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Software-Based Shielding: a machine learning approach to address RFID inventory accuracy in retail stores

Software-Based Shielding: un approccio di machine learning per risolvere il problema di accuratezza inventariale nel retail RFID

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Alla mia Famiglia

Abstract

Radio-Frequency Identification (RFID) technology has been widely used primarily for tracking and identifying objects in supply chains. The fashion retail industry has been leading its adoption, primarily for the manifold use cases the technology enables for manufacturers, retailers and end consumers.

These use cases range from increased productivity and accuracy in inbound outbound processes, to inventory accuracy and replenishment from the backroom in the stores. RFID deployments in fashion stores typically leverage both handheld RFID readers, which can be adjusted for different reading ranges, or fixed readers with wider coverage for real time inventory counts, but less precise localization.

To prevent errors and false reads (that is reading a tag in the store area from an inventory count carried out in the backroom and vice versa), both handheld and fixed readers need physical shielding materials, like metal foils on store walls, to contain the RFID signals within specific areas, typically backroom area and sales floor area. However, this approach has drawbacks, including cost, limited flexibility, low scalability, and aesthetic concerns, especially in open sales floor layouts.

A recent study by G. Esposito, Mezzogori, Neroni, Rizzi, and Romagnoli introduced a software-based shielding approach that eliminates the need for physical barriers between backrooms and store area. This method uses item-level tags and a machine learning algorithms to estimate tag locations without physical shielding. The SBS approach is more cost-effective and flexible, with an average accuracy of around 95%. However, it was tested in a specific scenario with plasterboard walls and fixed room sizes.

This study aims to assess various methods for indoor item localization using passive RFID tags, addressing stationary and moving objects' detection and tracking. It also evaluates the Software-Based Shielding approach with different wall types, thickness, tag arrangements, and densities. The findings related to this activity were published in a dedicated paper by Neroni, Rizzi, Romagnoli, and Rosa.

The performance of Software-Based Shielding was further tested in two fashion retail stores in Bologna and Milan, Italy, While the brand name is kept confidential, these tests evaluate the approach's accuracy in real retail environments considering factors like reader models, power levels, and classification methods. The results pertaining to this topic were published in a dedicated paper by Mezzogori, Rizzi, Romagnoli, and Rosa.

The study also aims at implementing the SBS algorithm into the id-Bridge RFID platform suite developed by Murata ID Solutions.

In conclusion, this research demonstrates that Software-Based Shielding is a practical solution for improving inventory count processes in fashion retail stores, avoiding the need of physical barriers between store backroom and sales floor. It saves time, ensures accurate item tracking, and is adaptable to various environments, making it a valuable tool for broader adoption.

Future work will be aimed at assessing the performance of the implemented algorithm in different real case applications, in order to better understand its practical scalability, implications and performances.

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Introduction

RFID technology

Radio-Frequency Identification (RFID) technology is a ubiquitous and versatile system employed for tracking and identifying objects, individuals, and animals through the utilization of radio waves. This technology is underpinned by three fundamental components: RFID tags, RFID readers, and accompanying software systems, collectively constituting an integrated framework for data capture and management.

RFID tags serve as the foundation of this technology. Comprising a microchip and an antenna, these miniature electronic devices store and transmit data. The microchip holds information relevant to the tagged object, which can range from a unique identification number to more complex details. The antenna facilitates the exchange of data by enabling communication between the tag and RFID readers. RFID tags are categorized primarily into passive and active types. Passive tags do not possess an internal power source and draw power from the radio waves generated by RFID readers. They are typically used for short-range applications. In contrast, active tags are equipped with their own power source, typically a battery, allowing them to transmit data over greater distances and at predetermined intervals, rendering them suitable for real-time tracking and monitoring.

RFID readers, also known as interrogators, are devices responsible for emitting radio waves and capturing data from RFID tags within their vicinity. These readers can be mobile, handheld devices or stationary installations integrated into various environments. Acting as intermediaries between the physical world of tagged items and the digital realm, RFID readers play a pivotal role in facilitating data exchange.

The RFID software complements the hardware components, serving to process and interpret the data captured by RFID readers. This software manages the information and integrates it into existing databases and systems, thereby rendering the collected data accessible for a multitude of applications. These applications encompass real-time visibility, data analytics, and actionable insights, enabling organizations to harness the full potential of RFID technology.

The operational sequence of RFID technology unfolds as follows: an RFID reader emits radio waves, creating an electromagnetic field in its proximity. When an RFID tag bearing an antenna enters this field, it becomes energized by the radio waves, thereby providing the necessary power for the microchip to function. Subsequently, the RFID tag responds by transmitting data, often in the form of a unique identification number or other information stored on the microchip. This transmitted data is captured by the RFID reader and subsequently processed and interpreted by the RFID software, rendering it available for a diverse array of applications, such as inventory management, access control, and security.

The usages of RFID technology traverse a multitude of industries, encompassing functions such as inventory management, access control, and security. The technology has become a fundamental enabler of operational efficiency and improved security across various domains, including healthcare, retail, supply chain management, and access control.

The intrinsic adaptability and capability of RFID technology to provide real-time data have established it as an indispensable tool for organizations striving to optimize operations and enhance the overall customer experience. This technology plays a pivotal role in modern-day industrial processes and has far-reaching implications for the seamless integration of the physical and digital realms.

RFID technology in the fashion retail industry

The integration of RFID technology into the fashion retail industry has brought about noteworthy advancements, offering a spectrum of advantages to retailers, manufacturers, and consumers. The fashion retail sector has wholeheartedly adopted RFID for several pivotal applications.

- **Inventory Management**: Within fashion retail, the utilization of RFID technology has yielded substantial improvements in inventory management. The affixation of RFID tags to individual clothing items allows for real-time tracking of stock levels. This fosters a significant reduction in stockouts and overstock scenarios, thereby enhancing sales performance and customer satisfaction. Retailers can readily pinpoint the location of items within their establishments, culminating in enhanced operational efficiency.

- **Loss Prevention**: RFID tags function as efficacious anti-theft devices in the fashion retail domain. When an RFID-tagged item passes through a store's exit sans the deactivation process, it promptly triggers an alarm, alerting security personnel to potential theft incidents. This robust security measure contributes to a diminishment in losses resulting from shoplifting.

- **Enhanced Customer Experience**: RFID technology has ushered in a transformative shopping experience within fashion retail. Retailers have seamlessly integrated RFID into fitting rooms, where RFID-enabled mirrors detect the items brought into the room. This facilitates customer requests for alternative sizes, colors, or styles directly through the mirror interface. As such, customers are not compelled to exit the fitting room to seek alternatives. These RFID mirrors further provide additional product information, proffer recommendations for complementary items, and overall enrich the interactive and convenient shopping experience.

- **Supply Chain Visibility**: The application of RFID tags to clothing items has engendered comprehensive supply chain visibility, spanning from the manufacturing stage to distribution and final retail destinations. This transparency facilitates the optimization of supply chain operations, a reduction in lead times, and the assured availability of products at their requisite destinations. Furthermore, it fosters seamless coordination among the various entities comprising the supply chain.

- **Authentication and Counterfeit Prevention**: High-end fashion brands have turned to RFID technology to authenticate their products. Each item is embedded with a unique RFID tag or label, affording customers the ability to ascertain the authenticity of the product via a smartphone application or an in-store reader. This measure significantly combats the pervasive issue of counterfeiting within the fashion industry.

- **Smart Garment Tracking**: RFID technology is adapted for the direct embedding into individual clothing items, especially in the realm of luxury and high-end designer fashion. This facilitates the tracing of the history and authenticity of each garment, thereby showcasing provenance and craftsmanship – factors of paramount importance to high-end consumers.

- **Personalized Marketing**: Through the monitoring of the movements of RFID-tagged products within a retail environment, retailers amass data on customer preferences and shopping behaviors. This valuable data serves as the foundation for the personalization of marketing efforts and recommendations, both in-store and through online channels. Retailers can proffer tailored discounts and suggestions to customers based on their historical behavior and preferences.

In summary, RFID technology has fundamentally redefined inventory management, security enhancement, and the shopping experience in the fashion retail sector. It avails the advantages of real-time tracking, operational efficiency, and data accuracy, all of which are pivotal in a fiercely competitive industry. Additionally, its applications in supply chain management and counterfeit prevention underscore its indispensable role in ensuring the integrity and success of the fashion retail domain.

Object and structure of this work

The main objective of this work is to explore, develop, and analyze the Software-Based Shielding solution in the context of indoor localization and RFID tag classification, with a specific focus on its performance in real-world retail environments.

The first chapter of this work is literature review of the existing RFID based solutions concerning indoor localization and the classification of RFID tags. This comprehensive review encompasses an examination of prior research, methodologies, and technological approaches within this domain.

Next, the second chapter explores and expands the Software-Based Shielding solution proposed by G. Esposito, Mezzogori, Neroni, Rizzi, and Romagnoli (2021): new approaches to the solutions are implemented and tested under different environment conditions, and the results are analyzed in detail.

In the third chapter, the focus is directed towards the examination of tests conducted within real-word retail environments, in particular two fashion stores. This chapter outlines the methodologies employed in these tests and undertakes a comprehensive analysis of the obtained results.

Chapter four is dedicated to the integration of the Software-Based Shielding solution into the id-Bridge RFID suite, developed by Murata ID Solutions.

The fifth and final chapter focuses on drawing conclusions and outlining directions for future developments.

Chapter 1

Review of RFID based solutions for indoor localization and location-based classification of tags

Wireless communication systems are widely employed for indoor item localization; specifically, two primary application areas can be distinguished:

- detection and localization of stationary items;
- real-time tracking of moving objects, with their movements being traceable over defined time intervals.

Among the various technologies utilized, Radio-Frequency IDentification (RFID), particularly when using cost-effective passive RFID tags, stands out due to its affordability and reasonable efficiency. This characteristic renders RFID suitable for both of the previously mentioned applications, especially in scenarios involving a substantial number of tagged objects. The rationale behind this suitability lies in achieving a balanced compromise between the low cost of implementing the position sensing system and its precision and accuracy. Nonetheless, RFID-based solutions do face limitations in terms of reading range and accuracy.

Both academia and industry have proposed solutions to address these challenges. However, a structured analysis of these developed solutions, which could serve as a valuable reference for future implementations, is currently lacking.

The primary objective of this chapter is to highlight and evaluate the recently introduced methods for indoor item localization that utilize passive RFID tags, emphasizing on both the accurate and qualitative positioning of objects. The former concerns the precise placement of tags, specifically mapping their correct location in a 2D or 3D environment. The latter focuses on tag classification, which involves identifying the area in which a tag is located, irrespective of its specific position.

In section 1.1 the localization problem is introduced; in section 1.2, the perimeter of the research is fixed defining the indoor localization problem by defining characteristics of different localization systems.

In section 1.3, techniques and methods mainly adopted for developing indoor localization systems are provided.

In sections 1.4 and 1.5, the unstructured research methodology is introduced, and 18 documents retrieved are analysed, discussing typologies of indoor localization, technologies adopted, and methods developed, and in section 1.6 results are discussed.

1.1 Introduction to localization problem

The increasing availability of information, due to the growing potentialities and the increasingly popular adoption of wireless technologies, resulted in a high demand for localization systems in both outdoor and indoor environments (Hightower and Borriello, 2001; Pahlavan, Li and Makela, 2002; Huang et al., 2014). The request of information has become even more true because of the Internet of Things (Yao and Hsia, 2018). Several applications have been developed to provide services in many sectors including manufacturing, logistics, and operations management, as well as welfare optimization and daily life services, e.g., localization of assets in hospitals (Farid, Nordin and Ismail, 2013).

As a result, both research and commercial solutions for developing these systems have been proposed, and in the last 25 years localization systems have become very popular to the extent that a new branch of contributions in automation research field has been defined, namely the object location detection (Liu et al., 2007), which has further spread under the IoT era (Li, Mo and Zhang, 2019). The reason for the interest in these systems lies in the fact that further accuracy estimating positions and power consumption efficiency are increasingly demanded (Yao and Hsia, 2018).

This branch of contribution relates to obtaining location information of objects, and different names have been used for labeling it and relative systems developed. Yunhao and Zheng (2011) refers to ‘location-based services’ and Farid et al. (2013) to ‘location finding’. Other terms used in literature are ‘position location’, ‘geolocation’, ‘location sensing’, or generally localization (Liu et al., 2007). From now on, ‘localization’ is used as an umbrella term for generally identifying the process of estimating the position of objects. This literature review focuses of RFID technologies for indoor localization problems. RFID is an auto identification, consolidated, technology for the identification of assets, security, and track-and-trace applications (Ngai et al., 2008). The set is mainly composed by a reader that drives the communication, and tags that have an associated electronic code for being uniquely identified (Landaluce et al., 2020). The reader interrogates these tags using radio frequency (RF) signals, and the tags respond with their identification code (ID). Tags can be active (powered by a battery) or passive (harvesting the energy from the reader's RF signal).

The focus of the study is on RFID technology since RFID, especially passive RFID UHF, is the most adopted technology in industrial environments because of the good trade-off between costs to implement the system, and precision of localization and unique identification of objects (Wu et al., 2019). However other technologies can be used concurrently, e.g., GPS, WLAN, Bluetooth, NFC, Bluetooth, ZigBee technologies, and other Wireless Sensor Network technologies (Li, Mo and Zhang, 2019; Seferagić et al., 2020). The combination of technologies and methods constitutes the localization system. The review aims at discussing localization systems developed in terms of technologies and methods adopted for indoor localization. From now on, we refer to 'methods' as algorithms and techniques used for location estimation based on acquired signals, while 'technologies' relate to RFID sets (i.e., passive or active, and LF or HF or UHF tags), and other wireless communication technologies used in combination for acquiring the transmitted signal.

1.2 Definition of the localization problem

There are many different types of localization, such as physical localization, symbolic localization, absolute localization, and relative localization (H. Liu et al., 2007):

- Physical localization is expressed in the form of coordinates and identifies a point on a 2-D/3-D map by means of coordinate systems.
- Symbolic localization expresses a localization in a natural-language way, such as ‘in the room’, or ‘on the shelf’.
- Absolute localization uses a shared reference grid for all located objects.
- Relative localization depends on its own frame of reference, and information is usually based on the proximity to known reference points or base stations.

The indoor localization can be of different nature. Although, based on the research carried out, the field seems not strictly distinguishing among different localization problems, two cases can be identified, and we stick to lexicon consistent with discussion of Farid et al. (2013). The former relates to items to be localized that are static. We refer to this configuration as ‘location estimation’. The latter relates to moving items. This area of expertise relates to the real-time tracking of objects. Concerning the difference between outdoor localization and indoor localization, the outdoor real-time tracking relates to general real-time locating systems (RTLS) (Curran et al., 2011), while the indoor real-time localization relates to positioning systems (Rácz-Szabó et al., 2020).

Indoor positioning can be defined as any system that provides a precise position of items inside of a closed structure (Zhang et al., 2010. The field of expertise can be further organized distinguishing localization typologies according to Bergeron et al. (2018), and hence precise localization is different from qualitative estimates of position, and this stresses the needs for relative position of objects especially for qualitative applications.

As a result of the analysis so far, the localization problem has been structured as in Figure 1.1.

