A simple solution to locate groups of items in large retail stores using an RFID robot

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***Abstract*—This paper presents a simple solution to estimate the location of products in a retail store, using an autonomous ground robot with an RFID payload. The model used and explained in this paper is designed to be as simple and versatile as possible, while achieving accurate location estimations when compared with other proposed models in the state-of-the-art (SOTA). In addition, the solution developed meets the business requirements of the retail industry, such as locating at SKU (Stock Keeping Unit) level, as opposed to item level, or expressing the location in terms of store fixtures (e.g. shelf, rack) as opposed to (x,y) coordinates. The research results are obtained from experiments of the model in different environments, achieving accurate location estimations in a controlled laboratory environment. Moreover, for the first time, the model has been tested in a large retail store, where the results obtained met the requirements of the store owners.**

***Index Terms*—Radio Frequency Identification, Retail, Robotics, Location**

I. Introduction

Over the past few years, RFID technology is increasingly being adopted by the retail industry due to the beneficial impact it had in the field of Supply Chain Management (SCM) ([1], [2] and [3]) and as a valid alternative to Electronic Article Surveillance (EAS) [4]. Nevertheless, this technology has not yet been exploited to its full potential. One of the most well-known applications of RFID in retail is fast and accurate stock counting (inventory). However, there are several other interesting applications among which the location of products in the store has created a lot of interest in the retail business. The information about the location of products enables many important retail business cases, such as finding misplaced items, verifying store planograms, or preparing on-line orders to be collected at the store.

Products in a store are almost always identified by a barcode printed on a label, also known as Stock Keeping Unit (SKU, sometimes also know as Global Trade Identification Number, GTIN), which identifies all items of identical characteristics (e.g. model, color and size). In a retail store using RFID each label also has an RFID tag, which includes a universally unique Electronic Product Code (EPC [5]) that identifies each item individually. An EPC is essentially the SKU code plus a unique serial number and is sometimes referred to as Serialised GTIN (SGTIN).

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, [6]). 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, [7]), 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. In order to optimize the RFID readings, the RFID payload controls the navigation speed of the robot, making it go slower in areas with a high density of tags, and faster where there are few or no tags [8].

At the end of each mission, the list of unique EPCs read by the RFID payload of the robot constitutes the inventory of the store. The inventory accuracy is defined as the percentage of unique EPCs collected during the

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location mission with respect to the total number of EPCs actually present in the environment (inventory ground truth). SKU inventory accuracy is defined the same way, but for SKUs instead of EPCs. Also, the mission can be used to estimate the position of the items, by using the model presented in this article. In the same direction, location accuracy is defined as the number of successfully placed elements over the total present elements of the store. An element is considered successfully placed when the distance between the estimated and actual positions of the element is below a certain predefined threshold, or it is placed on the correct fixture, group of fixtures, or zone. While RFID robots have demonstrated that they can produce accurate inventories [9], locating products accurately in the store remains an open problem.

The models used by published solutions for the location of products ([10], [11], [12]) are complex and have only been evaluated in controlled environments where undesired effects are minimized. Consequently, presenting and assessing a new location model that can operate in real environments is a relevant advance towards a solution that can be broadly adopted in the retail industry.

Previous solutions have focused on estimating the location of a single item in a room, given as (x,y) coordinates. However, the retail industry needs to know the locations at the SKU level and referenced to fixtures. This means that retailers do not expect a location for a single object, but for each group of all identical objects which share the same SKU code, normally placed in one or only a few locations in the store. Additionally, most retailers prefer to receive the location information in terms of SKUs referenced to fixtures (e.g. shelves, racks), instead of in terms of coordinates. Other retailers prefer SKU locations to be referenced to groups of fixtures, or even store zones (e.g. the shoe area in a fashion store). In summary, while previous solutions provided the location information as (EPC,x,y) tuples, retailers expect (SKU, fixture), (SKU, group) or (SKU, zone) pairs.

Figure 1 shows the usual operation of the robot. The path and the map are created once for every store. During the mission, the robot follows the path and obtains as many readings as possible from the RFID tags of the items in the store. After the mission, the algorithm presented in this article is used to compute the estimated location of each SKU.

