.

In this chapter we present our recent advances in fuzzy logic-based RFID modelling using an autonomous robot. Our work follows in principle the work by (Joho et al., 2009), since we use both signal strength information and tag detection event for sensor modelling. However, our approach is different in that is based on a fuzzy reasoning framework to automatically learn the model of the RFID device. Furthermore, we consider not only the relative distance between tag and antenna, but also their relative orientation.

The main contribution of our work concerns supervised learning of the model of the RFID reader to characterize the relationship between tags and antenna. Specifically, we introduce the learning of the membership function parameters that are usually empirically established by an expert. This process can be inaccurate or subject to the expert's interpretation. To overcome this limitation, we propose to extract automatically the parameters from a set of



Fig. 1. The mobile robot Pioneer P3AT equipped with two RFID antennas and a laser range scanner.

training data. In particular, Fuzzy C-Means (FCM) algorithm is applied to automatically cluster sample data into classes and also to obtain initial data memberships. Next, this information is used to initialize an ANFIS neural network, which is trained to learn the RFID sensor model. The RFID sensor model is defined as combination of an RSSI model and a Tag Detection Model. Experimental results from tests performed in our Mobile Robotics Lab are presented. The robot used in the experimental session is a Pioneer P3AT equipped with two RFID antennas and a laser range scanner (see Fig. 1). The RFID system is composed by a SICK RFI 641 UHF reader and two antennas, whereas tags are passive UHF tag "DogBone" by UPM Raflatac.

The rest of this chapter is organized as follows. Section 2 describes the sensor modelling approach. Experimental results are shown in Section 3. Finally, conclusions are drawn in Section 4.

## 2. Learning the Sensor Model

In our work, modeling an RFID device means to model the possibility of detecting a tag given its relative position and angle with respect to the antenna. Building this sensor model involves two phases: data acquisition and model learning. The former refers to the strategy we apply in

order to collect data. The latter, instead, refers to the construction of the model actually learnt by using recorded data. To model the RFID device we use a Fuzzy Inference System and then to learn it the Adaptive Neuro-Fuzzy Inference System (ANFIS) is applied: the membership function parameters and the rule base are automatically learnt by training an ANFIS neural network on sample instances removing, in this way, the subjectivity of an observer. First sample data are automatically clustered into classes by using the Fuzzy C-Means (FCM) algorithm that at the same time gives an initial fuzzy inference system. Next this information is used to initialize the ANFIS neural network. In the subsequent, both algorithms FCM and ANFIS will be briefly reviewed before the sensor model description.

## 2.1 Data recording

Past approaches to data recording, presented in related works (Hähnel et al., 2004; Milella et al., 2008), fix a discrete grid of different positions and count frequencies of tag detections for each grid cell. These detections are collected by moving a robot, equipped with one or more antennas, on this grid in front of a tag attached to a box or a wall. This way of proceeding is advantageous in that measurements are taken at known positions and detection rates are computed as tag detection frequencies on a grid. However, this procedure could be tedious and slow if a huge quantity of measurements has to be taken. We follow a slightly different approach to collect the data useful for the sensor model construction. After having deployed a number of tags at different positions in our corridor-like environment, the robot, equipped with the antennas, is manually moved up and down the corridor, continuously recording tag measurements. With tag measurements we refer to the relative distance and relative orientation of the antenna with respect to the tag and RSSI value for each tag detection. Notice that, for each detected tag, the reader reports the tag ID, the RSSI value and which antenna detected the tag. True tag locations are computed by using a theodolite station, whereas the robot positions, in a map of the environment, are estimated applying an accurate self-localization algorithm called Mixture-Monte Carlo Localization (Thrun et al., 2000) by using laser data. Then the relative position between tags and robot are known. Notice that more tags can be simultaneously read by the antenna, therefore the recording phase is, at the same time, rich in data and faster with respect to the above reported ones. In addition, the proposed approach skips the tedious effort of choosing grid points, since a variety of positions for the robot (or antennas) is guaranteed during the guided tour of the environment.