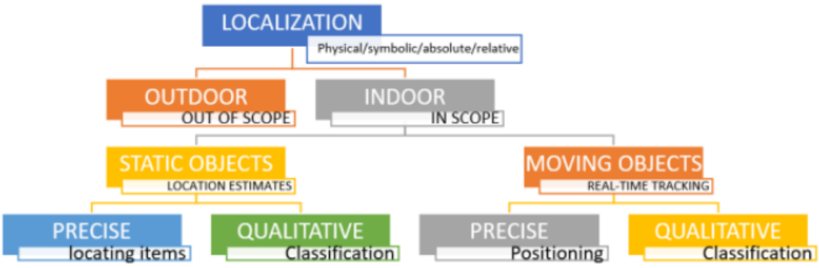


Figure 1.1: Hierarchy of localization problems

1.3 Techniques and Methods

Farid et al. (2013) and Liu et al. (2007) reviewed three main categories of localization techniques, namely:

- proximity;
- triangulation;
- scene analysis.

Proximity detection provides symbolic relative location information. The position of a mobile client is determined by cell of origin method with known position and limited range (Hu, Cheng and Zhang, 2011). Usually, it relies upon a dense grid of antennas, each having a well-known position, and attributing the position estimates on the basis of the acquired signal strength.

Triangulation uses the geometric properties of triangles to determine the target location. It has two derivations: lateration and angulation. Lateration techniques are based on the measurement of the propagation-time system, e.g., Time Of Arrival (TOA), Time Difference Of Arrival (TDOA), Round-Trip Of Flight (RTOF), and especially RSS-based and received signal phase (RSP) (Vossiek et al., 2003; Seco et al., 2009). These are distance-based techniques. On the contrary, angulation techniques also called estimation techniques, which are direction-based, are based on the Angle Of Arrival (AOA) that determines the angle of arrival of the mobile signal coming from a known location at which it is received at multiple base stations (Liu et al., 2007). Finally, scene analysis techniques estimate known current position based on last determined position and incrementing that position based on known or estimated speeds over elapsed time. In this case, new positions are calculated entirely from previous positions.

RF-based scene analysis refers to the type of algorithms that first collect features (fingerprints) of a scene and then estimate the location of an object by matching measurements with the closest a-priori location fingerprints. Research has been carried out in indoor localization (House et al., 2011; Pai et al., 2012) using dead reckoning process. While traditional outdoor localization relies on the triangulation and trilateration, such schemes do not work well indoors with obstacles and room partitions since both require line-of-Sight measurement (Liu et al., 2007).

Whatever the methods, the localization consists in a three-stage algorithm (Brena et al., 2017). First stage concerns measurement of characteristics of a signal acquired. The second stage concerns the ‘range estimation’, where devices use the measurements or evidence obtained to estimate distance to/from the objects to be located. The third stage concerns the combination of such range estimates in order to calculate the position of the objects. This combination could be carried out using various technique, e.g., optimization methods (Munoz et al., 2009) or matrix equation methods (Sayed, Tarighat and Khajehnouri, 2005; Vargas-Rosales et al., 2015). Several applications have been developed in industrial engineering, in the field of business intelligence models for operations optimization (Fantoni et al., 2020), building information modelling for facility management (Bellagente et al., 2018; De Cillis et al., 2020), and FMCG (Bottani et al., 2009; Wölbitsch et al. 2020).

1.4 Materials collected

The works of Bouet and Dos Santos (2008), Sanpechuda and Kovavisaruch (2008), and Zhou and Shi (2009) are the most noteworthy literature reviews discussing indoor positioning systems covering a timespan until 2009. Sanpechuda and Kovavisaruch (2008) limited their analysis to indoor localization, because of more efficient implementation of the system and reliability of the infrastructure. They distinguish between reader localization and tag localization.

Since the focus of this review on tagged objects, we stuck to the localization of tags. Generally, all the studies analysed build the environment using reference tags. Techniques adopted are lateration but also other methods such as Bayesian approach lying in the posterior probability of movement of objects.

One of the most important system is the LANDMARC (Ni et al., 2003) This technique places reference tags in known location as landmarks to the system. The signal intensity of the reference tags is used to calibrate the uncertainty of the distance for tracking tags. The distance calibration is performed by weighing summation of the K-Nearest reference tags location, which relate to fingerprinting techniques. The highest weight is assigned to the reference tag with smallest signal intensity. Usually, LANDMARC deploys active tags as reference tags since they can provide information about the signal strength to detect the range of tracking tags. One of the main limits of LANDMARC is the use of a large amount of reference tags that increase the cost and require high computational power.

Same localization algorithms have been reviewed also by Zhou and Shi (2009), who in addition discuss the use in different industries and sectors of proximity detection and Kernel-based Learning methods, which obey the rule that the smaller the distance between two nodes in signal space is, the closer they are in the physical space, and localize objects accordingly. Bouet and Dos Santos (2008) analysed three localization systems. First family relates to 'Distance estimation algorithms', that uses properties of triangles to estimate the target's location using RSSI, TOA, TDOA, and RSP. Second relates to 'Scene analysis' algorithms, lying in RSS and fingerprinting techniques. Finally, the 'Proximity' technique. For more information on these works, we suggest the reader of referring to the original papers.

Starting from these noteworthy studies, we identified 12 keywords for querying the Scopus database, given by combination of the following terms: 'indoor localization' and 'indoor positioning', 'localization algorithm / system' and 'positioning algorithm / system', 'accuracy', 'wireless (sensor) network', and 'RFID' and 'Radio Frequency Identification' (or 'Radiofrequency identification') of course.

By combining these keywords according to suitable Boolean operators (e.g., Radio Frequency Identification OR RFID), we retrieved 1,072 documents from 2010 to 2020 (documents published in 2021 were neglected for not biasing the review with partial results). Then we skimmed the list according to the following inclusion criteria:

- indexed documents with just partial information or language different from English were not considered;
- the same applied to documents not accessible on the web;
- at least one document per year has been considered, for an evaluation of the evolution of the research;
- when multiple documents were present for one year, the selection of the document to be reviewed was up to the authors of this review, on the basis of their feeling about the contents.

At the end of the process, a list of 17 papers was set, and these are discussed in the next section.

1.5 Localization systems using RFID technologies

Before the last 10 years, research on localization using RFID technologies, especially for indoor positioning, was focused on using active RFID tags, that are characterized by high implementation costs and short life cycles (Yao and Hsia, 2018). Therefore, the interest of research has been focused on using commercial products of passive technology (i.e., both reader and tags), already complying with reliable standards such as EPC Global Class-1 Gen2 and developing localization algorithms to determine the target coordinates in centimetres (Yao and Hsia, 2018). Two main information have been used, the RSSI and the phase of the received signal (Martinelli, 2015; Ma and

Wang, 2017). The increasing efficiency of RFID localization systems has hence attracted increasing attention in industrial practices (Dobrev et al., 2017).

Saab and Nakad (2010) developed a mathematical model for indoor positioning. Localization system relates to distance and position errors of RFID tag using instantaneous RSSI measurements received from the tags in the area, embedding an angle-dependent loss factor. The localization system uses a Kalman filter for the estimate of the RFID reader position.

Ni, Zhang, and Souryal (2011) presented an overview of RFID-based localization both indoor and outdoor. Solutions are both tag-based and reader-based, transceiver- free, and hybrid approaches. The paper is of value since authors also identified challenges to face still current (e.g., interferences due to the use of RSSI signals for localization), and possible solutions overcoming each type of challenge.

Brchan et al. (2012) presented a RSSI-based RTLS using active RFID technology. Reference tags and multiple propagation models are proposed and used to improve the performance of RSSI based ranging. Authors point out that this model uses fewer reference tags than the LANDMARC system. Yang et al. (2012) worked on RFID passive tag distribution, firstly defining a measure for accuracy and precision in a passive RFID localization system. The relationship between RFID tag distribution and positioning precision is then computed through an exponential-based function, and the localization precision is then correlated to density of RFID tag distribution adopting sparse tag distribution. The application of proposed sparse tag distribution strategy lies in the use of the localization algorithm of Park and Hashimoto (2009), which implies an effective rectangle-based feature selection method to filter RFID raw data. Chawla et al. (2013) presented an RFID passive system based on RSS decay model for RTLS in a 3D space.

Huang et al. (2014) proposed an indoor positioning system using active RFID technology based on Kalman-filter for drift removal and Heron-bilateration for location estimation. Kalman-filter instead of statistics methods and reference node. Heron-bilateration is deployed as landmark mapping instead of other methods such as proximity pattern matching, trilateration, and multilateration.

Kuo and Chang (2015) presented a learning algorithm which integrate an optimization version of an artificial immune network (named Opt-aiNET) (Timmis and Edmonds, 2004) and an artificial immune system (AIS) (Hart and Timmis, 2008), with clone selection for backpropagation neural network (aiNBSB). The result is a learning feed-forward neural network that learns the relationship between RSSI values received and a picking cart qualitative-position based on formulated weights of the forecasting model.

Scherhäufl, Pichler and Stelzer (2015) introduced a 2-D localization system for indoor precise position of static and moving objects, using passive UHF RFID tags. The system is based on evaluation of backscattered transponder signals. Authors state that ‘in contrast to a variety of common systems, where either the phase or the amplitude of the received transponder signal is evaluated, incorporating both parameters the method combines the advantages of both approaches’. The developed algorithm does not rely on reference transponders and computationally can be basically reduced to matrix multiplication.

Wang et al. (2016) proposed an indoor positioning system based on RSSI signal, using Particle Swarm Optimization to optimize the weights and threshold of a back propagation neural network. Authors state that the systems provided ‘better performance of PSO compared with some other heuristic method no matter in the accuracy, stability and convergence speed of the algorithm'. In addition, to reduce the influence of the large noise and big data acquired, a Gaussian filter method is used to process the received RSSI values.

Xiao et al. (2017) focused on the use of 2 tags for each object and introduced phase pre-processing using Multipath Propagation Model and Phase Ambiguity Elimination. Furthermore, by applying first-order Taylor series expansions to the distance functions between 'naïve' RFID tag positions and each known physical antenna, the corresponding error is evaluated. The choice of adding one- more RFID tag to the object relates to a three-fold will of:

- providing rich freedom in RFID reader's antenna spacing and placement;
- supporting accurate calibration of the reader antenna location and spacing;
- enabling fine-grained calculation on the orientation of the tags.

Gao et al. (2017) proposed an indoor RFID positioning system lying on a range-free algorithm named nonmetric multidimensional scaling (NMDS)-RFID(F), which combines NMDS algorithm and the fingerprinting localization algorithm, realizing a RFID multi-tag cooperative localization method in the indoor environment.

Zhou-guo, Fang and Yi (2017) used a K-Nearest Neighbor (KNN) algorithm to improve the LANDMARK system in indoor positioning systems. The proposed method rectifies the k nearest reference-tags computing the KNN algorithm k times to get each reference tag coordinate position, and overcoming limitations of indoor environments such as diffraction, reflection, multi-path, and non-line-of-sights.

Xu et al. (2017) proposed a method based on RSSI of UHF passive RFID signals, using KNN algorithm, a gaussian filter to reduce noise, and a Bayesian probability model for precise location estimation. Gaussian filter is used to filter abnormal RSS values and Bayesian estimation together with the K-Nearest Neighbor algorithm are used to improve positioning accuracy.

Ma et al. (2017) used Hyperbolic positioning optimization to overcome phase ambiguity and device diversity. The method consists in acquiring multiple hyperbola curves from different antennas, then combining the results. After that, a Polynomial Regression is modelled through Particle Swarm Optimization to filter out random phases.

Yao and Hsia (2018) built a dual-channel low-power passive RFID positioning system. The method uses the jitter variance of the received backscattered amplitude-shift keying signal, which is inverse-proportional to the jitter variance. Hence, the probabilistic positioning algorithm lies in measuring the jitter variance values corresponding to tags located at the grid coordinates for all readers, as inverse indicator of the signal strength, and then categorizing values into four levels of magnitude. Next, the level clustering tables and the probability for all readers are constructed.

Wu et al. (2019) proposed a two-step method for positioning static tags. First step is the construction of an Unwrapped Phase-Position Model, then the location is calculated using an ordinary nonlinear least squares algorithm. Authors state that 'the proposed method has a lower calculation burden compared with the grid-based methods'.

Wölbitsch et al. (2020) developed an interesting system for expressing precise location of objects in a retail shop, based on prediction of distances from referenced tags based on Density-based Spatial Clustering of Applications with Noise (DBSCAN) and Dynamic Time Warping (DTW).

Table 1 recaps all the systems analysed, with emphasis on typology of localization system with respect to hierarchy in Figure 1, methods adopted or developed. Moreover, the location typology is distinguished between 'qualitative' and 'precise' according to the hierarchy introduced in Figure 1.1.

1.6 Discussion of results

So far, it emerges that the RFID technology is mainly used in indoor environments for precise estimation of positions of moving objects (see Figure 1.2).

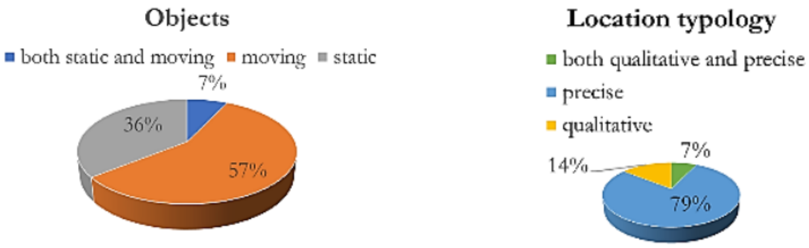


Figure 1.2: Focus of RFID indoor localization systems

However, two things are not strictly related, namely precise localization of static objects is also analysed, as well as classification problems of both static and moving objects. Instead, it is possible to state that a good amount of research is focused on positioning of objects that move in environments with or without safety barriers, e.g., robot arms.

On the contrary, if the interest of the early 2010's research was on only moving objects, static applications have gradually gained interest, and logistics use cases have paved the way for adoption of relative systems. Concerning technologies adopted (see Figure 3), just a single study combines RFID with other technologies, namely Bluetooth, while all others use readers, tagged objects, and reference tags that constitute the landmarks of grid environments.

UHF passive tags are the most used, and slightly more than half of the studies use the RSSI signal, while other studies criticize this signal and use either phase angle or both to mitigate the positioning error, since the accuracy of RSSI varies widely due to the tags' orientation and antenna gain, which make RSSI not a reliable indicator for some positioning methods.

Finally, innovative approaches have also been adopted, from different research fields, as statistics and artificial intelligence.

