A metric for assessing, comparing and predicting the performance of autonomous RFID-based inventory robots for retail

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***Abstract*—RFID technology is being widely adopted by retailers due to its accuracy, versatility and reduction of operational costs. Most commonly, RFID in retail is used for taking frequent and accurate inventories of items in the stores.**

Usually, RFID inventories use handheld RFID devices, which makes the task tedious, costly, and prone to human errors. More reliable, fully automatic alternatives exist, such as smart shelves, overhead RFID antennas, and RFID-equipped robots. Among them, robots seem to be the preferred choice by retailers with large stores. However, retailers need an objective way to compare the different options for inventory solutions and to calculate the return on investment (ROI) of each of them before they make and investment decision.

In this article we present a metric for assessing, comparing, and predicting the performance of autonomous RFID-based robots in retail stores. The metric models both the store and the robot, and predicts the performance of a given robot when inventorying a specific store. The metric also allows to compare the performance of different RFID robots in different stores. The metric has been developed using experimental data, and has been validated in a real store.

***Index Terms*—Applied Robotics, Inventory, Radio Frequency Identification, Metrics, Performance, Measurement.**

I. Introduction

In retail, the traditional strategy for inventory record inaccuracy (IRI, [1]) mitigation is to perform periodic manual inventories using autoidentification (Auto-ID) technologies. The most traditional AutoID technology choice has been handheld barcode readers, but using handheld RFID readers the accuracy and frequency of the manual inventories can be significantly increased. Nevertheless, these processes are costly, tedious and prone to errors, due to the involvement of humans in the process. Another possibility is the use of overhead antennas ([2]) or smart shelves ([3]), however their acquisition and installation price is very high, specially in large stores. Another approach is the use of robots equipped with RFID readers and antennas, which have demonstrated to drastically improve the accuracy and consistency of the inventories, while significantly reducing the cost even when the frequency of the inventories is increased ([4], [5], [6], [7], [8]).

An RFID robot consists of an autonomous robot vehicle carrying an RFID payload. The robot navigates autonomously around the store, while the RFID subsystem reads all RFID tags within reach. For the robot to navigate autonomously, an initial mapping phase is necessary, in which the robot is driven manually around the store so that it can use its sensors (mainly laser sensors) to create a 2D map of the store, and at the same time establish a sequence of waypoints that will later be visited. In order to locate itself while constructing the map, the robot uses the well-known algorithm Simultaneous Location and Mapping (SLAM, [9]). After that, every time a new inventory or location is required, the robot can start what is known as a mission by leaving its charging station, navigating to each successive waypoint, and finally returning to its initial position. To calculate its position within the map during the mission, the robot uses another well-known algorithm, the Adaptive Monte Carlo Localization (AMCL, [10]), which estimates the most likely position and orientation (collectively known as pose) by comparing the current input from the sensors with the previously stored map and computing likelihood metrics.

Nowadays, robot-based inventories are gaining momentum ([11]) and are starting to be adopted in real stores. Actually, there are several companies that already offer robot-based solutions for inventory (e.g. [12], [13] and [14]). Nevertheless, there is still much ground for further research. One of the most important issues that potential users of autonomous RFID-based inventory robots face is the absence of a common set of metrics that can be used to test and compare the performance of different robots among them, and against manual inventories and other automatic inventory solutions.

There have been several research efforts to define metrics in field robotics (navigation, coverage, human-robot interaction, multi-robots, rescue-robots, etc.). In the case of robots that navigate using a map, the complexity of the navigation is directly related to the complexity of the map. One approach for calculating such complexity is presented in [15], where

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the map's complexity is defined as a quantity inversely proportional to the map's image compression rate. However, establishing a proper complexity metric requires relating map features to the grid distribution. In this regard, several works have been conducted ([16], [17], and [18]) to assess the complexity of cartographic maps using information theory.

In the early stages of mobile robots it was very important to define metrics for coverage tasks. The coverage problem refers to the optimisation of the robot's navigation in order to completely cover a given area in the shortest time and/or with the shortest path. For example in [19], they define metrics for effectiveness and efficiency.

In the area of human-robot interaction, there have been some efforts to define quantitative metrics. For example in [20], they define five categories of metrics: navigation, perception, management, manipulation, and social metrics. For a different purpose, metrics are defined for modular (also called metamorphic) robots. For example in [21] and [22], they define metrics to optimise the process of self-reconfiguration of a modular robot. Also, in the field of body mapping for robot imitation, it is crucial to determine the quality of the imitation according to some defined metrics ([23]). In addition, metrics are also defined for assisting robots, for example in the case of robots assisting in surgeries ([24]).

