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ARTICLE

Stock visibility for retail using an RFID robot

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Purpose - The combination of the latest advancements in Information and Communication Technologies (ICT) with the latest developments in AutoID technologies, especially Radio Frequency Identification (RFID), brings the possibility of high-resolution, item-level visibility of the entire supply chain. In the particular case of retail, visibility of both the stock count and item location in the shop floor is crucial not only for an effective management of the retail supply chain, but also for physical retail stores to compete with on-line retailers. We propose an autonomous robot that can perform stock-taking using RFID for item level identification much more accurately and efficiently than the traditional method of using human operators with RFID handheld readers.

Design/methodology/approach - This work follows the design science methodology. The article highlights a required improvement for an RFID inventory robot. The design hypothesis leads to a novel algorithm. Then the cycle of development and evaluation is iterated several times. Finally, conclusions are derived and a new basis for further development is provided.

Findings - An autonomous robot for stock-taking is proven feasible. By applying a proper navigation strategy, coupled to the stream of identifications, the accuracy, precision, consistency and time to complete stock-taking are significantly better than doing the same task manually.

Research limitations/implications - The main limitation of this work is the unavailability of data to analyse the actual impact on the correction of Inventory Record Inaccuracy (IRI) and its subsequent implications for supply chain management. Nonetheless, it is shown that figures of actual stock-tacking procedures can be significantly improved.

Originality/value - This paper discloses the potential of deploying an inventory robot in the supply chain. The robot is called to be a key source of inventory data conforming item-level, high-resolution supply chain management and omnichannel retail.

Theoretical/scientific contribution - The paper shows that a fully automated inventory process with an accuracy above 99% is possible combining RFID and autonomous robot technologies.

Managerial contribution - This paper shows the managers of traditional retail chains how they can obtain in a cost-effective way a high resolution visibility of the stock in the retail floor. This visibility is necessary in order to both manage the supply chain more efficiently, and to implement the omnichannel processes necessary to remain competitive with respect to on-line retailers.

Keywords - Retail, Omnichannel retail, Stock visibility, Cycle counting, Inventory Record Inaccuracy (IRI), Radiofrequency Identification (RFID), Robotics

Paper type - Research paper

1. Introduction

The Fourth Industrial Revolution, based on the latest developments of Information and Communication Technologies (ICT), is expected to have a significant impact on Supply Chain Management (SCM). In particular, the wide adoption of RFID technology provides supply chain managers with item-level, high resolution information that, in turn, require a higher level of automation of the decision-making processes and the actions taken in response.

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To achieve this objective, RFID-based Cyber-Physical systems (CPS) are expected to play a key role, according to Hofmann and Rüsch (2017). More specifically, they claim that the use of ICT and RFID brings three customer value components to SCM: the "value of availability", which refers to the availability of goods or services; the "value of digital integration", which enables traceability along the supply chain and in turn, a seamless and efficient order processing and business executions; and the "value of digital servitization", an additional value created by adding a digital dimension to physical objects. Also Richey et al. (2016) support the view that the availability of item information at each stage of the supply chain will be a key factor in tuning up operational efficiency.

Of the different aspects of SCM, inventory management is key. Inventory Record Inaccuracy (IRI), the discrepancy between recorded and physical inventory, implies a loss of value of the elements of the supply chain (Fleisch and Tellkamp 2005; DeHoratius and Raman 2008). In retail, the unexpected unavailability of a product is a main source of customer frustration. Interestingly, the source of IRI resides primarily on shop floors, rather than at backrooms (Goyal et al. 2016). This can be explained by: transaction errors, for instance a wrong cash check out or return; misplacements; and shrinkage, which includes theft, spoilage and damage of items (Rekik 2011). IRI is considered one of the main causes of uncertainty and performance deterioration in information exchange in supply chains (Kang and Gershwin 2005; Sahin and Dallery 2009; Cannella et al. 2015).

The usual strategy for Inventory Record Inaccuracy (IRI) mitigation is inventory correction by manual stock-taking using either barcodes or RFID technology. Unfortunately, even RFID-based stock-taking procedures are both labour intensive and inaccurate. The use of robots to automate stock-taking using RFID technology can relieve humans of a repetitive and tedious task inherently prone to errors (Sahin and Dallery 2009), and increase the frequency of inventories (DeHoratius and Ton 2015; Bruccoleri et al. 2014). More specifically, the use of an autonomous inventory robot can mitigate IRI and provide an almost real time visibility of items in the store, a significant reduction in stock-outs (Moussaoui et al. 2016), a fine control of inventory levels, and the elimination of overstocking (the current strategy to ensure availability) (Sarac et al. 2010).

RFID technology is able to uniquely identify items without the need of line-of-sight visibility, at a rate of up to 750 identifications per second. RFID is increasingly being adopted by retailers given its reliability at item-level tracking and tracing (Hardgrave and Patton 2016; GS1 US 2015*a*; White et al. 2008).

In the particular case of traditional retail (as opposed to on-line retail), this information is critical to implementing omnichannel processes (Verhoef et al. 2015; Piotrowicz and Cuthbertson 2014), such as ordering on-line and picking up at the store ("click and collect"), or fulfilment of on-line orders from the store ("pick and pack"). Although the solution is applicable to any retail store with a majority of items tagged with RFID, it is particularly suited for fashion and apparel stores.

This paper proposes an improvement to the traditional RFID-based cycle counting, done by human operators using hand-held RFID readers, by using a system that combines mobile robotics with RFID to achieve an automated, accurate, less expensive, and close to real-time visibility of items and their location in the store (Vaishnavi and Kuechler 2004).

Given that in a typical retail store the density of items varies greatly from one area to another, and that RFID technology has a limited throughput in reading RFID labels, we make the hypothesis that an optimum accuracy and duration of the inventory can only be reached if the speed and other navigation parameters of the robot adapt to the different item densities in the store. On the one hand the robot needs time to identify all items in high density areas. On the other hand, if the robot is too slow in low density areas, inventories may last too long. In this paper we propose and assess a navigation control algorithm with the purpose of reaching an optimum in the trade-off between accuracy and speed.

The article follows the design science methodology (Vaishnavi and Kuechler 2004), since it pursues to expand the state of the art by designing a prototype, and operating it in order to test

the research hypothesis. The designed prototype is operated in a university library, a real but controlled environment. After the initial evaluation in the library, the results of the experiment validating the research hypothesis are further tested in an actual retail store, a less controlled, but more realistic environment. In both cases, the evaluation consists in comparing robot inventories to state-of-the-art technology used for stock-taking, namely, RFID handheld devices. The comparison aims at assessing the differential contribution of the robot compared to actual store operations. A set of specific parameters are proposed as a framework for the comparison.

The work presented offers a thorough analysis of the contribution of an RFID-driven inventory robot in real scenarios. The idea of an inventory robot has been already presented in the literature but only as proof-of-concept in a laboratory environment, not completely implemented, assessed and validated in real scenarios. Therefore, the main contributions of this work are both the inventory navigation algorithm, and the proposed framework for evaluation of the system.

The paper is organized as follows. A discussion of related works is provided in Section 2. The design of the proposed inventory robot is introduced in Section 3, including the RFID and navigation subsystems. Section 4 explains the proposed evaluation methodology and metrics. In Section 5, the accuracy of the robot at stock-tacking is assessed, focusing on its relation to the navigation strategy, including results from experimentation in a real store. Section 6 discusses the implications to managers of retail chains. Finally, Section 7 summarizes the results obtained and discloses future work.

2. Related work

Warehouse operational problems are manifold, and a lack of collaboration between academic research and industry has been identified by Gu et al. (2007), who conclude that solutions should be "simple, intuitive and reliable". A literature review on RFID in the warehouse identifies opportunities and obstacles for RFID adoption (Lim et al. 2013). An uncertain return on investment (ROI), closely related to a perceived RFID failing performance, is stressed. Fan et al. (2014) analyse the benefits of RFID technology for reducing inventory shrinkage and their results show that the contribution of RFID to accuracy improvement is critical to motivate adoption. Musa and Dabo (2016) reviewed RFID in SCM literature and found few references that address inventory taking in terms of accuracy and duration. A recent literature review of retail store operations (Mou et al. 2018) points out that the adoption of new technologies is a must to facilitate both research and operations in the store.

