Indoors Localization of a Robot Using RFID Tags

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Abstract

Radio Frequency Identification - RFID - has become widely popular in recent years. In robotics it has been implemented mainly for localization and object detection. This dissertation proposes two methods using RFID technology for both people and robot localization in social robotics scenarios, in a pediatric infirmary of an oncoligical hospital. A novel approach for people localization with passive RFID tags is proposed, involving the estimation in real time of a measure of the probability of tags carried by people being detected. The method estimates the location of the tag relative to the RFID reader with an accuracy suitable for a wide range of human-robot interactions. The method for robot localization is implemented using Support Vector Machines, with tags sparsely placed on walls and doors. Through learning classification, the robot is able to estimate its position, which can be used as a complement for other localization systems. Experimental results show that both methods provide useful information for purposes of human-robot interaction and for robots to be accepted in human social scenarios.

Keywords: RFID, Social Robotics, Human-Robot Interaction, Passive Tags, Support Vector Machines

1. Introduction

This thesis is part of MOnarCH project, which focus on social robotics using networked heterogeneous robots and sensors to interact with children, staff, and visitors in the pediatric infirmary at the Portuguese Oncology Institute at Lisbon (IPOL), Portugal. MOnarCH aims the development of a novel framework to model mixed human-robot societies, establish and explore bidirectional human-robots relationships, and engage in edutainment activities with the children in the pediatric infirmary at IPOL without being invasive and to improve the children well-being. This thesis objective is to explore the potentialities of RFID technology for purposes of people detection and localization and of robot self localization in this social robotics environment, subjected to the restrictions imposed by the hospital. The goal is to develop a system capable of providing information that can be fused with other localization systems for the interaction between humans and robots to be effective and as well for robots to be accepted in human social scenarios. Radio Frequency Identification, commonly know as RFID, is a technology based on radio waves, originally developed for electronic identification and tracking, as a promising upgrade of the bar code.

Today this technology plays a key role in pervasive networks and services [11]. RFID systems are composed by tags and a reading device which communicates with them through radio frequency energy. There is an extensive work on RFID-based localization systems, with both active, and passive and semipassive tags, and single and multiple reading antennas. Reviews of key techniques are presented in [1, 7]. RFID detection can be used solo or as a complementary system to other localization techniques. For instance, [8] uses tag detection to resynchronize Inertial Measurement Units (IMU) based information; In indoor scenarios it is common to use dense grids of tags on the floor or ceiling. One or more moving readers can then be easily detected if the positions of the tags are known a priori. However, at IPOL this type of approach is not feasible as it may be too invasive. Furthermore, localization often assumes that the tag detection areas are of circular shape [4, 5], and tags are distributed according to regular patterns [6], which is seldom the case.

On the other hand, Giampaolo and Martinelli [2], propose a sparse placement of tags with a novel antenna design which guarantees fairly regular and stable detection regions. Senta et al. [10], address a method for localization using Support Vector Machines (SVMs), which enables the robot to localize itself, even if it does not know the location of tags.
placed in its environment.

Basic detection experiments readily showed that often in indoor environments the propagation conditions are such that the sphere detection volume can widely change. This can happen for a variety of reasons, namely multipath, absorption, reflection, and diffraction, [1], and often cannot be controlled. For example, empirical observation has shown that in a typical indoor corridor the detection volume can have the section of the corridor and be about 6–8 meters long, for the reader considered in this work, even though the manufacturer sets the maximum range in 3 m. In a sense, given a generic environment it is very difficult to predict the shape of the detection volume. Often, the spherical (or half-spherical) volume assumption is not realistic. Moreover, additional testing also determined that a tag can be in a close neighborhood of the reader without being detected, particularly happening if there is no relative motion between tags and reader. Hence, this thesis proposes a solution with methodologies which aim to overcome these RFID characteristics and adapt state-of-art approaches to MOnarCH context. Experiments were performed at Instituto for Systems and Robotics (ISR), located at Instituto Superior Técnico (IST), Lisboa.