Another approach is the creation of test arenas were robots can be deployed, operated and evaluated in some specific conditions. In this direction, the National Institute of Standards and Technology (NIST) has been leading the efforts to develop methods for quantitatively evaluating the performance of robots, specifically in the field of rescue robotics ([25]). Using this approach, one testbed is composed by several arenas representing different challenges and levels of difficulty. The robots have to perform specific rescue tasks in each of these arenas. Then, they are evaluated using metrics based on the number of victims identified, but including penalties like contacts with the victim or collisions with the environment.

In a similar direction, more general testbeds have been designed for learning or research purposes. It is the case of [26], where a multi-robot testbed is created allowing the testing of different capabilities in a collision-safe environment. Unfortunately, testbeds are only widely accepted by the community either when there is a standardization organization behind them (like NIST) or when there is no commercial competition.

In the specific case of metrics for inventories, the only published research previous to the present work is [8]. In this work, similarly to the robot coverage task, the metrics are extracted from the characterization of both, the store and the robot. However, the metrics were very simple and defined only empirically, which were useful to compare a robot performance against another but in the same scenario, or to compare scenarios but without obtaining a relation with the robot performance.

Even if this previous research is the origin of our work, the metric we propose is much more ambitious since we elaborate a complete model than quantitatively characterises RFID robots, retail stores, and the inventory task of the robot in the store. Our idea leverages metrics used heterogeneous systems to normalise their performance. For instance, two sailboats can compete with each other, even though one is faster than the other in equal conditions, by using what is called a "Rating", which normally consists in applying a Time Correction Factor (TCF) to the racing time ([27]) to calculate a corrected time. When competing using the corrected time, the competition is based almost solely on the performance on the crew, not on the speed of the boat. Interestingly enough, the TCF requires a predictive model to be able to estimate the time that the boat would take with a standard performing crew. A similar method is used in golf but in this case the handicap is not a factor, but an offset to the course's par.

In this paper we will present the first metric to predict and compare the performance of autonomous RFID-based robots: the effective inventory velocity, which is an estimated average velocity at which a specific RFID robot completes an inventory in a specific store. This metric can be used to quantitatively evaluate the performance of this task and can be used independently of the specific characteristics of the robot or the store. It has been obtained using experimental data and it has been validated both in, a laboratory with $1,000$ RFID tags encoded with a unique Electronic Product Code (EPC), and in an actual fashion store of $1,000\,m^2$ with $11,041$ items, each of them tagged. The store contained many different types of garments displayed in different types of fixtures (tables, racks, shelves, etc.)

This metric enables several use cases that are currently not possible, for example predicting the performance of one robot in one store without the need to purchase it, or compare theoretically the performance of different RFID robot solutions. Due to the cost and technical difficulties of setting up these types of robots in real stores, these are two use-cases that the market is demanding.

This paper is organised as follows. In section II we explain the current performance metrics for an inventory task, we propose the effective inventory velocity, and we outline the methodology for its computation and use. In section III, we define how to characterise a store and in section IV we define how to characterise a RFID robot. In section V, we provide a common ground for the task feasibility. In section VI, we show how to predict the performance of an RFID robot in a store using the metric. In section VII, we validate the model with experiments. Finally, in section VIII, we present our conclusions.

II. METHODOLOGY

In this section we introduce the two aspects that define the performance of an inventory, and we present the metric. Finally, we explain how to use the proposed methodology to compute it.

A. Inventory performance

As it has been already introduced, the inventory performance is currently assessed using the accuracy obtained and the time required.

1) Inventory accuracy: it is the fraction of detected items over all the items present in the store.

Obtaining the baseline, which is the list of all the items present in the store, can be complex and not always an exact baseline can be achieved [8]. In any case, once the baseline is obtained, the inventory accuracy is defined as the number of unique identified items by the robot divided by the number of unique items in the store, as seen in Equation 1.

$$\text{Inventory Accuracy} = \frac{\text{\# of identified items}}{\text{\# items present in the baseline}} \quad (1)$$

2) Inventory time: is defined the total time needed to complete an inventory mission.

