Indoors Localization of a Robot Using RFID Tags

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**Electrical and Computer Engineering**

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Duarte Lopes Gameiro
Resumo

Identificação por radiofrequência - RFID - tornou-se bastante popular nos últimos anos na área da identificação automática e seguimento em cadeias de distribuição. As vantagens da tecnologia em comparação com outros sistemas de localização sem fios são indiscutíveis: funcionamento fora do campo de visão, baixo custo e tamanho das tags. Em robótica tem sido implementada principalmente em localização e em detecção de objectos.

Esta dissertação propõe dois métodos que usam tecnologia RFID para localização de pessoas e localização de robôs num cenário de robótica social, especificamente na pediatria de um hospital oncológico onde robôs interagem com crianças, pessoal médico e visitantes, participando em actividades educacionais de entretenimento que ajudam a melhorar o bem-estar das crianças.

Estado da arte relevante é discutido, nomeadamente, estratégias comuns para sistemas de localização baseados em RFID e o uso de RFID em ambientes hospitalares.

Para localização de pessoas, uma nova abordagem com tags RFID passivas é proposta, envolvendo a estimação em tempo real de uma medida de probabilidade das tags (transportadas pelas pessoas) ser detectada. O método estima a localização de tags relativamente ao leitor RFID com uma exactidão adequada para uma grande variadade de interações humano-robô. O método de localização do robô é implementado usando Support Vector Machines, com tags colocadas em paredes e portas de forma dispersa. Através de aprendizagem supervisionada via SVM, o robô consegue estimar a sua posição, que pode ser conjugada com outros sistemas de localização.

Resultados experimentais mostram que ambos os métodos fornecem informação útil para aplicações de interacção humano-robô e para que os robôs sejam aceites em ambientes sociais humanos.

Palavras-chave: RFID, Robótica social, Interacção Humano-Robô, Máquina de Vectores de Suporte
Abstract

Radio Frequency Identification - RFID - has become widely popular in recent years in the area electronic identification and tracking. The technology advantages compared to other wireless positioning systems are undeniable: availability in non line-of-sight, low-cost and compactness. In robotics it has been mainly implemented for localization and object detection.

This dissertation proposes two methods using RFID technology for both people and robot localization in social robotics scenarios, specifically in a pediatric infirmary of an oncological hospital where robots interact with children, staff and visitors, engaging in edutainment activities which help to improve the children well-being.

Relevant state-of-the-art is presented, namely, common strategies for RFID-based localization systems and the use of RFID in healthcare environments.

For people localization, a novel approach with passive RFID tags is proposed, involving the estimation in real time of a measure of the probability of the 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 fused with 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, Support Vector Machines
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## Glossary

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<td>EM</td>
<td>Electromagnetic</td>
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<tr>
<td>HF</td>
<td>High Frequency</td>
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<tr>
<td>HRI</td>
<td>Human-Robot Interaction</td>
</tr>
<tr>
<td>IPOL</td>
<td>Portuguese Oncology Institute at Lisbon (Instituto Português de Oncologia de Lisboa Francisco Gentil)</td>
</tr>
<tr>
<td>ISR</td>
<td>Institute for Systems and Robotics</td>
</tr>
<tr>
<td>IST</td>
<td>Instituto Superior Técnico</td>
</tr>
<tr>
<td>IT</td>
<td>Instituto de Telecomunicações</td>
</tr>
<tr>
<td>LF</td>
<td>Low Frequency</td>
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<tr>
<td>MOnarCH</td>
<td>Multi-Robot Cognitive Systems Operating in Hospitals</td>
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<tr>
<td>RFID</td>
<td>Radio Frequency Identification</td>
</tr>
<tr>
<td>RF</td>
<td>Radio Frequency</td>
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<tr>
<td>ROS</td>
<td>Robot Operating System</td>
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<tr>
<td>SVM</td>
<td>Support Vector Machines</td>
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<tr>
<td>UHF</td>
<td>Ultra-high Frequency</td>
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<td>UWB</td>
<td>Ultra-wideband</td>
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Chapter 1

Introduction

1.1 Motivation

This thesis is part of MOnarCH project (Multi-Robot Cognitive Systems Operating in Hospitals)\(^1\), 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 - Instituto Português de Oncologia de Lisboa Francisco Gentil (IPOL), Portugal. MOnarCH aims at 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, in order to improve the children’s well-being. MOnarCH is funded by European Commission as part of the 7th Framework Programme for European Research and Technological Development and includes several partners such as the Association of Instituto Superior Técnico for Research and Development (IST-ID), two spin-off companies from Instituto Superior Técnico (IST) - SELFTECH\(^2\) and IDMind\(^3\), Örebro University (ORU), University Carlos III of Madrid, École Polytechnique Fédérale de Lausanne (EPFL), and University of Amsterdam.

The project is built on models from social sciences and state-of-the-art technologies and techniques, such as state-of-art imaging, voice sensing and radio frequency identification (RFID), that provide a fair amount of data to perception components. In addition, ethical regulations enforced by IPOL for the pediatric ward introduce important constraints on the use of some of these technologies, representing a challenging research opportunity.

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. A study is done in order to understand the best methodologies to be followed, the added value and limitations of RFID, specifically

\(^1\)www.monarch-fp7.eu
\(^2\)www.selftech.pt
\(^3\)www.idmind.pt
for the MOnarCH context. This thesis contains all RFID-related developments for the project.

1.2 RFID based Localization

Localization is a key problem in mobile robotics. For a robot to have autonomous capabilities, it needs to estimate its own pose - position and orientation - relative to the environment. On the other hand, recognizing the localization of a person with respect to the robot (or vice-versa) is of uttermost importance if it is to behave according to the social norms enforced by the context the robot is inserted in. Even if robots do not have senses as good as human beings, researchers have been for decades developing different technologies that allow them to perceive their surroundings in ways that go way beyond human capabilities.

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 [1]. RFID systems are composed by tags, usually attached to objects to be identified, and a reading/writing device which communicates with tags through radio frequency energy. Among different indoors wireless positioning systems, RFID has been constantly highlighted by researchers due to its advantages, namely availability in non line-of-sight, low-cost and compactness.

In the last few years RFID has been introduced in mobile robotics, mainly for purposes of localization and of object detection. 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, [2, 3], and tags are distributed according to regular patterns, [4], which is seldom the case.

Basic detection experiments readily showed that often in indoors 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 [5], 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 meters. 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 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 the MOnarCH context.

Experiments were performed at Institute for Systems and Robotics (ISR), located at IST, Lisboa.