## 2.2 Fuzzy C-Means (FCM)

FCM is one of the most popular family of clustering algorithms that is C-Means (or K-Means), where  $C$  refers to the number of clusters. These algorithms base on the minimum assignment principle, which assigns data points to the clusters by minimizing an objective function that measures the distance between points and the cluster centers. The advantages of these algorithms are their simplicity, efficiency and self-organization. FCM is a variation of C-Means. It was introduced in (Bezdek, 1981). The peculiarity of fuzzy clustering is that data points do not belong to exactly one cluster, but to more than one cluster since each point has associated a membership grade which indicates the degree to which it belongs to the different clusters.

Given a finite set of data point vectors  $Z = \{Z_1, Z_2, \dots, Z_N\}$ , FCM algorithm partitions it into a collection of  $C \leq N$  clusters such that the following objective function is minimized:

$$J_q = \sum_{i=1}^C \sum_{k=1}^N w_{ik}^q \|Z_k - V_i\|^2$$

where  $V_i$  are the cluster centers for  $i = 1, \dots, C$ ;  $w_{ik}$  is the membership value with which point  $Z_k$  belongs to the cluster defined by  $V_i$  center and  $q > 1$  is the fuzzification parameter. This parameter in general specifies the fuzziness of the partition, i.e. larger the value of  $q$  greater is the overlap among the clusters.

Starting by an initial guess for the cluster centers, FCM algorithm alternates between optimization of  $J_q$  over the membership values  $w_{ik}$  fixed the cluster centers  $V_i$  and viceversa. Iteratively updating  $w_{ik}$  and  $V_i$ , FCM moves the cluster centers to the optimal solution within the data set. Membership values and cluster centers are computed as follows:

$$w_{ik} = \left[ \frac{D_{ik}^2}{\sum_{j=1}^C D_{jk}^2} \right]^{\frac{-1}{q-1}} \quad \text{under the constraint } \sum_{i=1}^C w_{ik} = 1 \quad \forall k$$

$$V_i = \frac{\sum_{k=1}^N w_{ik}^q Z_k}{\sum_{k=1}^N w_{ik}} \quad \text{for } i = 1, \dots, C$$

where  $D_{ik}$  is the distance between  $i$ -th cluster center and  $k$ -th sample point. The iterative process ends when the membership values and the cluster centers for successive iterations differ only by a predefined tolerance  $\epsilon$ .

### 2.3 Adaptive Neuro Fuzzy Inference System (ANFIS)

ANFIS (Jang, 1993) implements a Sugeno neuro-fuzzy system making use of a hybrid supervised learning algorithm consisting of backpropagation and least mean square estimation for learning the parameters associated with the input membership functions.

A typical  $i$ -th if-then rule in a Takagi and Sugeno fuzzy model is of the type:

$$\text{if } x_1 \text{ is } A_i \text{ and } x_2 \text{ is } B_i \text{ then } f_i = p_i x_1 + q_i x_2 + r_i$$

where  $A_i$  and  $B_i$  are the linguistic terms associated with the input variables  $x_1$  and  $x_2$ . The parameters before the word "then" are the premise parameters, those after "then" are the consequent parameters. Thereafter the case of two input variables  $x_1$  and  $x_2$  and two if-then rules is considered for simplicity. The main peculiarity of a Sugeno fuzzy model is that the output membership functions are either linear or constant.

The architecture of the ANFIS network is composed by five layers as shown in figure 2.

**Layer 1** The first layer is the input layer and every node has a node function defined by the membership functions of the linguistic labels  $A_i$  and  $B_i$ . Usually the generalized bell membership function:

$$\mu_{A_i}(x) = \frac{1}{1 + \left(\frac{x-c_i}{a_i}\right)^{2b_i}}$$

or the Gaussian function is chosen as node function:

$$\mu_{A_i}(x) = e^{-\left(\frac{x-c_i}{a_i}\right)^2}$$

where  $a_i$ ,  $b_i$  and  $c_i$  are the *premise parameters*. The same holds for  $\mu_{B_i}(x)$ .

**Layer 2** In the second layer each node computes the firing strength or weight of the corresponding fuzzy rule as product of the incoming signals.

$$w_i = \mu_{A_i}(x_1) \mu_{B_i}(x_2) \quad i = 1, 2$$

Each node of this layer represents the rule antecedent part.