Several authors have assessed the performance of RFID-based stock-taking. Bertolini et al. (2015) compared the performance of RFID and barcode inventory counting using handheld devices at a real store. They conclude that RFID inventory is more reliable than using barcodes, reporting accuracy figures that range from 90.6% to 98.7%. Rizzi and Romagnoli (2017) studied the performance of overhead RFID antennas installed on the ceiling of a retail store. The average accuracy of the overhead antennas was found to be 93.0%. Surprisingly, no other works addressing the accuracy of RFID stock-taking in real scenarios were found in the literature.

Early works exist that introduce the combination of mobile robotics and identification technologies. Thirumurugan et al. (2010) presented a line following robot that reads barcodes in a library. Harik et al. (2016) introduce the combination of a ground robot and a drone for barcode scanning goods on shelves in a warehouse. The use of RFID in robotics has been generally exploited to support indoors mapping, guidance and navigation (Milella et al. 2008; Kulyukin et al. 2004; Park and Hashimoto 2009; Kämpke et al. 2012). However, few works presented experimental solutions combining RFID with autonomous robotics for stock-taking. Ehrenberg et al. (2007) presented a mobile platform equipped with an RFID reader that takes inventory and finds misplaced books in a library. The RFID technology used (HF) differs from the de facto standard (UHF) adopted by the industry. Their work focuses on location in one library shelf that encloses less than 30 books

and does not analyse the inventory accuracy. Schairer et al. (2008) presented a prototype of a robot that uses RFID to identify products in a mock-up of a supermarket. RFID data is fused with vision and placed in a 3D model of the environment. Although the system is promising in the demo scenario, further experimentation and a detailed analysis of inventory figures are missing. In (Nur et al. 2015) RFID data captured with an early prototype of an inventory robot is exploited to create indoor enriched views of a store. Yet, performance regarding the inventory is not in scope. Zhang et al. (2016) share experiments with a robotic inventory system on a mock sales floor. The accuracy measured for different types of products ranges from 84.5% (405 items) to 100% (27 items). The amount of items is not representative of a real store and the accuracy decreases with the increase in the number of items. None of the former addressed the specific navigation strategy of an inventory robot.

The automation of stock-taking on retail shop floors has been tackled in recent years also outside the academic environment. The first commercial design was AdvanRobot (Keonn Technologies 2015), whose first prototype was presented in 2013. AdvanRobot was granted the first patent for RFID autonomous robots in 2018 (Pous and De Porrata-Doria 2018), describing the architecture and algorithms on which the robot is based, which are also presented in this work. To the best of our knowledge, only two other commercial inventory RFID robots are available: StockBot (PAL Robotics 2017) and Tory (MetraLabs 2017). The navigation strategy and performance of such robots have not been disclosed to date.

In summary, this paper addresses the questions of whether it is possible to design a system that can use RFID tags to inventory and locate items in a store much more consistently than a human operator with a handheld RFID reader, and whether it is possible to optimize the effectiveness (accuracy), efficiency (time needed) and consistency over time of such system, a need that has been discussed by Buckel and Thiesse (2014), Becker et al. (2010), and Bertolini et al. (2012), among others.

3. Robot design

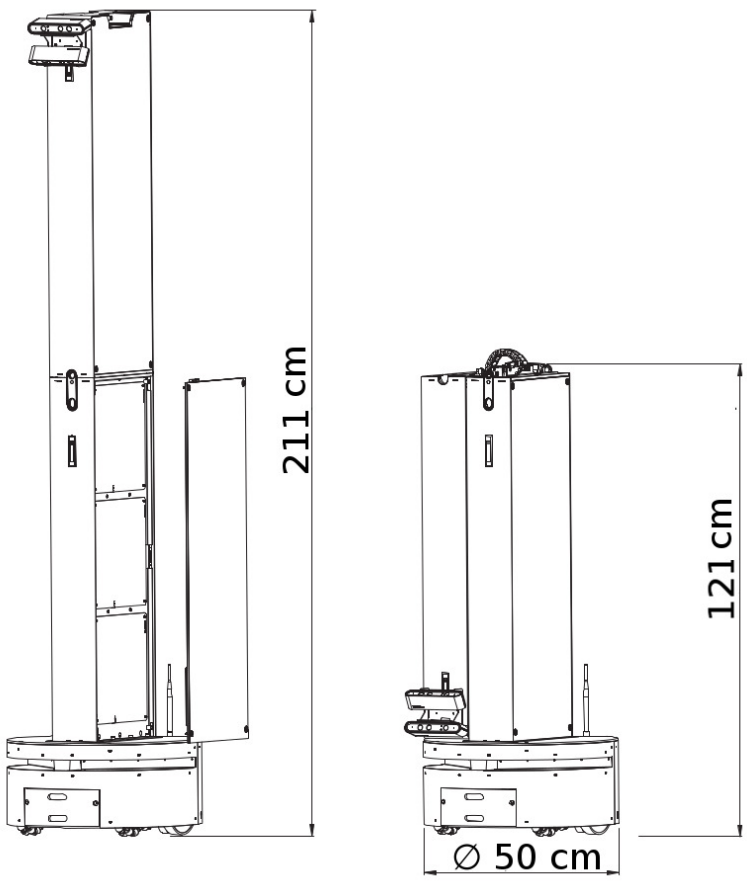
The robot is based on the combination of two subsystems: an identification subsystem, which uses RFID technology, and a robotic subsystem that provides mobility and autonomy. The communication between them using a navigation control oriented to inventory is essential to achieve the goal of simultaneously optimising the accuracy and speed of the robot.

3.1 *Identification subsystem*

The identification subsystem is an RFID system that can identify items from as far as 6 m. It consists of two sets of vertically mounted antennas, with its radiation patterns pointing sideways, perpendicular to the robot's forward direction. In this way, the robot can simultaneously identify items on both sides of an aisle. There are 6 antennas on each side overlapping their identification volumes in order to maximize read rate and minimize missed detections. The antennas are fed and controlled by 3 RFID readers, each in control of 4 antennas. Using 3 readers there is no need for additional hardware (e.g. multiplexers) to connect the antennas, avoiding additional insertion losses and maximizing the power radiated. Furthermore, a number of readers working together imply an increase of simultaneous identifications, which helps in reducing the time to complete the inventories. The antennas used are Advantenna-p22 and the readers used are AdvanReader-150, both manufactured by Keonn Technologies[1].

The robotic subsystem is based on Robotnik's RB-1 commercial autonomous base (Guzman et al. 2016), but with customizations specified by our team. It includes sensors and actuators (laser

[1] www.keonn.com



(a) (b)

Figure 1. Schematic of the robot. (a) The RFID tower is shown with a lateral cover open exposing three RFID antennas. On its top, two RGBD cameras are placed. (b) The RFID tower is folded, which eases manual manoeuvring and transport.

rangefinder, RGBD cameras, IMU and motors); a CPU, the brain of the robot; and a battery. Robotics logic is based on ROS (Open Source Robotics Foundation 2017), adapted and extended to the specific needs of the solution. The navigation is performed by sections (a large store area is divided into smaller sub-areas, or sections) for efficiency and scalability, and it is a two-stage process. The first stage, recognition (a.k.a. mapping), consists of driving the robot around the section of interest in order to capture a map of the environment. This stage requires the intervention of a human operator. The second stage, inventory, is the stage in which the robot navigates autonomously, without the intervention of any human operator, based on the information collected during the recognition stage.

Overall, the robot can identify with high accuracy items placed up to 2.7 m and is foldable for ease of transportation. An application running on an Android handheld allows the control and monitoring of the robot by non-technical users. A schematic of the robot is shown in Figure 1.

3.2 *Navigation control for inventory*

The design hypothesis is that the robot's navigation must take into account the density of undetected tags in its current environment, which it infers from the throughput of identifications (new RFID tags detected per unit time), and that without this information the inventory accuracy

will be unsatisfactory or its duration will be too long. This assumption comes from observing the procedure of scanning items for inventory with an RFID handheld reader. When doing so, the operator follows auditive or visual cues on the device to understand when the items in a position have been identified. After that, the operator moves on to another position. In addition, during manual scanning, axial and radial local movements (twists) are applied to diversify the orientations of the handheld antenna. In this way, the set of relative orientations between the antenna mounted on the handheld and the RFID tags in the vicinity varies, increasing the probability of detection.