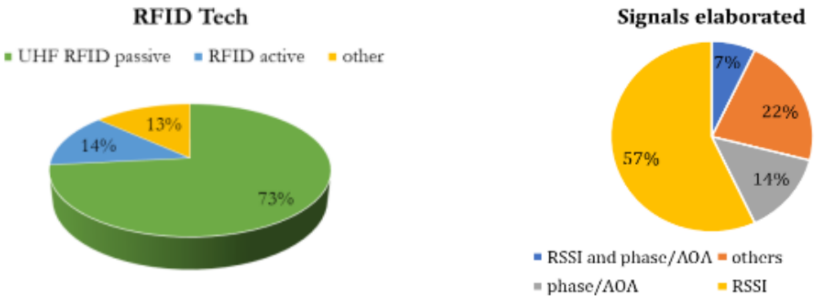


Figure 1.3: Technologies and signals adopted

Reference	Objects	Location typology	Signal	Method	Technologies
Saab and Nakad (2010)	moving	precise	RSSI	Proximity / Triangulation: instantaneous location method based on RSSI, using a Kalman filter to reduce the estimation error	RFID passive tags (labels) and off-the-shelf readers/antennas
Ni, Zhang, and Souryal (2011)	both static and moving	both qualitative and precise	RSSI	Localization via systems as LANDMARC (tag-based) or however based on reference tag (reader-based), data mining techniques for transceiver-free object tracking (transceiver-free technologies), LANDMARC or Support Vector Regression applied in a referenced grid area (hybrid technologies)	RFID active tags (for both tag- based and reader-based systems), beacons (for transceiver-free systems), and passive tags and Wireless Sensor Network (for indoor hybrid systems)
Brchan et al. (2012)	moving	both qualitative and precise	RSSI	Proximity + Triangulation: based on RSSI, first step detects the subarea (quadrant), then a propagation model is used to provide precise location, consisted with proximity elimination, range averages, and linear least squares (LSQ)	RFID active tags, and off-the- shelf readers and antennas (303MHz)

Reference	Objects	Location typology	Signal	Method	Technologies
Yang et al. (2012)	moving	precise	-	Proximity: the reader is moved over a grid of passive tags and the position is estimated using a well-known localization algorithm. The main goal is to evaluate different grid patterns and densities	RFID passive tags (button tags), and off-the-shelf reader and antenna
Chawla et al. (2013)	moving	precise	RSSI	Triangulation: based on RSSI, uses an RSS decay model to establish the relationship between the tag's RSS behavior and the tag-reader distance.	Wide selection of UHF RFID passive tags, Alien ALR-9900+ and ThingMagic Mercury6 readers
Huang et al. (2014)	moving	qualitative	RSSI	Triangulation: based on RSSI, uses Kalman filter (drift removal) to to solve the RSSI drift issue, then a Linear-Like RSSI-to-Distance Transformation, then Heron- bilateration (location estimation)	Active RFID tag (with bluetooth), Android device with RFID indoor positioning device (bluetooth)

Reference	Objects	Location typology	Signal	Method	Technologies
Kuo and Chang (2015)	moving	qualitative	RSSI	Based on RSSI, uses AIS (artificial immune systems, a class of computationally intelligent systems inspired by the principles and processes of the vertebrate immune system) and Opt-aiNET (inspired by specific immunological theories that explain the function and behavior of the mammalian adaptive immune system)	OMRON V750-series UHF RFID System (tags and readers)
Scherhäufl, Pichler and Stelzer (2015)	static	precise	RSSI and phase/A OA	Localizaton model based on both Phase-of-Arrival and Amplitude signals	RFID passive tags (labels), and off-the-shelf readers and antennas
Wang et al. (2016)	static	precise	RSSI	Based on RSSI, uses Particle Swarm Optimization (PSO) to optimize the weights and threshold of a back propagation neural network	Laird-S8658WPL UHF RFID System (965 MHz) (passive tags and antennas)

Reference	**Objects**	**Location typology**	**Signal**	**Method**	**Technologies**
Xiao et al. (2017)	both static and moving	precise	Distance between two readers	Focuses on the use of 2 tags for each object, performs phase preprocessing (Multipath Propagation Model + Phase Ambiguity Elimination) and naïve localization	Impinj R420 RFID reader, Impinj H47 RFID passive Tag (label)
Gao et al. (2017)	static	precise	RSSI	NMDS-RFID(F) algorithm combines fingerprint localization and Nonmetric Multidimensional Scaling (NMDS)	Simulated environment
Zhou-guo, Fang and Yi (2017)	moving	precise	RSSI	Uses a KNN to improve the LANDMARK system	-
Xu et al. (2017)	moving	precise	RSSI	Based on RSSI, uses KNN, a gaussian filter to reduce noise, and a Bayesian estimation (probability model)	Impinj R420 RFID reader, UHF passive tags

Reference	**Objects**	**Location typology**	**Signal**	**Method**	**Technologies**
Ma et al. (2017)	static	precise	phase/A OA	Uses Hyperbolic positioning optimization to overcome phase ambiguity and device diversity acquires multiple hyperbola curves from different virtual antennas, then combines the results. After that, uses Polynomial Regression to filter out random phases	Commercial off-the-shelf readers and passive UHF tags
Yao and Hsia (2018)	moving	precise	TDSNR	Initial analysis: Time-Domain Signal to Noise Ratio, then categorization based on the jitter variance, then probabilistic positioning algorithm	Dual-channel passive RFID tags (915 MHz + 433 MHz), dual channel RFID reader
Wu et al. (2019)	static	precise	phase/A OA	First step is the construction of an Unwrapped Phase- Position Model, then the location is calculated using a nonlinear least squares algorithm	Impinj Speedway R420 (UHF), passive UHF tags
Wölbitsch et al. (2020)	static	precise	RSSI	Calculation of probability of distance on the basis of DBSCAN and DTW	UHF passive tags

Chapter 2

RFID Software-Based Shielding: implementation of further approaches under varying surrounding conditions

RFID systems might use different tools to provide inventory count and localization. To this aim, portable RFID readers, known as handheld readers, can be used by store clerks with different reading ranges that can be achieved by setting reading power and mode (Rizzi & Romagnoli, 2017).

Also, fixed infrastructures can be used, with readers whose power and mode are typically set to achieve a wide read range, and thus a quicker inventory count and often a less precise localization. Both these tools, however, to avoid inaccuracies and false reads, must use physical shielding materials to limit the RF field to the area where the inventory count is performed (G. Esposito, Mezzogori, Neroni, Rizzi, & Romagnoli, 2021). These physical shielding commonly consist of metal foils applied to the walls that separate different store areas, to prevent the RF field from penetrating the walls, and to provide adequate confidence that the read tags are located in the area where the reading takes place (Bertolini, Romagnoli, et al., 2017).

We note, however, that this solution presents some limits, as false tag reads can produce inventory and location errors (Metzger et al., 2013). Also, other issues can be connected to the physical shielding of store areas, such as the cost of the solution, its limited flexibility, its aesthetic aspects, and the fact that physical barriers cannot always be installed, especially between different areas of the same sales floor (Swedberg, 2019).

In a recent paper, an alternative software-based shielding solution has been proposed by G. Esposito, Mezzogori, Neroni, Rizzi, and Romagnoli (2021). This solution relies on item-level tags and, without any need of physical shielding between different areas, it applies a logistic regression model to estimate whether the tags that are read in a reading session are located in the same area of the reader or not. This solution is cheaper and more flexible, as it does not need physical shielding, and it provided interesting results, with an average positioning accuracy of tags around 95%.

As that study highlighted, the proposed solution was only tested in a specific scenario, namely that of a plasterboard partition wall with fixed rooms sizes and a given tags disposition and density. Also, the paper by G. Esposito et al. tested only a logistic regression approach. In this chapter, different approaches with increasing complexity, such as a neural network and a convolutional neural network are proposed, alongside with a simple heuristic approach. Thus, the aim is that of investigating software-based shielding (SBS) performances with different wall types and thickness, as well as with varying tags dispositions and densities, under different approaches, namely:

- a simple heuristic approach;
- the logistic regression introduced by G. Esposito et al.;
- the same logistic regression, with the support of reference tags;
- a neural network (NN);
- a convolutional neural network (CNN).

In Section 2.1 we report an overview of the software-based shielding solution proposed by G. Esposito, Mezzogori, Neroni, Rizzi, and Romagnoli (2021), that is the tested scenarios. Section 2.2 describes the test enviroment and the variables considered, while in Section 2.3 are explained the approaches that we used.

The results we achieved are reported and discussed in Section 2.4, and Section 2.5 draws conclusions.

2.1 Software-based shielding

In the software-based shielding solution study proposed by G. Esposito, Mezzogori, Neroni, Rizzi, and Romagnoli (2021) three key environmental variables have been identified and used as parameters for the tests:

- **the door in the partition wall**: this variable relates to the state of the door within the partition wall that separates the front (sales floor) and the back (storage area) of the store. The door can be either open (at 30 degrees) or closed. Closed doors provide better results due to enhanced shielding between the front and the back;
- **the model of the RFID Reader**: different RFID reader models have varying impacts on the inventorying process. Two commonly used reader models in commerce, Bluebird RFR900 and Zebra RDF8500 have been used for evaluation. With the aim of anonymizing results with respect to the reader model, readers will be reported as Reader A and B, without connection to the specific brand and model, but with consistent results (i.e., reader A is always reported with the same brand and model);
- **Effective Radiated Power (ERP) of the reader**: ERP, expressed in milliwatts (mW), represents the reader's transmit power. The ERP have been categorized into three levels: 65 mW, 125 mW, and 500 mW. The first two levels are considered representative of selective inventorying, while the latter represents a condition of massive inventorying. Higher ERP values may increase the likelihood of reading tags in the back and add complexity to the shielding of different areas. Additionally, a particular case is considered where the Reader A, capable of delivering up to 1500 mW of ERP, is used with a closed door.

The data collection process aimed to simulate the conditions of a typical retail store environment as closely as possible. The test area used for this study is divided into a front area of 50 square meters and a back area of 15 square meters. These two areas are separated by a plasterboard wall with a door for transition between them. It should be noted that the material and thickness of the partition wall (usually plasterboard or bricks) could influence the results, but due to time constraints, variations in wall materials and thickness were not explored in this research. The scientific community is encouraged to investigate these factors in future studies. However, it is generally accepted that, concerning radio waves, brick walls offer better shielding than plasterboard walls (Wang et al., 2017). As a result, the results presented here may be considered a worst-case scenario due to the use of plasterboard.

For each of the 13 scenarios defined by a single reader model, door state, and ERP level, 10 reading sessions of 1 minute each were conducted. In each reading session, 100 RFID tags were placed in the front area and 300 in the back area, following a proportion typical of a fashion retail store. Tags and their positions within the rooms were shifted between reading sessions and scenarios. To expedite testing, the same set of tags and tag positions were used for scenarios i and i+1, where i ranged from 1 to 13.

To better replicate a real-world situation, several measures were taken. In the front area, 50 of the 100 tags were placed on shelves or in cardboard boxes, while the other 50 were hung on bars, similar to clothing items like jackets or shirts. In the back area, 150 tags were placed in cardboard boxes along with the corresponding clothing items, and the remaining 150 were hung. During the reading sessions, the person using the handheld reader was instructed to move randomly within the room, simulating the behavior of a store employee.

Furthermore, 4000 additional non-registered tags were placed throughout the simulated store, with 1000 in the front and 3000 in the back. These non-registered tags served as a source of noise for the reader, mimicking the real-world scenario where such noise is present. This noise includes signal collisions and interference, which are crucial to consider in any practical application.

Notably, in each reading session, the tagged items placed in the front and back, whether hung or folded, were evenly distributed within each room. Specifically, 50% of the items were placed within the first 1.5 meters from the partition wall, and the remaining 50% were positioned further away from the wall.

The information collected to estimate the tag location included the number of times a tag was read (Read Rate, RR) and the Received Signal Strength Indicator (RSSI) of each tag that was read.

The problem of classifying the location of garments in a retail store is approached using logistic regression. The objective is to categorize items as either in the front or back room based on RFID data. Before applying the classification model, data preprocessing is employed to consolidate multiple readings for each item. The key features considered are the Read Rate (RR) and the Received Signal Strength Indicator (RSSI).

The dataset used for experimentation consists of 4000 records per scenario, with 400 tags in each reading session (100 in the front room and 300 in the back room), across 10 reading sessions for each scenario. The study's focus is to evaluate the performance of the classification model in specific scenarios, treating each dataset as an independent experiment.

To address the challenge of class imbalance, where only 25% of tags are in the front room, class weights are set to 'balanced' during model training.

This weighting strategy helps the model handle the imbalanced dataset more effectively, with the ultimate goal of accurately categorizing the location of garments in the retail store.

The study results are highly promising. The logistic regression model achieved an average accuracy of 95.54% without normalization and 95.55% with normalization, with even better performance in the best-case scenarios (96.87% and 96.92%). Minimal differences between overall and best results suggest the model's consistency.

Environmental variables have some impact, with the model performing better when the door is closed as expected. However, certain scenarios, particularly involving the Reader B, exhibit slight accuracy improvements when the door is open, necessitating further investigation.

The choice of reader has a substantial influence on accuracy. The Reader B outperforms the Reader A by 2%, which can be crucial for large-scale retail environments.

There's no linear correlation between Effective Radiated Power (ERP) and accuracy, indicating the unique configurations of each reader. The best results occur in the second and fourth scenarios, with accuracy exceeding 99%. Statistically, the fourth scenario outperforms all others, making it a prime choice.

Overall, the results are robust, suggesting the approach's potential for practical implementation in various settings.

2.2 Test environment and variables

The main focus of this section is the testing of Software-Based Shielding (SBS) under several different conditions. The portable reader used for these tests is the Reader A, and the testing took place in a lab environment, i.e., a simulated situation.

The analysed aspects are:

- the ERP power the reading sessions are carried out with;
- the partition wall type and width;
- the disposition of tags and their density.

2.2.1 Wall type and thickness

Four different kinds of wall type and thickness have been considered:

- 80 mm partition plasterboard masonry;
- 100 mm partition brick masonry;
- 250 mm load-bearing reinforced concrete masonry;
- 350 mm double load-bearing masonry in reinforced and insulated concrete.

In the remainder of this chapter, these wall types and thickness will be labeled with the words in bold font;

2.2.2 ERP power levels

Two ERP power levels have been used:

- 125 mW;
- 600 mW.

We note that the two power levels we've considered are similar from those of G. Esposito, Mezzogori, Neroni, Rizzi, & Romagnoli (2021), with the only difference of a higher power level of 600 mW (instead of 500 mW). This is due to the empiric evidence collected so far, as well as to discussions with retail store managers and fashion companies, which led us to review this power level to a slightly higher value, to allow quicker inventory reads, and to better reflect industry practice.

2.2.3 Dispositions of tags

Three different dispositions of tags have been considered:

- low density (approx. 15 tags per square metre) and hanging garments;
- high density (approx. 165 tags per square metre) and hanging garments;
- low density and folded garments.

We note that these dispositions were selected, with respect to the starting condition of low density and hanging garments, as they provide two kinds of issues: the localization problem of high-density tags and that of localizing folded garments, whose tags are typically parallel to the field direction, and therefore harder to read.

The combinations of these aspects gave rise to the 24 different scenarios reported in Table 2.1. For each scenario, we also report the Jensen-Shannon divergence (JSD) between the read rate of tags in the front (i.e., the room where the readings are carried out), and the tags in other rooms (i.e., the back). We will use in the following the general terms of front and back, to differentiate between the room or area where the reading is performed, and any other room or area.

We note that the JSD value should be read as an indicator of difficulty of the localization: the closer the JSD is to 1, the stronger is the distinction between the tags in the front and those in the back, the easier is the task for the proposed classification model.