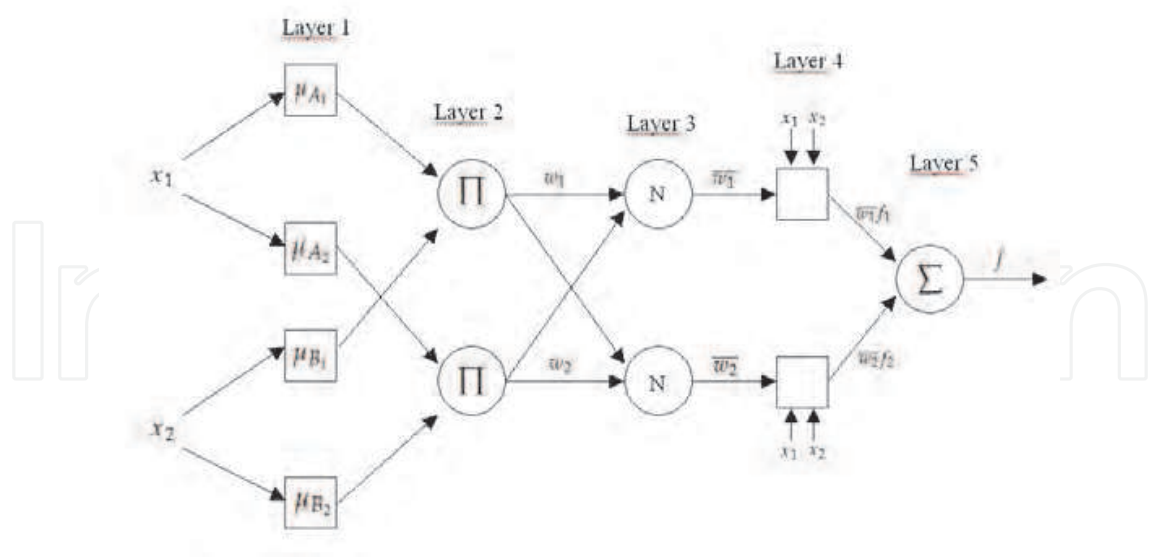


Fig. 2. The ANFIS architecture.

**Layer 3** The third layer normalizes the rule weights considering the ratio between the  $i$ -th weight and the sum of all rule weights:

$$\bar{w}_i = \frac{w_i}{\sum_i w_i} \quad i = 1, 2$$

**Layer 4** In the fourth layer the parameters of the rule consequent parts are determined. Each node produces the following output:

$$\bar{w}_i f_i = \bar{w}_i (p_i x_1 + q_i x_2 + r_i)$$

where  $\{p_i, q_i, r_i\}$  are the *consequent parameters*.

**Layer 5** Finally the fifth layer computes the overall output as following:

$$f = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

In this work we use Gaussian membership functions and their parameters, the premise parameters, are initialized by using the FCM algorithm described in the previous section. Training the network consists of determining the optimal premise and consequent parameters. During the forward pass the consequent parameters of layer 4 are identified by least square estimate. In the backward pass, instead, the premise parameters are updated applying gradient descent. For more details see (Jang, 1993).

2.4 Sensor Model

Our RFID system, at each tag detection event returns two pieces of information: the tag unique ID and its signal strength. Note that receiving a signal strength measurement implicitly involves that a tag has been detected, but we consider both information in order to make a distinction among the different tags deployed in the environment. However in the rest of the paper, for simplicity, all the variables that will be defined will refer to a generic unique tag, assuming that only relative pose between tag and antenna is relevant. This last assumption is