The robot includes a control layer that listens to the throughput of identifications and commands the navigation. The control layer triggers the transitions between two states. On the *Journey* state the robot moves forward while scanning, an acceptable behaviour if the amount of surrounding items is low enough so that they can be identified while moving forward. On the *Twist* state the robot stops and twists in place in order to diversify the scanning orientations, a reasonable behaviour if the amount of items is so high that they cannot all be read while moving forward. The control layer takes as input the live stream of identifications S [items]. Note that, during the inventory, items are detected several times and the live stream of identifications includes all of them. However, the navigation control considers only the new items detected N [new items] in order to make decisions. Then, the stream of new items is time-windowed to get the rate of new identifications within a time window, R [items/s]. The rate of new identifications R is compared against a pair of thresholds (th_{twist}, $th_{journey}$ [$tags/s$]) and state transitions are triggered accordingly.

The navigation control is outlined in Algorithm 1. Initially the robot does not move forward, and it only twists around its axis (*Twist* state). It will continue in this state as long as the rate of new tags (tags never read before) read per unit time (R) stays above a certain threshold value $th_{journey}$. In this state the robot does not need to advance because it is reading many new tags from its current position. But as soon as the rate of new tags drops below $th_{journey}$ the robot changes to the *Journey* state and starts moving forward. It will remain in this state until the rate of new tags is higher than the threshold value th_{twist}, then the robot will stop moving forward and it will start twisting again. In this fashion the average speed of the robot adapts to the density of tags in its environment, optimizing both the effectiveness and the efficiency of the mission.

Algorithm 1 Navigation control algorithm

```
State ← Twist                                   ▷ Robot starts in the Twist state
I ← ∅                                           ▷ I: inventory initialized to the empty set (no items)
N ← ∅ ▷ N: newly identified items in last time window initialized to the empty set (no items)
procedure ControlNavigation(S_i, t_i)           ▷ S_i: stream of all items identified at instant t_i
    N_i ← S_i \ I                               ▷ N_i: newly identified items (not yet in the inventory set) at instant i
    N ← N ∪ N_i                                 ▷ Latest newly identified items added to the set
    N ← {n ∈ N | (t_i − t_n) < T}               ▷ Items identified outside the last time window filtered out
    R ← |N|/T                                   ▷ R: rate of new identifications in number of tags per second
    if R > th_twist then                        ▷ th_journey < th_twist
        State ← Twist                           ▷ If rate of new identifications is higher than high threshold, stop
    else if R < th_journey then
        State ← Journey                         ▷ If rate of new identifications is lower than low threshold, forward
    else
        State ← State                           ▷ If rate of new identifications is between thresholds, continue as before
    I ← I ∪ S_i                                 ▷ Add latest identifications to inventory set (list of items identified)
```

4. Evaluation framework

This section presents a set of specific layout characteristic measures and figures of merit as a framework for the comparison. Given no former works have approached an equivalent or similar comparison, the measures proposed are a novel contribution.

4.1 *Accuracy computation*

The robot is intended for stores that contain tens of thousands of products. Nowadays, there are no means to know accurately the actual inventory of the store, also known as baseline or ground truth. For this reason, a novel methodology for the assessment of an inventory robot's accuracy is proposed.

The assessment of inventory accuracy requires of a good estimation of the baseline. Doing a physical inventory, counting manually all the items is a possible solution in uncrowded environments. However, in this work, environments comprise tens of thousands of items and manual inventories are not only prohibitive, but also not 100% accurate. The next possible option is using the perpetual inventory, a stock record kept up to date by the retailer's ERP system, calculated by subtracting and adding items that are withdrawn and replenished respectively from an estimated initial stock. However, such records are known to diverge from reality over time due to wrongly reported transactions, system flaws, theft or item misplacement.

Since obtaining the real baseline is not possible, we propose a method to estimate the baseline, calculating it in several steps, involving robot inventories, handheld inventories and the perpetual ERP inventory. It is important to note that RFID never outputs false positive detections. If the identification of an item is reported, it means the item is there. The actual challenge for an accurate baseline is finding the false negatives, that is, the missed detections, items that are in the store but are not detected.

To produce an estimated baseline, all available robot inventories and handheld inventories taken of the same target area are merged into a single item list, formed by the union set of all those inventories. These inventories must all have been taken in a short time window during which the inventory has not changed (typically during the night). The more inventories used to estimate the baseline, the closer this estimation will be to the real baseline. The union set of all detected items in all the inventory rounds, including robot detections $r_1, r_2, r_3, ..., r_m$ and handheld detections $h_1, h_2, h_3, ..., h_n$ represents the set of positive detections D. Note that the union set does not have any repeated elements, only one instance of any item detected in at least one of the inventory rounds.

$$D = r_1 \cup r_2 \cup ... \cup r_m \cup h_1 \cup h_2 \cup ... \cup h_n \tag{1}$$

Second, the set of alleged negative detections or alleged misses $\widehat{M}$ is computed by subtracting the positive D detections from the perpetual inventory record IR kept by the ERP. Since this perpetual record is known to be inaccurate, the set $\widehat{M}$ is an estimation of what could be missed rather than the actual misses.

$$\widehat{M} = IR \setminus D \tag{2}$$

where $IR \setminus D$ denotes the subtraction of sets, that is, the set of elements that belong to the inventory record set IR but do not belong to the set of positive detections D.

Third, we manually search for the items contained in $\widehat{M}$. If an item is found, we remove it from

the shelf and attempt to detect it with a handheld without obstructions. This is done to discard the RFID tags being damaged or not properly coded. Items that are both found and detectable are added to the set of actual misses M.

$$M = \{\widehat{m}_i \in \widehat{M} \mid \widehat{m}_i \quad \text{found and detectable}\} \tag{3}$$

In other words, M is the subset of $\widehat{M}$ after excluding the elements that were either not found, or with defective, unreadable tags.

Finally, the estimated baseline B is computed as the union of positive detections and true misses.

$$B = D \cup M \tag{4}$$

The estimated baseline B will only differ from the real baseline in those items that have not been detected by any of the robot or handheld round, and are not recorded in the ERP, which should be a very small set, which makes B a very good estimation of the actual baseline.

When the ERP perpetual inventory IR is not available, the estimated baseline is computed as only the sum set of all detections:

$$B^* = D \tag{5}$$

The accuracy of each robot inventory round is then estimated as:

$$accuracy_i^r = \frac{|r_i|}{|B|} \text{ or } \frac{|r_i|}{|B^*|} \tag{6}$$

and the accuracy of each handheld inventory round is estimated as:

$$accuracy_i^h = \frac{|h_i|}{|B|} \text{ or } \frac{|h_i|}{|B^*|} \tag{7}$$

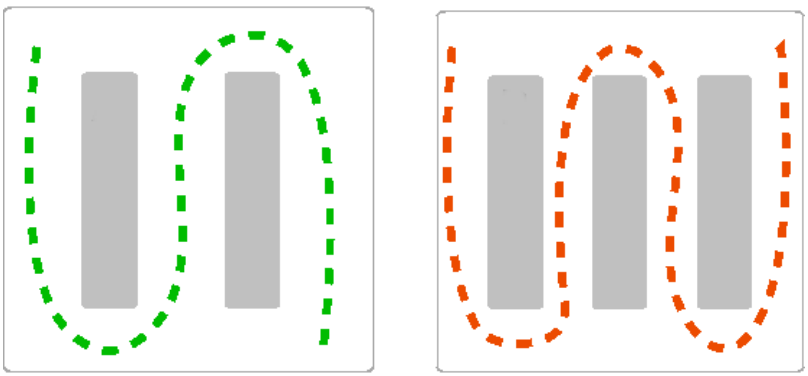
where $|r_i|$, $|h_i|$ and $|B|$ denote the integers representing the cardinality (number of elements) of sets $|r_i|$, $|h_i|$ and $|B|$.

4.2 *Layout characteristics definitions*

Since the performance at stock-taking is strongly influenced by the layout of the area to inventory, we propose three parameters that quantify the specific complexity of a particular store layout. These parameters are chosen to be a MECE (Mutually Exclusive Collectively Exhaustive) set of metrics to measure the difficulty of the robot's inventory task in a given store.