The solution has been tested in a laboratory environment and twice in a real fashion store with an area of around $1,000\ m^2$ and with approximately $11,000$ items. Each of the experiments had its own objective. Laboratory experiments were done in order to validate the model and the hypotheses used in it, and also to obtain a reference that could be used to compare against other solutions in the SOTA. The first experiment on the fashion store focused on adjusting parameters and to assess the change on performance due to the complexity of real environments as compared to a laboratory environment. The second experiment in the retail store was done to verify that the solution meets the requirements of the retailer and provides a final assessment of the model.

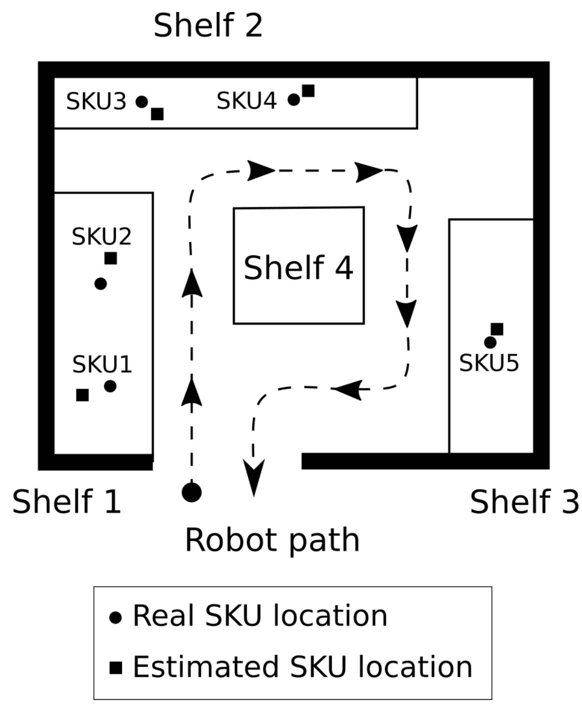

Fig. 1. Normal operation of the robot during an inventory and location mission.

This article is organized as follows. In section II we present and analyze existing methodologies for locating RFID-tagged items. In section III the proposed solution is presented. In section IV the experiments are explained and discussed. Finally, in section V we expose our conclusions.

II. Background

Over the past two decades, the scientific community has done great effort to provide RFID systems with location capabilities ([13], [14]). This effort has resulted in several contributions to the literature and various methods developed so far with relative success ([15]).

Range-based methods consist of simpler hardware solutions and are severely affected by multi-path and non-line-of-sight (NLOS) effects typical of complex indoor environments. Therefore, their location accuracy is low, and their computational cost is high. In contrast, methods based on scene analysis can achieve higher location accuracy and are more robust against errors introduced by indoor environments, at the cost of having to deploy large numbers of reference tags in the case of fingerprinting methods ([16]) or having to deal with complex probabilistic models in the case of non-fingerprinting methods.

It is worth mentioning that range-based methods make use of wave propagation models and the geometrical relation between the antennas and tags to obtain the position of the tag using multilateration (MLAT) ([17], [18], [19], [20]) or probabilistic algorithms ([21]). On the other hand, range-free methods are based on the analysis of the scene ([15]). For instance, fingerprinting techniques ([22]) generally make use of reference tags with a priori position to construct a map of the scenario. Non-fingerprinting methods such as holographic and Synthetic Aperture Radar (SAR) methods are based on the modeled behavior of some parameters to obtain the estimated position ([23]).

A fair comparison between the different methods would require the homogenization of testing elements and characteristics of the environment. Nevertheless, results ([15]) show that there are important differences between the two main methods in terms of location accuracy. When the actual position of the element is known, we use the mean distance error, defined as the average of the differences between the estimated and actual positions of each element in the store. When the known location of the element refers to a fixture, group of fixtures, or zone in the environment, we refer to fixture location accuracy, group location accuracy and zone location accuracy respectively. Elements can be either individual items, SKUs (groups of identical items), or any other grouping the retailer may consider relevant. In the following, we use SKUs as the elements for accuracy and error calculation. Since a SKU is a group of items, its position is considered to be the centroid of the set (simple average of the positions of each item).

The use of robots for locating items is not a new idea, as several studies already have been conducted in the past ([23], [24], [25]). In contrast to solutions using a fixed infrastructure readers and antennas, the use of robots results in a dramatic reduction of acquisition, installation, and maintenance costs for large facilities, with the additional advantage of avoiding static null electromagnetic field zones (blind spots).