Two methods are proposed using RFID technology. On one hand, for people localization for human-robot interactions (HRI), the RFID reader is modeled using a probabilistic-like technique where each point in the neighborhood of the reader is assigned a probability of a tag being detected in case it is
located at that point, with tags carried by people. This probability is the quotient between the number of times a tag is detected over the total number of times the tag is placed in that position. Then an algorithm based on medial skeleton gives an estimate of the tag position relative to the robot. On the other hand, the approach used for robot self localization is implemented using Support Vector Machines, while tags are sparsely placed on walls and doors. Through learning classification the robot is able to estimate its position which can be used as a complement to other localization systems, e.g., in places where it can get lost or needs to reset its position.

1.3 Contributions

The methods previously described are being implemented in MOnarCH robots at IPOL. Firstly, the system can detect people for HRI purposes carrying RFID tags and secondly it can provide useful localization information which, despite not being precise, can help the overall system in some common situations.

Based on this work, a paper entitled "RFID-Based People Detection for Human-Robot Interaction" was presented at the ROBOT’2015 - Second Iberian Robotics Conference.

1.4 Thesis Outline

The remainder of this dissertation is organized as follows: relevant state-of-the-art in the area of mobile robotics and RFID is addressed in Chapter 2. Chapter 3 describes RFID technology in more detail and the main characteristics of MOnarCH robots and the reader and tags used in this work; Methodology and results for People Localization are presented in Chapter 4, and for Robot Localization in Chapter 5. Finally, Chapter 6 includes a conclusion to the accomplished work and establish directions for future developments.

Figure 1.1: MOnarCH robot at IPOL.

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4ROBOT’2015 - web.fe.up.pt/robot2015
Chapter 2

Related Work

2.1 RFID-based localization

Literature regarding RFID-based localization systems include both active [6, 7], and passive tags [8, 9, 10], and single and multiple reading antennas [11]. Finkenzeller's book [12] is an introduction to the physical principles of RFID technology and key techniques are presented in [5, 13, 14]. M. Bouet and A. L. Santos [5] explain that active tags have an internal battery which continuously powers it and transmit to the reader high-level signals. On the other hand, passive tags have no internal power supply and usually backscatter the carrier signal received from a reader. Detailed description of tags is address in Chapter 3.

RFID detection can be used solo or as a complementary system to other localization techniques. For instance, [15] uses tag detection to resynchronize Inertial Measurement Units (IMU) based information; [16] describes a method with RFID tags to coarsely localize an object and afterwards laser scan allows a precise position estimation; and in [17], a precise localization of objects is achieved by ceiling cameras with particle filters.

Lionel M. Ni et al. in [13] address different RFID-based technologies and classify based on the tracking component. These include Tag-based and Reader-based technologies. Tag-based is the most common approach according to the authors, in which the readers are in fixed positions and tags are attached to mobile tracked objects. LANDMARC [6] is given as an example, where some RFID active tags are used to periodically transmit beacon messages as references (fixed tags) and others are moving (tracking tags). Radio Signal Strength (RSS) is used to compute the position estimate of tags and has been used in low density tag distribution scenarios to yield localization errors around 1 m. RSS information is a measure of power, usually represented in dBm (decibels referenced to $1 mW$). However, RSS is not available in the RFID system used in this work.

In reader-based localization systems, the traditional roles of tag and reader are reversed: tags are placed at fixed, known locations, and a portable reader is carried by the mobile user or object being tracked. The location of the mobile user is determined from the tag IDs (and possibly the RSS values) detected by the portable reader. This approach to RFID-based localization is sometimes referred to as
reversed RFID [13]. The RFID system used in this work for robot localization falls under reader-based category, as tags are placed on walls and the reader is carried by the robot. According to the authors, the motivation behind reverse RFID is to remove the dependence on an infrastructure of networked readers. In fact, in the context of MOnarCH this would not be feasible for both cost and discretion reasons. On the other hand, for people localization the method follows a hybrid approach since tracking tags are attached to people to be identified and the reader is portable.

Beside the classification of RFID technologies, the authors also address some practical considerations that easily influence the performance of the system, namely multipath and interference. Multipath is the radio propagation phenomenon that results in radio signals reaching the receiving antenna by two or more paths. Severe multipath occurs indoors, since the structure, objects and humans cause the reflection, refraction, diffraction and absorption of radio signals. Interference occurs when unwanted signal(s) alter, modify or disrupt the signal of interest and naturally presents a challenge to RFID localization and it is difficult to eliminate [13].

In indoor scenarios it is common to use grids of passive tags [8]. One or more moving readers can then be easily detected if the positions of the passive tags are known a priori. Arrays of readers can be used to provide information on the direction of the tag [7].

On the other hand, Giampaolo and Martinelli in [9] propose an innovative tag antenna design to achieve a near circular detection region that allow a sparsely placement of tags on the ceiling, in the order of 1 tag per meter. The tag has overall dimensions of 30 x 30 x 15 cm. Despite having fairly regular and stable detection regions and being useful for this work, would not be possible to install this tag at the IPOL due to its dimensions.

Furthermore, 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.

Fingerprinting, i.e., recognition of tag detection patterns, has been reported to yield errors in the order of tens of centimeters for a tag density of 3.8 tag/m² [18]. Localization often assumes that the tag detection areas are of circular shape [2, 3] and tags are distributed according to regular patterns [4, 8]. Simulation results are claimed to yield a localization error as low as 3 cm for a mobile robot moving up to 2 m/s and a high enough tag density.

Variations of the base technique include changing the power level of the reader(s) and knowing the sensitivity of specific tags to such variations [19]. If the tags are active then by placing the tags in a carefully selected distribution, accounting for RF interferences, it is possible to use the RSS indicator generated by each tag to select the most probable regions [7].

Scanning delays and the tag density are often referred as the most important factors generating errors [4]. By carefully controlling the reading strategy, the effect of the scanning delay can be minimized. Multipath propagation and interference have also been referred as key factors that induce disturbances [13].

In [20] two different antenna polarizations are presented. An antenna converts electrical current into electromagnetic waves that are then radiated into space in a particular pattern at a given level of inten-
Horizontal linear polarization

Circular polarization

Figure 2.1: Antenna polarizations.