Aisles length

Although the robot can identify items as far as 6 m, the presence of metallic or partly metallic shelves can block the RFID signal. Therefore, rather than relying on its reading reach for planning the navigation, the robot prefers visiting all the traversable aisles. In this manner, unpredictable signal blockages are minimized and the accuracy is not compromised.



(a) Lower intricacy (b) Higher intricacy

Figure 2. Within the same area, layout (b) includes longer aisles length than layout (a). Therefore, the degree of intricacy in layout (b) is higher than in layout (a). Note that a complete navigation of layout (b) involves three 180° turns and narrower aisles in contrast with the two 180° turns and wider aisles in layout (a).

We call aisles length the total length of aisles found in a given area, expressed in meters. In contrast with the area, the aisles length gives an idea of the extent of the inventory task, since it gives the actual distance the robot must travel to identify all the items.

Other factors being equal, the duration of the robot's inventory task will be proportional to the length of the aisles.

Intricacy

The speed of a robot navigating a given space depends on its proximity to obstacles and the type and amount of turns involved. When obstacles are close by and at turns the robot speed is reduced. Therefore, a complete navigation in wide and straight aisles is faster than in narrow aisles with many turns. Consequently, the duration of inventories will be dependent on the characteristics of the layout.

Intricacy quantifies this effect and is computed as the aisles length per unit area,

$$\text{Intricacy} = \text{Aisles length}/\text{Area} \qquad [m/m^2] \tag{8}$$

Intricacy can be thought of as the distance that should be travelled to scan a square meter, giving an idea of the intricacy of the layout, since the more meters within a given area, the more turns are expected. Further, it is a comparative measure of the width of the aisles when shelves at layouts to be compared are similar in size. Figure 2 is a graphical representation of two simple layouts with different degrees of intricacy.

Note that intricacy is a measure which is independent of the store size, since if the store grows in area maintaining the same type of layout, the length of the aisles will grow in direct proportion, maintaining a constant intricacy figure.

Other factors being equal, the duration of the robot's inventory task will increase if the intricacy increases.

Density

At stock-taking, a high amount of items per unit area can be a notable challenge. A usual consequence of a significant amount of references in a confined space is their placement in a very packed manner, which means RFID labels can be occluded or interfere with each other. In addition, the

more items the RFID signal has to traverse, the more it is attenuated. Density is expressed as:

$$\text{Density} = \text{Number of items/Area} = \text{Number of items/Aisles length} \cdot \text{Intricacy} \qquad [\text{items}/m^2] \quad (9)$$

Other factors being equal, the duration of the robot's inventory task will increase if the density increases.

4.3 *Figures of merit*

Inventory accuracy

Inventory accuracy, referred in this text simply as accuracy, is defined as the percentage of positive identifications of an inventory with respect to a baseline. The difference with inventory record inaccuracy (IRI) lies in that IRI is widely accepted to assess the accuracy of a retailer's perpetual inventory record while inventory accuracy is a measure applicable to any inventory (section 4.1).

Effective speed

A robot that navigates in cluttered and changing environments constantly faces situations in which it needs to reroute and navigate away from the most direct course, for instance due to unexpected obstacles or prohibitively narrow aisles. As a result, travelled distances are generally longer than the optimal path. On the contrary, a person in similar situations most of the times can manoeuvre without increasing its journey. A figure for comparing inventory speeds needs to include the excess of time resulting from distance overheads. For that, instead of looking at the actual distance travelled, the effective speed considers the length of the aisles. In addition, we propose to normalize the effective speed with a function that will penalize this figure of merit when the accuracy is low, to take into account the fact that the most probable cause of a low accuracy is that the robot is moving faster than it should.

The normalization function η is not linear because the contribution of time to accuracy is not linear. Looking at a typical plot of accuracy over time (Figure 3) one can see a typical behaviour: a fast growth followed by a slow growth. Indeed, the slow growth is contributed by the difficult identifications, which are the critical to achieve an inventory accuracy above 99%.

The normalization function η must be 0 when the accuracy is 0%, 1 when the accuracy is 100%, and in between should compensate the growth of accuracy with time, in order not to give high values for robots that go fast but miss a lot of tags. The proposed expression for the normalization function η is:

$$\eta(\text{Accuracy}) = 2^{\text{Accuracy}} - 1 \quad (10)$$

Finally, the definitions of robot speed v, effective speed v_{eff} and normalized effective speed $\bar{v}_{eff}$ are

$$v = \text{Travelled length/Duration} \qquad [m/s] \quad (11)$$

$$v_{eff} = \text{Aisles length/Duration} \qquad [m/s] \quad (12)$$

$$\bar{v}_{eff} = (\text{Aisles length/Duration}) \cdot \eta(\text{Accuracy}) \qquad [m/s] \tag{13}$$

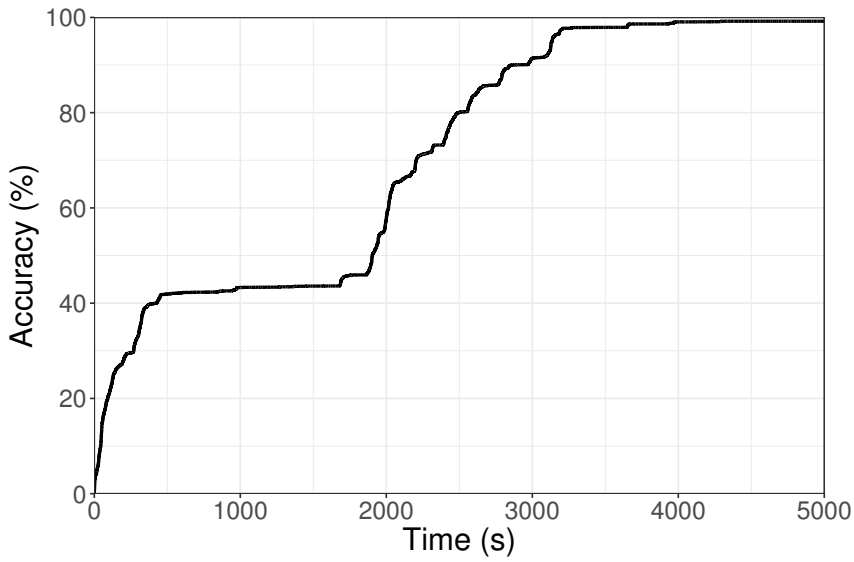


Figure 3. The evolution of accuracy over time in a real-world scenario. A fast growth is followed by a slow growth. Around time 2000 s the discovery of a new crowded area restarts the typical growth sequence. Effort does not contribute linearly to accuracy. Note the two quasi-flat regions, where a prolonged time period is needed to gain a small share of accuracy. The most likely reason is the fact that easy identifications happen in bulks while difficult ones need a continued effort.

Effective read rate

The effective read rate measures the throughput of new identifications. That is, the new identifications per time unit that are actually registered during an inventory. It is dependent on the navigation (time) and the density of items (if there are few items the effective read rate will be low). It gives an idea of the actual reading capacity in a given environment. In contrast, the read rate is usually defined as the maximum number of items that can be detected within a given period of time and it gives an idea of the amount of simultaneous identifications (not necessarily new) an RFID system can deal with.

$$rr_{eff} = \text{Number of unique tags read/Duration} \qquad [\text{tags}/s] \tag{14}$$

5. Design iterations

This section describes the development-evaluation cycle based on design science. The main idea behind design science is that the design iterations are also based on the learnings obtained from the performance on the previous iterations rather than on fundamental principles alone. First it starts evaluating the relevance of the main parameters that drive the algorithm, namely, twist motion and thresholds. Then, the evaluation focuses on the optimization of the two threshold parameters. Finally, the solution is taken to a real department store for a full assessment.

