Relative Tag Locations based on Time-Differences in Read Events for Practical Applications

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***Abstract*—Over the course of recent years, Radio Frequency Identification (RFID) technology has been applied in many different business domains to solve, for example, the problem of monitoring stock. However, keeping track of the exact (geo-)locations of items in stock is still an open problem. This is particularly problematic for logistics, retail as well as warehouses, where information about relative locations of items can drastically increase staff efficiency and business process efficacy. In this paper we set out to tackle the problem of determining relative distances between RFID tags based on time-differences in read events, without the introduction of additional hardware. To that end, we first present a novel approach, which leverages time-based distances for inferring relative RFID tag distances. We then qualitatively and quantitatively evaluate our proposed approach by inferring tag locations for different experimental setups, and comparing our results to ground truth data. Finally, we present and discuss the results of a case study, which emulates real-world conditions of retailers using RFID technology for stock taking. Our results show that time-differences in read events are suitable for calculating and approximating the relative position of RFID tags in several setups. We strongly believe that the results presented in this paper represent a novel and important step towards new approaches, which leverage time-differences in read events for inferring relative tag distances.**

***Index Terms*—RFID, localization, multidimensional scaling**

I. Introduction

The *Radio Frequency Identification* (RFID) technology is widely adopted and used in a variety of different applications in retail [1], logistics [2], security [3], and health care [4], among others. One of its main features is the ability to track and identify objects over several meters, without direct line-of-sight, which builds a solid foundation for practical applications, such as stocktaking. Further, the costs of these RFID-based systems are relatively low, which make them particularly interesting for inventory management in logistics, retail, and warehouses.

Problem. However, while RFID-based inventory management is able to solve the problem of monitoring which items are in stock at any given point in time, keeping track of the exact (geo-)locations of items is still an open problem [5]. In general, staff of retail stores and warehouses conduct stocktakes using mobile RFID readers, which collect identifiers (i.e., the Electronic Product Code or EPC) of tagged products and the timestamps of when each individual tag was read. While this data suffices for taking stock, the exact (geo-)location of the read RFID tags is still unknown. In practice, this means that common tasks, such as the picking of items requested by customers become tedious and time-consuming, especially if items are not in their designated locations.

Such misplaced articles can lead to financial losses, as customers and store or warehouse staff are unable to (quickly) retrieve these articles. Raman et al. [5] presented a study, where they showed that customers of a retail store could not find 16% of items as they were misplaced (e.g., on the wrong shelf) in the store. Finding such misplaced items on the sales floor is time-consuming, even for RFID-based inventory management systems, as they mostly lack the ability to locate RFID tags.

The localization of misplaced items usually requires additional hardware [6] (e.g., antennas or high-power RFID readers). An approach which circumvents this requirement [7], leverages the signal strength of RFID read events to estimate the distance to a tag. However, this approach suffers from several limitations. First of all, the reader needs to be in close proximity to the tag in the first place (i.e., UHF RFID tags commonly used in retail settings can usually only be read over the range of a few meters using standard mobile RFID readers). Second, read signals are also inaccurate due to the fluctuation of the signal strength of RFID tags. Third, localization via this approach can only be performed for one RFID tag at a time.

Approach. In this paper we set out to tackle the problem of determining relative distances between RFID tags based on time-differences in read events, without the introduction of additional hardware. Specifically, we leverage information that is already generated during stocktakes, such as the timestamp and the received signal strength indication (RSSI) of every read event, which we use to infer relative (temporal) distances between RFID tags. As read events can be very noisy (e.g., a particular RFID tag can be read multiple times due to signal reflections, even though it is not in focus), we preprocess our data to estimate the point(s) in time when an RFID tag was in focus of the mobile reader. Based on this information, we can infer temporal distances between RFID tags, which we map into two-dimensional space using *Multidimensional Scaling* (MDS). As a result, we obtain relative geospatial information (i.e., relative distances between RFID tags), which allows us to locate misplaced items by relating them to the relative position of other items.

Contributions. This paper is an extended version of our previous work [8], where we presented two approaches to determine relative locations of RFID tags, based on the timestamps and RSSI values of read events. Specifically, we used temporal distances between read events, which we map to estimated geometrical distances using MDS. We extend our previous work by conducting a case study with adapted evaluation methods, which represent a more realistic and challenging setup for our approaches. The key contributions of our work are:

- First, we present a novel approach to leverage time-differences between read events for inferring relative RFID tag distances.
- Second, we further extend our approach by incorporating RSSI values into the calculation of geometrical distances.
- Third, we conduct a case study to better reflect real-world scenarios for calculating relative distances of RFID tags using time-differences.
- Fourth, we publish the data[1] used in our experiments to enable researchers not only to reproduce but also develop additional extensions to our presented approaches.