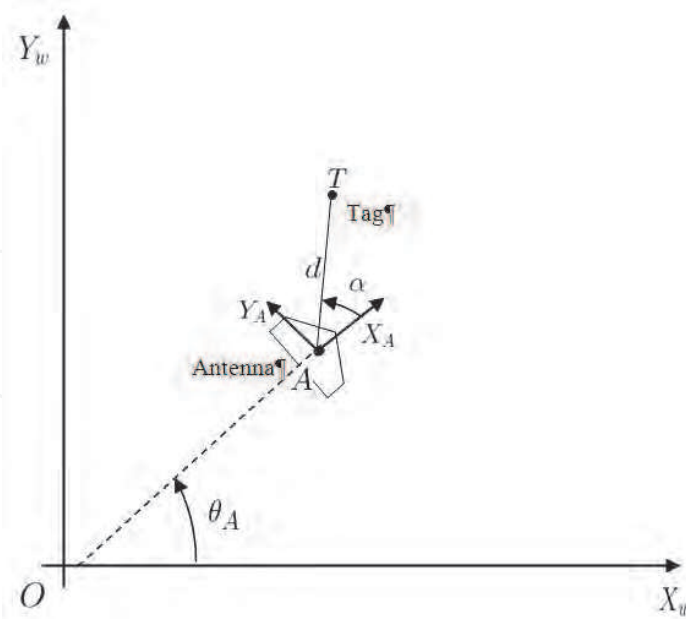


Fig. 3. Relative pose between tag and antenna.

a strong one since, as discussed in the introduction section, the propagation of an RFID signal is influenced by a set of factors dependent on the particular location of each tag: for example the materials the tag is attached on or the surface materials around the tag that can reflect or absorb the electromagnetic waves or the orientation of the tag. While location-dependent models certainly provide more precision they involve a high computational cost. In this work we tried to find a good trade-off between computational overhead and precision, developing a model that bases on both the relative location and the relative orientation of the antenna with respect to the tag.

First of all some variable definitions are needed: we define  $\alpha$  the relative orientation between antenna and tag (see Figure 3). As shown in figure 3 points  $A$  and  $T$  are antenna and tag position in the world reference system  $X_w O Y_w$ , whereas  $d$  is the distance between  $T$  and  $A$ . Angle  $\theta_A$  is the absolute orientation of the antenna in the world reference system. Each antenna is mounted on the robot and its pose with respect to the robot is known, therefore  $\theta_A$  as well as each antenna position is simply obtained by using the absolute pose of the robot in the  $X_w O Y_w$  system.

As introduced before the sensor model specifies the possibility of detecting a tag given the relative position between antenna and tag. This is modelled by multiplying the expected signal strength  $f_s(d, \alpha)$  and the frequency  $f_T(d, \alpha)$  of detecting a tag  $T$  given a certain distance  $d$  and a certain relative orientation  $\alpha$  between tag and antenna. In formula:

$$\rho = f_s(d, \alpha) f_T(d, \alpha) \quad (1)$$

In other words the sensor model is obtained combining an RSSI Model (SSM) and a Tag Detection Model (TDM). These two models are learnt by using Fuzzy Inference System, applying ANFIS networks. Both models are detailed in the next two subsections.

#### 2.4.1 RSSI Model (SSM)

RSSI Model is learnt applying the ANFIS network with two inputs,  $d$  and  $\alpha$ , and one output  $f_s$ . Data samples used as input to FCM and ANFIS are the ones stored during the data acquisition



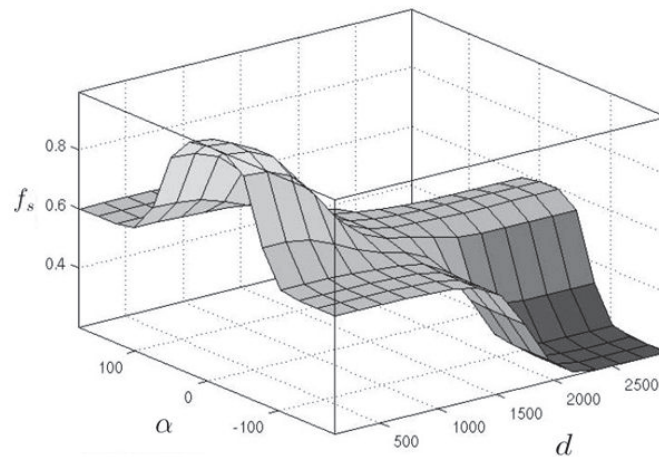


Fig. 4. Input-Output surface for RSSI Model.

phase, as described in section 2.1. First FCM algorithm is applied to initialize the membership function parameters of the input variables considering  $C = 3$  clusters (see section 2.2), then ANFIS is trained by using an additional training data set with 12395 samples. Each training data sample is composed by the couple of input variables  $(d, \alpha)$  and by the relative signal strength  $s$ , stored during data acquisition, opportunely normalized in  $[0,1]$ . For simplicity data with distance  $d < 3\text{meters}$  has been considered. Figure 4 shows the surface that models the if-then rules of the obtained fuzzy inference system. Lighter areas denote higher received signal strength.