Similarly, if the JSD is close to zero, the distinction between the tags in the front and those in the back is not clear, and the task for the classification model gets harder (Menéndez et al., 1997). Looking at the JSD, it is possible to identify three main clusters corresponding to three different levels of localization difficulty. These clusters mainly depend on tags disposition and density. More in detail, we can identify a first cluster characterised by an average JSD ∼0.8 where the distinction between the tags in the front and those in the back is very clear. This cluster comprises scenarios 1-8 (from 1 to 8) that are characterised by a low density of hanging clothes.

Conversely, in scenarios 9-16, the average JSD is ∼0.56 and this is a clear indicator that, as the density of tags increases, the classification get more and more difficult. Finally, scenarios with laid clothes (from 17 to 24) have an average JSD of ∼0.62: the classification in these cases is not as simple as in the first scenarios, although they are characterised by great variability depending also on other factors (i.e., power and wall type) as the JSD goes from ∼0.2 in scenario 17, up to ∼0.83 in scenario 19.A further difference with the experiments carried out in occasion of our previous work is the presence of reference tags (highlighted in blue in Figure 2.1).

The reference tags are four known tags which have been placed on the partition wall (i.e., two on the front side and two on the back side).

The proposed models are supposed to benefit from these reference tags, by comparing their key indicator such as Read Rate (RR) or Received Signal Strength Indicator (RSSI) with the same indicators of the tags whose location must be estimated. As Table 2.1 clearly show, the investigated scenarios have much different JSD values, ranging from 0.289 to 0.892. These scenarios will be the boundary conditions under which performances of the software approaches reported in the following section will be tested.

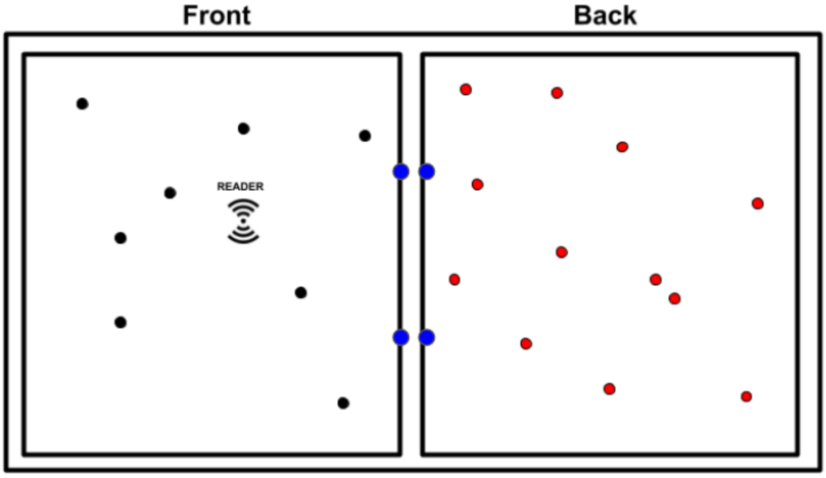


Figure 2.1: Schematic representation of the scenario

Table 2.1: Tested scenarios.

Scenario	**Power [mW]**	**Wall**	**Disposition of tags**	**JSD**
1	125	Partition plasterboard	Low density of hanging clothes	0.818
2	125	Reinforced and insulated concrete	Low density of hanging clothes	0.776
3	125	Partition brick	Low density of hanging clothes	0.892
4	125	Reinforced concrete	Low density of hanging clothes	0.818
5	600	Partition plasterboard	Low density of hanging clothes	0.822
6	600	Reinforced and insulated concrete	Low density of hanging clothes	0.821
7	600	Partition brick	Low density of hanging clothes	0.832
8	600	Reinforced concrete	Low density of hanging clothes	0.822
9	125	Partition plasterboard	High density of hanging clothes	0.467
10	125	Reinforced and insulated concrete	High density of hanging clothes	0.645
11	125	Partition brick	High density of hanging clothes	0.430
12	125	Reinforced concrete	High density of hanging clothes	0.537
13	600	Partition plasterboard	High density of hanging clothes	0.554
14	600	Reinforced and insulated concrete	High density of hanging clothes	0.637
15	600	Partition brick	High density of hanging clothes	0.563
16	600	Reinforced concrete	High density of hanging clothes	0.586
17	125	Partition plasterboard	Low density of laid clothes	0.289
18	125	Reinforced and insulated concrete	Low density of laid clothes	0.741
19	125	Partition brick	Low density of laid clothes	0.803
20	125	Reinforced concrete	Low density of laid clothes	0.501
21	600	Partition plasterboard	Low density of laid clothes	0.685
22	600	Reinforced and insulated concrete	Low density of laid clothes	0.647
23	600	Partition brick	Low density of laid clothes	0.616
24	600	Reinforced concrete	Low density of laid clothes	0.716

2.3 Proposed approaches

An overview of the proposed approaches is provided in this section.

2.3.1 Heuristic approach

The first proposed model is a simple heuristic approach. The proposed heuristic uses the reference tags as a sort of reference point. Since the reference tags are placed on the partition wall between the room where the reader is (i.e., front) and the back shop (i.e., back), the heuristic compares the Read Rate (RR) of each tag with the average RR of the reference tags: when the RR of the considered tag is lower than the RR of the reference ones, the tag is assumed to be in the back, otherwise it is considered in the front.

2.3.2 Logistic Regression

The logistic regression is the same model we already implemented in our previous work. The input of the logistic regression, as described in Esposito et al. (2021), is a vector of 7 elements:

- the RR of the tag (i.e., how many times it has been read);
- its average RSSI;
- the median of its RSSI;
- four quantiles (respectively 5%, 25%, 75%, and 95%).

2.3.3 Logistic Regression with reference tags

This model is very similar to the previously described one, although it tries to take advantage of the reference tags. Each time a reading is carried out and the model must define which tags are in the front and which in the back, it is provided with not just the information concerning the tag to be localised, but also the information concerning the reference tags.

Hence, given for example the global number of reference tags, g, the input of the model is a vector of 7 + 7g elements, where the first 7 values are the same inputs of the previously described model (respectively the RR of the tag to classify, its average RSSI, its median RSSI, and the 5%, 25%, 75%, 95% quantiles of its RSSI), while the remaining 7g values are the same parameters for all the g reference tags.

2.3.4 Neural Network

The next implemented and tested model is a deep neural network. In order to avoid complicated parameters tuning we implemented one of the most widespread configurations with three hidden layers of 32 nodes each.

The size of the input layer is the same of the logistic regression with reference tags (i.e., 7 + 7g where g is again the global number of reference tags) and in this case it was therefore of 35 nodes.

Finally, the output layer is made of a single node with the sigmoid activation function. All the nodes of the network (except for the output node) use a classic ReLU activation function, and the training is made using the Adam algorithm (Jais et al., 2019) and batches of 1024 rows.

During the training a slight dropout regularisation technique (Srivastava, 2013) is used in all three layers to avoid overfitting. A representation of the implemented neural network is reported in Figure 2.2.

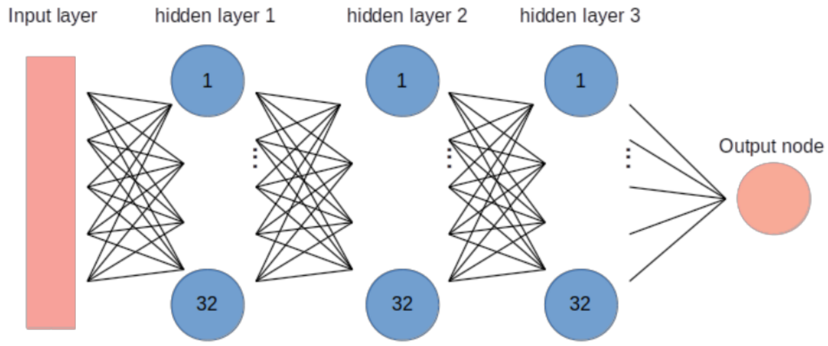


Figure 2.2: Implemented neural network

2.3.5 Convolutional Neural Network

In the last model, the concept of time is also considered. Since the readings are essentially made by an operator who walks around the shop for the entire duration of the reading session (∼60 seconds), it might happen that, given a tag to classify, some readings result having a very high value of RSSI (because the operator is close to the tag) and others result having a very low value of RSSI (because the operator is on the opposite side of the area).

This behaviour might be confusing for a model that does not consider the instant of time in which the readings take place and therefore deteriorate the classification accuracy. Given a tag to be classified, using a Convolutional Neural Network (CNN) offers the possibility to split the readings depending on the time in which they took place and provide them separately to the model. More precisely, the input of our CNN is a T x (7 + 7g) matrix where g is again the number of reference tags, and T is the number of time windows in which the reading session has been split.

If a reading session lasts 60 seconds and the number of time windows considered is T = 3, the first line of the input matrix contains the monitored parameters (i.e., RR, average RSSI, median RSSI, 5%, 25%, 75%, 95% RSSI) relative to the tag to classify and the reference tags with respect to the first 20 seconds of the reading session, the second line contains the same information with respect to the readings occurred between 20 and 40 seconds from the reading session's beginning, and, similarly, the third line contains the same information with respect to the last 20 seconds of the reading session. In this way, the model has information relative to the tag to be classified in T different instant of time, and not just a single view of the whole reading session (see Figure 2.3).

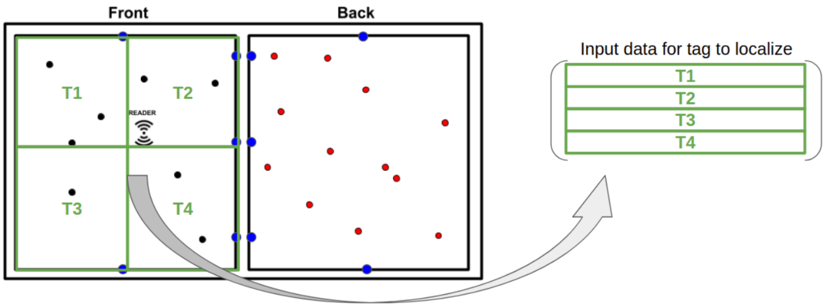


Figure 2.3: representation of the time windows concept

Concerning the architecture of the CNN, we used a common topology mostly used with the MNIST dataset, made of the following elements:

- An input layer T x (7 + 7g) x 1 where T = 3 and g = 4.
- A 2D convolution layer with 32 output filters and a 3x3 kernel.
- A max pooling layer of size 2x2.
- A 2D convolution layer with 64 output filters and a 3x3 kernel.
- A max pooling layer of size 2x2.
- A 2D convolution layer with 128 output filters and a 3x3 kernel.

- A max pooling layer of size 2x2.
- A flattener.
- A dense layer of 128 nodes.
- An output node with the sigmoid activation function.

All the nodes (except for the output node) make use of the LeakyReLU activation function, the Adam algorithm (Jais et al., 2019) is used for training, and a dropout regularisation (Srivastava, 2013) is used for the dense layer in order to prevent overfitting. The choice of the LeakyReLU depends on fact that the available dataset was too small to provide a correct training of a CNN, and, as proved by Dubey & Jain (2019), the LeakyReLU results very efficient in cases characterised by sparse gradient (due to a not big enough dataset). The architecture of the implemented convolutional neural network is shown in Figure 2.4.

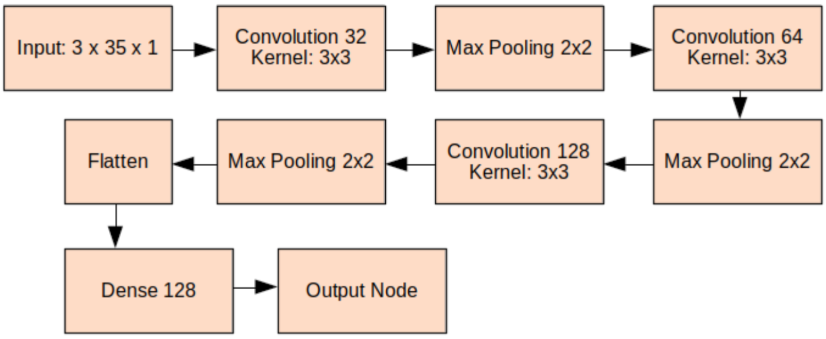


Figure 2.4: Implemented convolutional neural network

2.4 Experiments and validation

With the aim of anonymizing results, the different approaches used from now on will be referred as Method X (MX), where X is an index from 1 to 5.

Indexes used will be consistent throughout the presentation of the results. Tables 2.2 to 2.6 report respectively the results obtained by the above-described models in the 24 different scenarios.

Table 2.2: Results of the Method 1.

Scenario	**Accuracy**	**Precision Front**	**Recall Front**	**Precision Back**	**Recall Back**
1	0.832	1.000	0.773	0.635	1.000
2	0.949	1.000	0.934	0.837	1.000
3	0.918	1.000	0.904	0.709	1.000
4	0.980	1.000	0.976	0.933	1.000
5	0.984	0.983	0.988	0.986	0.980
6	0.993	1.000	0.988	0.985	1.000
7	0.993	1.000	0.988	0.987	1.000
8	0.979	0.965	1.000	1.000	0.950
9	0.356	0.988	0.304	0.112	0.987
10	0.431	0.995	0.329	0.212	0.991
11	0.257	0.952	0.097	0.191	0.990
12	0.207	1.000	0.091	0.138	1.000
13	0.570	0.986	0.365	0.412	0.990
14	0.514	0.998	0.273	0.406	0.998
15	0.447	1.000	0.154	0.384	1.000
16	0.361	1.000	0.116	0.302	1.000
17	0.358	0.933	0.166	0.266	0.974
18	0.101	1.000	0.057	0.049	1.000
19	0.103	1.000	0.071	0.037	1.000
20	0.529	0.966	0.500	0.143	0.866
21	0.692	1.000	0.440	0.600	1.000
22	0.671	0.968	0.547	0.483	0.957
23	0.507	1.000	0.309	0.359	1.000
24	0.824	0.992	0.755	0.636	0.987

Table 2.3: Results of the Method 2.

Scenario	**Accuracy**	**Precision Front**	**Recall Front**	**Precision Back**	**Recall Back**
1	1.000	1.000	1.000	1.000	1.000
2	0.995	0.994	1.000	1.000	0.976
3	1.000	1.000	1.000	1.000	1.000
4	0.990	0.994	0.994	0.972	0.986
5	0.987	0.983	0.994	0.993	0.980
6	0.990	0.994	0.988	0.985	0.993
7	1.000	1.000	1.000	1.000	1.000
8	0.996	0.994	1.000	1.000	0.993
9	0.964	0.992	0.968	0.666	0.967
10	0.979	0.996	0.980	0.896	0.981
11	0.975	0.994	0.974	0.895	0.977
12	0.926	0.988	0.926	0.665	0.928
13	0.942	0.971	0.944	0.870	0.950
14	0.975	0.988	0.974	0.949	0.976
15	0.973	0.985	0.972	0.949	0.974
16	0.969	0.985	0.971	0.928	0.962
17	0.834	0.937	0.845	0.636	0.827
18	0.945	0.992	0.950	0.466	0.933
19	0.965	0.988	0.976	0.333	0.666
20	0.973	0.993	0.978	0.853	0.900
21	0.954	0.960	0.958	0.952	0.948
22	0.983	0.994	0.982	0.960	0.988
23	0.936	0.978	0.934	0.860	0.959
24	0.930	0.962	0.934	0.867	0.920

Table 2.4: Results of the Method 3.