We strongly believe that the results presented in this paper represent a novel and very important step towards leveraging the information of temporal distances for inferring relative RFID tag distances.

II. Related Work

In this section we highlight related work on positioning algorithms (see Section II-A) and indoor location systems (see Section II-B).

A. Positioning Algorithms

Liu et al. [9] analyze different schemes for location estimation. Specifically, triangulation/trilateration and proximity are applicable to our setup under certain circumstances.

Triangulation/Trilateration. Both, triangulation and trilateration, are methods to position an object using three reference points. While the former uses the angles between an object and reference points to estimate the position, the latter takes the distances between an object and reference points into account.

The distances for the lateration approach are typically derived from measurements such as time-of-arrival (i.e., the one-way propagation time of a signal to a receiver) [10], [11], or received signal strength [10], [12]. For each of the reference points, the distance approximation creates a circle with potential locations of the tag. A basic trilateration approach would be to calculate the intersection of the circles to determine its position. In contrast to trilateration, triangulation uses the angle-of-arrival (i.e., the angle from which the signal arrives at the receiver) instead of the distances to calculate the positions [13].

In contrast to work on trilateration, we only consider one RFID reader, scanning many passive tags. As the reader is the only active device and the location of the reader is unknown during our experiments, triangulation or trilateration methods are not applicable to our problem.

Proximity. Proximity methods are usually implemented with a dense grid of antennas. If a tag is in the range of an antenna (i.e., the reader detects the tag), it is considered to be collocated to this antenna. If multiple readers detect the tag, the antenna with the highest signal strength is selected.

Song et al. [14], for example, use a proximity-based algorithm to locate materials on construction sites with 20 reference tags arranged in a dense grid, and an RFID reader, which also leverages GPS to determine its own position. Other location systems, which use proximity methods are proposed by Simic and Sastry [15] and He et al. [16].

In this paper we build upon the underlying idea of proximity based location algorithms to infer relative distances between RFID tags. However, in our setup we only use a single mobile RFID reader and passive RFID tags, without the reader knowing its actual position.

B. Indoor Location Systems

Hightower and Borriello [17] provide a brief introduction into the problem of indoor localization and provide a taxonomy of location systems.

Further, they discuss different techniques for localization, such as infrared (*Active Badge* [18]), ultrasound (*Active Bat* [19] and *Cricket* [20]), and computer vision (*Easy Living* [21]).

RFID-based Location Systems. The *SpotON* system proposed by Hightower et al. [22] was one of the first location systems relying on RFID technology. However, instead of using conventional RFID tags they use custom-built active RFID tags, specifically designed for localization, with the primary requirement of being able to provide exact signal strength measurements. In addition to the custom RFID tags, they use multiple stationary RFID readers, distributed over space, reporting signal strength of detected RFID tags to a central server, to triangulate the position of the RFID tag.

Alippi et al. [23] propose a stochastic approach that also requires multiple readers to cover the area under investigation. Several other approaches exist, which usually require either a setup of multiple readers or antennas [6], [24], [25].

The LANDMARC system [26] uses a similar method, but instead of expensive readers as base stations, they work with active RFID tags as reference tags. The number of reference tags to use and where to position them has to be decided based on the environment for the localization. In their experiments, the authors used a dense grid of reference tags, where the position of an object is calculated as a weighted sum of the coordinates of the k nearest reference tags.

Saab and Nakad [27] estimate the position of a vehicle or a person in an indoor environment. More specifically, they use RFID technology and track an RFID reader along a path that has passive RFID tags next to it. They store the positions of

[1] https://github.com/DetegoDS/tag_localization

these tags in a database and estimate the distances between the reader and the tags using the RSSI of the backscattered signals. Subsequently, they use the estimated distances to calculate the position of the reader via trilateration.

Joho et al. [28] propose a probabilistic sensor model that can be trained using unsupervised learning. The sensor model specifies the likelihood to get a measurement $\mathbf{z}$ given the orientation $\mathbf{x}$ of the antenna and the location $\mathbf{l_g}$ of tag with ID g. This probabilistic model $p(\mathbf{z}|\mathbf{x}, \mathbf{l_g})$ can be learned from data, and using Bayes' rule the posterior $p(\mathbf{l_g}|\mathbf{x}, \mathbf{z})$ can later be evaluated. However, due to the vast number of combinations between antenna orientations and locations of the tag, this calculation is unfeasible for practical applications. Therefore, Joho et al. [28] use locations relative to the antenna rather than absolute locations. As a result, to be able to localize tags using this model, the position of the reader has to be known at all times. In their setup, they drive a shopping cart that has the RFID reader and a laser range scanner mounted on it. They use laser-based FastSLAM [29] to localize the antenna and estimate the distances of the tags afterwards.