B. Effective inventory velocity

We propose the effective inventory velocity as the only required metric to assess the inventory performance. Hence, the effective inventory velocity v_e is defined as the total length travelled by the robot during the inventory mission, divided by the inventory time, conditioned to the fact that the robot has achieved a minimum inventory accuracy.

Note that the effective inventory velocity and the inventory accuracy form a classic engineering trade-off pair: the slower the inventory, the higher the accuracy (up to a maximum value) and vice-versa. Hence, if the objective is to compare inventory missions, we have to fix one in order to use the other for comparison.

Since the accuracy is given as a requirement by the retailer, the following assumes that the inventory robot will have completed its mission when the accuracy reaches a value of 99%. If the accuracy value is not met, it will mean that the robot parameters (e.g. velocity) are not properly adjusted. Note that the adjective 'effective' refers to the fact that the velocity is conditioned by a minimum predefined accuracy goal.

As we will see in the following, the effective inventory velocity can be predicted given the characteristics of the store and the robot. Hence, the proposed metric can be used in multiple use cases, such as

- Predicting the performance of several robots in a given store, in order to select which robots are going to perform better.
- Predicting the performance of a particular robot type in all the stores of a particular retailer, to help plan the inventory schedule.
- Comparing the actual velocity with the predicted velocity to detect possible incidents or malfunctions.
- Defining and characterising a standard store, and use it as a benchmark to compare the performance of different robots. The velocity of each robot in the benchmark store can be considered the 'Rating' of the robot.
- Defining and characterise a standard robot, and using it as a benchmark to compare the difficulty of different stores. The effective inventory velocity of the benchmark robot in the store can be considered the 'par' of the store, similar to the par of a golf course.

C. Proposed methodology

The straightforward process to measure the effective inventory velocity is by performing an inventory mission with the robot in the store. Then, the length of the path that the robot took is divided by the time it required to finish it, and the value obtained is the effective inventory velocity for this specific robot in this specific store.

However, we have developed a methodology in order to predict this value from the characteristics of the store and the robot, without requiring to perform an inventory mission. Therefore, in order to compute the effective inventory velocity we propose the following steps:

1) Characterise the store.
2) Characterise the robot.
3) Verify the feasibility of the inventory task.
4) Compute the effective velocity v_e.

The following four sections provide a detailed description of each step.

III. Store characterisation

This section describes the parameters used to characterise the store.

A. Store parameters

A store to be inventoried is characterised by a 7-tuple $\bar{S} = \{A, B, C, L, W, H, \Lambda\}$ where:

- A (m^2) is the area of the store,
- $B = \{epc_n\}$ is the baseline, or set of items present in the store, represented by their EPC codes.
- $C = \{c_i\}$ is the list of aisles,
- $L = \{l_i\}$ (m) is the list of lengths of each aisle,
- $W = \{w_i\}$ (m) is the list of widths of each aisle,
- $H = \{h_i\}$ (m) is the list heights of each aisle, and
- $\Lambda = \{\lambda_i\}$ (# tags$/m$) is the list of linear item densities of each aisle.

Two aisles are considered different if there is a turn of more than 45^o between them. Aisles with complex shapes are simplified to a rectangle using the average width of the aisle if it is not uniform.

We define the list of linear item densities of aisles Λ as the total amount of items of each aisle in C divided by their length, as found in L. We can calculate the number of items in aisle c_i as $n_i = \lambda_i \cdot l_i$.

We define the intricacy of a path p (a more elaborated discussion on the definition of path is found in section V), a parameter that aims to measure the difficulty of navigating a path due to the presence of turns, as the inverse of the average aisle length. Let C_p be the list of aisles of a certain path p, then the intricacy is:

$$I = \frac{1}{\bar{l}} = \frac{1}{\left(\frac{\sum_{c_i \in C_p} l_i}{|C_p|}\right)} = \frac{\mid C_p \mid}{l} \quad (2)$$

where l is the total length of the path p, $\bar{l}$ is the average length of the aisles l_i of p, and $\mid C_p \mid$ is the number of aisles that form the path p.

IV. Robot characterisation

As previously done with the store, in this section we explain how to characterise the RFID inventory robot.