One parameter of great interest is the antenna polarization (or the reader antenna wave's electric field vector, orientation, and direction). A linearly polarized antenna radiates entirely in one plane in the direction of signal propagation, Fig.2.1(a). Dipole antennas, for example, are most sensitive to RF fields whose polarization is aligned with the orientation of the element. This means the success of the system depends on the proper orientation of the tag relatively to the reader signal, which in some application can be restrictive. However, due to the concentrated emission, linear polarized antennas typically have greater read range than circular polarized antennas of the same gain. In a circularly polarized antenna the plane of polarization rotates in a circular fashion (effectively a corkscrew when considered in time), making a complete revolution during one period of the wave, Fig.2.1(b). Compared to linear polarized antennas, circular polarized antennas lose about 3 dB per read because they split their power across two separate planes [20].

If tags are on the same plane and about the same height and proper orientation then it should be considered a linear polarized antenna. If tag orientation is not something that will be reliable or consistent, then a circular polarized antenna is likely to be a better choice to use. In the context of MONarCH, since there are tags on the walls for robot localization and as well tags carried by people, both adults and children, a circular antenna is indeed a better solution.

2.1.1 Comparison of RFID readers

In this subsection a table with different RFID readers is presented. The goal is to analyze the most common frequencies in use, as well as the type of system (active, passive or semipassive) and the reader’s range. The chosen RFID system for MONarCH project is addressed in Chapter 3. RFID systems generally use the low-frequency (LF, around 125 kHz), high-frequency (HF, 13.56 MHz) and ultrahigh-frequency (UHF, between 860 to 960 MHz, depending on the country). LF RFID systems work with ranges around a few centimeters or less and are used for people access control. On the other hand, HF systems can have a maximum range of about 1 meter and typical applications include tracking library books, patient flow tracking and transit tickets. Finally, UHF are commonly used in electronic tolls and
parking access control, with a maximum detection range around 3–6 meters [21].

<table>
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<th>Frequency</th>
<th>Tag Type</th>
<th>Detection range</th>
<th>Paper</th>
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<tbody>
<tr>
<td>IDTec</td>
<td>915 MHz</td>
<td>Active</td>
<td>6 m</td>
<td>[22]</td>
</tr>
<tr>
<td>IET</td>
<td>134.2 kHz</td>
<td>Active</td>
<td>Not specified</td>
<td>[23]</td>
</tr>
<tr>
<td>SHARP RZ -2TG1</td>
<td>2.45 GHz</td>
<td>Passive</td>
<td>2.8 m</td>
<td>[24]</td>
</tr>
<tr>
<td>TI S6350</td>
<td>13.56 MHz</td>
<td>Passive</td>
<td>17 cm</td>
<td>[8]</td>
</tr>
<tr>
<td>CAEN OEM A528</td>
<td>870 MHz</td>
<td>Passive</td>
<td>0.8 m</td>
<td>[9]</td>
</tr>
<tr>
<td>IDS R901G</td>
<td>868 MHz</td>
<td>Passive</td>
<td>Not specified</td>
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<tr>
<td>Ivengo XCRF-804</td>
<td>928 MHz</td>
<td>Passive</td>
<td>10 m</td>
<td>[16]</td>
</tr>
<tr>
<td>ThingMagic M6e</td>
<td>868 MHz</td>
<td>Passive</td>
<td>Not specified</td>
<td>[26]</td>
</tr>
<tr>
<td>Trolley Scan EcoTag</td>
<td>860 - 960 MHz</td>
<td>Active</td>
<td>Not specified</td>
<td>[27]</td>
</tr>
</tbody>
</table>

Table 2.1: Comparison of RFID readers.

2.2 RFID systems in hospitals

The use of RFID technology in hospital environments is addressed in this section. The purpose is to understand how RFID is being used in hospitals and healthcare facilities, what is its acceptance, and if the radio transmissions from the readers do no interfere with other electronic devices in the hospital. Different authors suggest it can bring advantages to both patients and medical staff. In truth, RFID is beginning to be accepted in these environments. For example, some hospitals use it for access control. Cangialosi et al. in [28] describe how patients are processed from admission to discharge and consider where RFID can be applied. They examine cases with fixed and moving readers to interrogate both fixed and mobile objects and conclude that RFID can significantly aid medical staff in performing their duties. In addition, Wicks et al. in [29] suggest that RFID can also increase patient safety and provide better tracking of patient treatment. Finally, Christe et al. [30], studied the effects of RFID antennas on healthcare equipment. It was determined that RFID systems did not influence the performance of those devices, such as physiological monitors and intravenous pumps, and are suitable to be used in hospital environments.
Chapter 3

RFID technology and MOnarCH robots

3.1 RFID reader and tags

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 (the tag), and the interrogator or reader, which can be a read/write device depending on the design and technology, but usually is simply called the reader. Figure 3.1 represents a typical RFID system. 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 [12]. 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 (known as ID), 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, and the encapsulation protects it from environmental conditions or reagents, as described in [1]. All types of tags use radio frequency energy to communicate with the reader, however the method of powering them differs, and thus they use fundamentally different technology to function.

Figure 3.1: Typical RFID system.
Figure 3.2: Some passive tags developed at IT. Tag (a) is used for luggage tracking at airports. Tag (b) is for human on-body applications at several frequencies, while (c) works at one frequency only. Tag (d) includes a Ultra-wideband (UWB) tag. Courtesy of Professor Carlos Fernandes and Eng. António Almeida of IT.

3.1.1 Tags

Active Tags

Active tags require a power source. They are either plugged to an external source or have their own battery, allowing them to be continuously operating, whether in the reader field or not, [31]. Because of that, they only require very low-level signals to be transmitted to the tag since the reader does not need to power them. The tag can then generate high-level signals back to the reader. Often called beacons, active tags can even broadcast their own signal and start a communication with a reader. In addition, they have a memory capacity up to 64 KB and work with longer distances, generally up to 500 meters. Active tags are used in the aviation industry, for example, attached to an aircraft identifying its national origin or to store large volumes of aircraft part and maintenance history data [32]. However, batteries make the cost and size of tags impractical for some applications. And the tag’s lifetime is limited by the stored energy, balanced against the number of read operations the device must undergo.

Passive Tags

Passive tags on the other hand do not require autonomous power supply, as it is provided by the reader when the tags are within its interrogation zone, which means they have a virtual unlimited lifetime. Tags reply by backscattering the carrier signal received from the reader (or by load modulation) [31]. 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. Nowadays passive tags can cost as little as 7 to 15 U.S. cents, while active tags typically cost around $25 each. Figure 3.2 shows some examples of passive tags developed at Instituto de Telecomunicações (IT), located at IST.
Semipassive Tags

Semipassive tags (also known as semiactive) have an internal battery in order to be constantly powered, which removes the need for the antenna to be designed to collect power from the incoming signal and can be optimized for the backscattering signal [31]. They are more expensive and generally larger, but have greater communication ranges than passive tags [33].