In contrast to existing work, our approach builds upon the premise that we can infer relative RFID tag locations only by leveraging timestamps and RSSI values of read events. Note that all approaches based on RSSI values are fundamentally subject to multipath propagation [30], which potentially affects reading performance and thus, the overall quality of the obtained results.

III. Methodology

A. Data Collection & Preprocessing

For all experiments described in this paper, we store (i) the Unix timestamp in milliseconds, (ii) the EPC encoded on the RFID tag, and (iii) the RSSI in dBm of the received signal for each read event. The amount of data that we collect varies between experiments and depends on the duration of the experiment, as well as the amount and frequency of read RFID tags.

For data preprocessing, we first remove all read events of RFID tags, which are not part of the set of tags used in our experimental setup. Next, we scale timestamps for each experiment to start at $t = 0$, while each following entry corresponds to the number of elapsed milliseconds since the beginning of the experiment. Note that we publish our dataset[2] to support the development of new approaches that build upon the presented methodology.

B. Estimating Relative Tag Distances

For estimating relative tag distances we first introduce a naïve approach—Temporal Distances—which leverages only the timestamp of each RFID tag read event. Furthermore, we present an additional approach—RSSI Peaks—which also leverages RSSI values, targeted towards reducing noisy reads.

Temporal Distances. For our first approach we solely leverage timestamps of RFID tag read events. Given that distance is a function of speed and time, we assume that the former is constant, so that distance equals time scaled by constant speed. The relative distance between pairs of RFID tags is determined by the minimum duration (i.e., elapsed milliseconds) between all read events of these tags (see bottom part of Figure 1). We see this setup as a very naïve baseline, against which we can measure other approaches that include additional information.

[2]https://github.com/DetegoDS/tag_localization

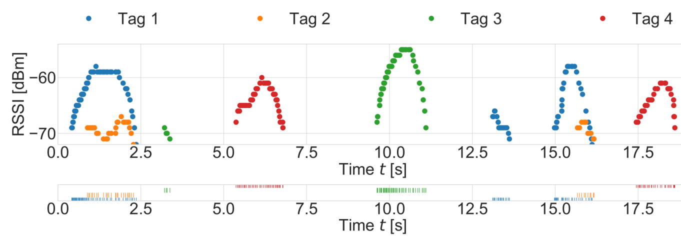
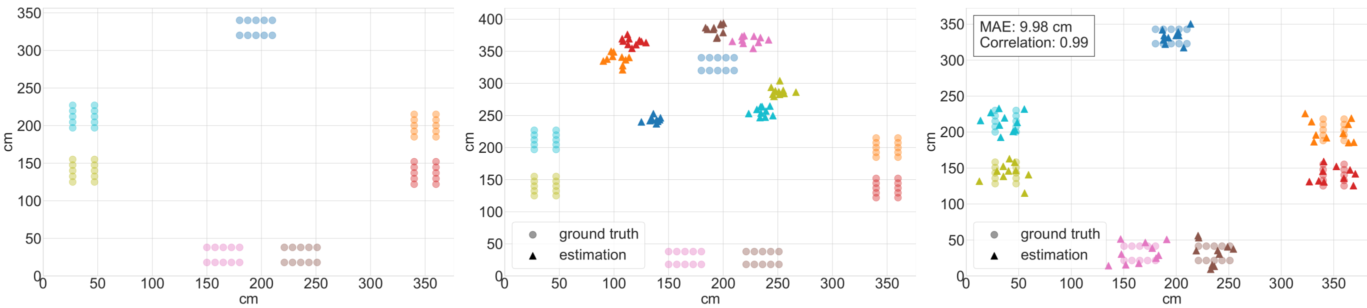


Fig. 1: **Temporal Distances Illustration.** This figure illustrates the calculation of temporal distances for RFID tag read events. **Bottom:** We have highlighted the read events of 4 different RFID tags (vertical bars) over time (x-axis), which is the foundation for our *Temporal Distances* approach. For this approach, we calculate minimum pairwise differences between the timestamps of all read events of the different RFID tags. **Top:** We show the corresponding RSSI values (y-axis) over the same period of time (x-axis), illustrating our *RSSI Peaks* approach. In contrast to the previous method, we first group RFID tag read events into segments. In this case, we set the segment separation threshold $\Delta = 1,000$ milliseconds. For example, for Tag 1 (blue), we would obtain 3 segments (from 0 to 2.5, 13 to 14, and 15 to 16 seconds). Due to our stray read filtering (each segment has to contain at least 5 read events), we would only obtain one segment for Tag 3 (green) (from 9 to 11 seconds), as the other segment (starting at $t = 3$ seconds) only contains 4 read events. Finally, we select the timestamp corresponding to the center of RSSI maxima per segment and again calculate minimum pairwise differences only between the timestamps of these peak RSSI values to determine temporal distances.