5.1 *Evaluation of the relevance of the algorithm parameters*

The first evaluation of the robot's navigation algorithm is conducted at the Pompeu Fabra University, in the Poble Nou campus Library. The testbed is built by coding and placing RFID labels on books. The RFID tags used are Smartrac's Shortdipole using the Impinj Monza 5 chip[2]. Overall, the library contains more than 3000 labelled books. The library is chosen for four main reasons: first, books are known to be challenging to detect due to the absorption of the radio signal by paper; second, the library's perpetual inventory is available and accessible to use it in the computation of an accurate baseline; third, the density of items is rather high at 260 $items/m^2$, which stresses the validation challenge; and fourth, the layout does not present major complications, a prerequisite to avoid its interference on the accuracy-oriented navigation control verification. A more detailed description of the advantages and challenges of using RFID in a library environment can be found in Feng (2010). Table 1 summarizes the characteristics of the testbed. Figure 4 shows the robot in the library during the verification tests.

Figure 4. The robot taking inventory at the library. As can be seen, it is equipped with six RFID antennas per side.

5.1.1 Methodology

The main evaluation goal is to prove that the parameters of the navigation algorithm (twisting motion and thresholds) are essential to guarantee that the minimum accuracy is 99%. This minimum accuracy has been obtained by interviewing different retail logistics and operations managers, who consider this the minimum accuracy to make the inventory results usable for omnichannel. This figure is consistent with figures reported in the literature (Esposito et al. 2015).

We will study first the relevance of the twisting motion during the *Twist* state, and then the relevance of the two threshold parameters th_{twist} and $th_{journey}$.

A set of tests is conducted in order to verify the parameter relevance. In test (i), the robot is set to traverse the aisle without adapting the navigation to detections, that is without stopping due to threshold, or twisting to read. In test (ii) the robot is set to traverse the aisle and stop using the

[2]https://www.smartrac-group.com/shortdipole.html

thresholds, but without twisting. For that, a threshold to stop, th_{stop}, is used analogously to th_{twist} introduced in Section 3.2. The most restrictive thresholds are applied ($th_{stop} = 1, th_{journey} = 0$). In this fashion, the robot does not move from a position until it has identified all items at reach, and stops again as soon as a new tag is detected. These values are used to assess the contribution of twisting to accuracy. In test (iii) test (ii) is extended by applying a twist at every stop (and keeping the same threshold values $th_{twist} = 1, th_{journey} = 0$). While twisting, the relative orientations between RFID tags and antennas varies during the twist motion and consequently the probability of detection increases. Noteworthy, the library presents the worst case regarding the effect of orientation in detections due to the tag placement inside the books, which is perpendicular to the antennas when the robot is traversing the aisle.

In addition, we can evaluate the impact on the accuracy of the number of consecutive passes through the same aisle. Our previous experience in RFID indicates that repeated passes contribute with a small, but significant, share to the overall accuracy. The number of passes is determined by the incremental contribution to accuracy of each new pass. When the contribution to accuracy of a new pass is not significant anymore no more passes are done and the inventory round is finished. During our experiments, typically the 4 first passes contributed significantly to the accuracy.

5.1.2 Results

Figure 5 shows the average and variance of the accuracy of 7 repetitions of each test. Each repetition included 4 passes of the robot along the aisle. The results of test (i) show that the 99% lower bound cannot be reached by setting the robot to navigate without an interaction with the progress of RFID identifications, even after 4 passes. The results of test (ii) reveal that by applying a control based on listening to identifications, after a second pass the average accuracy reaches 99%, albeit the 99% figure is not guaranteed in all repetitions unless four passes are used. The results of test (iii) show that including a twist is critical to consistently yield an accuracy above the requirement. Indeed, the accuracy averages of test (iii) are above 99.5% with two or more passes, and are above the 99% threshold in most repetitions with a single pass. In conclusion, the best setting regarding accuracy is ($th_{twist} = 1, th_{journey} = 0$), which involves twisting, and a minimum of two passes. Hence, relevance of the parameters is demonstrated since the robot can only consistently achieve an accuracy above 99% if the twist and the thresholds are used.

Additionally, seven inventories were performed by store associates with RFID handhelds. These associates were experienced in the use of the RFID equipment, and had been doing RFID inventories for several months in that store, so these inventories can be considered as representative of what this inventory method can achieve. The average accuracy of these handheld inventories is also higher than 99%. Table 2 shows a comprehensive view of the measures during the seven repetitions of the handheld and the robot's best configuration. The robot shows a slightly better accuracy, most likely due to the fact that thresholds are applied strictly as opposed to the handheld case, which relies on the operator response. Unsurprisingly, accuracy figures are very similar, which is explained by the fact that handheld inventories were performed extremely thoroughly and in a reduced area, implying a marginal chance for execution errors and oversights. Regarding duration, average times measured are comparable. Given that nowadays current stock-taking procedures involve the use of RFID handheld readers, the handheld duration is considered the benchmark. Therefore, it can be stated the robot performs the inventory in a timely manner.

5.2 *Optimization of the threshold values*

The importance of the algorithm parameters to achieve the desired accuracy has been assessed in the previous evaluation. Now, the threshold values $th_{stop} = 1$ and $th_{journey} = 0$ need to be adjusted in order to optimize the inventory duration. The main goal of this evaluation consists in obtaining the best accuracy within a time comparable to a handheld. A different evaluation is also

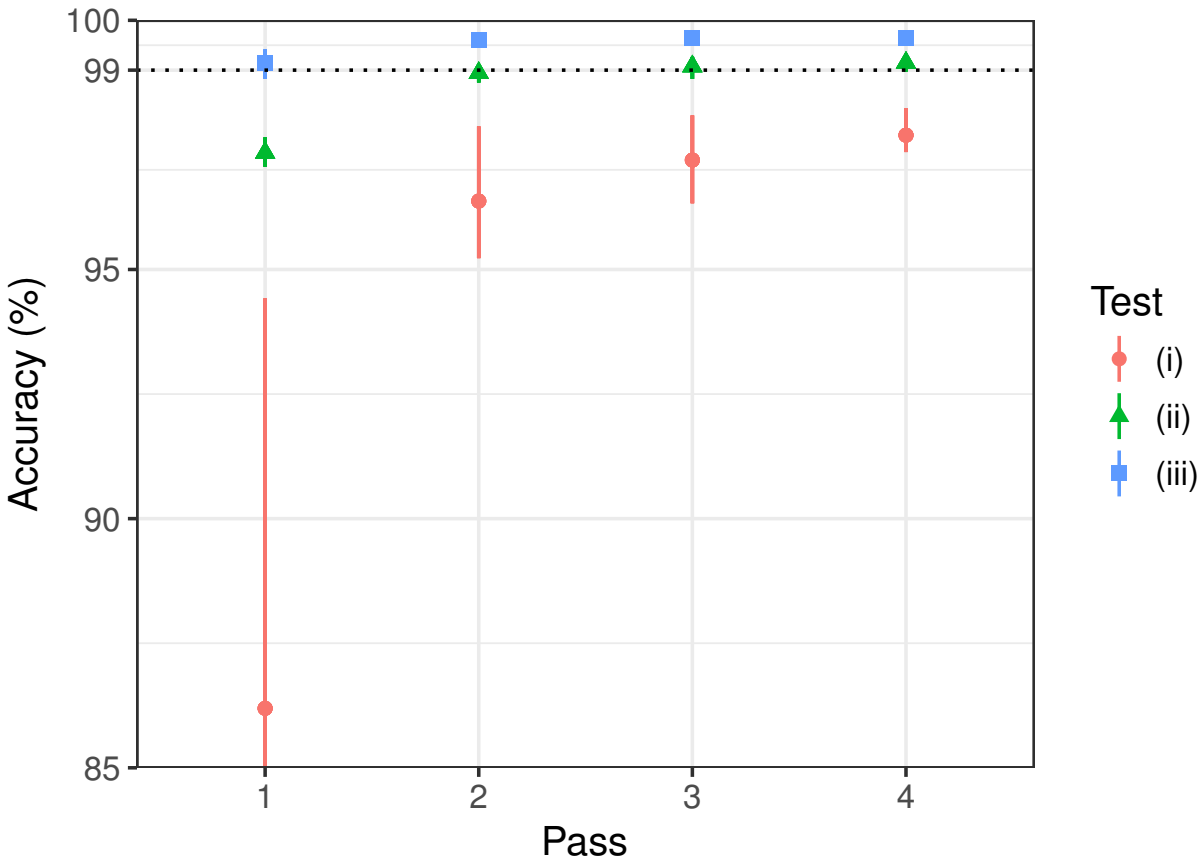


Figure 5. Accumulated accuracy as a function of the number of passes for each of the three types of tests. (i) The robot traverses the aisle without stopping. (ii) The robot stops to read tags ($th_{stop} = 1, th_{journey} = 0$), but with no twisting. (iii) The robot stops to read tags ($th_{twist} = 1, th_{journey} = 0$) with twisting. Symbols mark average values and vertical lines mark the span of results across the 7 repetitions. The dotted line at 99% marks the limit of the minimum acceptable accuracy.

undertaken aiming at bringing the duration to a minimum without compromising accuracy. The evaluation is again performed in the university library.