There is still the open challenge of locating tags accurately using robots in complex indoor environments, such as retail stores, due to the induced significant RF multi-path fading effects ([11]). In [10] and [26], the authors used a SAR-based localization method, using the phase of the tag in achieving mean distance errors of only a few centimeters. However, due to the limitations of the phase-based method they had to fix one of the dimensions. When they fixed a distance to the tag ([26]), the SAR-based method provided a mean distance error of less than $1cm$. But when a more realistic set-up was used the performance deteriorated to a mean distance error of $28\,cm$ ([10]). In both cases the testing environment consisted of 38 RFID tags placed within a volume of $7m \times 5\,m \times 1.5\,m$.

In [12], the authors use phase unwrapping and non-linear optimization to locate the target tags with a mean distance error of $32\,cm$. The authors compare their method's performance with the SAR-based one presented above, and they conclude that SAR-based and holographic methods may require more than 20 minutes of computation to compute the estimated location of around 80 tags. Using optimizations, they were able to speed up the computation by a factor 55, at the cost of a slight increase of the error and the complexity of the method. The authors claim that by adding reference tags in the environment the mean distance error can be reduced to $17\,cm$.

On the contrary, in [11], the authors present a localization method applying Bayesian filtering and using a new RFID model of variable transmitted power. The method uses the RFID readings at different powers to create a grid of possible positions for each individual tag. Then they used a Bayesian filter to predict the most likely position inside this grid. The authors claim that they obtain a $50\,cm$ mean distance error in a much more complex scenario than the ones presented before. Specifically, they use a mock apparel store composed of 674 items with a total area of $204\,m^2$.

It is worth mentioning that there is no study in current SOTA targeting real large-scale stores. Our target scenario is a real retail store with more than $11,000$ unique tags within an area of approx. $1,000m^2$. We also made it a requirement that location mission can be completed in a similar time as an inventory mission [8]. From previous works, we can conclude that even if SAR-based methods provide the best accuracy, their vulnerability to multi-path effects and their computational cost prevents them from being used in complex scenarios. On the other side, power based probabilistic methods like the one presented in [11], are much more suitable in large scenarios.

In this article, we present a new location model. Similarly to [11], we optimize the irradiated power to obtain a better accuracy, however, we simplify the positioning of the tag by using a fixed position for each reading and a clustering method to refine the result. Hence, we avoid the use of a grid and a Bayesian filter. The proposed solution allows us to solve the large-scale location problem in a very short amount of time at a very low computation cost, which makes it scalable to very large stores. We will show that our simplified model can be compared in terms of mean distance error to the ones presented above. Once validated, we show that the presented model can be applied to real large retail store providing retailers, for the first time, with a solution they can actually deploy.

III. A SOLUTION FOR LOCATING ITEMS IN STORES

We aim to create a model that results in a solution that is adequate to the needs of the retail industry. In this section we address the problem, explain the methodology, and present the solution.

A. Defining the problem

The retail industry requires a solution for locating groups of EPCs, which means all items with the same SKU, and locations must be referenced to fixtures or zones of the store. Two hypotheses have been considered for developing the solution model:

- **Hypothesis 1:** The RFID parameters for a location mission will be different from those of an inventory mission.
- **Hypothesis 2:** The complexity of a given model does not correlate with its location accuracy when it is used in different environments.

The first hypothesis is based on the observation that while for completing an inventory mission the robot only needs to read each tag once, for computing an estimated location, due to the existence of multi-path and other unwanted signals in the environment, it is paramount to obtain repeat reads of the same tag, as the location accuracy increases with the number of reads.

The second hypothesis is based on the observation that the strong interaction of the RFID waves with the environment will make complex models that take the environment into account less accurate as the environment changes. Therefore, a simpler model will have an acceptable and consistent performance in any environment.

The location mission's objective is to assign SKUs to fixtures (and optionally to groups of fixtures or zones in the store). This means that a successful location mission will be assigning as many SKUs as possible to the fixture, group, or zone where they are actually located. Accuracy measurements are used to illustrate results of the model. Hence, it is not only important to place the SKUs correctly, but also to detect as many of them as possible, to maintain a high inventory accuracy. Since retailers are mostly interested in fixture based location accuracy, we will assume that the location is in 2D.