A. Characteristics of the RFID inventory robot

An RFID robot for doing an inventory is characterised by a 7-tuple $\bar{R} = \{v_0, t_t, w_m, w_0, h_m, r_c, \lambda_h\}$ where:

- v_0 (m/s) is the maximum linear speed of the robot,
- t_t (s) is the average turning time, that is, the average time it takes the robot to change direction,
- w_m (m) is the minimum aisle width through which the robot can navigate,
- w_0 (m) is the optimal width, that is the minimum aisle width that allows the robot to navigate at the maximum linear speed v_0,
- h_m (m) is the minimum height clearance for the robot to be able to navigate,
- r_c (m) is the coverage range, that is, the maximum range at which the robot can detect tags reliably, and
- λ_h (# tags$/m$) is the density of items that forces the robot to reduce its linear speed to half of its maximum value in order to keep the accuracy at the predetermined goal.

Although in reality it is more complex, we can simplify the movement of the robot as being only composed of straight paths and turns. Autonomous robots operating in retail stores typically spend a significant amount of time planning and executing turns, due to the complexity of turning in crowded spaces (sensors dead zones, complexity of path planning, etc.) In order to do such simplification of the model, we have considered that in turning angles below 45^o the robot turning time is negligible, and for any larger turn, the average time to turn (t_t) is approximated by the average time needed to perform a 90^o turn.

To navigate in a given area, the robot characterised by $\bar{R}$ should be able to pass between obstacles (usually fixtures) in a given aisle. However, it is possible that a free space is too narrow to be navigated at all. Therefore, we need to define two different minimum values. The minimum height h_m and the minimum width w_m are the minimum clearance values of height and width at which the robot can navigate, which means that any aisle with width $w < w_m$ or height $h < h_m$, cannot be navigated by the robot, and is not an accessible aisle. A more elaborated discussion on the implications of these two values can be found in section V.

Navigating in narrow spaces is more difficult than navigating in wide spaces. We define the optimal width w_0 as the value which when $w \geq w_0$, the robot can navigate at its maximum linear speed v_0 without being slowed down by obstacles. Note that we do not define an optimal height, since we consider that the robot only moves in two-dimensional space and, once the height is greater than the minimum, this third dimension will not influence the navigation.

Due to the nature of the RFID technology, it is impossible to use theoretical models to obtain the exact coverage area of an antenna in real scenarios [28]. Hence, we simplify and assume that a standard RFID robot will be able to radiate at 360º (if not, it will have to spin), meaning that the robot detection area can be approximated by a circle centered on the robot. The radius of this circle is defined as r_c and its length can be calculated as the distance at which the robot can read 80% of a large number (we have arbitrarily set $1,000$) of RFID tags directly placed together at a fixed distance from the robot's RFID antennas.

To maintain a given accuracy as the density of items increases, the velocity of the inventory needs to decrease. Not only because the readers have a maximum read rate (the maximum number of tags per second they can identify), but also because the influence of other RFID variables increases with the density. Hence, we define an empiric parameter λ_h which is the lineal density of items at which the robot has to decrease its maximum linear speed to half i.e. $v = \frac{1}{2}v_0$, in order to reach the accuracy goal of 99%.

The above parameters can be measured by doing experiments in a simple environment. For example, v_0 and t_t can be obtained by measuring the robot in an empty aisle. Similarly, w_m and w_0 can be obtained by measuring the velocity of the robot at different aisle widths. Also, r_c can be obtained by placing the robot in front of $1,000$ tags at increasing distances until 80% of the tags are read. Finally, λ_h can be obtained measuring the velocity in a single aisle and different tag densities.

V. Task feasibility

This section presents the criteria to analyse whether the RFID inventory robot can successfully accomplish the inventory mission in a given store.

We define the list of accessible aisles C_a as the list of aisles of C with width greater than w_m and height greater than h_m, where w_m and h_m: $C_a = \{c_i \in C \mid w_i \geq w_m, h_i \geq h_m\}$.

We define a path p in the store, as a trajectory that traverses one or more aisles in C_a. We define C_p as the list composed of the aisles that have been traversed in p where $\forall c_p \in C_p$ then $c_p \in C_a$. Note that if an aisle of C_a is traversed more than once in p, this aisle will appear more than once in C_p. The length of path p is then $l = \sum_{c_i \in C_p} l_i$, with l_i being the length of aisle c_i.

We define a covered area as the union of the surfaces that have been covered by a robot when moving along the path p. Accordingly, we define a covering path as a path that completely covers all the area A. Finally, we define the optimal path p_o as the covering path with minimum length.