3.1.2 Designs for transferring power and data in passive RFID systems

Since tags used in this work are passive, this subsection focuses specifically on this technology. Two different approaches exist for transferring power from the reader to the tag and transmitting the data back: magnetic induction and electromagnetic wave capture. They are respectively associated with the EM proprieties of an RF antenna - near-field and far-field - and both can transfer enough power to the remote tag to sustain its operation, which is typically between $10\mu W$ and $1mW$ (The nominal power of an Intel XScale processor consumes is approximately $500 mW$, while an Intel Pentium 4 consumes up to $50W$ [1]).

Near-field

In a near-field RFID system, the coupling between the reader and the tag is based on Faraday’s principle of magnetic induction. When the reader's coil is passed by an alternating current, an alternating magnetic field appears in its vicinity. A tag placed close to this field will have, through its own coil (antenna), an alternating tension cross it and via a capacitor can be used to power the chip. To send data back to the reader, tags use load modulation technique. The current drawn from the coil will also create its own magnetic field, which will oppose the reader’s field. This means the reader coil can detect it as a small increase in current flow through it, being proportional to the load applied to the tag’s coil. If the tag electronics varies the applied load in time, a signal can be encoded as tiny variations in the magnetic field strength. The reader can then recover the signal by monitoring the change in current though the reader coil. Near-field communication is the most straightforward method to implement a passive RFID system. However, it has some physical limitations in terms of the frequency of operation. Near-field communications operate at frequencies less than 100 MHz and only for distances between the reader and tag up to a few centimeters [1].

Far-field

In far-field design, 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 not 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. However, 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. Systems using this principle operate at greater than 100 MHz, usually in the ultra high frequency (UHF) band. 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 two attenuations: first when the waves radiate from the reader to the tag and second when the signal travels back to the reader [1].

3.2 RFID System for MOnarCH

The RFID system to be implemented on the robots in MOnarCH, which would be used for both people and robot self localization, had to be in accordance with the project characteristics, including the constraints imposed by IPOL. Working on a realistic scenario, RFID tags needed to be the least invasive as possible. As so, placing a dense number of tags, either on the floor, walls or ceiling, as some authors suggest, would not be possible. The solution converged to sparsely-spaced tags, which had to be discretely placed around the corridor and rooms, and carried by people, both children and adults. The tags size and their expected needed number (between 50 to 100 tags) were also factors which made the choice fall into the passive category. In terms of the reader, it had to allow a detection range in the order of several meters, meaning the UHF band would be the most suitable band.

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 has, according to the manufacturer, a circular polarization and an effective range of about 3 meters using a 8 dBi antenna, 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. 3.3(a) and therefore suitable for the project requirements. The reader on a tripod, Fig. 3.3(b), was used for experiental testing, but also installed onboard the MOnarCH robots.

To communicate with a reader, a controller must send commands through the RS232 interface and wait for its response. For example, in order to detect tags, an Inventory command must be sent periodically and the reader replies with all detected tags’ IDs (blue box in Fig. 3.5).

Figure 3.3: RFID system used in this work.
3.3 MOnarCH robots

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 [34].

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. 3.4. 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 teleoperation or using a state machine. Both robots and controlling operations were used for the experiments.

Robot Operating System

The Robot Operating System (ROS) is a flexible framework for writing robot software. It is a collection of tools, libraries, and conventions that aim to simplify the task of creating complex and robust robot behavior across a wide variety of robotic platforms [35]. ROS combines together different processes that perform computation (called nodes) and communicate with one another using streaming buses over
which they exchange messages. These nodes are meant to operate at a fine-grained scale; a robot control system will usually comprise many nodes. For example, one node can control a laser range-finder, one node can control the robot’s wheel motors, one or more nodes can perform localization, one node can perform path planning, one node can provide a graphical view of the system, and so on [36].

The RFID methods include several nodes for the localization of people and robots (the main nodes are shown in Fig. 3.5 and explained in more detail in Chapters 4 and 5). Code is mostly written in Python\(^1\) programming language and plots use Python Matplotlib library\(^2\).

![Figure 3.5: Main RFID nodes for People and Robot Localization.](image)

\(^1\)www.python.org/

\(^2\)matplotlib is a python 2D plotting library - matplotlib.org/
Chapter 4

People Localization

4.1 Methodology

4.1.1 Probabilities Model

In an ideal scenario a RFID tag is assumed to have a perfect circular detection shape, as shown in Fig. 4.1. Some authors do suggest this in their work, however in most experimental situations this approximation is not realistic. As mentioned in Chapter 1, preliminary experiments with the RFID reader showed the reader’s range can widely change depending on the environment where it 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, especially if there was no relative motion between the tag and the reader. Figure 4.2 depicts three different situations where this happens. In Fig. 4.2(a) a tag is placed on a wooden door. The maximum detection range is around 1 meter but highly non-uniform and non-circular. Figure 4.2(b) illustrates an example where the RFID reader is on a corridor. If a tag is placed on the other side, approximately 10 meters away, it can be detected. This exceeds by far the 3 meters range described by the manufacturer and highlights the influence of propagation conditions. Finally, Fig. 4.2(c) represents a situation where the tag is placed on a tripod and facing the reader. Although the distance between them is less than 3 meters, there is no detection. As so, these characteristics created the necessity to come up with a new way to model the RFID reader.

Figure 4.1: Ideal tag detection circular shape.
Figure 4.2: Examples of situations of non-ideal detection shape.

The solution was to use 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.

**First RFID reader Model**

Figure 4.3 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. Figures 4.4 and 4.5 represent the first model probability values and diagram, respectively. Measurements were taken along three circumferences of radius 1, 2, and 3 meters, with nine measurements each at regular angular intervals. Alternatively, non-regular spacing for the measurement points could be used, though as can be seen in the interpolated surface this may not have a significant impact on the results. 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\(^1\). The tag was

\(^1\)scipy.interpolate.griddata function is used to compute the cubic surface. SciPy is a Python-based ecosystem of open-source software for mathematics, science, and engineering - www.scipy.org.
always kept at the same height relative to the reader (approximately 1.10 m) and hence the interpolated surface is two-dimensional. The model has a central lobe, slightly deviated to the left, corresponding to the high detection probabilities.

![Figure 4.4: Estimated probabilities for basic RFID reader model.](image)

In order to compute the probability of a tag being detected faster, a counting algorithm was introduced. In the previous model, each measurement correspond to a single tag detection. However, in the following model it corresponds to the result of Algorithm 1 instead, which means that each measurement is in fact a probability. 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 ($T$) is then $N\Delta t$, where $N$ is the total number of reads. By default, $N$ was set to 100, yielding $T = 5$ s.