5.2.1 Methodology

The robot is configured to traverse the aisle with different pairs of navigation thresholds. Starting from an initial setting with ($th_{twist} = 1, th_{journey} = 0$), thresholds are increased until the accuracy falls below an acceptable value. Following former observations, the robot is configured to do four passes with twisting, and each test is repeated seven times.

5.2.2 Results

Figure 6 plots the duration and accuracy measured for each setting and pass. Noticeably, the inventory duration can be reduced by nearly one third by adjusting the navigation parameters without a significant effect on the resulting accuracy. For instance, a second pass on ($th_{twist} = 2, th_{journey} = 1$) results in an average of 423 s and 99.6% accuracy. If a slight reduction of accuracy is acceptable, always above 99%, the duration can be further reduced. For instance ($th_{twist} = 16, th_{journey} = 8$) and two passes yields 99.3% of accuracy in only 235 s.

One would initially expect the duration after 4 passes to be 4 times longer than after the first pass, but it is not the case. The reason is that with each pass, the number of new tags (tags never read before) decreases quickly, so the robot is much more often in the *Journey* state than in the

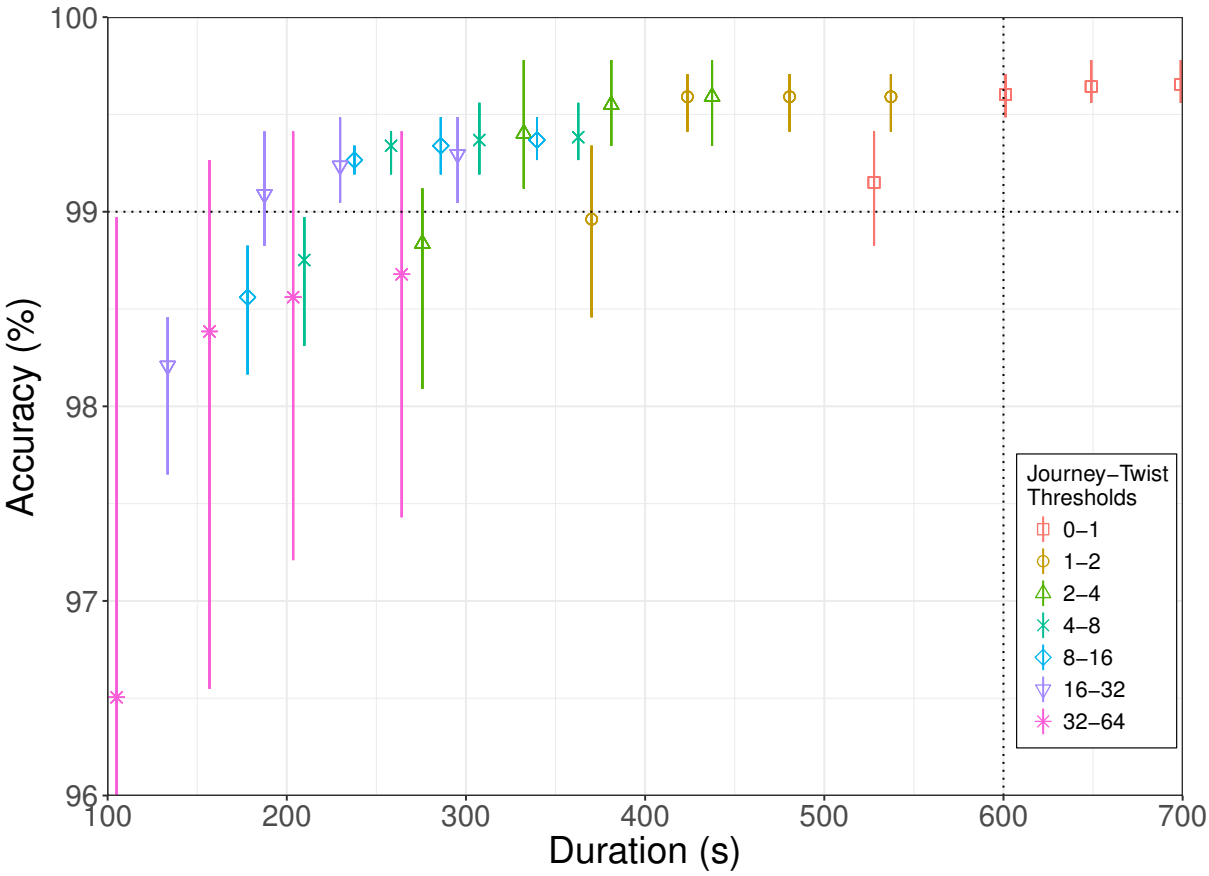


Figure 6. Accuracy versus duration for several pairs of thresholds. The duration values correspond to 1, 2, 3 and 4 passes. Symbols mark average values and vertical lines mark the span of results across the 7 repetitions. Dashed lines mark the minimum accuracy requirement and the benchmark duration.

Twist state, so that the duration of each pass is normally shorter than the previous one.

The results show that the duration of the robot inventory can be optimized by adjusting the navigation control parameters, becoming notably shorter than the handheld. Table 3 shows a comparison of the figures of merit between the robot's optimized configuration and the handheld. While the robot is traveling more distance - it is doing two passes - its duration is nearly one third, which is reflected in a higher speed. However, the figure of interest is the effective speed, since it ignores the journey in favour of the aisles length. Yet, the robot effective speed nearly triples that of the handheld.

Finally, the effective read rate shows that the robot clearly surpasses the handheld's identifications throughput. Albeit one could expect a higher difference, an intuition from Figure 3 is that there are items difficult to identify, and those are similarly difficult for the robot as for the handheld.

Remarkably, these figures are not distorted by the effects of navigating extended and complex spaces and represent the theoretical capacity of the devices rather than their actual performance in a scaled scenario. This will be disclosed in Subsection 5.3 by analysing stock-taking in an actual retail store.

5.3 *Evaluation in an actual store*

The relevance of the algorithm parameters has been proven and their values optimized to outperform a handheld device. Now, the assessment of the robot's performance in a real-world scenario is undertaken at a department store. This last step is required in order to prove that all previous adjustments on the algorithm are still valid in an uncontrolled environment.

5.3.1 Methodology

The robot is handled by the associates of the store, that are in charge of managing both robot and handheld inventories. Hence, experimentation is unsupervised after an initial training period.

Validation focuses on a comparative analysis of the performance between the robot and the handheld. In an actual store, handheld scans are performed by associates as one of their usual duties. Thus, the robot accuracy and duration are benchmarked against a state-of-the-art stock-taking procedure. Furthermore, the analysis is done section by section, in sections with different layouts, which reveals the impact of the layout on the performance.

Three target sections, A, B and C, are selected by the retailer based on the known challenges they pose to stock-taking. Table 4 shows the main characteristics of the selected sections. Interestingly, the merchandise involved are garments, more specifically garments with lots of variations of models, colours and sizes. Consequently, they are the ones with the highest incidence and impact of inventory inaccuracies and the top priority to retailers.

Table 4 shows the layout characteristics of the sections. It is noteworthy the increase of density from section A to section C. Aisles length in section A are about half than in sections B and C. Intricacy shows a regular increase which, along with the increase in density, poses a considerable increase of the overall complexity. Although complexity is not formally defined and quantified, it can be understood as a growing function of density, aisles length and intricacy and gives an idea of the challenge at stock-taking. Another actual challenge is the width of the aisles. Since the robot is programmed to be very cautious with the environment, the narrower the aisle, the slower the robot manoeuvres. Moreover, if aisles are narrower than the nominal width, $0.70\,m$, the robot may not traverse them and the final accuracy can be compromised. In this regard and exceptionally, given that the typical aisle width in section C is under the nominal value, the navigation constraints have been relaxed for the robot to attempt to traverse aisles as narrow as $0.65\,m$. Although negative consequences are expected, namely a slower navigation and a critical increase of the risk of getting stuck, this is preferred over missing aisles. Overall, the main goal is demonstrating the accuracy of the robot at inventorying cluttered spaces.