Finally, we can conclude that the inventory task will be feasible only if a covering path exists. If for whatever reason there does not exist a covering path, the metric will not be valid.

VI. Performance prediction

A. Calculation of the effective inventory velocity

We have already introduced the effective inventory velocity in section II. The final goal of this section is to be able to predict its value for a given robot in a given store, characterised by $\bar{R}$ and $\bar{S}$ respectively. Firstly, we will characterise and predict the velocity of that robot in three canonical scenarios. Secondly, we will use these velocities to calculate the predicted effective inventory velocity in a store.

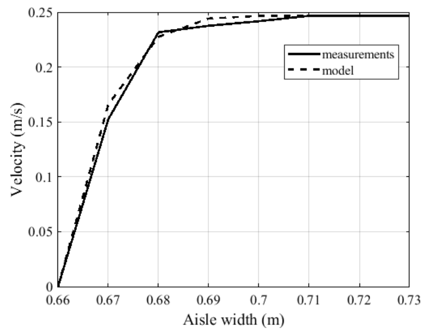

Fig. 1. Model extraction from the measurements of the velocity of the robot for different aisle widths.

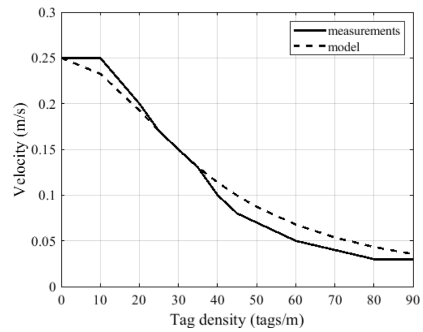

Fig. 2. Velocity of the robot as a function of the density of items ($v_0 = 0.25$ m/s and $\lambda_h = 36$ tags/s).

1) Intricacy-based velocity v_i: In this first scenario, only the difficulty of navigation in a path p with lots of turns is considered, as opposed to a path consisting of a single straight aisle. This difficulty can be quantified by the intricacy I of the path, as defined in section III.

We can calculate the intricacy-based velocity as the velocity of a robot in a store of intricacy I, but with wide aisles, empty of tags, so neither the width of the aisle nor the tag density limit the velocity, only the intricacy. First we calculate the time it takes for the robot to navigate the path p, considering that in the straight aisles l_i it navigates at velocity v_0, and that for each turn the robot spends a time t_t:

$$t = \frac{l}{v_0} + \mid C_p \mid \cdot t_t$$

hence, the intricacy-based velocity can be obtained:

$$v_i = \frac{l}{t} = \frac{l}{\frac{l}{v_0} + \mid C_p \mid \cdot t_t} = \frac{l}{\frac{l}{v_0} + I \cdot l \cdot t_t}$$

and finally we can define the intricacy-based velocity depending only on v_0, I and t_t as follows:

$$v_i = \frac{v_0}{1 + I \cdot v_0 \cdot t_t} \tag{3}$$

2) Width-based velocity v_w: In this second scenario, we consider that if one aisle is narrow, the difficulty to navigate such aisle increases. Hence, we should also define the formula of the velocity depending on the widths of the aisles and the minimum and optimal widths of the robot.

The effect of the aisle width on the robot velocity has been studied experimentally where several tests have been conducted in laboratory facilities. The base cases are when $w_i \leq w_m$ where the velocity is zero and when $w_i \geq w_0$ where the velocity is v_0. When $w_m < w_i < w_0$, the velocity increases very fast for widths just above w_m and then it increases more slowly when the widths approach w_0. This behaviour is modelled by Equation 4 and can be seen in Figure 1, where the experiment on a specific robot is shown ($w_m = 0.66\,m$, $w_0 = 0.71\,m$). The experiment consisted in travelling different aisles of different widths, and measuring the velocity for each one of them.

We define the width-based velocity as the velocity of a robot in a straight aisle, empty of tags as:

$$v_w = v_0 \cdot \left(1 - \left(\frac{w_0 - \max(w_m, \min(w_0, w))}{w_0 - w_m}\right)^\alpha\right) \tag{4}$$

where α is a parameter to be adjusted using experimental data from the experiment depicted in Figure 1. According to our measurements $\alpha \approx 5$.

3) Density-based velocity v_d: In this third scenario, we consider that when doing an inventory with a preset accuracy, as the density of the items increases the velocity decreases, since the robot needs more time to identify all the items.