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.4.5 changed substantially when the

![Figure 4.5: Interpolated surface for basic probabilities RFID reader model.](image)


Algorithm 1 Tag robability

Require: total number of reads \( N \), time between readings \( \Delta t \)

\[ \text{tag.count} \leftarrow 0; \]

if tag detected then

for \( i = 1 \) to \( N \) do

re-read the tag;

if tag is detected then

\[ \text{tag.count} \leftarrow \text{tag.count} + 1; \]

end if

wait for \( \Delta t \);

end for

probability = \( \text{tag.count}/N \);

return probability updated

else

return probability not updated

end if

environment around the reader also changed.

The reader's antenna was placed on the MOnarCH robot's head and space constraints imposed that it was placed facing upwards. Figures 4.6(a) and 4.6(b) display the location of the RFID antenna installed in the robot. Figures 4.6(c) and 4.6(d) show a top view of the robot without and with its head shell, respectively.

Figure 4.6: RFID antenna placement onboard the MOnarCH robot
For purposes of comparison, 4 tests were conducted with different reader setups in order to analyze the effect of the robot shell in the tags detection, Fig. 4.7. The following list describes each test.

(a) The reader with the same orientation as the one onboard the robot;
(b) The reader onboard the robot, with the head shell with a capacitive sensor;
(c) The reader onboard the robot, with the head shell without a capacitive sensor;
(d) The reader onboard the robot, with no head shell.

The capacitive sensor, shown in Fig. 4.7(b) is used to interact with children. When they touch the robot’s head, the system can trigger some interaction function. However, this metallic surface interferes with the RFID operation, as depicted on the probabilities models in Fig. 4.8. Measurements, from Algorithm 1, were taken along a circumference of radius 1 meter, with 8 points in total, from which then was computed the interpolation surface. As in the previous surface from Fig. 4.5, zones in red mean high probability of detection, while blue zones tend to probabilities near 0. The center of the antenna was assumed to have probability 1. As observed in models of Fig. 4.8, there is a big difference on the detection by placing

![Figure 4.7: Comparison of head shells in MOnarCH robot.](image)

the reader’s antenna onboard the robot. While much of the probabilities are high on reader outside the robot, onboard with the capacitive sensor the maximum range of detection can not even reach 1 meter. When the sensor is taken away, the model becomes a bit better, similar to the model without the head shell. In sum this means that the robot hardware and/or shell decrease significantly the reader’s detection shape and range.

The probabilities model for the RFID reader inside the MOnarCH robot was obtained using a head shell without the capacitive sensor. Simple tests showed that the range of 3 meters specified by the man-
The manufacturer was not verified for this setup, due to the non-existing omnidirectionality of the antenna and the fact that the reader had to face upwards. Hence the model was only defined for a maximum range of 2 meters. Measurements were taken along four circumferences of radius 0.5, 1, 1.5 and 2 meters, with sixteen measurements each (of probabilities from Algorithm 1) at regular angular intervals, Fig. 4.9. The probabilities were estimated as an average of 5 measurements. Figure 4.10 illustrates the interpolated surface, corresponding to the two-dimensional probabilities model of the reader.
As the previous reader model setup, the tag was kept always at a height of 1.10 m, corresponding to the height of the robot. This was assumed to be a good height to carry a tag, around the region of the waist, for an adult. 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.

Carrying the RFID tag

Two ways of carrying the tag are suggested, as shown in Fig. 4.11. Both allow the tag to be approximately around the height the models were created. Experiments in 4.2 use the placement of Fig. 4.11(a). It would be more practical to carry the tag for example inside the pocket, however this does not allow it to be detected because the human body interferes with the antenna radiation.

![Image of ways of carrying the RFID tag](image)

Figure 4.11: Ways of carrying the RFID tag.

4.1.2 Relative location estimation

The interpolated surface found in the previous section represents a model that embeds both reader and environment characteristics. As the robot moves, detection probabilities are being updated. If a tag is 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 person.

Once a probability is obtained, the reader model is used to estimate the position of the person carrying the tag relative to the position of the robot (Algorithm 2). Figure 4.12(a) illustrates a realistic situation where the person standing up is wearing a RFID tag on his shirt. The plot in Fig. 4.12(b) shows the region corresponding to the estimated probability within a $\epsilon = 0.1$ margin (blue points). This means that if a tag is detected with $p = 0.7$, than points in the model with $p \in [0.6, 0.8]$ are taken into account. Red
points are the result of the medial axis skeletonization\(^2\) (often called topological skeleton) and the yellow point is the one in the skeleton with the biggest distance to the boundary of the blue region. This point is chosen as the position estimate.

![Camera View](image1.png) ![Position estimate algorithm](image2.png)

**Figure 4.12:** Estimating the position of the RFID tag.

**Algorithm 2** Relative position estimation

**Require:** Reader Model, detection probability \(p\) and probability margin \(\epsilon\)

- Obtain the area \(a\) according to the model, with \(a \in [p - \epsilon, p + \epsilon]\);
- Compute the medial skeleton for \(a\);
- Retrieve the point in the skeleton with the biggest distance to the boundary of \(a\) (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). The strategy chosen to disambiguate the output is then to mask the region around the reader (see section 4.2 ahead). The diagram for people detection is depicted Figure 4.13, where the boxes in green correspond to ROS nodes for **Algorithm 1** and **Algorithm 2**, respectively.

**People Localization**

![Read tag](read_tag.png) **→** ![Tag probability](tag_probability.png) **→** ![Relative position](relative_position.png)

**Figure 4.13:** RFID nodes for People Localization.

\(^2\)skimage.morphology.medial_axis function is used. scikit-image is a collection of algorithms for image processing in Python - scikit-image.org.
4.2 Experiments and Results

This section describes the experiments at ISR with a MOnarCH robot and a person carrying a RFID 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 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 only a $180^\circ$ area behind the reader is taken into account.

For the purpose of analysis one additional grouping is taken into account. The objective 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 $180^\circ$.

Although figures join results from all directions, Fig. 4.14 illustrates an example of how each result should be interpreted: in 70% of the experiments the localization algorithm was able to guess that the person position was around the direction of $0^\circ$, within an angular interval of $90^\circ$, Fig. 4.14(a), or $180^\circ$, Fig. 4.14(b).