Working in a real world scenario implies constraints. The main pitfall was the absence of a perpetual inventory record since the store's database was not accessible. As a result, the baseline was computed directly from robot and handheld inventories (Equation 5). Also, there were no repetitions on the same day and not even on consecutive days. Thus, the baseline was built from one robot and one handheld pass. Summing up, the validation baseline is inherently less accurate than the verification baseline. Furthermore, handheld data provided by the retailer did not include the time stamps of the identifications and the duration could not be computed individually for each pass. Alternatively, the average duration of handheld scans was informed by the retailer. Nonetheless, results provide a one-to-one comparison between the robot and the handheld.

The tags used by the retailer were not disclosed. Anyway, the retailer follows the Tagged-Item Performance Protocol (TIPP) Guideline (GS1 US 2015*b*), which serves as a framework for the harmonization of tag performance assurance once it is attached to a product.

5.3.2 Results

Accuracy

During the experimentation period the robot completed 32 inventory passes. Out of those, 14

coincided with a handheld inventory on the same day and section. Although the initial target was a higher coincidence rate for comparison, working in a non-controlled environment eventually yielded a lower outcome. In Table 5 the accuracy of the robot is shown along with that of the handheld by section. The first conclusion is that the robot is very precise, delivering a consistent accuracy between 99.4% and 100.0% across all the passes. On the contrary, the handheld is rather imprecise, with inconsistent accuracy, that reaches the threshold only in one of the passes. Comparatively, the inconsistent handheld accuracy can be explained by the fact that the robot as an RFID system is more thorough and powerful than a handheld. The imprecision throughout the measures is due to the known fact that humans are error-prone at repetitive and cumbersome tasks. For instance, the lower bounds in handheld figures could be due to oversights such as skipping a subset of the scanned section. Obviously, the robot is not error free and suffers failures. However, in the case of the robot, errors are traceable. In this regard, Table 5 does not include robot inventory attempts that were unsuccessful, self-detected and reported. A last interesting trend from the results is the decrease of average handheld accuracy with the combined increase of density, intricacy and aisles length (Section A to Section C). The most likely reason is that the more complex and prolonged a repetitive task is, the less thorough and precise and the more prone to oversights a person becomes. Note that not only the average accuracy decreases, there is also a decrease of precision. While the robot is capable of dealing with complex repetitive tasks the person is not. In conclusion, the robot excels in accuracy and precision yielding more than 99.4% of accuracy in all the passes, clearly surpassing the handheld.

Inventory duration

Duration was measured on the 32 inventory passes the robot completed. On the other hand, the average handheld inventory duration was reported by the retailer. Figure 7(d) shows the duration measured in each section. At a first glance, the time it takes the robot to complete a section is comparable to that of a handheld. Noteworthy, in the simplest section (A) a person with a handheld is able to complete the inventory in less time than the robot. This is explained by a person's efficiency in simple sections: low density, aisles length and intricacy. On the contrary, when approaching complex sections, the handheld's efficiency decreases and the trend is inverted, becoming the robot quicker.

The density, aisles length and intricacy of the three sections (A, B and C) are represented graphically in Figures 7(a), 7(b), and 7(c). Figure 7(d) shows that the duration of both the robot and the handheld inventories are very similar, and increase with the intricacy. Figure 7(e) shows that the distance travelled by the robot increases with intricacy while the handheld's distance remains proportional to the aisles length. This can be explained by a person's enhanced manoeuvrability. First, a person can traverse narrower aisles. Second, a person can overcome or put aside unexpected obstacles, for instance a fallen garment on the floor. In the same situations the robot needs to seek and follow an alternative path, which implies doing a walk around, and consequently increasing its journey. Thus, a person is more efficient regarding distance travelled. Besides, the robot is consistently faster since it walks more meters than the handheld in equivalent times (Figure 7(f)). A confirmed trend is that intricacy is negatively correlated to the robot's speed (Figures 7(c) and 7(f)). More interestingly, the person's speed seems to be correlated to the items density. The latter would confirm the superior power of the robot as an RFID system compared to a single handheld. The robot is able to simultaneously identify more items. Hence, it deals with higher densities comparatively faster.

Figures of merit are shown in Figures 7(g) and 7(h). Looking at the effective speed, a person is faster at completing the simplest section due to its better spatial efficiency. Notwithstanding, the trend is inverted when facing an increase of aisles length. The decrease of effective speed for the robot is correlated to the intricacy while the handheld is affected by the increase in aisles length (section B) and density (section C). The effective read rate is computed as the amount of identified items per time unit and gives an idea of the identification capacity. Remarkably, the

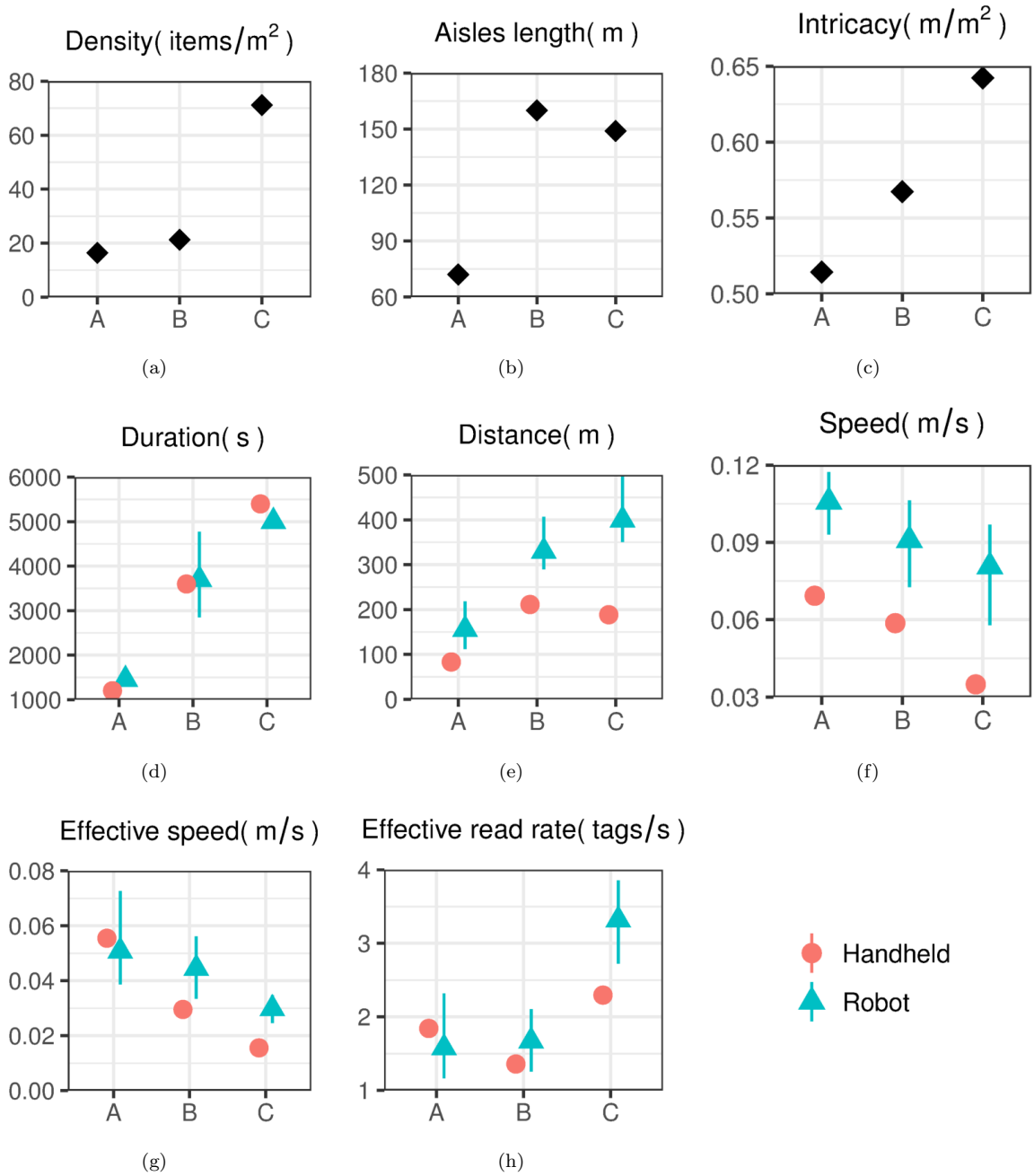


Figure 7. The grid displays a set of plots that include both robot and handheld measures for each section. On the first row, the plots depict the characteristics of the sections. On the second row, the trends of inventory duration, distance and speed. The third row displays the figures of merit.

robot effective read rate is correlated to the density, which implies that the robot can assume the increasing density without compromising its pace. On the contrary, the number of identified items by the handheld decreases with density and so does the effective read rate.