We propose an empiric approach based on experimental results to compute the velocity depending on the lineal density of tags of an aisle given a certain accuracy. It can be empirically proved that, when the lineal density is low, the robot can navigate at maximum speed, so $v_d = v_0$ for that aisle. As the density increases, at some point the robot has to decrease its velocity or otherwise it will not be able to achieve the preset accuracy, as it would be travelling too fast to be able to identify all the tags.

To model such function, several tests have been performed in the laboratory, where different aisles with different lineal densities have been inventoried and the velocity measured, see Figure 2. The resulting behaviour can be approximated by the following equation:

$$v_d = \frac{v_0}{1 + \left(\frac{\lambda}{\lambda_h}\right)^2} \tag{5}$$

where λ_h is the value of λ for which $v_d = \frac{1}{2} v_0$. Figure 2 shows an average of the experiment results compared to the proposed equation.

B. Estimation of the effective inventory velocity

Now we are ready to compute the proposed metric, the effective inventory velocity. We will obtain its expression as a combination of the canonical velocities: Equations 3, 4, and 5. For instance, in the case of an aisle of width w, linear density λ but no turns, we can compute $v_e(\bar{S}, \bar{R}) = v_{wd} = v_w \cdot v_d$:

$$v_{wd} = v_0 \cdot \left(1 - \left(\frac{w_0 - \max(w_m, \min(w_0, w))}{w_0 - w_m}\right)^\alpha\right) \cdot \frac{1}{1 + (\lambda/\lambda_h)^2}$$

Using the same logic, we can create v_{iw} and v_{id}.

We can easily aggregate the three velocities, if their parameters are constant along the entire path. So, when there are turns, the aisles are narrow but all of the same width w with $w_m < w < w_0$), and the density of tags $\lambda > 0$, the combined effective inventory velocity can be calculated as:

$$v_e(\bar{S}, \bar{R}) = v_{iwd} = \frac{v_{wd}}{1 + I \cdot v_{wd} \cdot t_t} \quad (6)$$

Where we are using Equation 3 and substituting v_0 by the computed speed over a straight path with a fixed aisle width and density.

However, when the path p is composed of aisles of different lengths l_i, widths w_i, and densities λ_i we need to split the computation according to these changes:

$$v^i_{wd} = v_0 \cdot \left(1 - \left(\frac{w_0 - \max(w_m, \min(w_0, w_i))}{w_0 - w_m}\right)^{\alpha}\right) \cdot \frac{1}{1 + (\lambda_i/\lambda_h)^2}$$

In this case, we calculate the total time it takes for the robot to navigate entire path p as the sum of each part of the path:

$$t = \sum_{c_i \in C_p} \left(l_i / v^i_{wd} + t_t\right)$$

and compute the velocity as follows:

$$\begin{aligned} v_e(\bar{S}, \bar{R}) = v_{iwd} = \frac{l}{t} &= \frac{l}{\sum_{c_i \in C_p} \left(l_i / v^i_{wd} + t_t\right)} \\ &= \frac{l}{\sum_{c_i \in C_p} l_i / v^i_{wd} + \mid C_p \mid \cdot t_t} \\ &= \frac{1}{\frac{\sum_{c_i \in C_p} \frac{l_i}{v^i_{wd}}}{l} + \frac{|C_p|}{l} \cdot t_t} \end{aligned}$$

which can be expressed as:

$$v_e(\bar{S}, \bar{R}) = v_{iwd} = \frac{\bar{v}^h_{wd}}{1 + I \cdot \bar{v}^h_{wd} \cdot t_t} \quad (7)$$

where $\bar{v}^h_{wd}$ is the weighted harmonic mean of the aisle velocities:

$$\bar{v}^h_{wd} = \frac{\sum_{c_i \in C_p} l_i}{\sum_{c_i \in C_p} l_i / v^i_{wd}}.$$

So the effective inventory velocity of the robot in the store, $v_e(\bar{S}, \bar{R})$, can be calculated from Equations 6 or 7 depending on whether the aisles in the path have the same or different widths or item densities.

VII. Validation

In order to validate the model, we have performed an experiment in a laboratory and an experiment in one floor of a fashion retail store. In the laboratory (Figure 3 left), the tags were placed in boxes over 7 metallic shelves. In the store (Figure 4 left), the tags were placed in the garments, which were of different sizes, colours and materials and which were placed in different positions inside the furniture of the store. The robot used in both cases was Keonn's AdvanRobot® [12] which is a map-based inventory robot as it can be seen in both figures. The experiments consist of 3 missions.