The remainder of this dissertation is organized as follows: Section 2 describes the physical principles of RFID technology and the main characteristics of the reader and tags used in this work; methodology and results for People Localization are presented in Section 3, and for Robot Localization in Section 4. Finally, Section 5 includes a conclusion to the overall accomplished work and delineates directions for future developments.

2. Background

RFID is an automatic identification technology with a contactless transfer of data between the data-carrying and reading devices. A basic RFID system consists of two components: the transponder, usually known as tag, and the interrogator or reader. A RFID reader normally contains a radio frequency module, including a transmitter and a receiver, a control unit, an antenna to provide coupling to the tag and an additional interface to enable forwarding the data received to another system, [3]. A tag is located on the object or place to be identified and is typically made up of an antenna, an electronic microchip and an encapsulation. To each tag there is a unique identifier associated, as well as additional data, depending on its memory capacity. The antenna captures energy and transfers the tag’s data, stored in the chip, back to the reader. All types of tags use radio frequency energy to communicate with the reader, but the method of powering them differs, and thus they use fundamentally different technology to function.

Methods proposed in this thesis use passive tags, which do not require autonomous power supply, as it is provided by the reader through the coupling unit when the tags are within the interrogation zone of a reader. Therefore, passive RFID operation requires very strong signals from the reader and returns with a low-level strength due to the tag limited energy. Detection ranges vary between a few millimeters and over tens of meters, depending on the frequency used. Despite having limited memory (around 128 bytes or less) and range, the absence of internal power source makes passive tags smaller and cheaper compared active tags and therefore have become by far the most common type in use. RFID systems generally operate at low-frequency (LF, around 125 kHz), high-frequency (HF, 13.56 MHz) and ultrahigh-frequency (UHF, between 860 to 960 MHz)

The reader used in this thesis operates in the UHF band and hence, the communication is based on a far-field design (rather than near-field which is used in lower frequency bands). This means that tags are powered through capturing the EM waves propagating from a dipole antenna in the reader. As tags are beyond the reader’s near field, data can’t be transmitted back using load modulation, but use a technique called back scattering. The antenna is designed with precise dimensions, tuned for a particular frequency and is able to absorb most of the energy that reaches it at that frequency. With an impedance mismatch, the antenna reflects back some of the energy towards the reader as tiny waves. By varying it over time the tag can encode the data and reflect it back. Finally, the reader can detect the incoming waves using a sensitive radio receiver. Far-field system range is limited by the amount of energy that reaches the tag and the sensitivity of the reader radio receiver to the returned signal, which is the result the two attenuations: first when the waves radiate from the reader to the tag and second when the signal travels back to the reader, [11].

2.1. RFID System for MOnarCH robots

The RFID system implemented on the MOOnarCH robots, had to be in accordance with the project characteristics, including the constraints imposed by IPOL. Tags have to be discretely placed around the corridor and rooms, and carried by people, both children and adults.

The RFID reader used in this work is a commercial SYNCO, model SR-RU-1861S, operating in the UHF band, between 902 ~ 928 MHz, with far-field powering design. The antenna is described as omnidirectional by the manufacturer with an effective range of about 3 meters, using a 8 dBi antenna (manufacturer’s data), which is the forward...
gain of an antenna compared with the hypothetical isotropic antenna that uniformly distributes energy in all directions. The reader uses a serial RS232 interface to connect to an external device.

Tags are blank card-shaped, 86x54 mm, as shown in Fig. 1(a) and suitable for the project requirements. The reader is shown on a tripod in Fig. 1(b).

![RFID tag](image1.png) ![RFID reader](image2.png)

**Figure 1:** RFID tag and reader used in this work.

The MonarCH robots are omnidirectional robots based on four Mecanum wheels actuated by four independent motors. The use of this kind of kinematics substantially increases the manoeuvrability and performance of the platform.

There are two types of robots in MOnarCH: a more sophisticated one targeting social interactions with children, staff and visitors (SO robot) and a simpler one that is used to increase the perception of the environment (PO robot), as depicted in Fig. 2. Both of them are equipped with a RFID reader. Moreover, they also have several sensors which allow them to perceive the environment and interact, such as sonars, laser range finder or *Microsoft Kinect*™.