Temporal Distances and RSSI Peaks. In contrast to Temporal Distances, we include the RSSI of each read event in our calculation of relative distances. Specifically, we are interested in approximating the actual point in time when the mobile RFID reader points directly towards any given tag; assuming best reading performance. In theory, this should correspond to the point in time when the RSSI value reaches its maximum for a given tag. As depicted in the top of Figure 1, we receive smaller RSSI values for a tag as it enters the reading field of the reader. The value increases until it reaches its peak when both the reader and the RFID tag are aligned (i.e., the reader points at the RFID tag), and decreases until it leaves the reading field again. Note that several factors can influence the magnitude of the RSSI values, such as RF power or orientation and placement of RFID tags (e.g., many other nearby RFID tags, or metal surfaces).

To calculate temporal distances leveraging RSSI peaks,



(a) Ground Truth (b) Estimation after MDS (c) Estimation after MDS & Procrustes Analysis

Fig. 2: **Methodology.** The figures depict the different steps of our methodology. First, we generate a ground truth dataset for each layout, which we infer from empirical distances between our RFID tags (Figure 2a). Then, we apply MDS on the temporal distances between our RFID tags (Figure 2b), which yields results invariant to scale, translation and rotation. After applying Procrustes analysis (i.e., scaling, rotating, flipping and translating) on the estimated coordinates (Figure 2c) we calculate Mean Absolute Error between RFID tag coordinates for the controlled lab experiments. Additionally, we calculate correlation between the estimated temporal and empirical distances of our RFID tags.

we first partition the RSSI sequences for each RFID tag by time-differences larger than a threshold Δ between read events (i.e., segment separation threshold in milliseconds). Hence, we obtain several segments per RFID tag, for which we determine the timestamp of the RSSI peak values (i.e., center of maxima), which we then use for calculating pairwise minimum differences, instead of using every single read event. Furthermore, we remove segments with fewer than 5 read events to minimize noise in our data (i.e., stray read filtering). Note that our approach is subject to multipath propagation [30] and results might suffer from noisy RSSI values. At this point, we leave further investigations into noise minimization open for future work.

C. Postprocessing

To be able to evaluate our proposed approaches, we first generate a ground truth for each of our experiments, consisting of coordinates for each tag in two-dimensional space (see Figure 2a). We then apply MinMax scaling individually on the x- and y-coordinates to obtain the scaling factors, which are the differences between the minimum and maximum values in each dimension. These scaling factors are later applied on the estimated distances so that we can compare them to the placement of the tags in the ground truth.

Next, we apply metric MDS [31], [32] on our estimated RFID tag distances to obtain estimated coordinates for each individual RFID tag. Specifically, MDS is a method for visualizing data based on similarity or dissimilarity measurements, referred to as proximities. Given the proximity proxies of a set of points, MDS finds a geometrical representation of these points so that the pairwise distances match the proxy measurements as close as possible (see Figure 2b).

We then normalize the estimated coordinates using MinMax scaling and receive coordinate values in the range of 0 and 1. To evaluate our results we translate the estimated and ground truth coordinates, such that the center of mass of both sets of coordinates are in the point of origin. However, as the solutions of MDS are invariant with respect to rotation we additionally apply Procrustes analysis [33] to determine the required rotation which minimizes the error to the ground truth. Finally, we apply the ground truth scaling factors on all coordinates.

IV. Controlled Lab Experiments

We start by conducting controlled lab experiments to measure the impact of several scenarios on our approach. To that end, we control different experimental parameters such as the walking patterns or the placement of the RFID tags (layout).

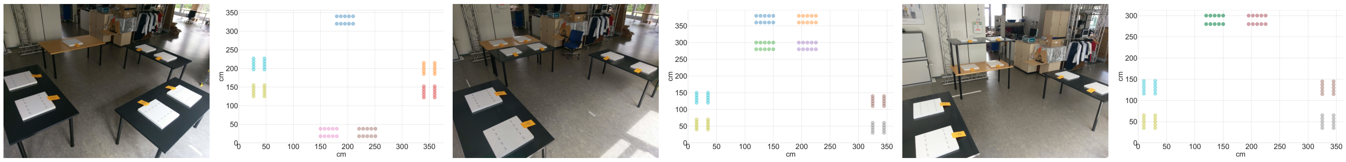
A. Setup & Evaluation

We conduct all controlled lab experiments in a large room, containing several wooden and metal constructions, which largely represent a real-world setting with high potential for noisy reads. Further, we use a mobile *ZEBRA RFD8500* RFID reader with maximum power level (30 dBm) configured to use Session 0 in all presented experiments.