Scenario	**Accuracy**	**Precision Front**	**Recall Front**	**Precision Back**	**Recall Back**
1	0.996	1.000	0.994	0.988	1.000
2	0.972	0.988	0.976	0.952	0.948
3	1.000	1.000	1.000	1.000	1.000
4	0.995	0.994	1.000	1.000	0.972
5	0.996	1.000	0.994	0.993	1.000
6	0.990	0.994	0.988	0.986	0.993
7	1.000	1.000	1.000	1.000	1.000
8	1.000	1.000	1.000	1.000	1.000
9	0.977	0.997	0.976	0.819	0.990
10	0.976	0.995	0.977	0.889	0.976
11	0.970	0.988	0.975	0.898	0.946
12	0.900	0.991	0.893	0.601	0.944
13	0.920	0.975	0.902	0.958	0.950
14	0.973	0.987	0.972	0.947	0.974
15	0.965	0.981	0.966	0.937	0.965
16	0.970	0.984	0.974	0.935	0.960
17	0.864	0.950	0.869	0.941	0.809
18	0.938	0.986	0.950	0.383	0.733
19	0.804	0.988	0.809	0.133	0.666
20	0.973	0.993	0.978	0.900	0.900
21	0.947	0.969	0.934	0.928	0.963
22	0.894	1.000	0.851	0.859	1.000
23	0.961	0.987	0.952	0.926	0.977
24	0.921	0.969	0.916	0.850	0.934

Table 2.5: Results of the Method 4.

Scenario	**Accuracy**	**Precision Front**	**Recall Front**	**Precision Back**	**Recall Back**
1	0.973	1.000	0.964	0.946	1.000
2	0.929	0.949	0.970	0.761	0.757
3	0.970	0.970	1.000	0.833	0.833
4	0.990	0.988	1.000	1.000	0.958
5	0.990	0.994	0.988	0.986	0.993
6	0.983	0.988	0.982	0.978	0.986
7	1.000	1.000	1.000	1.000	1.000
8	0.982	0.971	1.000	1.000	0.959
9	0.983	0.993	0.986	0.900	0.949
10	0.917	0.991	0.910	0.727	0.957
11	0.927	0.955	0.961	0.715	0.750
12	0.805	0.952	0.830	0.469	0.674
13	0.899	0.926	0.939	0.876	0.840
14	0.954	0.970	0.962	0.926	0.940
15	0.936	0.934	0.975	0.954	0.861
16	0.925	0.956	0.941	0.862	0.886
17	0.732	0.797	0.904	0.128	0.238
18	0.959	0.972	0.985	0.233	0.333
19	0.977	0.977	1.000	0.333	0.333
20	0.792	0.965	0.807	0.502	0.566
21	0.882	0.925	0.857	0.546	0.546
22	0.894	0.939	0.916	0.916	0.831
23	0.831	0.925	0.845	0.505	0.644
24	0.904	0.956	0.904	0.806	0.907

Table 2.6: Results of the Method 5.

Scenario	**Accuracy**	**Precision Front**	**Recall Front**	**Precision Back**	**Recall Back**
1	0.987	1.000	0.982	0.923	1.000
2	0.980	0.988	0.988	146.6	0.952
3	0.994	0.994	1.000	1.000	0.916
4	0.990	0.988	1.000	1.000	0.958
5	0.993	0.994	0.994	0.993	0.993
6	0.996	0.994	1.000	1.000	0.993
7	1.000	1.000	1.000	1.000	1.000
8	0.989	1.000	0.982	0.977	1.000
9	0.981	0.980	0.996	0.975	0.921
10	0.848	0.997	0.819	0.807	0.987
11	0.968	0.973	0.991	0.955	0.872
12	0.971	0.974	0.992	0.816	0.827
13	0.956	0.959	0.972	0.943	0.933
14	0.961	0.976	0.965	0.936	0.954
15	0.963	0.976	0.968	0.945	0.956
16	0.963	0.974	0.975	0.944	0.933
17	0.992	0.991	1.000	1.000	0.219
18	0.971	0.988	0.973	0.628	0.666
19	0.931	0.931	1.000	0.000	0.000
20	1.000	1.000	1.000	1.000	1.000
21	1.000	1.000	1.000	1.000	1.000
22	0.966	0.976	0.976	0.949	0.943
23	0.851	0.814	0.863	0.718	0.877
24	0.966	0.972	0.982	0.956	0.931

As it is visible from the tables, and represented in Figure 2.5l the proposed models are very accurate except for the Method 1. More in detail, looking at Table 2.2, we can see how the Method 1 has a good accuracy ($\sim$95%) in the first scenarios characterised by a low density of hanging clothes, but quickly deteriorate in more complex scenarios where the density of tags increases and the disposition of clothes changes.

The comparison between other models is clearer in Figure 2.6. All the models represented in Figure 2.6 are surprisingly accurate, however, Method 3 and Method 4 are less accurate than Method 1.

As this might seem strange, a possible justification could be the, probably unsupportive, presence of reference tags. Indeed, reference tags could be a negative reference point when the operator is moving in the front area, introducing some noise that could deteriorate the model's efficiency.

As it clearly emerges from Figures 2.5 and 2.6, the best results are achieved by Method 5. This approach, in fact, outperforms the others in terms of accuracy.

This could be justified by the introduction of the time variable, which also explains why the use of reference tags alone, i.e., without an implicit information concerning the position of the operator in the specific time window, cannot help the model to better localize the tags.

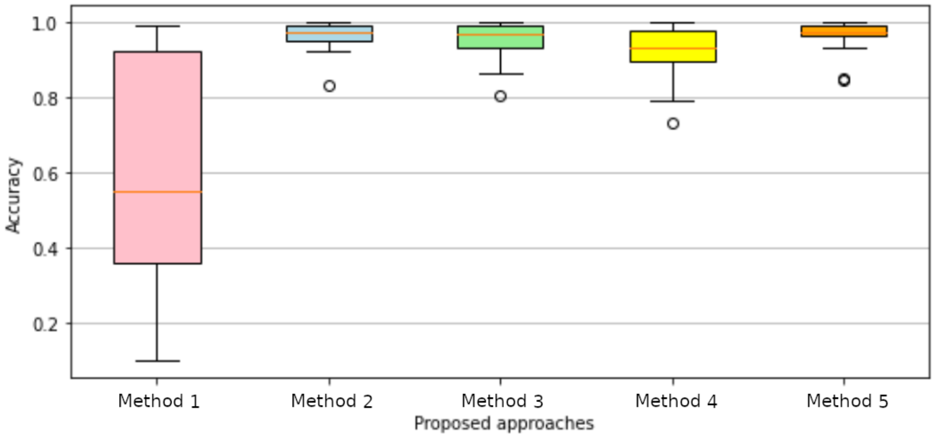


Figure 2.5: Comparison of the proposed models

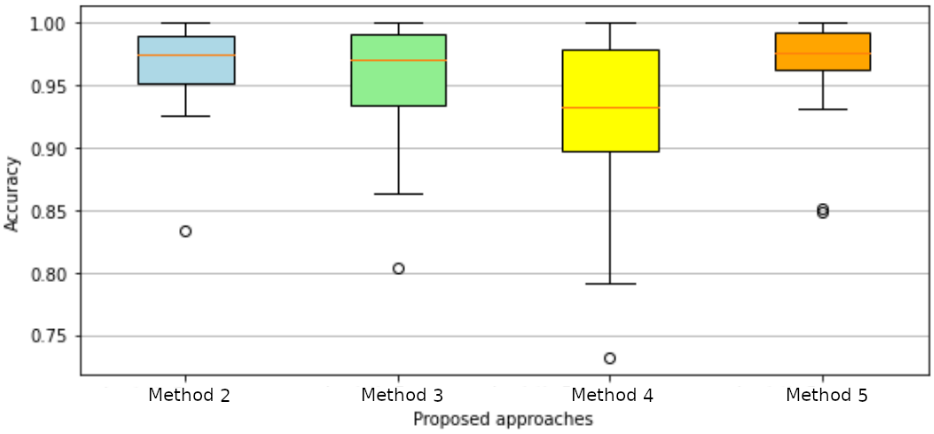


Figure 2.6: Comparison of proposed models except for Method 1

For sake of clarity, and in order to provide a more extensive analysis of the surrounding conditions, an analysis of variance (ANOVA) has been performed on the accuracy of the most performant approach (i.e., Method 5). These results are presented in Table 2.7. The p-values of the ANOVE show that the disposition of tags and their density, as already guessed by the JSD values (see Table 2.1), are the aspect with the greatest impact on the model accuracy.

The wall type also has a considerable impact, but it is still not comparable to the above-mentioned disposition of tags. The combination of wall type and disposition is also a relevant aspect, which is however accentuated again by the great effect of the tags disposition. Moreover, a comparison of Table 2.1 and Table 2.7 provides very interesting information.

It is clear that the choice of a classification model over another is a non-negligible aspect for a correct implementation of SBS (see Figure 2.5 and 2.6). However, there is a great correlation between the deterioration of the accuracy of Method 5 (Table 2.6) and the JSD values presented in Table 1. The lowest accuracy of Method 5 is obtained in scenarios 10, 19 and 23, which are among those with the lowest JSD value (and therefore the least sharp distinction between tags in terms of read rate).

We can conclude that, for a correct and efficient implementation of the SBS, the key aspects are:

- the classification model;
- the way in which items are stored and placed inside the retail shop.

None of these two aspects should be neglected or prevail over the other.

Table 2.7: Results of Method 5.

Source	**SS**	**DF**	**MS**	**F**	**p-value**
Power	8.1753326e-05	1.0	8.1753326e-05	0.015027030	0.90265174
Wall	0.028304476	3.0	0.009434825	1.734209652	0.16394858
Disposition	0.041377175	2.0	0.020688587	3.802756983	0.02519070
Power * Wall	0.021743701	3.0	0.007247900	1.332232273	0.26742616
Power * Disposition	0.012215785	2.0	0.006107892	1.122688115	0.32897458
Wall * Disposition	0.077897464	6.0	0.012982910	2.386381100	0.03291425
Power * Wall * Disposition	0.024671108	6.0	0.004111851	0.7557969	0.60611003
Residual	0.620207655	114.0	0.0054404		

2.5 Conclusions

The RFID software-based shielding solution proposed by G. Esposito, Mezzogori, Neroni, Rizzi, and Romagnoli (2021) is further investigated. The solution, based on item-level tags and particularly suitable for the fashion and apparel sector, provides greater flexibility, and it could be linked to economic savings, as it can work without a physical shielding between different store areas. In the present study, SBS has been tested with different software approaches of increasing complexity and different wall types and thickness, as well as with varying tags dispositions and densities.

Also, reference tags have been introduced to support the classification model. Firstly, the impact of wall type and thickness, and of tags dispositions and densities is non negligible. By using the Jensen-Shannon divergence (JSD) between the read rate of tags in the front and that of tags in the back, JSD values show three main clusters corresponding to three different classification difficulties: namely, low density hanging tags can be classified quite easily between the front and the back, regardless of reading power and partition wall type and thickness, as their average JSD is ∼0.8 (scenarios 1-8 in Table 2.1).

If we increase the density of hanging garments, the classification becomes more difficult (scenarios 9-16 in Table 2.1, average JSD ∼0.56). Similarly, folded garments present a complex classification even at low density, with an average JSD of ∼0.62 and the greatest JSD variability (scenarios 17-24 in Table 2.1).

In these conditions, 5 different software approaches were used for the proposed classification problem, ranging from a naive heuristic approach, to a Convolutional Neural Network. All these approaches have been evaluated in each of the 24 scenarios in terms of precision and recall, both in the front and in the back, and summarized with a global accuracy value.

It emerges that a simple approach can be effective with low density of hanging tags, with a global accuracy ranging from 83% to over 99%. The accuracy of this simple model, however, is completely inadequate with higher tags density or folded garments.

Method 1 is both effective and robust, with an average accuracy value of 96,6% and just one outlier scenario of accuracy below 90% (scenario 17).

Quite surprisingly, the addition of reference tags do not improve average accuracy.

The only model that is capable of improving the results is Method 5. Indeed, the use of time windows improves the overall performance, by providing a slightly higher average accuracy (96,7%), and also an improvement in the median of accuracy (97,6%, against 97,4% median accuracy of previous approaches). We note that these results have been achieved by Method 5 with two outlier scenarios with an approximate accuracy of 85%, namely scenario 10 and 23.

Thus, Method 5 proves to be a promising field of research for improving SBS. As per the impact of surrounding conditions, we note that the ANOVA we performed on Method 5 accuracy only reports Disposition (i.e., tags disposition and density) as a significant factor at common levels (i.e., p value of 0.025). The second-most significant factor is Wall (i.e., wall type and thickness), with a p value of 0.164, while the power level is insignificant.

This is also proved by the fact that the combined factors *Disposition * Wall* are also significant (p value around 0.033). We can therefore conclude that tags disposition and density play a key role in the SBS accuracy results calculated using Method 5, that is the most performing one.

Chapter 3

Application and testing of RFID Software-Based Shielding in real fashion retail stores

To further validate the results described in the previous chapters, SBS performances have been tested in two different store settings of a fashion retailer located in Bologna and Milan (Italy). Due to secrecy reason, the name of the company is not reported in this study, and we will refer to it as Fashion Retailer (FR).

The firm we cooperated with, however, belongs to an important Italian Fashion Group, and it is an established women's fashion company with flagship stores in main Italian cities and worldwide.

Thus, the present study aims to answer to the following research question: is it possible to use SBS in a real fashion store without compromising on reading and classification accuracy? And, if so, what are SBS performances in real life stores?

The remainder of the chapter is organized as follows: Section 3.1 provides the materials and methods of our analysis, with particular attention to the factors and levels that we tested, and to the output variables we considered. Section 3.2 reports and discusses our results, and Section 3.3 draws conclusions.

3.1 Materials and methods

The present study is based on a qualitative research methodology, as a very significant uncertainty exists about SBS performances in real-life stores. Indeed, no pre-existing data are available on SBS in retail stores, so our goal here is to building theory by defining and testing new variables.

More specifically, we adopted a double case study analysis, that is we deeply examined two different cases, aiming to provide analytic validity to our results (Haq, 2014). The factors and the levels that we considered in our research are summarized in Table 3.1 and reported below.

We note that a combination of the specific levels of each factor reported below define an experimental scenario, which was carried out in five different repetitions.

Table 3.1: Factors that were considered for the study and respective levels

Variable	**State 1**	**State 2**
Store	Bologna	Milan
Reader model	Reader A	Reader B
Power level [mW ERP]	125	600
Classification method	Method 1 (M1)	Method 2 (M2)
Training data sets	Front reads only	Front and back reads
Reference tags	Front reference tags only	Front and back reference tags

3.1.1 Store

Performances of SBS have been tested in two different retail stores of a fashion retailer. The two stores are located in Bologna and Milan, respectively. Both the stores were open and running at the time of testing, with the only attention of testing the SBS solution on off-peak working times, to avoid perturbation of both store and testing operations in a busy period; also, both stores have been investigated in specific areas located on a single floor level.

The area of the Bologna store has a surface of around 35 square meters, and the Milan store, which has an overall surface of around 180 square meters, has been used for a total surface of around 85 square meters.