The SO robot has two onboard computers: the Navigation Computer which is running Linux OS (Ubuntu) and is responsible for navigation, localization, system control and actuation of some low-level interaction devices, like LEDs; and the Human Robot Interaction Computer, which is also running Linux OS (Ubuntu) and is responsible for the control of the interaction devices, like the Kinect camera, projector and touch-screen monitor.

The PO robot, being a simpler robot, has only the Navigation Computer, similar to the one in SO. In addition, the PO robot does not have arms and a moving head and also does not include the Kinect camera, projector and touch-screen.

The robots have path planning and obstacle avoidance algorithms and can be controlled through tele-operation or using a state machine. Both robots and controlling operations were used for the experiments.

![SO robot](image3.png) ![PO robot](image4.png)

**Figure 2:** MOnarCH robots.

![Setup](image5.png)

**Figure 3:** Setup for the first probabilities model.

3. **People Localization**

3.1. **Probabilities Model**

As mentioned in Section 1, preliminary experiments with the RFID reader showed the omnidirectional antenna pattern proposed by the manufacturer can widely change depending on the environment where was tested. In addition, testing also exposed that tags were not always detected with the same frequency over time, even if their relative position to the reader was the same, particularly if there was no relative motion between the tag and the reader. As so, the reader was modeled using a probabilistic-like technique by which to each point in a neighborhood of the reader was assigned a probability of a tag being detected in case it was located at that point. The probability is the quotient between the number of times a tag was detected over the total number of times the tag was placed in that position. Figure 3 shows the setup for a first model of the reader, obtained in an easy environment, i.e., wide indoors open area. The reader and tag can be seen duly aligned in tripods.

Measurements were taken along three circumferences of radius 1, 2, and 3 meters, with nine measurements each at regular angular intervals. The probabilities were estimated from 100 measurements. All models assumed the origin, where the center of the RFID antenna is located, had probability 1. These were then used to interpolate a cubic surface\(^2\) (Fig. 4). The tag was always kept at the same height relative to the reader and hence the

\(^2\)Python function scipy.interpolate.griddata was used to compute the cubic surface.
interpolated surface is two-dimensional. The model shows a central lobe, slightly deviated to the left, corresponding to the high detection probabilities.

In general, placing the RFID reader inside the robot reduces its capabilities due to shielding and/or interference. Therefore, it could be expected that the model in Fig. 4 changed substantially when the environment around the reader also changed. Figure 5 shows the RFID antenna, without its shell, installed in the MOnarCH robot. The antenna is located in the head of the robot and space constraints imposed that it was placed facing upwards.

Figure 6 illustrates the interpolated surface, corresponding to a series of estimated probabilities at specific points in the neighborhood of the reader, placed inside the robot. The tags were kept always at the same height relative to the reader and hence the interpolated surface is two-dimensional.

In a more general setting a tag can change height in time, e.g., depending on the height of the person carrying it. This means that the detection conditions may vary and hence also the interpolated surface. The distribution of points obtained from the raw readings can be used to interpolate a cubic surface. This surface is in fact the probabilities model of the reader.

### 3.1.1 Relative location estimation

The interpolated surface found in the previous subsection represents a model that embeds both reader and environment characteristics.

As the robot moves, detection probabilities are being updated. If a tag is suddenly detected then the robot may stop to better estimate the corresponding probability. In general, this will have a reduced impact on the effectiveness of the interaction with the people.

Once a probability is estimated, the interpolated model for the reader can be used to obtain a region of the most probable locations of the tag. Figure 7 illustrates a realistic situation. The person standing up is wearing a RFID tag on his shirt whereas the white robot shown carries the RFID reader inside its outer shell. The plot shows the region corresponding to the estimated probability within a $\epsilon = 0.1$ margin.

Overall, the probability of a tag being detected is simply estimated by the counting Algorithm 1.

**Algorithm 1 Tag detection probability estimation**

```python
Require: total_reads
tag_count ← 0;
if tag detected then
    for i = 1 to total_reads do
        re-read the tag;
        if tag is detected then
            tag_count ← tag_count + 1;
        end if
        wait for $\Delta t$ s;
    end for
    prob = tag_count/total_reads
    publish prob
    return probability updated
else
    return probability not updated
end if
```

The waiting time between readings, $\Delta t$, is chosen empirically as $\Delta t = 0.05$ s. It corresponds to the
time required for the reader to return meaningful data. The detection time is then $N \Delta t$, where $N$ is the total number of reads. By default, $N$ is set to 100, yielding $N \Delta t = 5$ s, which is acceptable for a number of HRI applications.