For our experiments, we attach RFID tags in groups of ten on polystyrene panels, where each panel simulates a group of products of the same class. We then place the panels on wooden tables and arrange them in different layouts. Note that RFID tags with the same color in our visualization are placed on the same panel.

Two-Dimensional Layout (2D). For this layout we arrange four tables in a rectangular shape, and distribute seven panels (70 RFID tags) across them, with one table only containing a single panel. Figure 3a shows a photograph of the setup on the left, and the corresponding ground truth dataset on the right.

Asymmetric Two-Dimensional Layout (Asymmetric 2D). To evaluate if we can use temporal distances to recover depth information, we adapt the 2D Layout by adding an additional panel (i.e., 80 RFID tags in total) and putting one table behind another one (i.e., having an asymmetric layout with two panels



(a) Two-Dimensional Layout (b) Asymmetric Two-Dimensional Layout (c) Three-Dimensional Layout

Fig. 3: **Layout of Experiments.** The figures depict the layouts (left) and their corresponding ground truth datasets (right), which we use to test our proposed methodology under different conditions. Figure 3a depicts a Two-Dimensional Layout, with all panels aligned in a rectangular shape. The second layout, depicted in Figure 3b, shows the Asymmetric Two-Dimensional Layout, where two panels are put behind two other panels. Finally, Figure 3c depicts the Three-Dimensional Layout, where two panels are stacked upon two other panels. Note that due to the two-dimensional representation of our ground truth, panels are put on top of each other, resulting in overlapping markers in Figure 3c.

in the front and two in the back). See Figure 3b for a picture of the setup and the corresponding ground truth.

Three-Dimensional Layout (3D). In contrast to the previous layouts, we are now interested in measuring the impact of differences in height on temporal distances. To simulate this setup, we use 8 panels (80 RFID tags) and stack two tables—with two panels each—on top of each other (see Figure 3c). In any two-dimensional setting, RFID tags placed on top of each other will overlap in coordinates, which is also true for our corresponding ground truth dataset. Note that our ground truth and estimated coordinates for this layout are in two-dimensional space.

For every layout, we perform multiple experiments (see # iter in Table I). In particular, we repeat all 2D Layout and the Asymmetric 2D Layout experiments three times, doing one iteration, two iterations, and four iterations, while we only conduct one and two iterations for the 3D Layout, as four iterations perform similar to two iterations in all previous experiments. Note that once we start one experiment, we activate the RFID reader and continuously scan for RFID tags, while walking along the tables in a clockwise, circular motion (i.e., a circular walk; see Figure 4 for a schematic of the Circular Walk Layout and Table I for an overview of the characteristics of the performed experiments).

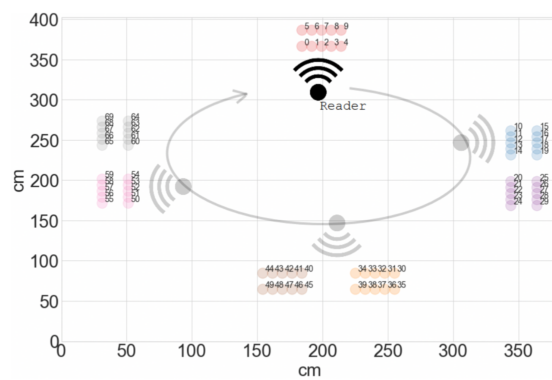


Fig. 4: **Circular Walk Reading Pattern.** For every different layout (i.e., 2D, Asymmetric 2D and 3D), we try to read RFID tags following always the same circular path (see arrow) for multiple repetitions (i.e., iterations).

TABLE I: **Circular Walk Dataset.** For each layout we conduct several experiments (# iter, defining how often we follow the circular walk). We perform all experiments three times and list the median number of read events (# Events), the median number of read events by tag (# Events per Tag) and the median duration (Duration) of the experiment in the corresponding row. Further, we depict the median number of read RFID tags (Tags Read) and their corresponding percentage of overall RFID tags read.