We note that these surfaces comprehend both the store area (which we will refer to as front) and the backroom (or back), with the backroom areas respectively of 9 square meters (Bologna) and 30 square meters (Milan). In both cases, the front is separated from the back by a plasterboard wall with a door.

3.1.2 Reader models

Two different handheld readers have been used for the tests:

- Bluebird RFR900 reader;
- Zebra RDF8500.

These two well-known reader models were selected because of their widespread use in 2022. With the aim of anonymizing results with respect to the reader model, however, the reader will be reported as Reader A and B, without connection to the specific brand and model, but with consistent results (i.e., reader A is always reported with the same brand and model).

3.1.3 Power level

Three different power levels have been used, measured by their effective radiated power (ERP) in mW; namely, the 125 mW and 600 mW values have been used, since empirical evidence and discussion with retail store managers attested that these values are representative of selective and massive inventory counts, respectively, as in Neroni et al. (2022).

3.1.4 Classification method

For confidentiality reasons, the two methods will be labelled as Method 1 and Method 2, without providing full details of their specific settings.
The Method 1 (M1) is the same model that was already implemented in previous works (G. Esposito, Mezzogori, Neroni, Rizzi, & Romagnoli, 2021; Neroni et al., 2022).
The M1 uses as first input a 7 elements vector that considers:

- the read rate of the tag (i.e., how many times it has been read);
- the average Received Signal Strength Indicator (RSSI)
- the median of its RSSI;
- four RSSI quantiles (respectively 5%, 25%, 75%, and 95%).

However, since reference tags were also considered in this study, the model uses them as follows: whenever tag reads are available and the model wants to classify object tags and assign them to a specific store area, the system does not only use the information of the aforementioned vector related to the object tag, but it also leverages the information from the same vectors of the reference tags.

If we assume that the total number of reference tags used during a classification instance is equal to r, the MI model is a vector of $7 + 7r$ elements, with the first 7 values being the data vector of the object tag, and the remaining $7r$ values being the same parameters for all the r reference tags.

The second model is labelled as Method 2 (M2), and it also uses reference tags. To avoid complicated tuning of the parameters, we implemented a very common configuration with three hidden layers of 32 nodes each. The size of the input layer is the same of the M1 with reference tags that we just mentioned, i.e., a $7 + 7r$ vector, with r being the total number of reference tags.

The output layer consists of a single node with the sigmoid activation function. All the network nodes (except for the output node) use the classic ReLU activation function, and the training is made using the common Adam algorithm (Jais, Ismail, & Nisa, 2019) and with batches of 1024 rows. During the training, a minor dropout regularisation technique was used in all three layers to avoid overfitting (Srivastava, 2013).

3.1.5 Training data sets

We note that, since we operated in a real store, the data collection method, and the amount of collected data are vital research details. Firstly, we started by building the two databases of the tags located in both areas of each store. To achieve this, we performed two preliminary reading sessions in each store at very low power levels (i.e., 40 mW ERP) and with a quasi-line of sight between the reader and the tags.

Each of these reading sessions was separated between reads in the front and in the back, and it was performed until no new tag was read per store area, by practically ensuring as much as possible that every tag was read and correctly located in the store area where it belonged.

The results of these reading sessions are summarized in Table 3.2. We note that the number of tags per area of each store is comparable, with the Milan store having around 200 more tags than the Bologna one, most of which are in its backroom area.

Also, by considering the store characteristics, we reported the density of tags per store area and in total. From this perspective, we note that the density of tags is significantly higher in Bologna, with data reporting around 2–2.5 higher tags' densities than in Milan.

Table 3.2: Summary of the two databases of the tags located in both areas of each store

Store location	**Bologna**		**Milan**	
	Number [#]	Density [tags/square metre]	Number [#]	Density [tags/square metre]
Tags in the front	271	10.4	296	5.4
Tags in the back	585	65.0	756	25.2
Total tags	856	24.5	1,052	12.4

Once the reference databases have been created, reading sessions were performed in different area of each store.

We performed 10 different reading repetition per each scenario, by alternating reading sessions in the two different areas, so that, given a reading scenario, a session in the front was always followed by the corresponding reading session in the back. In this way, 20 reading session were performed per each scenario, that is 10 in the front and 10 in the back.

Thus, the total maximum number of tags that could be read per each reading scenario equals to 8,560 in Bologna, and 10,520 in Milan. We refer to the maximum number of tags, as this is the total number of tag reads that can be achieved if every session indeed achieves 100% accuracy.

The classification methods were trained, in each scenario, by means of the common 80% training set, i.e., by 8 randomly selected reading sessions, per each store. We note that the possible reading session to train the models could be the front reading ones, only, or the combination of 8 corresponding reading sessions in both the store areas in the front and in the back.

In this latter case, of course, consecutive front and back reading sessions were randomly selected. The algorithm used for training is the Limited-memory Broyden–Fletcher– Goldfarb–Shanno (D. C. Liu & Nocedal, 1989), with the default parameters suggested by authors. Finally, the test set is composed by the remaining 20% of the reading sessions.

3.1.6 Reference tags

Reference tags were located in the partition wall between the front and the back. The number of reference tags used varies according to the dimensions of the wall itself, as they are applied in couples every two linear metres of the partition wall.

Each couple of reference tags is located on the same point in the store plant, with two different heights (i.e., 1.00 and 1.80 metres). Thus, we achieved an average of 1 reference tag per linear metre of the partition wall per each side of the wall itself.

Although the reference tags were available and they were read whenever it was possible, their use by the classification model is strictly connected to the training data sets.

More specifically, when the training data set of readings from the front area was used, reference tags from the very same area were also used for classification. Similarly, when the training data set of readings from both the front and the back areas were used, then also reference tags from both the sides of the partition wall were used by the classification models.

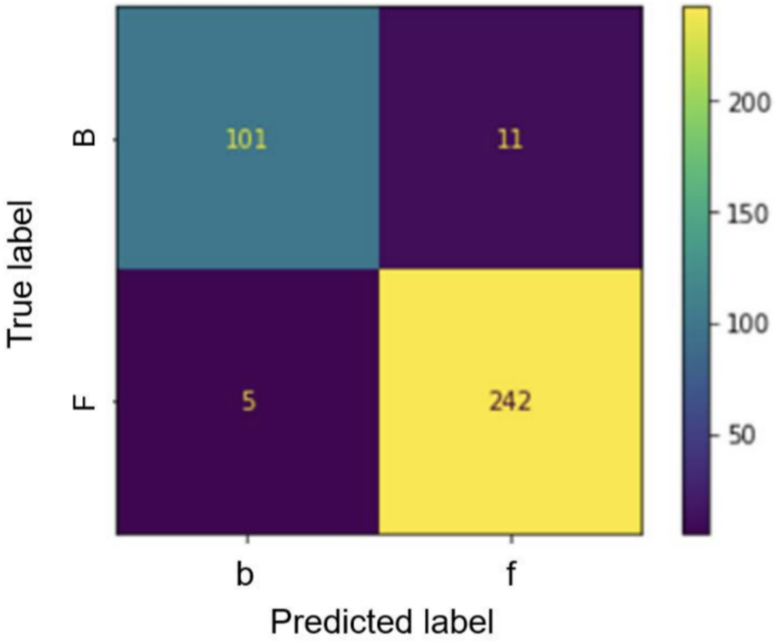


Figure 3.1: Example confusion matrix for the store Bologna store (Reader A, 125 mW, LR with front reads training)

3.1.7 Output variables

The combinations of these factors and levels produced a total of 40 different scenarios.

For each scenario, we calculated the standard confusion matrix as in Fawcett (2006), with the true classes derived from the database, and predicted classes achieved in each scenario.

With respect to Fawcett (2006), in our case we do not deal with positive or negative, but with true (or predicted) locations in the front or in the back. With this respect, we refer to true front (fF, that is tags correctly located in the front by the classification method), true back (bB, that is tags correctly located in the back by the classification method), false front (fB) and false back (bF), with the true label being identified by capital letters (F and B), and predicted labels being identified by normal letters (f and b).

With this respect, we define:

$$Accuracy = \frac{fF + bB}{F + B} \tag{3.1}$$

$$Front\ accuracy = \frac{bB}{B} \tag{3.2}$$

$$Back\ accuracy = \frac{fF}{F} \tag{3.3}$$

$$Percentage\ of\ false\ front = \frac{fF}{F + B} \tag{3.4}$$

We note that the concept of accuracy and front accuracy are also used in standard confusion matrix, with the names of accuracy and recall (respectively).

On the contrary, we introduce the concepts of Rear Accuracy and Percentage of False Front after brainstorming and discussion with store managers, software integrators, and academic colleagues. The former, in fact, allows us to estimate the percentage of tags that has been correctly located in the back and, consequently, the percentage of *fB* tags.

Furthermore, the percentage of false front is used to identify, among all tags in the store, the percentage of those that have been located in the front, although they are not (i.e., *fB* tags).

3.2 Results and discussions

Tables 3.3 to 3.6 report the results obtained by the different readers, reported in column, and by classification method, training data sets and power levels [mW ERP], reported in rows.

These results are reported with average values of lines and columns, and they are detailed in average accuracy values of Equation 3.1 (reported in Table 3.3), average front accuracy values as in Equation 3.2 (and reported in Table 3.4), average rear accuracy values of Equation 3.3 (Table 3.5) and average percentages of false front, as detailed in Equation 3.4 (and whose results are reported in Table 3.6).

At first, we note that the overall accuracy of the different factors and levels tested in the two stores is of 0.90 (Table 3.3). This general value, however, can be achieved as an average of the two accuracies of reader A (0.94) and B (0.87).

In particular, reader B with M2 classification method achieves a relatively low value of accuracy (0.81), with lower values of accuracy at higher power levels.

Conversely, by means of reader A, higher values of accuracy can be achieved, especially by means of M2 classification method and at higher power levels (accuracy of 0.95–0.96).

Also, due to the low performances of the M2 with reader B, this classification method results to perform worse than the M1 in terms of accuracy (with average values of 0.88 and 0.93, respectively).

Table 3.3: Accuracy per reader (column), by classification method, training data sets and power level in mW ERP (rows)

Reader model	Reader A	Reader B	Line average
M1	0.93	0.92	0.93
Front reads only	0.93	0.92	0.92
125	0.93	0.91	0.92
600	0.93	0.93	0.93
Front and back reads	0.94	0.93	0.93
125	0.93	0.92	0.92
600	0.96	0.94	0.95
M2	0.94	0.81	0.88
Front reads only	0.94	0.81	0.87
125	0.93	0.89	0.91
600	0.95	0.73	0.84
Front and back reads	0.95	0.81	0.88
125	0.95	0.85	0.90
600	0.96	0.77	0.87
Column average	0.94	0.87	0.90

Table 3.4: Front accuracy (same details of Table 3.3)

Reader model	Reader A	Reader B	Line average
M1	0.93	0.90	0.91
Front reads only	0.93	0.90	0.91
125	0.92	0.88	0.90
600	0.95	0.91	0.93
Front and back reads	0.93	0.90	0.92
125	0.92	0.89	0.90
600	0.95	0.92	0.93
M2	0.95	0.68	0.81
Front reads only	0.93	0.68	0.80
125	0.96	0.85	0.90
600	0.90	0.51	0.70
Front and back reads	0.96	0.69	0.83
125	0.97	0.80	0.88
600	0.96	0.58	0.77
Column average	0.94	0.79	0.86

Table 3.5: Rear accuracy (same details of Table 3.3)

Reader model	Reader A	Reader B	Line average
M1	0.93	0.97	0.95
Front reads only	0.91	0.96	0.94
125	0.92	0.99	0.95
600	0.91	0.94	0.92
Front and back reads	0.95	0.97	0.96
125	0.94	0.98	0.96
600	0.97	0.97	0.97
M2	0.93	0.99	0.96
Front reads only	0.92	0.99	0.96
125	0.88	1.00	0.94
600	0.97	0.99	0.98
Front and back reads	0.94	0.98	0.96
125	0.92	0.97	0.94
600	0.96	0.99	0.98
Column average	0.93	0.98	0.95

Table 3.4 details the reasons behind the lower accuracy values of reader B with M2: its Front accuracy performances are definitely perfectible. The Front accuracy of the M2 with reader B is in fact below 0.70, with particularly low performances at higher reading power levels.

Although this defect might be specific of the configuration of the classification method that we tested, we note that the application of M2 to reads from reader B has not been very effective in predicting the front label (f) for tags whose true label was in the front (F).

On the contrary, the Front accuracy of reads from reader A is promising, with particularly high values of the M2 trained with front and back reads (0.96–97 Front accuracy); confusion matrices of this case are reported in Figure 3.2 and Figure 3.3.

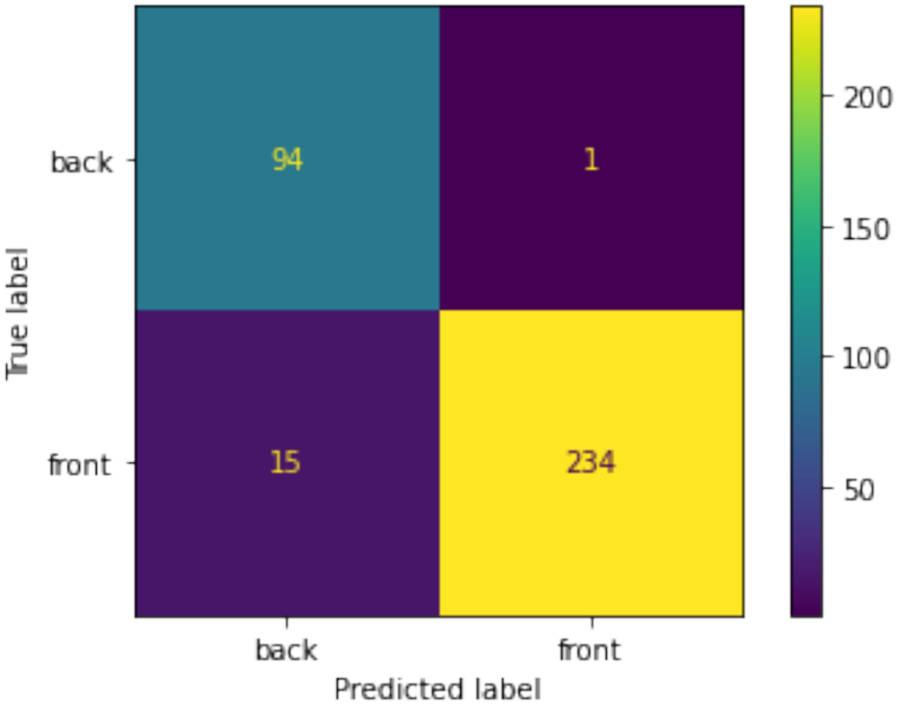


Figure 3.2: Confusion matrix for the Bologna store (reader A, 125mW, M2, front and back reads training)