Once a probability estimate is available, Algorithm 2 is run to select an estimate for the position of the tag, relative to the position of the robot.

Algorithm 2 Tag position estimation

Require: Reader Model, $\epsilon$

Compute the area, according to the model, with $\text{prob} \in [\text{prob} - \epsilon, \text{prob} + \epsilon]$

Compute the medial skeleton of that area

Compute the point in the skeleton with the biggest distance to the boundary of the area (this point is the position estimate)

Algorithm 2 can return more than one point and it may even return one or more line segments (i.e. segments of the skeleton for which all points lie at the same distance of the border of the estimate region).

3.2. Experiments and Results

This section describes the experiments in ISR with a MOnarCH robot and a person carrying a tag. These are grouped in two classes, differing on the amount of time used for detection. In the first group $N = 100$, resulting, as aforementioned, in $T = 5$ s. The second group $N = 30$, resulting in $T = 1.5$ s. The objective is to assess the influence of the time taken for measurement of the detection probability on the location estimate.

To increase the flexibility of the detection one additional parameter is introduced, namely, prior information on the location of the person. This parameter masks the area around the reader such that only part of it is considered for detection. Acceptable values are (i) no information, meaning that no mask is applied and the full area around the reader is used to search for a solution, (ii) person in front of the robot, meaning that only an area of angular with $180^\circ$ centered with the longitudinal axis of the reader is used, and (iii) person behind the robot, which means that a $180^\circ$ area behind the reader is taken into account.

For the purpose of analysis, the measurements are grouped. The objective of this grouping is to provide a confidence measure that a tag is detected at some angular direction that is meaningful from the perspective of HRI. In fact, for most applications involving HRI, a high accuracy in the tag position estimate it is not required. Therefore, an angular interval around the real direction of the tag is defined and a counting of the number of detections lying inside that interval provides a rough estimate of the probability that a tag approaching some direction is correct. Two widths for this interval were considered, namely $90^\circ$ and $180^\circ$.

The experiments evolved as follows ($\epsilon = 0.1$ was always used). The robot is placed at the center of a circle with 3 m radius. A person walks from outside the circle towards the robot, keeping the same angle relative to the longitudinal axis of the reader. Algorithm 1 and Algorithm 2 compute the tag angle estimate 10 times for each angle. A total of 8 angles (or 5 in the cases where a mask is applied) is used for the person approaching the robot. For these experiments only the angle relative to the robot was considered for the estimate. The person was carrying the tag at approximately the height of the robot.

Figures 8 to 13 represent the probability of the computed angle being inside the angular width region of the real angle (corresponding to the person angular position). Each experiment is shown for the two angular width values considered.

In the first experiment, Fig.8, the probabilities that the detection is correct when the person approaches the robot by the front are clearly much higher than approaching from behind. The higher values for the $180^\circ$ threshold are natural as the region considered for the counting is higher and can
catch a larger number of detections. The same experiment for detection time 1.5 s yields similar results. Though the regions in the back get lower detections than those in the front, the regions of higher detection have similar locations. The conclusion is naturally that detection confidence gets larger as the detection time increases (the results support the 5 s maximum value a priori assumed).

Figures 10 and 11 show the second experiment masking the back part of the robot, i.e., detection is considered to be always in the front of the robot. The results follow in the line of those of the previous experiment, namely detection confidence increases with the angular threshold and detection time. In the last experiment, Figs. 12 and 13, the detection mask is on the frontal area of the robot. The experiment shows much higher probabilities, suitable for HRI applications. In addition, results are fully consistent with the conclusions drawn from the two previous cases.