B. Methodology

The presented methodology for locating SKUs in fixtures is very simple and is based on three steps: (1) estimating the reading position, (2) obtaining the cluster centroid, and (3) assigning the cluster to a given fixture, group, or zone. The rest of the section explains these steps in further detail. Further information can be found in [27].

1) Estimating the reading location: An estimated reading position for an RFID tag is computed every time it is read. The tag is positioned with respect to the antenna that performed the reading, at a fixed distance. To keep the model as simple as possible this distance is considered to be constant for every type of store, and it is a parameter for the algorithm called *reading_distance*. Then, the relative position of the tag with respect to the antenna is transformed to a position relative to the map, given the position and orientation of the antenna with respect to the robot, and the position and orientation of the robot with respect to the map at the precise time of the reading.

2) Obtaining the cluster centroid: At the end of each mission, all the readings of the same SKU are processed to obtain an estimated centroid for each SKU. A straightforward possibility is to aggregate all the positions of the readings and compute the average. However, this solution will not consider the frequent case of having more than one location for a given SKU (same product found in two or more locations in the store). Moreover, it will not discard outlier reads, common occurrence due to the multi-path effect.

A more advanced implementation is to use a clustering method, for example DBSCAN [28]. The output of this algorithm is a set of clusters composed by reading's positions and a set of outliers (readings that are not assigned to any cluster). The readings that are labeled as outliers are discarded while all the obtained clusters are considered valid positions. The centroid of each cluster is calculated as the simple average of all the estimated positions of its readings.

The DBSCAN algorithm has two parameters, called eps and $min\_samples$. The eps parameter is defined as the maximum distance between two readings for one to be considered the neighbor of the other, while the $min\_samples$ parameter is defined as the minimum number of readings required to consider a cluster. By using these two parameters, it is not required to know beforehand the number of actual locations of a SKU.

We added another parameter, called min_epc, defined as the minimum number of unique EPCs for a cluster to be considered. Using this parameter, we avoid the situation where a misplaced item is considered a cluster.

3) Assigning the cluster to a given fixture, group, and zone: We assign the centroid of each cluster to their closest fixture, using the Euclidean distance. However, the parameter $max\_distance$ is used to avoid assigning clusters that are too far from the closest fixture. When groups or fixtures or zones are used, the precise methodology for assigning the SKU to a group or a zone is detailed for each experiment.

IV. EXPERIMENTATION

The experiments done to assess the results of the location methodology presented in this work took place in three different phases and in two environments: a laboratory and a real store. Each of these phases had different objectives: the first phase, in the laboratory, was designed to validate the solution and compare it with the SOTA. The second phase was designed to evaluate the solution in a real environment. The third phase was designed to validate that the solution met the business requirements of the retailer.

The RFID robot used was Keonn's Robin® [29] which uses 2 Keonn RFID readers (AdvanReader-160® [30]). Each reader is connected to a set of 4 Keonn RFID antennas (Advantenna-SP11® [31]) placed on either side of the robot, as shown in Figure 2.

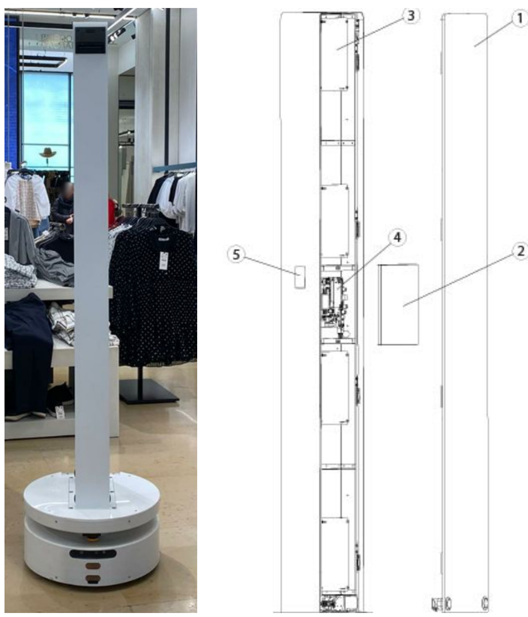

Fig. 2. The robot operating at the store, and a detail of the RFID payload. Number 3 is one of the two 4-antenna sets of and number 4 is the reader controlling the antenna set on that side.