![Figure 4.14: Illustration of results in terms of the angular interval.](image-url)
The experiments evolved as follows: 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 ($\epsilon = 0.1$ was used). A total of 8 angles is used (or 5 in the cases where a mask is applied). For these experiments only the angle relative to the robot is considered for the estimate and the person is carrying the tag at approximately the height of the robot as in Fig. 4.11(a).

Figures 4.15 to 4.20 represent the probability of the computed angle being inside the angular width corresponding to the real angle of the person. Each experiment is shown for the two angular width values considered.

![Figure 4.15: Results for $T = 5$ s and no prior information.](image)

![Figure 4.16: Results for $T = 1.5$ s and no prior information.](image)
In the first experiment, Fig. 4.15, 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).

Figure 4.17: Results for $T = 5$ s and person in front of the robot.

Figure 4.18: Results for $T = 1.5$ s and person in front of the robot.
Figures 4.17 and 4.18 represent 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. 4.19 and 4.20, the detection mask is on the frontal area of the robot. The experiment reveals much higher probabilities, suitable for HRI applications. In addition, results are fully consistent with the conclusions drawn from the two previous cases.

![Figure 4.19: Results for $T = 5\, s$ and person behind the robot.](image1)

![Figure 4.20: Results for $T = 1.5\, s$ and person behind the robot.](image2)
Experiments demonstrate 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 $180^\circ$, 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.
Chapter 5

Robot Localization

5.1 Methodology

5.1.1 Delaunay Triangulation and Tag Placement

Even though RFID tags do not have a perfect circular shape of detection in real situations, this subsection addresses a study where ideal tags are assumed. The goal is to come up with a method to cover an entire environment with tags for purposes of robot localization. Each point in space must detect at least 3 tags, empirically defined to lead to acceptable uncertainties in the robot position. A maximum range of 2.5 meters is fixed (similar to the readers onboard MOnarCH robots), with tags being placed on the ceiling.

The proposed method is based on Delaunay Triangulation algorithm (see for instance [37]). For a set $P$ of points, it defines a triangulation $\text{DT}(P)$ such that no point of $P$ is inside the circumference of any triangle in $\text{DT}(P)$. The Delaunay triangulation of a discrete point set $P$ corresponds to the dual graph of the Voronoi diagram for $P$, [37].

Figures 5.1 and 5.2 depicts two simulation results, done in Matlab R2012a\(^1\) The first is a simple ideal L-shaped 10x10 corridor and the second represents a floor of ISR. Triangle vertices represent tags. The results are shown in Table 5.1.

<table>
<thead>
<tr>
<th>Map</th>
<th>Tags</th>
<th>Max</th>
<th>Mean</th>
<th>Std</th>
<th>Time(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>L-shaped</td>
<td>25</td>
<td>9</td>
<td>5.15</td>
<td>1.14</td>
<td>0.640</td>
</tr>
<tr>
<td>ISR corridor</td>
<td>40</td>
<td>9</td>
<td>5.89</td>
<td>1.43</td>
<td>19.547</td>
</tr>
</tbody>
</table>

Table 5.1: Simulation results for Delaunay Triangulation for two maps.

For L-shaped map, the total number of necessary tags is 25, while for ISR the number increases to 40. $Max$ is the maximum number of detected tags (and the minimum is always 3), $Std$ stands for standard deviation and $Time$ is the computation time in seconds. Although quantification of uncertainty is not

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\(^1\)http://www.mathworks.com/products/matlab/
addressed, a conclusion can be drawn with this approach and respective results: a bigger number of tags is placed where the path changes direction, which is highly beneficial in terms of localization as robots tend to get lost more easily in these areas. Moreover, it is curious to note that although the minimum number of detected tags in each point is defined as 3, both maps exhibit a mean between 5 and 6. But a higher number of tags would yield to a more precise position estimation.

![Figure 5.1: Result of Delaunay Triangulation for a L-shaped map.](image1)

![Figure 5.2: Result of Delaunay Triangulation for ISR corridor map.](image2)

5.1.2 Robot Localization using Support Vector Machines

In general it is very hard to predict the range and shape of RFID detections, therefore, a sparsely placement of tags requires a analysis of the environment characteristics where the system will be used. 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]. SVM is a supervised machine learning method used for binary classification, whose goal is to find an hyperplane to perfectly separate d-dimensional data between two classes. SVM introduces the notion of a “kernel induced feature space” which casts the data into a higher dimensional space where the data is separable [38].

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 height and surface of placement have a determinant influence on the number and range of detections. The ceiling would be a less invasive location to put tags, however it's an infeasible option because it is made of metal and short-circuits tags' antennas, becoming invisible to the reader.

Figure 5.3 shows a map of ISR (8th floor, North Tower, in IST) where tests were conducted. This map was created through Gmapping\(^2\) package of ROS. 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 but in future work the rest of the floor will be included.

![ ISR floor map and corridor](image)

\[\text{(a) ISR floor map} \quad \text{(b) Corridor.}\]

**Figure 5.3: ISR 8th floor corridor where tags were placed.**

In Fig. 5.4(a) 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 of that specific tag on that position. Figure 5.4(b) shows the robot trajectory to obtain this dataset. Based on the detection patterns, tags were inserted into different categories, mainly depending the placement height and surface material.

\(^2\)http://wiki.ros.org/gmapping
Figure 5.4: Tag detections and robot trajectory at ISR corridor.

**Precision tags**

Tags placed approximately at a height of 2 m, either on walls or doors (Figs. 5.5 to 5.8). The reader is only able detect them within a 0.5–1 m range in most samples. This makes these tags suitable to be placed in areas where more precise localization information is needed.

Figure 5.5: Tag on room 8.11 door.

Figure 5.6: Tag on common room door.

Figure 5.7: Tag on room 8.17 door.

Figure 5.8: Tag on room 8.18 lab door.
Zone tags

Tags placed on walls (in this case behind posters), at the level of the robot's head, around 1.10 m (Figs. 5.9 and 5.10). These are indispensable tags which allow the robot to easily identify the zone where it is located. The reader can detect them with a maximum range of 2–3 m.

Figure 5.9: Tag behind MOnarCH poster.  
Figure 5.10: Tag behind ITER poster.

Hybrid tags

Tags in between previous categories (Figs. 5.11 and 5.12). The maximum range is higher than precision tags, but they fail to have the detection characteristics of zone tags.

Figure 5.11: Tag on wall near workshop room.  
Figure 5.12: Tag on Professor Sequeira office door.
Idle tags

Tags placed in surfaces where the detection is approximately or completely null (Figs. 5.13 and 5.14).
In this experiment, both cases were in doors. It is worth saying that no tag was placed on the concrete
wall (left side of the corridor in the map) since previous tests showed that tags would become practically
invisible to the reader. This hampers the overall strategy of placement for this specific environment, as
only one side of the corridor can be filled with tags.