Experiments show that the angle estimate is better for the first group, with 5 s detection time, but both groups have good results, namely if the output is to be used for HRI purposes. In terms of the prior information of the person position, experiments demonstrate that in the first case, i.e., the full area around the robot is used, the model only performs acceptably if the person is in front of
the robot. However, if the robot is only interested in detecting people from behind, the quality of the results improves significantly. Higher probabilities appear when the angular width of the detection region is 180°, as expected. In sum, experiments yield a performance that is acceptable for most HRI applications, namely speech interaction where there is no need to know accurately the orientation of the person relative to the robot.

4. Robot Localization

4.1. Methodology

Unlike the approach for people localization, based on a probabilities model of the reader, the Robot Localization method only depends on the ID of the passive tags and is built upon Support Vector Machines (SVM), similarly to the proposal of Senta et al. [10]. Experimental tests were performed at ISR, where tags were placed on a corridor, namely on walls at different heights, and on metallic and wooden doors. As expected, the place where tags are fixed has a determinant influence on the number and range of detections.

Figure 14 shows a map of ISR (8th floor, North Tower, in IST) where tests were conducted. A total of 10 passive tags were used in these experiments, represented on the map by colored squares. For the study in question only one section corridor was taken into account.

In Fig.15 transparent circles are samples that represent the robot position where different tags were detected. Areas with a similar color to a tag correspond to several detections around that position.

Based on the observations of detections, the corridor was divided into 5 zones, as seen in Fig.16. To utilize the SVM, vectorizing the events that the robot needs to learn is mandatory. For this work, these events include (i) ID of the tags read by the robot and (ii) the ID-read count. The vectorization consists of the ID and the ID-read count $k$ as $0,1,2..., n$ where $n$ is the number of tags in the environment.

$$X = (ID_1, ID_2, ..., ID_n, k_1, k_2, ..., k_n). \quad (1)$$

This means that the dimension of a vector is equal to the two-fold number of existing tags within the environment. Therefore, if the number of tags increases greatly, the system can be at risk of breakdown, but this vectorization is adequate with the 10 tags used for this study.

For this work Support Vector Classification (SVC)$^4$ was used, with Radial Basis Function (RBF) Kernel, $exp(-\gamma \cdot |x_i - x_j|^2)$, where $x_i, x_j \in \mathbb{R}^N$ are rows of the dataset $X$ and $\gamma = \frac{1}{2n}$ is the kernel coefficient.

One classifier is associated with each zone. As SVM is a 2-class categorizer, they are implemented hierarchically, meaning that each SVM depends on the prediction of the previous one, starting at zone A and finishing at zone E.

Additionally, as SVM is a supervised learning algorithm, labeling is required. In this case, the label $\gamma = \frac{1}{2n}$

$^4$Python sklearn function svm.SVC
is whether the robot is truly inside or outside the current training zone.

4.2. Results

Common statistical measures of performance were computed to evaluate the quality of predictions of the classifier. In this setting, where $X$ denotes any of the 5 defined zones, the following elements were used:

- True positive (TP): Robot inside zone $X$ correctly identified as inside;
- True negative (TN): Robot outside zone $X$ correctly identified as outside;
- False positive (FP): Robot outside zone $X$ incorrectly identified as inside;
- False negative (FN): Robot inside zone $X$ incorrectly identified as outside.

And also the following functions:

- **Sensitivity** measures the proportion of positives that are correctly identified as such:
  \[ \text{Sensitivity} = \frac{TP}{TP + FN} \]  
- **Specificity** measures the proportion of negatives that are correctly identified as such:
  \[ \text{Specificity} = \frac{TN}{TN + FP} \]  
- **Precision** (or **Positive Predictive Value** (PPV)) measures the proportion of true positives compared to all positives predictions:
  \[ \text{Precision} = \frac{TP}{TP + FP} \]  
- **Negative Predictive Value** (NPV) measures the proportion of true negatives compared to all negative predictions:
  \[ \text{NPV} = \frac{TN}{TN + FN} \]

The following analysis includes two cases where SVMs are presented for each zone independently and a third case where the classifier is operating for all zones.

4.2.1 Case 1 - Independent zone analysis

Tables 1 and 2 show the results for the statistical functions previously addressed, directly from a test dataset of each SVM, without any modification. Samples were collected right after the training was completed for each zone and before training the next. Some classes are imbalanced, i.e., there are more elements in one the classes. Variable $L$ denotes the total number of test samples for each zone.