#### 2.4.2 Tag Detection Model (TDM)

Tag Detection Model has been built similarly to RSSI model. The input variables are the same  $(d, \alpha)$ , whereas the output variable is the frequency  $f_T$  of detecting a tag given  $d$  and  $\alpha$ . In order to build the training set, the proper  $f_T$  value must be associated to each couple  $(d, \alpha)$ . This has been done by first discretizing the space into a grid of cells and then counting the number of tag detection events ( $n_T^+$ ) and the number of no-tag detection events ( $n_T^-$ ). For each cell the frequency value  $f_T$  is evaluated by using its definition formula:

$$f_T = \frac{n_T^+}{n_T^+ + n_T^-}$$

FCM, with  $C = 3$  (see section 2.2), is then applied on a first training set of data to obtain an initial fuzzy inference system used as input for ANFIS network. A second training set with 12395 sample data is used to train the network. In this case each sample is composed by the input couple  $(d, \alpha)$  and the output value  $f_T$ . The obtained input-output surface is displayed in figure 5.

### 3. Experiments

Some tests have been carried out in our laboratory by using the Pioneer P3AT robot shown in figure 1. The robot has been moved randomly in front of a tag. During navigation a number of points  $P_i$  for  $i = 1, \dots, M$  have been generated uniformly distributed within a circular area around each robot pose. Knowing the absolute position and orientation of the robot and the

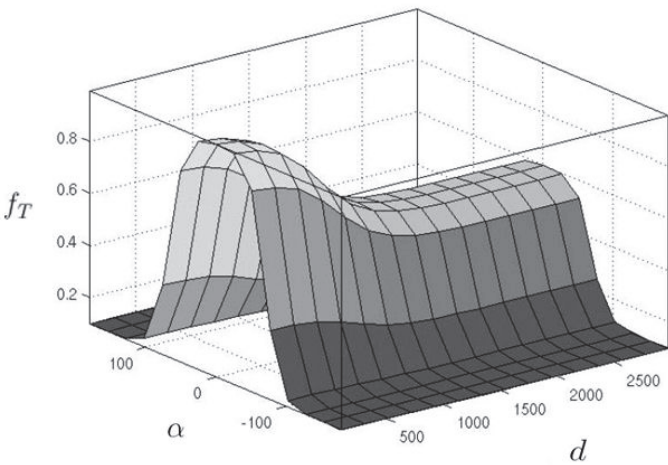


Fig. 5. Input-Output surface for Tag Detection Model.

absolute position of each generated point, the distance and relative orientation between each point  $P_i$  and each antenna can be estimated. These data are used as input to the RFID sensor model and the output  $\rho_i$  is obtained for each  $P_i$ . Figure 6 shows some plots of the described procedure in different poses of the robot. For clarity of display, data relative to only one antenna are plotted. In particular in each plot the green points refer to the set of randomly generated points, the red oriented triangle is the antenna, the blue star point denotes the position of one tag. The green area of each point changes depending on the confidence value  $\rho_i$  defined by the sensor model. Higher  $\rho_i$  larger the green area around point  $P_i$ . As can be seen in figure 6 larger areas are for those points close to the antenna current position and in front of it. Points located behind the antenna have very low  $\rho_i$  values and then are represented by smaller green areas.

At the same time, during navigation, the signal strengths  $s_j$  received by the RFID reader have been stored and compared with the  $f_s$  values returned by the RSSI model. More specifically a path of 200 robot poses  $Q_j$ , for  $j = 1, \dots, 200$ , has been considered and for each pose the average  $\bar{f}_s^j$  has been estimated considering only those points localized close to the tag:

$$\bar{f}_s^j = \frac{\sum_{k \in \mathbb{P}} f_s^k}{|\mathbb{P}|}$$

where  $\mathbb{P} = \{P_i : \|P_i - T\| < 10cm\}$ . Figure 7 shows the error  $Error = |\bar{f}_s^j - s_j|$  estimated in each robot pose. As can be noticed the error is below 20% which is a good result considering the high fluctuations of RSSI signals. Furthermore this proves the high reliability of RSSI model and then of RFID sensor model which combines both SSM and TDM.