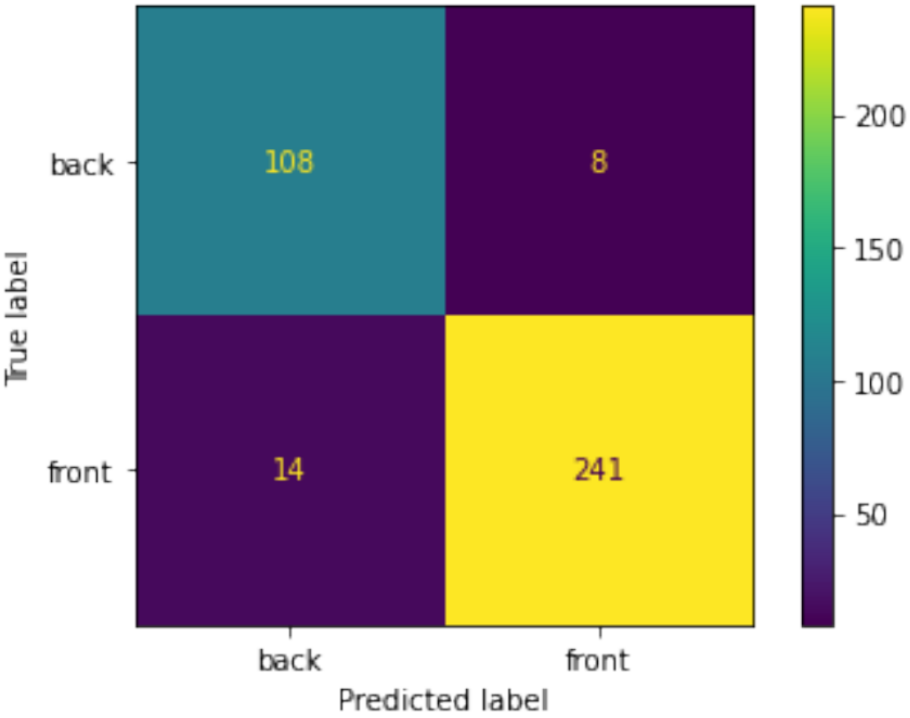


Figure 3.3: Confusion matrix for the Milan store (reader A, 125mW, M2, front and back reads training)

Table 3.6: Percentage of false front (same details of Table 3.3)

Reader model	Reader A	Reader B	Line average
M1	0.03	0.01	0.02
Front reads only	0.04	0.02	0.03
125	0.03	0.00	0.02
600	0.05	0.03	0.04
Front and back reads	0.03	0.01	0.02
125	0.03	0.01	0.02
600	0.02	0.02	0.02
M2	0.03	0.01	0.02
Front reads only	0.03	0.00	0.02
125	0.05	0.00	0.03
600	0.02	0.00	0.01
Front and back reads	0.03	0.01	0.02
125	0.03	0.01	0.02
600	0.02	0.01	0.01
Column average	0.03	0.01	0.02

The results of Table 3.5 add another interesting point of view on our results; although all methods and trainings perform relatively well in terms of Rear accuracy, reader B looks much more promising from this point of view, with Rear accuracy values as high as 0.99–1.00 (M2 trained with front reads only) that never drop below 0.94, regardless of the power level, training data set and classification method.

Indeed, reader A also performs relatively well in terms of Rear accuracy, with an average value of 0.93, and better results with the use of front and back reads as training data sets and higher power levels.

These results are of course in line with the percentages of false front, which sees much better results produced by reader B, with an average percentage of false front of 0.01, and most data below 0.02, regardless of the power levels, training data sets and classification method.

As it can be expected from what was stated so far, the reader A slightly underperformed in terms of percentage of false front, with values between 0.02 and 0.05 and no clear path that can lead to identify differences in performance based on the mentioned variables.

Lastly, we stress the fact that the two different stores do not produce significantly different data, in terms of all the output variables, as it has been confirmed by a test on the analysis of variance (ANOVA) with p value equal to 0.05.

3.3 Conclusion

The RFID SBS solution proposed by G. Esposito, Mezzogori, Neroni, Rizzi, and Romagnoli (2021) is investigated in real-life environments, i.e., in two different fashion retail stores located in Northern Italy (Bologna and Milan, respectively).

The proposed solution relies on item-level RFID tags, and it particularly suits the needs of the fashion and apparel sector, providing flexibility and, possibly, economic savings, as it can classify tags belonging to different store areas without a physical shielding between the very same areas. SBS has been tested with different factors and levels, that is:

- reader models;
- power levels;
- classification methods;
- training data sets.

Also, reference tags have been introduced in the present work, to support both the classification methods. The output variables upon which the factors and levels were compared are their accuracy (overall, front, and rear accuracy, as in Equation 3.1–3.3) and the percentage of false front.

Firstly, we note that the two stores were operating during testing activities, so our results have been collected in normal working conditions. In these circumstances, SBS proves to be a viable solution, although some more testing and fine tuning is still requested to identify its best working conditions in a robust way. Also, we note that the use of reference tags has proved to be quite inexpensive, and non-intrusive, with respect to store operations.

The overall accuracy of all factors and level tested is of 0.90, with the reader A performing better than the reader B in terms of overall and front accuracy (both values of 0.94 with reader A, against 0.87 and 0.79 of reader B).

Reader B, on the contrary, has proved to perform better in terms of rear accuracy, and percentage of false front (0.98 and 0.01, respectively, against the values of 0.93 and 0.03 of reader A). From these values, we can deduce the fact that, despite the different power levels, classification methods, and training data sets, reads from reader B are more likely to be classified in the back, to the detriment of both front and overall accuracy values.

Reads from reader A, on the contrary, provide higher overall and front accuracy, at the price of higher percentages of false front. We note that false front is particularly undesired by store managers, as they relate to items that are indicated in the front (and therefore not considered for replenishment), while they are not, with potential generation of lost sales.

With respect to the classification method, no clear indications emerge from our study on the best performing one. M2, in fact, performs slightly better than M1 with reader A, but the contrary is true if we consider reads from reader B. In particular, the application of M2 to the reads from reader B has performed very bad in terms of front accuracy. Despite this mistake could be linked to the specific selection and tuning of the classification method that we used, we have not yet identified the possible cause behind these data, and therefore we call to action for more research on this point.

With respect to the training data, we note that, given the same reader model and classification method, when front and back reads data are used for training, the results are almost always better than the training with sole front data. This result suggests more research on the training of classification models with different data sets, regardless of the specific method used. Lastly, no clear indication can be drawn by the different power levels. Our results, in fact, are not importantly connected to the reading power levels, thus suggesting that both selective and massive inventory counts can by supported by SBS.

Chapter 4

Software-Based Shielding implementation in the id-Bridge RFID platform

In this chapter, a brief description of the id-Bridge RFID platform developed by Murata ID Solutions is presented, followed by an overview of the Software-Based Shielding's implementation and integration into the suite.
The current inventory process in retail fashion stores is then described, along with an explanation of how the integration of Software-Based Shielding could lead to an enhancement and deliver superior results.

4.1 The id-Bridge platform

The id-Bridge platform, developed by Murata ID Solutions, is a software suite designed to fully manage RFID systems.
An overview of the id-Bridge system architecture is shown in Figure 4.1.

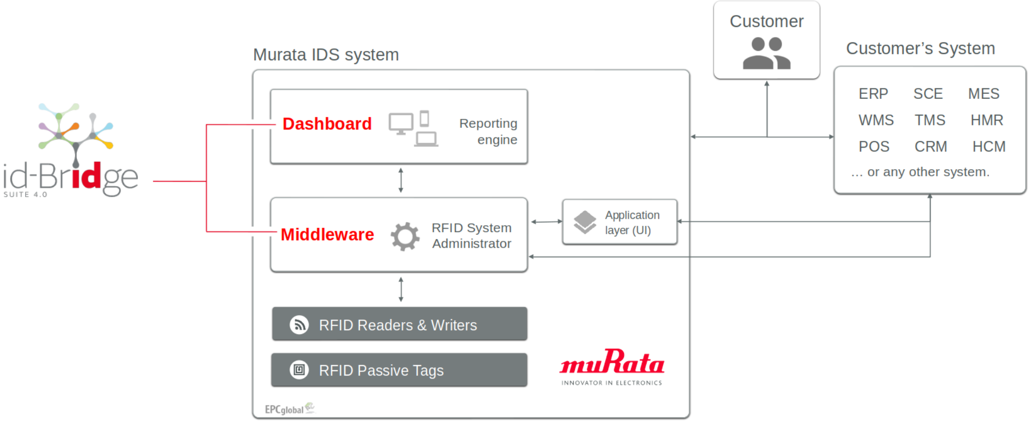


Figure 4.1: id-Bridge System architecture

The key components of the id-Bridge system are:

- **RFID Passive tags**: they consist of an antenna for energy capture and data transmission, a microchip for data storage and modulation, and operate at various frequencies. UHF RFID tags, in particular, operate within the ultra-high-frequency range and offer extended read ranges and versatility in a wide range of industries. They contain information relevant to the tagged object, which can range from a unique identification number to more complex details that are industry-specific.

- **RFID Readers and Writers**: devices that emit radio waves to activate and retrieve data from RFID tags. They operate at specific frequencies (e.g., LF, HF, UHF) and have varying read ranges. RFID readers come various formats (handheld, fixed, integrated) tailored to specific applications. They can communicate with the RFID Middleware in various ways: for fixed readers the most commonly used protocol is the Low Level Reader Protocol (LLRP), but other methodologies such as Bluetooth, REST web services and proprietary protocols could be employed depending on the manufacturer.

- **RFID Middleware**: software layer that serves to abstract and separate the low-level activities conducted by data acquisition devices in the field, like reading RFID tags, from higher-level applications that engage in the processing and manipulation of this data. The role of middleware in RFID systems is of paramount significance, as it standardizes diverse input types, enabling seamless access and manipulation of data originating from various sources in a uniform and standardized manner.
- **Application Layer (UI)**: this layer enables users to interact with the RFID system, and is tailored to the unique requirements of each domain. It has a strict correlation with the RFID Middleware in regard of device management and data input, and it may communicate with the customer's system through software integration (web services, databases, data export on file, etc.). User interaction can take place through various means, including mobile applications on handheld readers, touch screens on PC workstations or informative displays.
- **Dashboard**: specialized business intelligence tool that transforms raw RFID data from the field into actionable insights for end users. It offers focused shortcuts, key performance indicators (KPIs), and comprehensive visibility into processes and product flows. This Dashboard is organized into distinct modules and functions for enhanced usability. The end user has the capability to manually export data in multiple formats, depending to their specific needs.

Figure 4.2 further clarifies the data flow inside id-Bridge, from the RFID readings to the Customer's system.

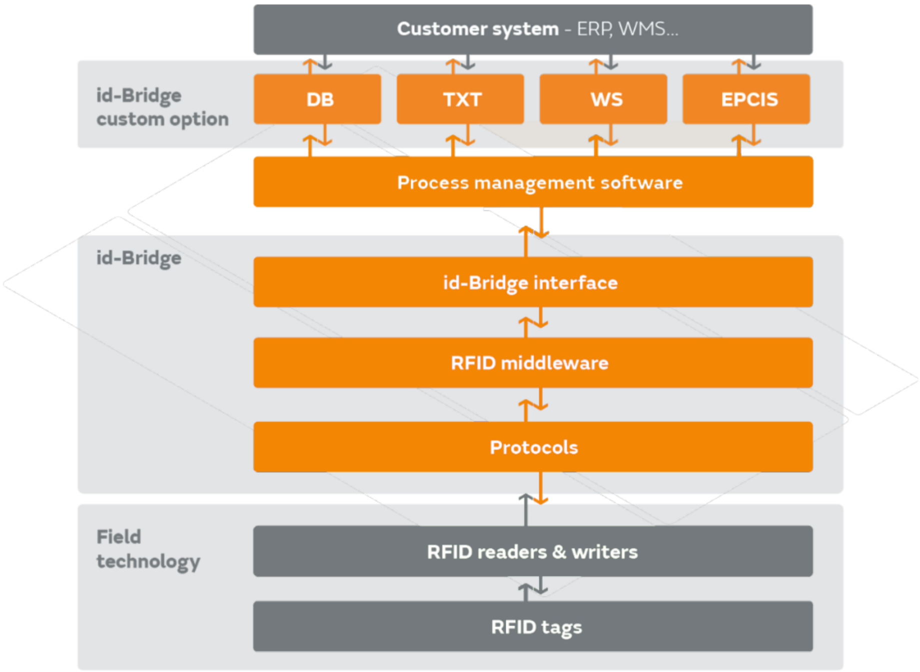


Figure 4.2: id-Bridge System data flow

At an implementation level, id-Bridge can be deployed either locally or in a cloud-based environment, providing flexibility across various usage scenarios.

- **Local installation (On-Premises)**: the system is installed and operated within the client's physical premises. It affords a high degree of control over hardware and software configurations. Pros include enhanced data security and compliance adherence, but cons encompass elevated initial setup and maintenance expenses, as well as limited scalability relative to cloud alternatives.
- **Cloud Environment**: this approach involves hosting the system on remote servers, accessible via the internet. This option offers benefits such as scalability, reduced upfront capital costs, and accessibility from anywhere. However, it entails ongoing operational expenses, potential

data security and compliance considerations, and reliance on cloud service providers.

The choice between these deployment methods hinges on factors like scalability requirements, cost considerations, data security, accessibility needs, compliance mandates, and the expertise available for system maintenance. In some instances, a hybrid deployment strategy, integrating both on-premises and cloud solutions, may offer an optimal balance to cater to diverse requirements.

4.1.1 Software-Based Shielding implementation in id-Bridge

A detail of the Software-Based Shielding integration in id-Bridge is depicted in Figure 4.3.

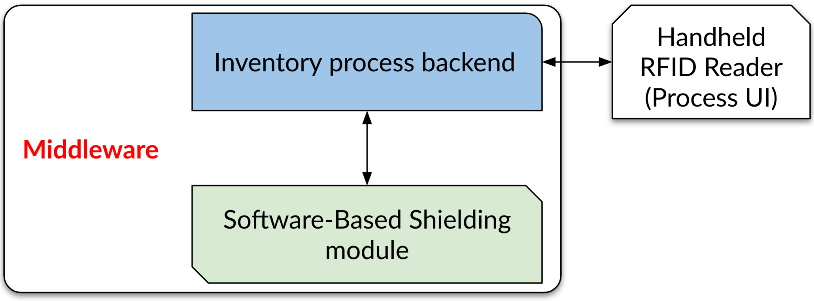


Figure 4.3: Detail of the Software-Based Shielding implementation in id-Bridge

Three main components are involved:

- **Handheld RFID reader (process UI)**: the main tool used to carry out the inventory. The clerk is guided through the procedure with and ad-hoc process designed for this particular use case.

- **Inventory process backend**: the software entity in charge of:
  - Gathering the RFID readings from the handheld reader;
  - Pre-processing the readings and sending them to the Software-Based Shielding module;
  - Acquiring the result of the elaboration and sending it back to the handheld reader.
- **Software-Based Shielding module**: the module responsible for data processing, storage, and the execution of the SBS algorithm.

The Software-Based Shielding module is mainly written in Python; it leverages the Gunicorn HTTP server for the interaction with the backend, using the well-known REST paradigm, and the data exchanged is carried out using the JSON format, which guarantees a streamlined interface allowing at the same time to extend it in future with new functionalities.

The training and prediction part is performed using core machine learning libraries such as Keras and scikit-learn.

Given the substantial computational demands of machine learning, the execution of the module is contingent upon the availability of hardware resources. Depending on resource accessibility, it may be deployed on a separate machine or, potentially, within a cloud-based environment.