Layout	# iter	# Events	# Events per Tag	Duration	Tags Read
2D	1	2,769	41	20s	66 (94%)
	2	6,010	85	46s	68 (97%)
	4	8,841	126	86s	70 (100%)
Asymmetric 2D	1	1,486	26	22s	43 (53%)
	2	3,710	46	41s	58 (72%)
	4	4,718	62	80s	61 (76%)
3D	1	2,334	36	22s	65 (81%)
	2	5,054	63	48s	75 (93%)

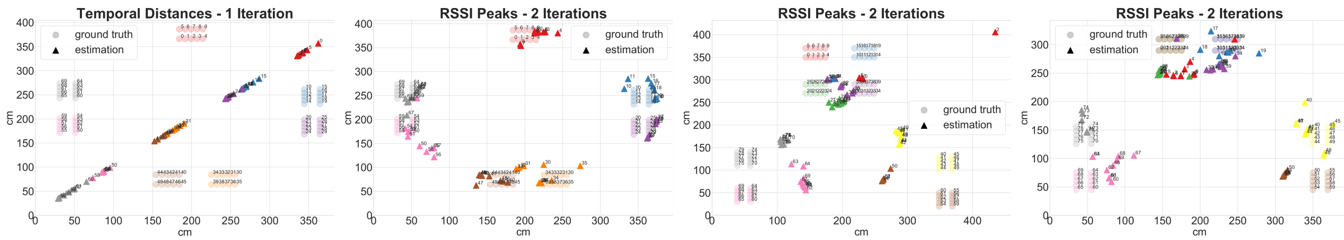
We evaluate our experiments based on the obtained ground truth data, which allows us to calculate Mean Absolute Error (MAE) in Euclidean distance. For n tags, we calculate the MAE of the coordinates as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i}^{n}\|\mathbf{c}_i - \hat{\mathbf{c}}_i\|, \tag{1}$$

where $\|\cdot\|$ denotes the Euclidean distance, and $\mathbf{c}_i$ and $\hat{\mathbf{c}}_i$ the ground truth and the estimated coordinate vector of the i^{th} RFID tag. Note that we neglect RFID tags that were not read during our experiments for the calculation of MAE.

Additionally, we calculate Pearson correlation coefficient between the ground truth and estimated distances. High correlation coefficients for our experiments indicate similar (relative) distances between the RFID tags in the ground truth and estimated distances.

Note that we set the segment separation threshold for all controlled lab experiments to $\Delta = 1,000$ milliseconds, so that



(a) Single Iteration (b) Multiple Iterations (c) Asymmetric 2D Layout (d) 3D Layout

Fig. 5: **Circular Walk Results.** This Figure depicts the results for a selection of our circular walk experiments. When only conducting a single iteration, without reading panels of RFID tags multiple times, our proposed methodology maximizes the distance between the first and the last read panel (see Figure 5a). Once information between the distance of the last and the first panel is available (i.e., for 2 and more iterations), positioning of the RFID tags works within reasonable error margins (see Figure 5b). Our method produces a larger error when trying to reconstruct depth information (see Figure 5c) as we ignore relative differences of RSSI values between RFID tags read close to each other. In contrast, when reading RFID tags that are positioned on top of each other (see Figure 5d), we achieve better results, as RSSI values are not needed (in two-dimensional space) to position RFID tags.

only roughly 5% of all observed time-differences introduce a new partition.

B. Results & Discussion

Two-Dimensional Layout. As depicted in Figure 5a, our approach struggles to correctly infer relative distances between RFID tags after only a single iteration (i.e., one round, without reading any of the starting RFID tags at the end of the experiment again). Once we add the missing temporal distances between the last and the first panel (e.g., by continuing the circular walk and reading the first panel twice), our proposed approach manages to group RFID tags close to their actual location in the ground truth (see Figure 5b). Specifically, we achieve an MAE of 28.36 cm for the Temporal Distance approach with the 2D Layout after two iterations, and a correlation coefficient of $r = 0.94$ (see 2D Layout in Table II). The RSSI Peaks approach performs similar with an MAE of 29.18 cm after four iterations and $r = 0.95$.

TABLE II: **Circular Walk Results.** In this Table we describe the results of our three layouts (rows), the different numbers of iterations (# iter) and the two implemented approaches (Temporal Distance and RSSI Peaks columns) in the form of MAE and the correlation coefficient r. We calculate MAE between the coordinates of our ground truth and estimated RFID tag coordinates, and the correlation coefficient between the temporal distances and the distances in our ground truth.