4. Conclusion

In this chapter an approach for developing an RFID sensor model has been presented. The model is a combination of an RSSI model and a tag Detection model. The main contribution of our work concerns the supervised learning of the model to characterize the relationship between tags and antenna. FCM and ANFIS networks have been used to learn the Fuzzy Inference Systems describing both SSM and TDM. Experimental tests prove the reliability of

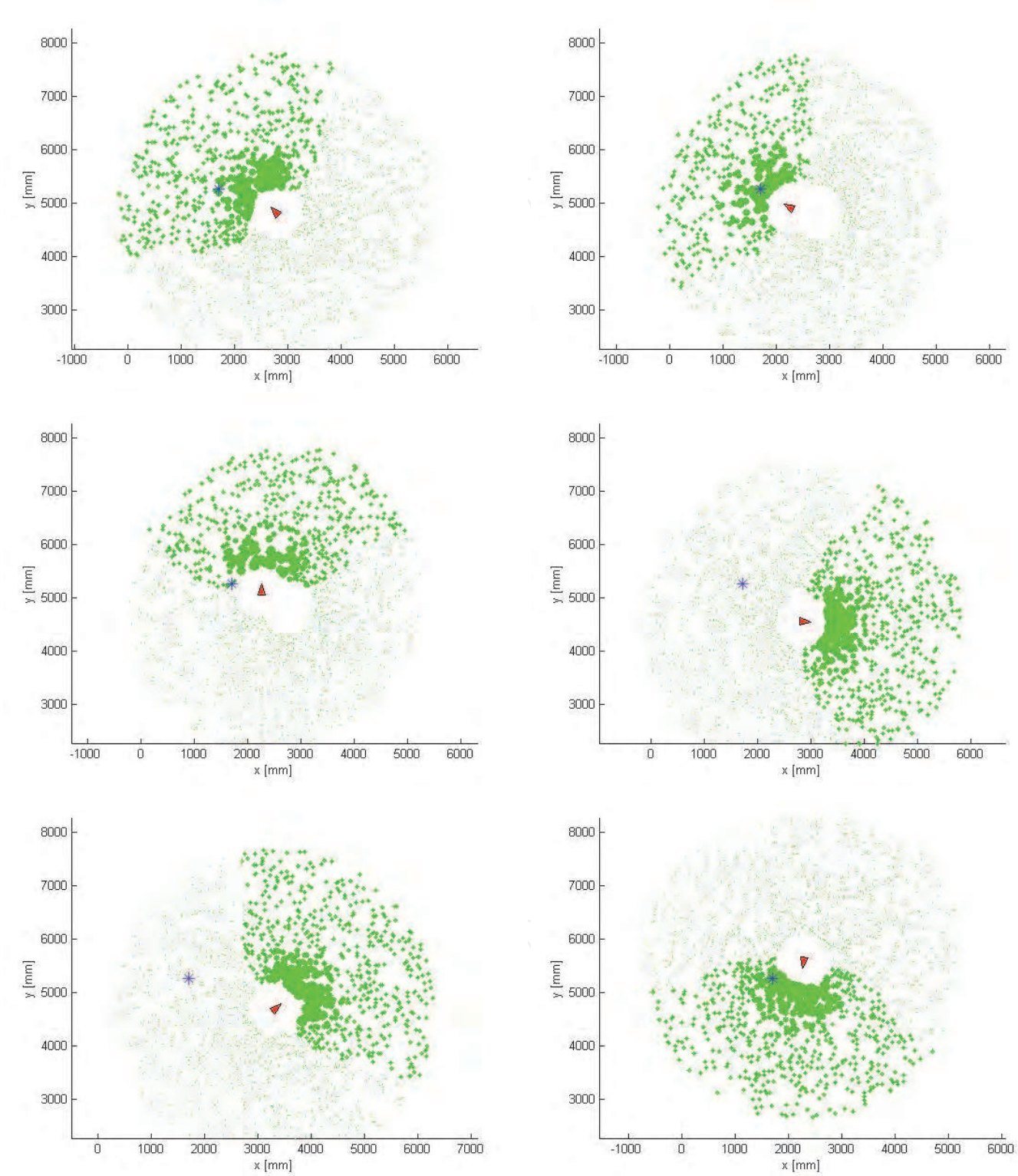


Fig. 6. Sample pictures of points randomly deployed around different robot poses with plotted importance weights (green blobs). The red oriented triangle is one antenna placed on the robot, the blue star point is the tag.