A. First phase: Laboratory environment tests

To validate the model and compare it with previous solutions several tests were performed in a laboratory, which provides a much more controlled environment than the real store, making root cause analysis, optimization and debugging easier. Additionally, performing these tests in the laboratory allows a priori knowledge of the complete ground truth of the tags in the environment, which is required to confirm hypothesis 1. The laboratory environment consists of an empty office space in which several aisles are created artificially with 49 cardboard boxes, as shown in Figure 3. RFID tags are placed on top of the boxes without a predefined orientation. The tags represent 49 different SKUs, between 10 and 50 tags are assigned to each SKU, and the location of each SKU is considered to be the top-center of each cardboard box that contains the tags.

Fig. 3. Laboratory environment for the first phase.

Experiments are done with a variable RF power, from 30 dBm to 15 dBm, and two sessions S2 and S0, the latter will not silence the RFID tags after the reading so they will continue answering the reader.

The other parameters of the methodology are simplified to focus on hypothesis 1. Therefore, the $reading\_distance$ parameter is set to 0.5 m since the aisles are 1 meter wide. No clustering is used in this phase, as each SKU is placed in only one location. The downside of this is that possible outliers will not be filtered. However, if the method works in these conditions, we estimate that it will work better with the use of clustering.

Table I shows the results. Seven tests are performed with varying power and session parameters, each of them with three repetitions. The accuracy values presented are the average of these repetitions. Each run consisted in the robot navigating the entire space while reading the RFID tags. In the columns we show the location accuracy, the mean distance error, and the inventory accuracy.

From Table I we observe that the best location accuracy is obtained with RFID session S0 and RFID power of 20 dBm, which validates hypothesis 1. The method with these parameters achieves a location accuracy of 81%, a mean distance error of 37 cm, and an inventory accuracy of 85%. This mean distance error is in line with the previous solutions in the SOTA, which were between 28 cm and 50 cm. Moreover, as shown in [11], the use of a lower power for reading tags maximizes the location accuracy and minimizes the distance mean error. However, it also reduces the inventory accuracy. This is the reason why inventory and location must be done in separate missions with different parameters. Power values above $20dBm$ result in lower accuracy because of the increase of outlier readings, and lower power values

Test	RFID power	RFID session	Location accuracy [%]	Distance mean error [m]	Inventory accuracy [%]
1	30	S2	2.04	2.50	99.62
2	25	S2	28.57	0.92	97.5
3	25	S0	71.43	0.45	97.18
4	20	S2	57.82	0.48	83.9
5	**20**	**S0**	**80.61**	**0.37**	**84.96**
6	15	S2	69.39	0.45	40.51
7	15	S0	76.53	0.43	40.10

TABLE I
RESULTS FOR THE FIRST PHASE OF TESTS.

result in lower accuracy because not enough readings are obtained to calculate the centroid. Finally, an accuracy above 80% is considered satisfactory as the distances between centers of cardboard boxes is only around $40cm$, and all errors are due to placing the SKU in an adjacent box.

B. Second phase: first set of store experiments

The experiments of the second phase were done in a real large retail store of $1,000\,m^2$ with around $11,000$ different RFID tags located in the labels of the items exposed. The store associates divided the ground floor in 11 different zones categorizing them by the type of products and the characteristics of each zone. In addition, they identified 88 fixtures in which the products were placed.

Figure 4 shows the distribution of zones and fixtures in the store. Each SKU is assigned as explained in section III, and zones cover all the ground floor without overlapping, so each SKU is assigned to the zone containing its estimated location.