Layout	# iter	Temporal Distance		RSSI Peaks	
		MAE	r	MAE	r
2D	1	126.80	0.75	101.96	0.73
	2	28.36	0.94	36.08	0.92
	4	28.65	0.94	29.18	0.95
Asymmetric 2D	1	108.11	0.65	103.08	0.65
	2	88.92	0.78	86.86	0.79
	4	89.91	0.64	94.02	0.63
3D	1	91.57	0.78	88.18	0.76
	2	46.91	0.74	40.92	0.83

Discussion. Due to the underlying mechanisms of how we infer distances, it is detrimental for all our approaches that we create overlaps between tags that we have read at the end and the start of each experiment. Without these overlaps, our proposed methodology maximizes the distance between the first and last group of read RFID tags, resulting in a diagonal line in two-dimensional space, as depicted in Figure 5a. However, while MAE between the estimated and ground truth coordinates of our RFID tags is rather high (126.8 cm), we can already clearly distinguish the different panels (see colors of estimated RFID tag coordinates). If we provide distance information between the last and the first panel (i.e., after two iterations), we can infer the circular layout from our data which now allows us to position RFID tags closer to their actual positions, with an MAE of 28.36 cm.

Additionally, we increase the correlation coefficient between our ground truth and estimated RFID tag distances from $r = 0.75$ to $r = 0.95$. This means that we can observe similar (relative) distances between our RFID tags in the ground truth and the estimated distances.

Asymmetric Two-Dimensional Layout. After only one iteration we obtain an MAE of 108.11 cm and a correlation coefficient of $r = 0.65$ for our Temporal Distances approach. In contrast to our 2D Layout, when running the experiment for multiple iterations, MAE for Temporal Distances improves by 19.19 cm to an error of 88.92 cm with a correlation coefficient of $r = 0.78$, with the RSSI Peaks approach performing similarly. When inspecting Figure 5c, we can see that some RFID tag panels of our estimated tag locations are still easily distinguishable (e.g., yellow, brown, grey, and pink), while the exact positions of the panels placed behind each other (i.e., the purple, green, blue, and red panels) appear to be harder to reconstruct with our approach.

Discussion. As we calculate temporal distances only based on the difference in time between read events of the corresponding RFID tags, reconstructing depth-information for this layout is very hard. Specifically, when standing in front of the four shifted panels (i.e., purple, green, blue, and red), we receive read events of RFID tags from all four panels, which is also visible in Figure 5c. One solution to better tackle this problem could be to add an additional stream of information, such as relative differences in RSSI of all RFID tags read around the same time, to properly infer depth information for the calculation of relative distances. However, given that RSSI is very unreliable, further research and experiments are warranted to validate if and to what extent results for this setup can be improved. Further, we can see from our experiments that more than two iterations do not help to improve the results, most likely due to the introduction of additional noise.

Three-Dimensional Layout. We achieve the best MAE (40.92 cm) and correlation coefficient ($r = 0.83$) for this layout after two iterations with the RSSI Peaks approach. As depicted in Figure 5d, we can detect the different RFID tag panels. As outlined in the description of this layout, there are two RFID tag panels (i.e., green and red as well as blue and purple) that overlap each other in this setup. According to our results, we can place these two clusters in very close proximity in our ground truth.

Discussion. Due to the way our approach handles differences in height, we can achieve better results for MAE (46.91 cm) and correlation coefficients (r=0.83) than for the Asymmetric 2D Layout, which also indicates that differences in height appear to be less problematic for inferring temporal distances than differences in depth.

V. Case Study

The results of our controlled experiments show promising first results, as they allow us to infer RFID tag positions with an MAE of 28.36 cm (see Section IV-B). Nevertheless, due to the inherent limitations of how our approach calculates tag distances, and also from a practical point of view, we are more interested in identifying relative locations between individual RFID tags as well as groups of RFID tags. As highlighted in Section IV-B, we are able to detect groups of items that are also close to each other in the ground truth throughout all of our experiments, which is evident by the correlation we achieve in our first experiments.

However, compared to real-world scenarios, our previous setups and layouts of our experiments are rather constrained, as the stock of a typical brick-and-mortar store consists of tens of thousands of items with sophisticated store layouts as well as predetermined product placements. To further evaluate the utility of our presented methodology, we have created a setup that better reflects real-world conditions, by (i) including shelves and tables (see Figure 6b for a schematic), (ii) using an order of magnitude more tags, and (iii) following no predetermined walking patterns.

A. Setup & Evaluation

Similar to our previous experiments, we are using the same RFID reader. However, the panels are now made of cardboard and contain 25 to 36 RFID tags each (see Figure 6a) to simulate stacks of the same product. Further, we conduct our experiments in Session 0, as well as in Session 1.

For our case study, we have distributed a total of 27 panels (colored circles in Figure 6b), holding a total of 915 RFID tags, across 7 tables (black dotted rectangles in Figure 6b) and 5 shelves (black solid rectangles in Figure 6b; overlapping panels in shelves are plotted with a small jitter for visualization purposes).