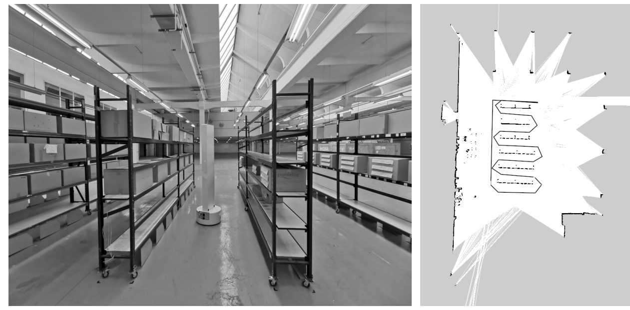

Fig. 3. The robot operating at the laboratory (left), and the map of the laboratory with the robot path containing the different aisles (right)

Fig. 4. The robot operating at the store (left), and the map of the store with the robot path containing the different aisles (right)

A. Verification of the accuracy goal

In the case of the laboratory, there were $|B| = 1,000$ tags. In the case of the store, due to the lack of a valid perpetual inventory record, three runs of the experiments gave $11,010$, $11,041$ and $11,039$ tags respectively, so we have estimated the presence of $11,041$ tags. Notice that the maximum discrepancy between the three runs is of 31 tags (less than 0.3%), so $|B| = 11,041$ is most likely a good estimate of the baseline, and the accuracy of the runs is $Acc \geq 99.7\%$. The accuracy value objective set in both cases is $Acc \geq 99\%$, which in the case of the store leaves a reasonable margin of error of 0.7%, in case the accuracy estimation differs from the actual accuracy.

B. Characteristics of the laboratory

The laboratory is placed in the storage room of Keonn facilities as shown in Figure 3.

The characterisation of the laboratory is the following ($\bar{S}$):

- $A = 91\ m^2$,
- C is composed of 9 aisles,
- B is composed of $1,000$ items,
- L (m) is [7.05, 6.72, 6.72, 6.72, 6.19, 6.19, 6.19, 11.19, 7.05],
- W (m) is a list with 9 widths of $1.5\,m$,
- H (m) is a list with 9 heights of around $10\,m$, and
- Λ (# tags $/m$) is [0, 18.9, 9.9, 17.9, 19.4, 17.2, 20.5, 0, 0].

The path had a length $l = 64.43\,m$, with an average aisle length of $\bar{l} = 7.15\,m$.

C. Characteristics of the store

The store is a floor in a real store of a fashion retailer. The floor is divided internally into 10 areas that contain 183 fixtures of different shape and size, mainly tables (where items are placed on top of the table) and hanger fixtures some of them fixed to the walls and some of them up to $1.5\,m$ high. Also there are some items at the floor level, like shoes.

The characterisation of the store is the following ($\bar{S}$):

- $A = 1,000\ m^2$,
- C is composed of 75 aisles,
- B is composed of $11,041$ items,
- L (m) is the list of lengths of the aisles,
- W (m) is the list of widths of the aisles,
- H (m) is the list of height of the aisles, and
- Λ (# tags $/m$) is the list of linear densities of tags of the aisles.

This data has been made available in [29] as open data. The designed path is composed by 75 aisles as shown in Figure 4 right. The path had a length $l = 343\,m$, with an average aisle length of $\bar{l} = 4.58\,m$.

D. Characteristics of the robot

The RFID robot used was the Keonn AdvanRobot® [12] which uses two Keonn RFID readers AdvanReader-150® [30] operating at $30\,dB$, have a reading rate of around 400 tags/s and a maximum read range of around 9 m. Each reader is placed in one side of the robot's payload and is connected to 4 Keonn RFID-Antennas Advantenna-SP11® [31].

The robot has a total height of 1.95 m and the base has a diameter of 55 cm. It has differential traction, which means that can turn on its own axis. The robot is provided with 3 sensors, 2 RGB-D cameras (one at the base and one at the top) and one LIDAR (a 220º degrees laser) to avoid obstacles and achieve automatic navigation.