6. Managerial implications

In this paper we have presented a technological system that, from a management point of view, is able to provide high resolution visibility of the stock in the retail floor. This visibility is in three dimensions: time, space and catalogue. The resolution in time is given by how often the robot can perform an inventory, typically every day, so the resolution is approximately 24 hours. The resolution in location is typically 2 meters (Morenza-Cinos et al. 2017). Finally, the resolution in catalogue is maximum, every single item is counted, timestamped and located. In summary, this solution could provide management with a daily report of what individual items are on the store (with an accuracy above 99%), and also where they are with a precision of about 2 meters. When one compares this with the usual inventories, normally performed for accounting or fiscal reasons, done at most every quarter, at the SKU level (not at the item level), and with no location information, the difference is abysmal (a comparison of traditional versus RFID-based inventories is found in Hardgrave et al. (2009)).

On the one hand, the positive effects that visibility of the downstream demand has on the performance of a supply chain have been reported in the literature (Holweg et al. 2005; Christopher and Lee 2004; Småros et al. 2003). And more specifically, the positive effects of RFID-based visibility in the retail industry have also been widely reported (Delen et al. 2007; Hardgrave et al. 2013; Sellitto et al. 2007; Pfahl and Moxham 2014).

But the most important managerial implication of having high resolution visibility of the inventory in the retail floor is that it opens the possibility of implementing omnichannel retail processes (Cao and Li 2015) such a fulfilment of on-line orders from the store closest to the customer, to be either shipped ("pick and pack") or to be collected at the store ("click and collect"). Without this omnichannel processes, traditional retail chains would have fewer strategies to compete with on-line retailers, which are growing in double digits (Laudon et al. 2016).

When considering the use of RFID, managers need to take into account the cost of tagging every item with RFID. At under 0.05 USD per tag in high volumes, and with almost all traditional label suppliers able to provide the service of tagging the items at source, the cost and complexity of tagging are less of a barrier for adoption for most retailers. On the contrary, RFID adoption is seen more and more as a necessity to stay competitive (Zhang et al. 2018).

In summary, the main question for managers that have decided to use RFID technology to achieve inventory visibility is whether an RFID autonomous robot is a better alternative than associates with RFID handheld readers, and this paper aims to provide information that can help make such decision.

7. Conclusions and future work

7.1 *Conclusions*

The value of combining robotics and RFID for inventorying is demonstrated. The RFID robot yields an accuracy above 99% in the two real-world scenarios analysed, a library and a department store. Coupling the navigation to the progress of identifications is proved indispensable to achieve satisfactory accuracy figures. Comparatively, the accuracy is higher than doing the same task manually, and the difference increases with the complexity of the space. Additionally, the robot's precision is better than the precision of a person equipped with a handheld. Besides, while a handheld is faster than the robot in simple and small spaces, when scaling the task, the trend is inverted and the robot shows higher effective speeds. However, intricacy has a negative impact on the robot's inventory duration, due to overheads in travelled distance and a reduction of the average speed. In conclusion, the automation of stock-taking in shop floors is proven to be feasible and figures show that it can contribute to reduce IRI. In addition, an RFID robot working continuously

implies an almost live monitoring of items, thus their participation as digital elements in any cyber-physical system. Overall, the connection between physical and digital worlds is proven feasible and the high-resolution, item-level SCM paradigm enabled.

7.2 *Future work*

After finishing the last evaluation on a real store, several improvement lines have been perceived, which are described below in order to keep improving the RFID-driven autonomous robot in the future.

In order to obtain a complete understanding of the value of the robot in the supply chain it is required to assess the robot's contribution to IRI correction. Also, it is desirable to compare and contrast the presented robot with other robots that are in the market. These tasks require the collaboration of partners. Work in the direction of having a closer collaboration with stakeholders is being done, but it is still in a preliminary stage.

Regarding the proposed methodology, it is considered using it in different environments and showing its convenience in cases where the ground truth of a system cannot be known. For instance, to perform fiscal inventories.

At an operation level, the main drawback detected by retailers is the need to follow a human assisted recognition procedure. In this regard, a fully autonomous solution is envisioned. For instance, this could be achieved by using exploration techniques. However, this type of solution can bring other challenges such as ensuring completeness, and efficiency. In addition, changing the navigation paradigm might challenge the current coupling between identifications and navigation.

A complete integration of the robot in an actual supply chain for a detailed analysis of the contributions and limitations will be pursued, as well as creating operational guidelines to ensure that the robot operates in the proper conditions that guarantee efficiency and safety of other operations.

The initial metrics indicate that the robot is able to perform the work of 4 store associates taking inventory full time, at a fraction of the cost, and with much higher accuracy and consistency. This projects a very high ROI and a very short payback period of the proposed solution, but more data is needed to provide quantitative proof of its economic feasibility.

Finally, the experience gained working with retailers leveraged new robot applications. The main one is the location of products, which would provide retailers with the ability to detect misplaced items or create efficient picking plans for online orders. Locating items with an RFID system is challenging due to the nature of radio frequency propagation. Nevertheless, preliminary work in this direction has shown promising results. In addition, other sensors could be added to the robot in order to increase its knowledge about the environment and supply retailers with additional information. For instance, it could take 3D maps of the environment, detect moisture and temperature, lighting conditions or dirt. All the observations could be combined in a monitoring store application to support managerial decision making. Adding new sensors with this purpose to the robot is not technologically challenging. However, assessing the value for the final user, the retailer and the shopper is not trivial.

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Table 1. Main characteristics of the validation setting.

Characteristic	**Value**
Type of item	Books
Area (m^2)	12.0
Number of items	3,115
Aisle width (m)	1.05
Density ($items/m^2$)	260
Aisles length (m)	5.0
Intricacy (m/m^2)	0.42

Table 2. Performance of the robot compared to the handheld during the tests to evaluate the relevance of the algorithm parameters.

	Robot	**Handheld**
Average accuracy (%)	99.6	99.3
Maximum accuracy (%)	99.7	99.7
Minimum accuracy (%)	99.5	99.0
Average duration (s)	601	598

Table 3. Figures of merit of the optimal robot configuration and the handheld in the library. The optimal robot configuration is the one with ($th_{twist} = 16, th_{journey} = 8$) and two passes.

	Robot	**Handheld**
Accuracy (%)	99.3	99.3
Duration (s)	235	598
Distance (m)	11.0	5.0
Speed (m/s)	0.047	0.008
Effective speed (m/s)	0.021	0.008
Effective read rate ($items/s$)	13.2	5.2

Table 4. Characteristics of the store sections where experimental tests were conducted.

	Section A	**Section B**	**Section C**
Merchandise	Jeans	Men's dresses	Women's underwear
Area (m^2)	140	262	232
Number of items	2,300	6,000	16,500
Typical aisle width (m)	0.95	0.80	0.65
Density ($items/m^2$)	16	21	71
Aisles length (m)	72	160	149
Intricacy (m/m^2)	0.51	0.57	0.64

Table 5. Robot and handheld inventory accuracies in the store. Average values in bold and extreme values in parenthesis.

	Section A	**Section B**	**Section C**
Robot (%)	**99.9** (99.9-100)	**99.9** (99.8-99.9)	**99.6** (99.4-99.9)
Handheld (%)	**96.2** (88.4-99.0)	**81.6** (68.0-85.2)	**75.3** (60.0-81.5)