![Figure 5.13: Tag on stairway door.](image)

![Figure 5.14: Tag on toilet door.](image)

Based on the observations of detections, the corridor was divided into 5 zones, as seen in Fig. 5.15. 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 as 0,1,2..., n and the ID-read count k of all tags in the environment:

\[
X = (ID_1, ID_2, ..., ID_n, k_1, k_2, ..., k_n).
\]  

(5.1)

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.

![Figure 5.15: Corridor divisions](image)
For this work Support Vector Classification (SVC)\(^3\) 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 \(\gamma\) is the kernel coefficient, which is equal to \(\frac{1}{2n} \) with \(n\) being the number of tags. The implementation is based on libsvm\(^4\).

Multiclass SVMs do exist, however this work follows a similar approach to the one from Senta et al.[10] as it yields to good results. One SVM 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. The classifier decides for zone A between:

1. Robot is inside zone A;
2. Robot is outside zone A.

For the remainder of zones decision is as follows:

1. Robot inside this zone, knowing that is outside the previous zone;
2. Robot outside this zone, knowing that is outside the previous zone;

As SVM is a supervised learning algorithm, labeling is required. In this case, the label is whether the robot is truly inside or outside the current training zone. This information is obtained while running the robot navigation and through a ROS node called amcl\(^5\) (Adaptive Monte Carlo Localization), which uses a particle filter to track the pose of the robot against a known map. The robot was controlled using teleoperation. Figure 5.16 depicts the main nodes (rectangles) used to estimate the robot localization.

![Figure 5.16: RFID nodes for Robot Localization.](image)

5.2 Results

Common statistical measures of performance were computed to evaluate the quality of predictions of the classifier, as well as a confusion matrix (also known as contingency table or error matrix), as presented in table 5.2.

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\(^3\)scikit-learn is a collection of algorithms for machine learning in Python - www.scikit-learn.org

\(^4\)LIBSVM – A Library for Support Vector Machines - www.csie.ntu.edu.tw/ cjlin/libsvm/

\(^5\)wiki.ros.org/amcl
Table 5.2: Example of confusion matrix for Robot Localization

<table>
<thead>
<tr>
<th></th>
<th>True</th>
</tr>
</thead>
<tbody>
<tr>
<td>In</td>
<td>TP</td>
</tr>
<tr>
<td>Out</td>
<td>FP</td>
</tr>
<tr>
<td></td>
<td>FN</td>
</tr>
<tr>
<td></td>
<td>TN</td>
</tr>
</tbody>
</table>

The diagonal elements represent the number of points for which the predicted label is equal to the true label, while off-diagonal elements are those that are mislabeled by the classifier. The higher the diagonal values of the confusion matrix the better, indicating many correct predictions. In this setting, where $Z$ denotes any of the 5 defined zones:

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

The following functions were used:

- **Sensitivity** (or **True Positive Rate** (TPR)) measures the proportion of positives that are correctly identified as such:

$$Sensitivity = \frac{TP}{TP + FN} \tag{5.2}$$

- **Specificity** (or **True Negative Rate** (TNR)) measures the proportion of negatives that are correctly identified as such:

$$Specificity = \frac{TN}{TN + FP} \tag{5.3}$$

- **Fall-out** (or **False Positive Rate** (FPR)) measures the proportion of positives that are incorrectly identified:

$$FPR = \frac{FP}{FP + TN} \tag{5.4}$$

- **Miss Rate** (or **False Negative Rate** (FNR)) measures the proportion of negatives that are incorrectly identified:

$$FNR = \frac{FN}{FN + TP} \tag{5.5}$$

- **Precision** (or **Positive Predictive Value** (PPV)) measures the proportion of true positives compared to all positives predictions:

$$Precision = \frac{TP}{TP + FP} \tag{5.6}$$

- **Negative Predictive Value** (NPV) measures the proportion of true negatives compared to all negative predictions:

$$NPV = \frac{TN}{TN + FN} \tag{5.7}$$
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.

### 5.2.1 Case 1 - Independent zone analysis

Table 5.3 shows the results for the statistical functions previously addressed, directly from a test dataset of each SVM, without any modification (case 1). 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 of the classes. 600 samples were taken for training. In addition, a variable number of new samples was used for testing. As these were obtained in the same conditions, the statistical properties still hold. Column test denotes the total number of test samples for each zone.

<table>
<thead>
<tr>
<th>Zone</th>
<th>test</th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
<th>Sens.</th>
<th>Spec.</th>
<th>FPR</th>
<th>FNR</th>
<th>Prec.</th>
<th>NPV</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>322</td>
<td>61</td>
<td>136</td>
<td>1</td>
<td>124</td>
<td>0.33</td>
<td>0.99</td>
<td>0.01</td>
<td>0.67</td>
<td>0.98</td>
<td>0.52</td>
</tr>
<tr>
<td>B</td>
<td>354</td>
<td>44</td>
<td>217</td>
<td>19</td>
<td>74</td>
<td>0.37</td>
<td>0.92</td>
<td>0.08</td>
<td>0.63</td>
<td>0.70</td>
<td>0.75</td>
</tr>
<tr>
<td>C</td>
<td>290</td>
<td>56</td>
<td>137</td>
<td>0</td>
<td>97</td>
<td>0.37</td>
<td>1.00</td>
<td>0.00</td>
<td>0.63</td>
<td>1.0</td>
<td>0.59</td>
</tr>
<tr>
<td>D</td>
<td>464</td>
<td>133</td>
<td>240</td>
<td>9</td>
<td>82</td>
<td>0.62</td>
<td>0.96</td>
<td>0.04</td>
<td>0.38</td>
<td>0.94</td>
<td>0.75</td>
</tr>
<tr>
<td>E</td>
<td>297</td>
<td>37</td>
<td>96</td>
<td>161</td>
<td>3</td>
<td>0.93</td>
<td>0.37</td>
<td>0.63</td>
<td>0.07</td>
<td>0.19</td>
<td>0.97</td>
</tr>
</tbody>
</table>

Table 5.3: Table with statistical functions to evaluate the classifiers performance - case 1

For all zones except 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.