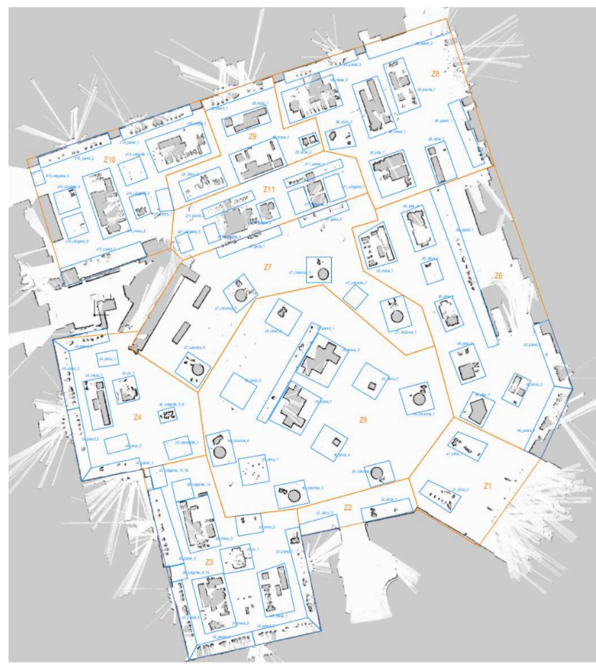

Fig. 4. Zones and fixtures of the store in the first set of tests.

The ground truth was collected manually while the robot mission was in progress. Approximately 70% of the SKUs in the store were recorded with their actual location (fixture and zone). Due to time constraints, it was not possible to record all 100% of the SKUs. The store was closed to the public while the experiments were performed.

This phase was conducted in two steps. In the first step a single run of the robot was used to adjust the DBSCAN and the $reading\_distance$ parameters. The RFID parameters were the same that provided the best results in the laboratory experiment (power of $20\,dBm$ and session S0). The filtering parameters min_epc and $max\_distance$ were not yet used in this phase. The second step was performed a week later with a newly collected ground truth but with the parameters of the first one. The results from the second step are used to evaluate the performance of the method.

The parameters $reading\_distance$, eps and $min\_samples$ are adjusted separately. First $reading\_distance$ is set to $1\ m$, then the DBSCAN parameters are adjusted. Properly adjusting these two parameters is relevant to improve the results, and they are dependent on the type of store. The parameter $min\_samples$ depends on the average and variance of the number of items that compose a SKU, and should be decreased if SKUs include few items, otherwise they will be discarded by the algorithm. Adjusting eps depends on the multi-path effects created while using RFID waves in the store. If few multi-path effects exist, eps can be decreased which will improve the accuracy of the result. Figure 5 shows the results of the process in this store. The location accuracy is the percentage of SKUs correctly placed in the expected area, the average distance error is the distance between the recorded position of the SKU and the estimated position, and the groups lost are the number of groups that have been discarded by the clustering method. The x-axis shows all the combinations of the two parameters (eps

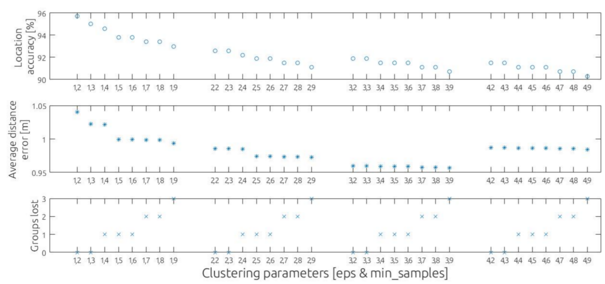

Fig. 5. Analysis of the performance as a function of the parameter's eps and $min\_samples$. The values shown on the x-axis are the different pairs of eps, $min\_samples$ values that where tested.

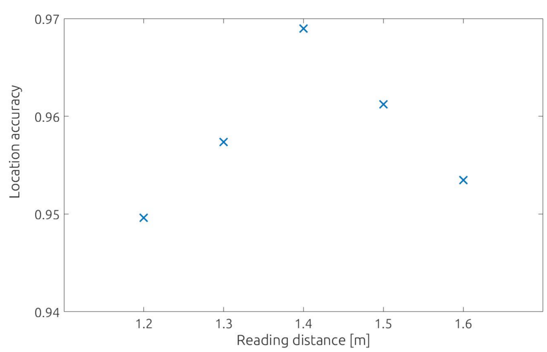

Fig. 6. Zone location accuracy obtained as a function of the $reading\_distance$.

and $min\_samples$) that were tested. We observe that best performance is achieved when $eps = 3\ m$ and $min\_samples = 3$.

On the following procedure, we try to find the best value for the $reading\_distance$ parameter after having determined the optimum values for eps and $min\_samples$. Figure 6 shows the zone location accuracy values obtained as a function of the $reading\_distance$. We observe that the maximum accuracy is achieved with $reading\_distance = 1.4\,m$.