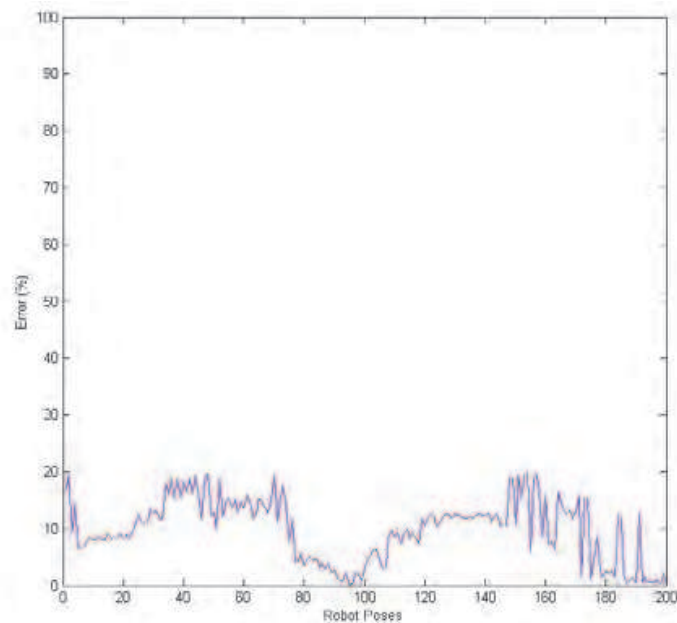


Fig. 7. Percentage average error on  $f_s$  values vs. robot poses.

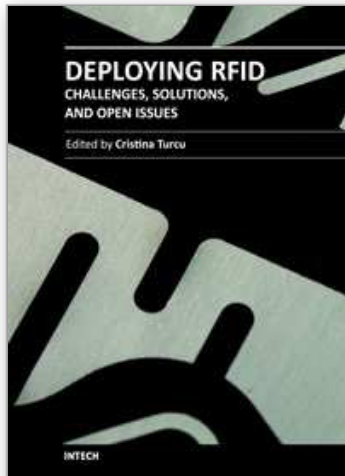
the obtained model. Constructing a reliable sensor model is very important for successive applications such as tag localization, robot localization, just to mention a few. Our future work, in fact, will address these two problems: automatic localization of tags displaced in unknown positions of the environment and, successively, absolute robot localization.

## 5. References

- Alippi, C., Cogliati, D. & Vanini, G. (2006). A statistical approach to localize passive rfids, *IEEE International Symposium on Circuits and Systems*, Island of Kos, Greece.
- Bezdek, J. C. (1981). *Pattern Recognition with Fuzzy Objective Function Algorithms*, Plenum, New York.
- Brusey, J., Floerkemeier, C., Harrison, M. & Fletsher, M. (2003). Reasoning about uncertainty in location identification with rfid, *IJCAI-03 Workshop on Reasoning with Uncertainty in Robotics*.
- Choi, B. S., Lee, J. W., Lee, J. J. & Park, K. T. (2011). A hierarchical algorithm for indoor mobile robots localization using rfid sensor fusion, *IEEE Transactions on Industrial Electronics* to appear.
- Gueaieb, W. & Miah, M. S. (2008). An intelligent mobile robot navigation technique using rfid technology, *IEEE Transactions on Instrumentation and Measurement* **Vol. 57**(No. 9).
- Hähnel, D., Burgard, W., Fox, D., Fishkin, K. & Philipose, M. (2004). Mapping and localization with rfid technology, *IEEE International Conference on Robotics and Automation (ICRA2004)*, New Orleans, LA, USA.
- Jang, S. R. (1993). Anfis: adaptive-network-based fuzzy inference system, *IEEE Trnas. on Systems, Man and Cybernetics* Vol. 23(No. 3): 665–685.
- Joho, D., Plagemann, C. & Burgard, W. (2009). Modeling rfid signal strength and tag detection for localization and mapping, *IEEE International Conference on Robotics and Automation (ICRA2009)*, Kobe, Japan.