The following figures show, for each SVM, the confusion matrix with normalization by class support size (number of elements in each class). In case of class imbalance, this kind of normalization has a more visual interpretation of which class is being misclassified. The diagonal of the normalized confusion matrix corresponds to Precision and NPV values. Furthermore, maps with true and false detections are presented. Blue circles correspond to TP, green to TN, red to FN and orange to FP. However, they show absolute values, which might not be similar to the values of the normalized confusion matrices.
In zone A there are 2 precision tags on doors and 1 additional zone tag belonging to B but easily detected in A. The confusion matrix shows two important results. Almost all positive predictions are true, but nearly half of the outside prediction are wrong, meaning that the robot was actually inside zone A. Since this area has three doors, including the entrance for the laboratory where robots normally operate, it is important to include at least one more precision tag to guarantee that there is always at least one tag detected. In the next case it is shown that samples without any detections are the cause of most of false negative predictions.

Zone B includes only 1 zone tag on the wall at the height of the robot which is clearly not enough to properly cover the entire zone (the tag on the toilet door is idle and practically not useful). However, the confusion matrix shows that more than two thirds of positive predictions and 75% of negatives were true. The level of detection would increase if at least one more non-idle tag would be on the left side of the corridor.
Zone C

Zone C yields interesting results. 100% of positives are true and mainly concentrated in a specific area inside the zone. On the contrary, approximately half of the negatives are false. Both zone C and A are composed by precision tags and there seems to be correlation between that and the values presented of negative predictions. Since this category of tags has a range between 0.5 to 1 meter, one possible solution would be to redefine the dimensions of these zones and limit them to the regions where true positive predictions mostly appear. The remaining regions would be similarly defined with extra precision tags. This approach would lead to better estimations of the robot position.

Zone D

From the observation of the confusion matrix and the maps of positive and negative samples, it is possible to conclude that the definition of the zone dimensions was adequate to tags. Similarly to zone B, there is one zone tag and the value of false negatives is 25%. In addition, the true positives are almost total.
Zone E

Zone E yields completely opposite results from previous zones. High number true negatives but a great percentage of false positives. The latter is caused, as explained in the beginning of this section, by an error of the classifier, which leaves the decision of zone E all samples that do not seem to belong to any other zone, i.e., samples without any tag detection. This issue is addressed in the next case.

5.2.2 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. Table 5.4 shows the results.

<table>
<thead>
<tr>
<th>Zone</th>
<th>test</th>
<th>TP</th>
<th>TN</th>
<th>FP</th>
<th>FN</th>
<th>Sens.</th>
<th>Spec.</th>
<th>FPR</th>
<th>FNR</th>
<th>Prec.</th>
<th>NPV</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>100</td>
<td>61</td>
<td>24</td>
<td>1</td>
<td>14</td>
<td>0.81</td>
<td>0.96</td>
<td>0.04</td>
<td>0.19</td>
<td>0.98</td>
<td>0.63</td>
</tr>
<tr>
<td>B</td>
<td>148</td>
<td>44</td>
<td>85</td>
<td>19</td>
<td>0</td>
<td>1.00</td>
<td>0.82</td>
<td>0.18</td>
<td>0.00</td>
<td>0.70</td>
<td>1.00</td>
</tr>
<tr>
<td>C</td>
<td>111</td>
<td>56</td>
<td>54</td>
<td>0</td>
<td>1</td>
<td>0.98</td>
<td>1.00</td>
<td>0.00</td>
<td>0.02</td>
<td>1.00</td>
<td>0.98</td>
</tr>
<tr>
<td>D</td>
<td>176</td>
<td>133</td>
<td>30</td>
<td>9</td>
<td>4</td>
<td>0.97</td>
<td>0.77</td>
<td>0.23</td>
<td>0.03</td>
<td>0.94</td>
<td>0.88</td>
</tr>
<tr>
<td>E</td>
<td>115</td>
<td>11</td>
<td>96</td>
<td>5</td>
<td>3</td>
<td>0.79</td>
<td>0.95</td>
<td>0.05</td>
<td>0.21</td>
<td>0.69</td>
<td>0.97</td>
</tr>
</tbody>
</table>

Table 5.4: Table with statistical functions to evaluate the classifiers performance - case 2: Samples with no detection are ignored.

As observed, false negatives have greatly decreased in general, proving that these were caused by empty detections. Moreover, in the case of zone E, the number of false positives has almost disappeared as well. True negatives in E have slightly decreased, but it still yields good results. The following figures depict true and false detections as in previous case.

Figure 5.21: Confusion matrix for zone E - case 1.
Values of false negatives have decreased in zone A, but they still represent more than one third of the samples. As expressed in case 1 analysis, these results demonstrate the need for more tags in this zone, mainly of precision category, and also for a redefinition of the zone dimensions.

Leaving out empty detections enables zone B classifier to detect the totality of negatives (robot outside zone B). On the other hand, the values of positives remain the same. It is interesting to find all false positive predictions are in zone A, meaning that the zone tag inserted in B influences the classifier of A and indirectly the one of B. A possible solution would be to place the zone tag further down the corridor and redefine B dimensions. This would lead the better results in both A and B.
Zone C classification becomes nearly perfect with this approach. The redefinition proposed in case 1 is still valid in case 2.

Zone D

False negatives decrease from 25% to 12%. Like zones A and B, there seems to be a relation between results of zone D and E, which stresses the importance of zone redefinition.
5.2.3 Case 3 - Simultaneous zone analysis

Statistical functions described in previous cases are defined for a 2-class problem. Hence, this case only shows results through a confusion matrix, in Fig. 5.27. A testing dataset with 340 samples is used. Besides the 5 zones, an extra class is included, for situations where the robot is outside of the corridor addressed in this study.

Results show that the classifier is able to guess zone B, C and D with values above 70% (C) and 80% (B and D). The results for zone A are very poor, partially related with what was discussed in the previous case. Zone E is confused with D in half on the predictions. It is interesting to note that mistaken zones are always adjacent to the correct ones (assuming that the robot can only go outside the corridor through zone A or E).
5.2.4 Final Remarks

The results presented in this chapter demonstrate that the proposed approach for robot localization can provide useful information for the overall localization system, specifically in situations where the robot gets lost or needs to reset its position. In some specific areas however, using tags of the precision category, it can estimate the robot location with an uncertainty of less than 1 meter, e.g., as in zone C. Additionally, the study of the shape and range of RFID tags detection, which allows to understand the category of tags that yield certain results depending on the surface and height to be placed, 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.

It is worth to remark that experimental tests lead to similar results as the Delaunay Triangulation algorithm, namely that more tags should be placed in areas where the robot will likely change its direction, such as zone A and E.
Chapter 6

Conclusions

6.1 Achievements

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.

6.2 Future Work

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 [39], 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.
Bibliography