In the second step, another run of the robot is performed with the previously fixed parameters: RFID power equals to $20\ dBm$, RFID session S0, $reading\_distance = 1.4\ m$, $eps = 3\ m$, and $min\_samples = 3$. The results obtained are shown in Table II, we can observe that both fixture and zone location accuracy values are above 90% which was the lowest location accuracy value accepted by the retailer. We observe that in comparison to the experiments done in the laboratory environment, the mean distance error increases ($73\ cm$) due to the complexity of the environment. These results validate the second hypothesis as although the complexity of the environment has drastically increased the simplified model managed to maintain accuracy figures above 90% with a reasonable value of mean distance error. Since no similar results were found in the SOTA, no results can be compared at this point.

C. Third phase: second set of store experiments

One year after having achieved successful results in the second phase of experiments, some changes were introduced in the model to better adapt to the requirements of the retail industry. A new definition of fixtures is used, specifically, fixtures are defined as points in the 2D plane, instead of polygons, which increases the maintainability of the solution. Also, the retailer gave us insights about the store to add two more filtering parameters. Finally, the assignment of SKUs to groups of fixtures and zones is done through the fixture assignment. The group and zone to which each fixture belongs is part of the ground truth, therefore, when a SKU is assigned to a fixture it is also automatically assigned to its group and zone. Therefore, the group and zone location accuracies are now dependent on the fixture location accuracy.

Therefore, together with the retailer, we redefined the store characteristics. First, 10 zones were defined instead of 11 due to changes in the store's layout. Second, the number of fixtures was increased from 88 to 183, with all of them being represented by points as it can be seen in Figure 7. The main reason for this increase is that a single fixture for the phase 2 may now be considered a group of fixtures, defined as several fixtures within a radius of $50cm$. In any case, due to changes in the layout, there were a total of 122 groups of fixtures. Therefore, in this last phase, the store components were fixtures, groups of fixtures and zones.

The retailer noticed that the number of SKUs placed in more than one spot in phase 2 was larger than expected. According to our study on phase 2, this might have happened due to misplaced items or staff operations. Nevertheless, the new introduced set of parameters were filtering parameters $min\_epc = 3$ and $max\_distance = 2m$. In this case the retailer was not interested in finding misplaced items, an information that could be obtained by setting $min\_epc = 1$.

Before initializing the test, we record the coordinates of the location of each fixture and the SKUs in it. This ground truth did not contain the specific coordinates of each SKU, as the retailer was not interested in the mean distance error.

The optimization of parameters is not performed at this phase because we want to prove that the method can work in different environments without the need of being adapted at each scenario.

It is important to recall that experiments done in phase 2 and phase 3 were in the exact same retail shop. However, during this year gap, considerable changes of the store layout were introduced making it a fairly different environment for the robot. The parameters and

Total SKUs	Identified SKUs	SKU inventory accuracy [%]	Zone location accuracy [%]	Fixture location accuracy [%]	Mean distance error [m]
379	366	96.6	95.9	92.1	0.73

TABLE II
SUMMARY OF RESULTS FOR PHASE 2 OF THE EXPERIMENTS

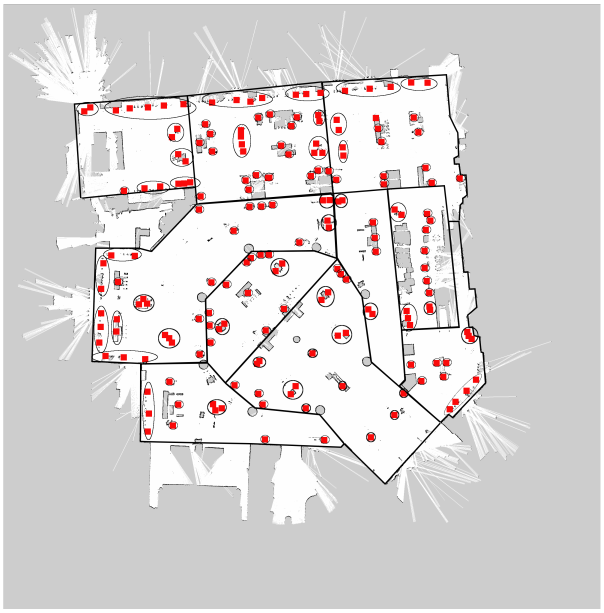

Fig. 7. Layout of the store for the third set of experiments. The zones, the fixtures (red squares) and the groups of fixtures are shown.

their value were the following: RFID power $= 20\, DB$, RFID session $= S0$, $reading\_distance = 1.4\ m$, $eps = 3\, m$, $min\_samples = 3$, $min\_epc = 3$ and $max\_distance = 2\, m$. The results are shown in Table III.