<table>
<thead>
<tr>
<th>Zone</th>
<th>$L$</th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>322</td>
<td>61</td>
<td>136</td>
<td>1</td>
<td>124</td>
</tr>
<tr>
<td>B</td>
<td>354</td>
<td>44</td>
<td>217</td>
<td>19</td>
<td>74</td>
</tr>
<tr>
<td>C</td>
<td>290</td>
<td>56</td>
<td>137</td>
<td>0</td>
<td>97</td>
</tr>
<tr>
<td>D</td>
<td>464</td>
<td>133</td>
<td>240</td>
<td>9</td>
<td>82</td>
</tr>
<tr>
<td>E</td>
<td>297</td>
<td>37</td>
<td>96</td>
<td>3</td>
<td>161</td>
</tr>
</tbody>
</table>

Table 1: Table with statistical functions to evaluate the classifiers performance - case 1

<table>
<thead>
<tr>
<th>Zone</th>
<th>Sens.</th>
<th>Spec.</th>
<th>Prec.</th>
<th>NPV</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.33</td>
<td>0.99</td>
<td>0.98</td>
<td>0.52</td>
</tr>
<tr>
<td>B</td>
<td>0.37</td>
<td>0.92</td>
<td>0.70</td>
<td>0.75</td>
</tr>
<tr>
<td>C</td>
<td>0.37</td>
<td>1.00</td>
<td>1.0</td>
<td>0.59</td>
</tr>
<tr>
<td>D</td>
<td>0.62</td>
<td>0.96</td>
<td>0.94</td>
<td>0.75</td>
</tr>
<tr>
<td>E</td>
<td>0.93</td>
<td>0.37</td>
<td>0.19</td>
<td>0.97</td>
</tr>
</tbody>
</table>

Table 2: Table with statistical functions to evaluate the classifiers performance - case 1

For all zones expect E, there is a large number of False Negatives (robot inside the training zone but predicted as outside). Through analysis of the training samples, it is possible to realize that these FN happen when no tags are detected, i.e., a training vector full of zeros. On the other hand, for zone E the classifier yielded an opposite result: practically no FN, but a huge number of False Positives (robot outside E but predicted as inside). Again most of them being all-zeros vectors. This can be explained by the fact that the SVMs are created hierarchically and the classifier of zone E, depending on all other zones, determined that all-zeros vectors belong to E.

4.2.2 Case 2 - Independent zone analysis without empty detections

In order to improve the SVM classifiers and overcome the significant number of false predictions, test samples with no tags detected were ignored. Tables 3 and 4 show the results.

As observed, false negatives have greatly decreased in general, proving that these were indeed caused by empty detections. In the particular case of zone E, the number of false positives almost disappeared as well. True negatives in E slightly decreased, but it still yields good results.

4.2.3 Case 3 - Simultaneous zone analysis

Statistical functions described in previous cases are defined for a 2-class problem. Hence, this case only
Table 3: Table with statistical functions to evaluate the classifiers performance - case 2: Samples with no detection are ignored

<table>
<thead>
<tr>
<th>Zone</th>
<th>L</th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>100</td>
<td>61</td>
<td>24</td>
<td>1</td>
<td>14</td>
</tr>
<tr>
<td>B</td>
<td>148</td>
<td>44</td>
<td>85</td>
<td>19</td>
<td>0</td>
</tr>
<tr>
<td>C</td>
<td>111</td>
<td>56</td>
<td>54</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>D</td>
<td>176</td>
<td>133</td>
<td>30</td>
<td>9</td>
<td>4</td>
</tr>
<tr>
<td>E</td>
<td>115</td>
<td>11</td>
<td>96</td>
<td>5</td>
<td>3</td>
</tr>
</tbody>
</table>

Table 4: Table with statistical functions to evaluate the classifiers performance - case 2: Samples with no detection are ignored