The characterisation of the robot is the following ($\bar{R}$):

- $v_0 = 0.247\,m/s$
- $t_t = 4\,s$,
- $w_m = 0.66\,m$,
- $w_0 = 0.71\,m$,
- $h_m = 1.95\,m$,
- $r_c = 5.5\,m$,
- $\lambda_h = 36\,tags/m$.

E. Task feasibility and calculation of the effective velocity

Comparing the widths, heights and covering radius of the robot and the characteristics of both environments, we can conclude that the selected paths shown in Figures 3 and 4 are both covering path. Hence, the problem can be completed (as corroborated by the accuracy verification).

Using the characterised elements (laboratory, store and robot), we can calculate the effective velocity. Specifically, using equation 7. In the case of the laboratory, $v_e = 0.1857\,m/s$, which predicts that the robot will finish its mission in $t = \frac{64.43}{0.1857}s = 347s = 5'47''$.

TABLE I
MEASURED VERSUS PREDICTED MISSION TIME AND VELOCITY, AND RELATIVE ERROR IN THE PREDICTION OF THE VELOCITY.

Inventory	Length (m)	Time (mm'ss")	Velocity (m/s)	Error
Lab Prediction	64.43	5'47"	0.1857	
Lab #1	64.43	6'05"	0.1765	-5%
Lab #2	64.43	5'29"	0.1958	5,4 %
Lab #3	64.43	5'50"	0.1841	-0,9 %
Store Prediction	343	46'39"	0.1227	
Store #1	343	46'15"	0.1238	0.9%
Store #2	343	48'54"	0.1171	-4.6%
Store #3	343	47'41"	0.1201	-2.2%

In the case of the store, $v_e = 0.1227\,m/s$, which predicts that the robot will finish its mission in $t = \frac{343}{0.1227}s = 2,799s = 46'39''$.

The empirical results for all the tests are shown in table I.

F. Comparison with previous solutions

Even if they are two different problems, the inventory task and the coverage task as explained in section I, have some similarities. Specifically, in the robot coverage problem ([19]), they characterize the area i.e. the space to cover, the robot i.e a movable shape of some specific size, and the task i.e. a robot being able to navigate the area and cover it as much as possible with its shape. Then, they define two metrics: effectiveness, which is the coverage percentage, and efficiency, which is the distance traveled. In our case, we also characterize the area (the store), the robot, and the task. Then we define one metric, the effective inventory velocity which has a direct relation with the area covered (in our case by the area covered by the RFID readers), and the length of the path.

In [8], they define some metrics for the store. Specifically, they define the accuracy of the inventory, the aisles length, the intricacy, and the item density. Note that in this previous work, the intricacy is simply defined as the length of the paths divided by the area of the store. Then they measure the effective speed, which is the real velocity at which the robot operates. Hence, they can somehow evaluate both, the store (intricacy, path length, and item density), and the robot (effective velocity) doing a specific task (inventory accuracy).

Since our goal is much more ambitious and we aim to predict the robot performance in a store, we leverage on this previous effort extending all these concepts and defining them in much more detail. Hence, we define a much more accurate intricacy, we introduce the width of the aisles (which limit the robot in real operations), and we extend the concept of item density to a much more precise concept based also on the RFID antenna coverage radius.

VIII. Conclusions

In this article we have presented a metric for assessing, comparing, and predicting the performance of an RFID inventory robot in a store. This metric can be estimated using a model based on the characteristics of the inventory task, the RFID robot and the store. The presented metric has demonstrated to be simple and accurate enough to be utilised in a real environment. Hence, several use-cases can leverage on this work, like comparing the performance of the different robot solutions without the need to purchase them, or predict the performance of a robot in a store.

The formulas used have been fitted to laboratory experiments but the validation has been done in both, a mock store in a laboratory and a real fashion store. The area of the latter was $1,000\,m^2$ and the number of RFID tags $11,041$, which is a large enough store to consider it a real challenge for the model validation. In order to create the model, several simplifications were made specifically, approximations to empirical values using mathematical formulas.

Nevertheless, the results were remarkably accurate, with the empirical values being deviated between 0.1% and 5.5% from the real velocity of the robot. In practical terms and in the case of the store, for a task that was theoretically predicted to last for $46'12''$, it took between $46'15''$ and $48'54''$ to finish when measured.

Hence, we think that the metric can be considered valid for assessing, comparing and predicting inventory tasks of RFID robots in retail stores. However, future work should validate it with more complex scenarios i.e collaborative robots, robots not based on maps, etc.

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