From Table III we observe that the number of SKUs found and the zone location accuracy results are similar to those in phase 2. However, the decrease in group location accuracy and fixture location accuracy is about 13 and 24 points respectively if they were to be compared with the fixture location accuracy of phase 2. There are several reasons that can explain this. The first reason is that the number of fixtures and groups of fixtures defined is much higher, the increase is more than a 100% for the fixtures and almost a 50% for the groups of fixtures. Logically, placing different fixtures closer than the mean distance error is clearly affecting the results. Additionally, the zone location accuracy and the group location accuracy are linked to the fixture location accuracy. Therefore, if the fixture assignment is wrong the other two may easily follow. Taking this into account, having a good zone location accuracy and a worse fixture location accuracy shows that our mean distance error is probably above $50\, cm$ but not much higher, as the zone location accuracy is kept as high as in phase 2. Another reason is using points instead of polygons to represent fixtures. For instance, a table of $1\, m^2$ is represented by a point in its center, and a few centimeters from the table there is another fixture, for instance a rack, also represented by a point. In such a case, it is possible that an SKU on top of the table is actually closer to the point representing the rack than the point representing the table.

These results can not directly be compared with the previous state-of-the-art since no previous work was evaluated in terms of fixture, group, or zone location accuracy. However, given the results and the store layout, we can confirm that the mean distance error is in line with the second phase of experiments and hence, also with the previous works.

V. CONCLUSION

The solution presented in this paper uses a simplified range-free RFID model and location method for RFID-based robots. The solution is based in two hypotheses. The first one is that for RFID tag location missions, RFID parameters must be different from those used in inventory missions, as a result unwanted distortions or noise signals are mitigated in the cost of lower detecting range. As anticipated in [32], the closer the robot is to the tag, the better the location accuracy. The second hypothesis is that a simple method can have equal or better location accuracy than a complex method. The strong interaction between the RF waves and the environment implies that any method based on a model of such interaction will not perform well when the environment changes. Hence, a simple method, less dependent on the environment, can adapt much better to these changes. Even if the presented model is much simpler than previous works in the state of the art (e.g. [15], [11]), it achieves similar or better results in comparable environments.

Following the requirements and needs of the retail industry, two simplifications are applied to the location problem. The first one uses the fact that, in most applications, the location of a single tag will not be as relevant as the location of an entire SKU. By grouping items, we can lower the RFID power to get more accurate readings without losing data due to not detecting all the RFID tags. The second one consists in providing the SKU locations as relative positions of the store such as a fixture, a group of fixtures, or even a zone in the store. Cartesian coordinates do not provide practical

Total SKUs	Identified SKUs	SKU inventory accuracy [%]	Zone location accuracy [%]	Group location accuracy [%]	Fixture location accuracy [%]
374	371	99.2	96.8	79	68

TABLE III
SUMMARY OF RESULTS FOR PHASE 3 OF THE EXPERIMENTS

information for retailer business applications. This means that the method should not focus on minimizing the mean distance error, but should focus on maximizing the location accuracies instead.

The algorithm has been tested in a real retail store of $1,000\ m^2$ and with around $11,000$ unique tags. This represents a breakthrough with respect to previous solutions from the SOTA, where they were only tested in laboratory environments or mock stores. We have shown that when moving the solution from the laboratory to the real store and focusing on the business needs, the location accuracies obtained are lower, as expected. However, with the presented solution our results are in accordance with the SOTA, and within the expectations of the retail industry. Moreover, our results show that it is possible to locate groups of items with high accuracy on fixtures that are separated more than the mean distance error which in our case is $28\ cm$ in the laboratory environment and $73\ cm$ in the real store. We show that in this case, we can get location accuracies above 90%.

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