Furthermore, given the heterogeneity of systems on which the module could run, configuring the software environment required may be complex and time-consuming.

Consequently, the module has been packaged within a Docker container, in order to facilitate and streamline the deployment process.

The focus of this section has been primarily on the Software-Based Shielding module and its interaction with the backend; a comprehensive description of the actual inventory process is provided in section 4.2.1.

4.2 Inventory process for fashion retail stores

The RFID inventory process offers several benefits in fashion retail stores, contributing to more efficient and effective operations. These advantages include:

- **Real-Time Visibility**: RFID technology provides accurate, real-time visibility into the inventory. Retailers can monitor stock levels, item locations, and product availability throughout the store, reducing the chances of stockouts and overstock situations.
- **Efficient Stock Replenishment**: RFID systems can automatically trigger stock replenishment orders when items reach preset inventory levels, streamlining the supply chain and reducing the likelihood of out-of-stock items.
- **Reduced Labor Costs**: RFID eliminates the need for manual stock counts and reduces the time and labor required for inventory management tasks. This allows staff to focus on more value-added activities.
- **Data Analytics**: RFID systems generate valuable data that retailers can use for business intelligence. This data includes customer traffic patterns, product popularity, and inventory turnover rates, helping retailers make informed decisions about merchandising and stock management.

The typical RFID inventory process involves the use of an handheld reader (like the ones used for the Software-Based shielding tests covered in the previous chapters), and unfolds as follows:

1. The clerks start the inventory process on the RFID handheld, and optionally enters an inventory ID (Figure 4.4);

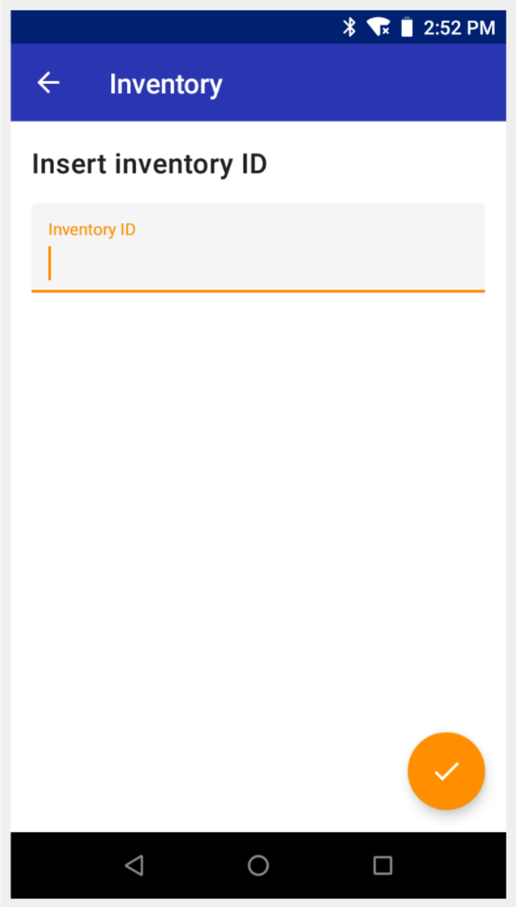


Figure 4.4: ID selection in the Inventory process

2. The clerk proceeds with the reading of the RFID items within the area chosen for the inventory session (Figure 4.5);

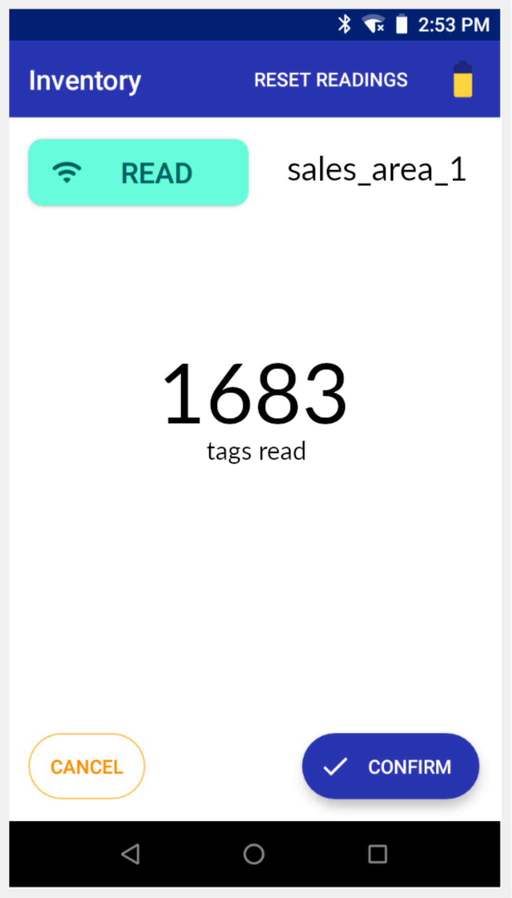


Figure 4.5: RFID tag reading in the Inventory process

3. The clerk confirms the inventory session, saving the list of EPCs read on id-Bridge. Typically, the tag list is also sent to the customer via software integration, to align the stock quantities on the customer's stock management system.

In order to optimize the efficiency of RFID reading processes and reduce the duration of inventory operations, it would be desirable to raise the power output of RFID handheld devices. However, this approach heavily limits the ability to differentiate between various store areas, which is a critical requirement in fashion retail settings.

Currently, the most widely used approach involves running several inventory session at reduced power within different store areas. This practice notably enhances the precision of inventory, but concomitantly necessitates a substantial increase in the time allocation required for store clerks to execute this operation, which is frequently undertaken once or twice a day.

4.2.1 Enhanced inventory process with Software-Based Shielding

Given the premises delineated at the end of the previous section, it becomes evident that the integration of Software-Based Shielding into the existing inventory process is paramount, potentially allowing to increase the reading power of the RFID readers without sacrificing inventory accuracy and at the same time reducing the number of inventory sessions.

Considering the inherent characteristics of the Software-Based Shielding solution, an initial setup phase is necessary. This step is essential to enable the underlying machine learning models to be properly trained and optimized for the specific store areas.

Assuming typical usage in a retail fashion store composed of two zones, a warehouse and the sales area, the flow of the improved process follows this pattern:

1. **Predisposition of marker tags *(optional)***: to enhance the system's performances and train the machine learning model effectively, it is advisable to position marker RFID tags in both the warehouse and the store area. According to the experiments detailed in the preceding chapters, the optimal location for the tags is along the border wall between the two areas.

2. **Training**: when the clerk starts the inventory process for the first time, he or she is required to carry out the first training. A guided wizard assists the operator through several sequential steps:
   - *Labeling*: a first, low power inventory is performed in the sales area, with the objective to mark the RFID tags in their area of belonging;
   - *Dataset creation*: a series of inventory sessions at higher RFID power is performed, in order to create the training dataset for the machine learning algorithms;
   - *Training*: once the previous step has been successfully executed, the RFID data collected is processed by the Software-Based Shielding module, as explained in the previous sections. This process results in the creation of a model tailored specifically for the selected areas.
3. **Ordinary use of the inventory process**: once the training phase is completed, the regular process can be employed. Unlike the one outlined in the previous section, this process allows the clerk to perform a full inventory of both the warehouse and sales area simultaneously, utilizing an higher RFID power. Upon completion of the inventory, the RFID readings collected are transmitted to the Software-Based Shielding module and queued for processing. As predicting the tag positions involves computationally intensive tasks that may necessitate some time, the results of the processing are generally not immediately displayed to the operator. Instead, they are stored in id-Bridge and optionally sent to the customer's system once the processing is finalized.
4. **Re-training and fine tuning**: after some time, it might become nec-

essary to retrain or fine-tune the model. This could be due to changes in the area's layout or if the accuracy are no longer meeting expectations. In such cases, the operator have the option to either conduct a completely new training session (1) or opt for a shorter fine-tuning session.

Please note that to attain optimal results and ensure adequate accuracy, it is essential to perform the training phase separately for each specific area that requires inventorying.

At the time of writing this thesis, a prototype of the process described has been developed. Figure 4.6 to Figure 4.9 illustrate the steps required for the training of the model.

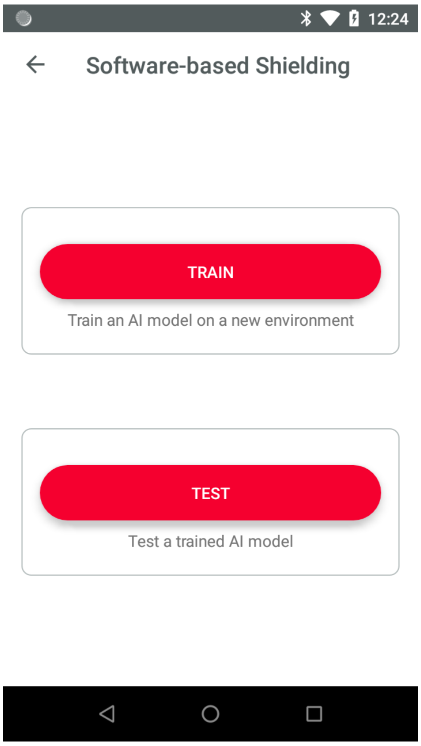
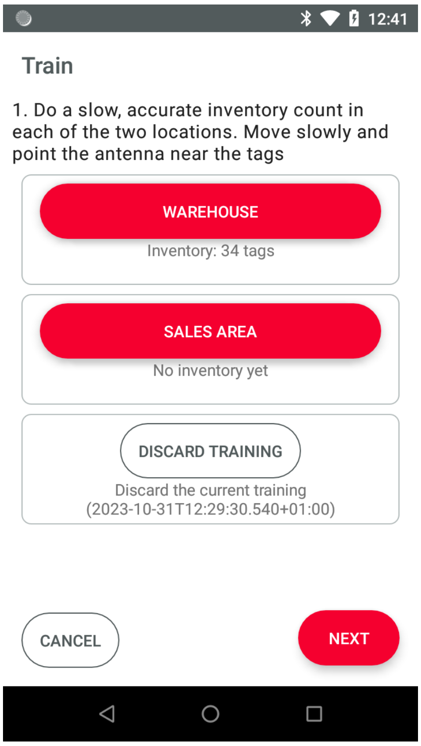


Figure 4.6: Mode selection menu (train and test)



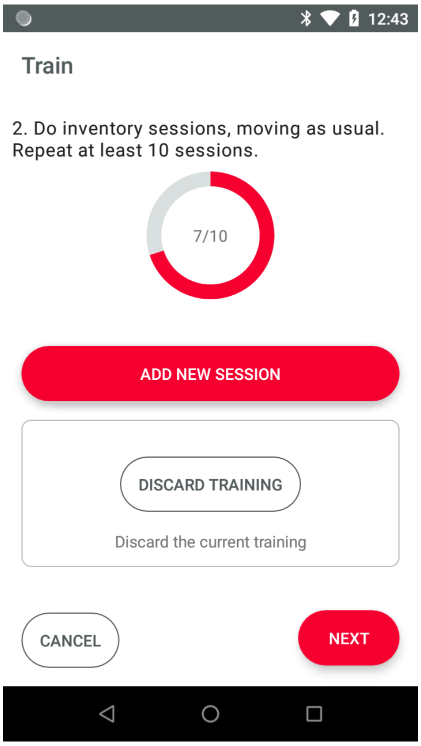
1. Do a slow, accurate inventory count in each of the two locations. Move slowly and point the antenna near the tags

Inventory: 34 tags

No inventory yet

Discard the current training (2023-10-31T12:29:30.540+01:00)

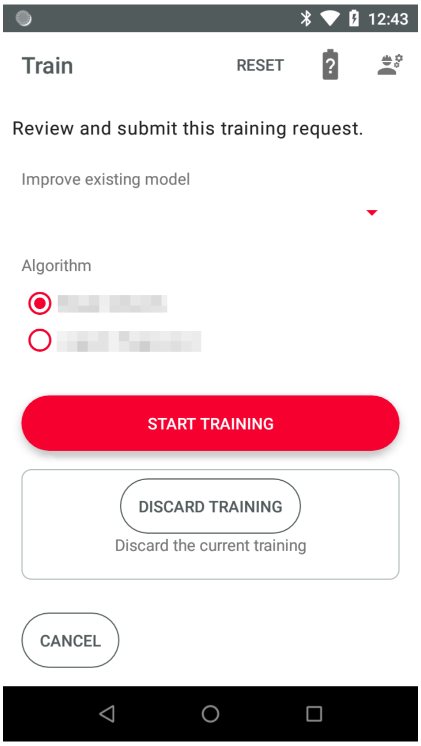
Figure 4.7: Low-power power inventory for tag labeling



2. Do inventory sessions, moving as usual. Repeat at least 10 sessions.

Discard the current training

Figure 4.8: Inventory sessions for dataset creation



Review and submit this training request.

Improve existing model

Algorithm

Discard the current training

Figure 4.9: Confirmation of the dataset and model training

Chapter 5

Conclusions and future developments

The primary aim of this work was to investigate, create, and assess the Software-Based Shielding solution proposed by G. Esposito, Mezzogori, Neroni, Rizzi, and Romagnoli within the realm of indoor localization and RFID tag categorization, particularly emphasizing its effectiveness in practical retail settings.

The first part consisted in a literature review covering existing RFID-based solutions for indoor localization and RFID tag classification, encompassing an examination of prior research, methodologies, and technological approaches within this domain.

Building upon this knowledge, we delved into the development and testing of the Software-Based Shielding solution. New approaches to the solution were implemented and tested under different environmental conditions. Tag density, tag disposition and wall types were found to significantly impact accuracy. Method 5, with time windows, offered the best results.

The following part of the study focused on real-world tests conducted within retail environments, particularly two fashion stores. We outlined the methodologies employed in these tests and provided a comprehensive analysis of the obtained results.

Lastly, the final part was dedicated to the integration of the Software-Based Shielding solution into the id-Bridge RFID suite, developed by Murata ID Solutions. This integration was discussed in detail, including its implications and the potential impact on the field of RFID-based solutions for the fashion retail industry.

Overall, this work has confirmed that the Software-Based Shielding solution is a viable and promising option for streamlining inventory processes in the fashion retail industry, save time and improve efficiency, all while ensuring an accurate tracking of the items residing in each store area. Experiments conducted in various environments and conditions have demonstrated the model's considerable robustness, a pivotal factor for its broader adoption.

It's important to acknowledge that the tests conducted so far are relatively limited in scope. To thoroughly validate the system and determine its effectiveness under various conditions, an expansion of the testing is required.

A wider range of use cases is key to investigate the generality of the system, in order to understand whether the models used are applicable to more than one store, or if a specific training for each area is required to obtain an acceptable classification accuracy.

Furthermore, it would be also very important to measure the robustness of the training over time, i.e. if and how many times it is required to repeat the training and fine tuning procedures in case the accuracy is no longer satisfactory.

Thus, the primary objective in the near-term is to broaden the adoption of the solution to additional retail fashion stores, aiming to collect more data and enhance the machine learning models underlying the system.

Additionally, collecting feedback from the operatives working in the field is crucial. This feedback will help enhance the user experience and provide valuable insights on areas that require improvement.

This in-depth investigation will help understand the actual applicability of the system, and if it can be considered a viable alternative to the current physical shielding approaches at a large scale.

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