- Kubitz, O., Berger, M., Perlick, M. & 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.
- Liu, X., Corner, M. & Shenoy, P. (2006). Ferret: Rfid localization for pervasive multimedia, *8th UbiComp Conference*, Orange County, California, USA.
- Milella, A., Cicirelli, G. & Distanto, A. (2008). Rfid-assisted mobile robot system for mapping and surveillance of indoor environments, *Industrial Robot: An International Journal* Vol. 35(No. 2): 143–152.
- Ni, M. L., Liu, Y., Lau, Y. C. & Patil, A. P. (2003). Landmarc: Indoor location sensing using active rfid, *IEEE International Conference on Pervasive Computing and Communications*, Fort Worth, Texas, USA.
- Thrun, S., Fox, D., Burgard, W. & Dellaert, F. (2000). Robust monte carlo localization for mobile robots, *Artificial Intelligence* Vol. 128(No. 1-2): 99–141.
- Tsukiyama, T. (2005). World map based on rfid tags for indoor mobile robots, *Proceedings of the SPIE*, Vol. Vol. 6006, pp. 412–419.
- Vorst, P. & Zell, A. (2008). Semi-autonomous learning of an rfid sensor model for mobile robot self-localization, *European Robotics Symposium*, Vol. Vol. 44/2008 of *Springer Tracts in Advanced Robotics*, Springer, Berlin/Heidelberg, pp. 273–282.



## **Deploying RFID - Challenges, Solutions, and Open Issues**

Edited by Dr. Cristina Turcu

ISBN 978-953-307-380-4

Hard cover, 382 pages

**Publisher** InTech

**Published online** 17, August, 2011

**Published in print edition** August, 2011

Radio frequency identification (RFID) is a technology that is rapidly gaining popularity due to its several benefits in a wide area of applications like inventory tracking, supply chain management, automated manufacturing, healthcare, etc. The benefits of implementing RFID technologies can be seen in terms of efficiency (increased speed in production, reduced shrinkage, lower error rates, improved asset tracking etc.) or effectiveness (services that companies provide to the customers). Leading to considerable operational and strategic benefits, RFID technology continues to bring new levels of intelligence and information, strengthening the experience of all participants in this research domain, and serving as a valuable authentication technology. We hope this book will be useful for engineers, researchers and industry personnel, and provide them with some new ideas to address current and future issues they might be facing.

### **How to reference**

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Grazia Cicirelli, Annalisa Milella and Donato Di Paola (2011). RFID Sensor Modeling by Using an Autonomous Mobile Robot, Deploying RFID - Challenges, Solutions, and Open Issues, Dr. Cristina Turcu (Ed.), ISBN: 978-953-307-380-4, InTech, Available from: <http://www.intechopen.com/books/deploying-rfid-challenges-solutions-and-open-issues/rfid-sensor-modeling-by-using-an-autonomous-mobile-robot>

**INTECH**  
open science | open minds

### **InTech Europe**

University Campus STeP Ri  
Slavka Krautzeka 83/A  
51000 Rijeka, Croatia  
Phone: +385 (51) 770 447  
Fax: +385 (51) 686 166  
[www.intechopen.com](http://www.intechopen.com)

### **InTech China**

Unit 405, Office Block, Hotel Equatorial Shanghai  
No.65, Yan An Road (West), Shanghai, 200040, China  
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元  
Phone: +86-21-62489820  
Fax: +86-21-62489821



© 2011 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the [Creative Commons Attribution-NonCommercial-ShareAlike-3.0 License](https://creativecommons.org/licenses/by-nc-sa/3.0/), which permits use, distribution and reproduction for non-commercial purposes, provided the original is properly cited and derivative works building on this content are distributed under the same license.

IntechOpen

IntechOpen