<table>
<thead>
<tr>
<th>Zone</th>
<th>Sens.</th>
<th>Spec.</th>
<th>Prec.</th>
<th>NPV</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.81</td>
<td>0.96</td>
<td>0.98</td>
<td>0.63</td>
</tr>
<tr>
<td>B</td>
<td>1.00</td>
<td>0.82</td>
<td>0.70</td>
<td>1.00</td>
</tr>
<tr>
<td>C</td>
<td>0.98</td>
<td>1.00</td>
<td>1.00</td>
<td>0.98</td>
</tr>
<tr>
<td>D</td>
<td>0.97</td>
<td>0.77</td>
<td>0.94</td>
<td>0.88</td>
</tr>
<tr>
<td>E</td>
<td>0.79</td>
<td>0.95</td>
<td>0.69</td>
<td>0.97</td>
</tr>
</tbody>
</table>

Table 5: Values of confusion matrix.

<table>
<thead>
<tr>
<th>Zone</th>
<th>Sens.</th>
<th>Spec.</th>
<th>Prec.</th>
<th>NPV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.04</td>
<td>0.91</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>0.00</td>
<td>0.83</td>
<td>0.17</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>0.00</td>
<td>0.17</td>
<td>0.72</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
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<td>0.00</td>
<td>0.11</td>
<td>0.82</td>
</tr>
<tr>
<td></td>
<td>0.00</td>
<td>0.00</td>
<td>0.59</td>
<td>0.41</td>
</tr>
<tr>
<td></td>
<td>0.00</td>
<td>0.00</td>
<td>0.50</td>
<td>0.50</td>
</tr>
</tbody>
</table>

Figure 17: Normalized confusion matrix for all zones

zones are always adjacent to the correct ones (assuming that the robot can only go outside of the corridor through A or E).

The results presented in this section demonstrate that the proposed approach for robot localization can provide useful information for the overall localization system and can be extended to IPOL. The pediatric infirmary has a long corridor and tags can as well be placed on doors and walls and zones can be defined based on study presented.

5. Conclusions

The thesis successfully presented two methods using off-the-shelf RFID technology for people and robot localization in scenarios where human-robot interaction is relevant. The technique for people localization has shown to have a detection accuracy in estimating the direction of movement of a person relative to a robot suitable for most HRI applications. Even though more accurate techniques do exist from an absolute perspective, such as vision, it is often the case that there are situations where they are unable to operate, e.g., in case of occlusions. Therefore, this approach is envisaged to be used either isolated or as complement to other techniques. Moreover, in the case of unstructured environments, where it may be difficult to install more accurate sensing, e.g., static cameras and the respective network infrastructure, this solution presents a clear advantage. The main limitation seems to be related to environments with difficult radio frequency propagation conditions. The proposed method for robot localization is able to locate the robot within certain defined zones, based on tags sparsely placed on walls and doors. Although the estimation is not precise, it can provide localization information to be conjugated with other technologies, and be helpful in cases where the robot gets lost or needs to reset its position.

Different interesting directions for future work naturally became clear throughout the research and writing of this dissertation. The most obvious one, which includes both people and robot localization, is to implement these methods at IPOL to interact with children, staff and visitors and to fuse the localization estimate with other systems. Specifically for people localization, future work includes...
(i) the tuning of parameters in the probability estimation algorithm, namely the time between readings and assessing the system in a wide variety of environments and with the people wearing the tags at a range of different heights (children are usually smaller than adults), (ii) obtain a 3D model based on various reader models from different heights, and (iii) overcome the limitation the effects of the human body in the tags detection, which has a high dielectric permittivity and is highly dissipative, affecting the antenna radiation. On-body RFID tag antennas do exist [9], and can even be used inside pockets, which is surely less invasive compared to proposed solution. In terms of robot localization, further developments include (i) filling the whole ISR floor with tags and integrate the system with the overall localization of the robot, (ii) a new SVM classifier can be trained, which learns if whether the robot is on the left or right side of the corridor, (iii) find a solution to place tags in concrete walls or metallic surfaces without influencing the quality of detection. This can possibly be achieved with a small volume which allows tags to be some centimeters away from the surfaces they are placed on, (iv) include the probabilities model to better estimate the robot position and (v) get an estimation of the orientation of the robot in some particular regions where it is most needed, based on both proposed methods.

References