For our case study we tasked three participants to read as many RFID tags as possible when walking through our case study setup. Note that the only constraint imposed on our participants was the usage of the same starting position (i.e., at panel 27 in the bottom left of Figure 6), which is not a requirement of our approach, but allows us to easily compare the results of the different experiments. Similar to our previous experiments, we collected the RFID read events of each participant while walking through our setup, with the objective of reading as many tags as possible. In contrast to our previous experiments with fixed walking patterns, each participant selected a path based on personal intuition and tried to read RFID tags as efficiently as possible. In total, we asked three different individuals to repeat our experiment three times, resulting in a total of 9 iterations (see Table III).

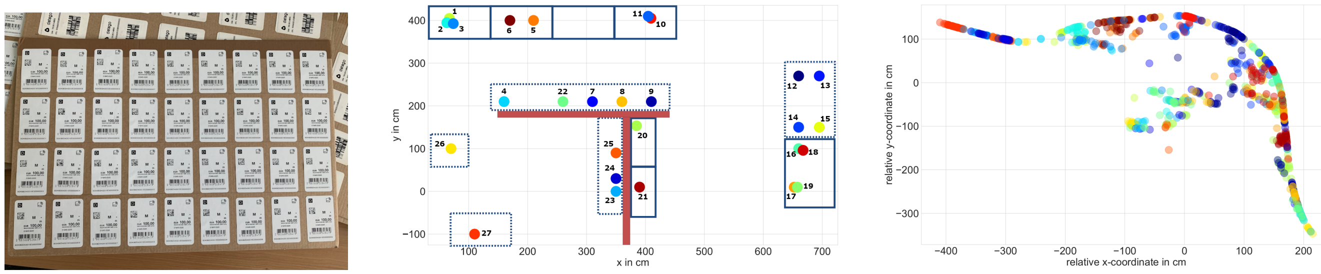
Due to the large number of RFID tags in our case study setup, the construction of a ground truth dataset based on coordinates of individual RFID tags was not feasible. Instead, we use the coordinates of the 27 panel centers as approximation.

We only present results for our RSSI Peaks approach (see Section III-B), as it performed better than our Temporal Distances approach. Note that we set the segment separation threshold to $\Delta = 15,000$ milliseconds for the case study, which better reflects the increased distances between panels.

Furthermore, we alter our evaluation metrics for this case study from MAE of RFID tag locations to the correlation of relative distances and cluster assignment. Specifically, we evaluate if we can group RFID tags to the same panel, using k-Means clustering to infer $k = 27$ clusters of RFID tags in our estimated RFID tag positions. We compare the cluster-assignment, as well as the relative distances between tags and

TABLE III: **Case Study Dataset.** For our case study, each of three different individuals walked through our setup three times, trying to read as many RFID tags as possible. For each iteration we show the session configuration of the RFID reader, the number of RFID tags that were read, the median number of read events per RFID tag and the duration of the iteration.

Iteration	Session	#Events	# Events per Tag	Duration	# Tags Read
1	0	4,847	5	85s	863 (94%)
2	1	3,461	3	72s	886 (96%)
3	0	4,484	4	77s	881 (96%)
4	1	3,513	4	70s	890 (97%)
5	1	3,011	3	66s	875 (95%)
6	1	3,093	3	62s	890 (97%)
7	0	4,111	4	66s	849 (92%)
8	1	2,892	3	58s	887 (96%)
9	1	3,059	3	63s	882 (96%)



(a) Case Study Panels (b) Case Study Schematic (c) Estimated 2D Locations

Fig. 6: **Case Study Panel, Schematic & Estimated 2D Locations.** For our case study we use a total of 27 panels (a), with each panel holding between 25 to 36 RFID tags. Panels are represented as colored circles in (b), while shelves/tables are represented by solid/dotted black rectangles. We print overlapping panels on shelves (e.g., same position but different height) with a jitter to make them visible in this schematic. The red lines represent physical walls. Each circle in (c) represents a single RFID tag, with colors assigned according to the corresponding panel of the ground truth. The x- and y-axes represent our estimated relative 2D locations. We can observe that RFID tags with the same color also form clusters in our estimation, however, we are not able to infer exact geo-locations (cf. (b)).

clusters to the ground truth.

To that end, we use three different entropy-based clustering measures [34] which can be used to intuitively evaluate the computed cluster assignments. First, we calculate homogeneity h, which is a bounded measure (between 0.0 and 1.0; higher is better) that reflects the number of different classes in a single cluster. Preferably, a cluster should only contain a single class (i.e., a cluster corresponding to a panel should only contain RFID tags actually belonging to that panel), which would correspond to a homogeneity score of $h = 1.0$. Furthermore, we calculate the completeness score c for our cluster assignments, which is bounded as well (i.e., between 0.0 and 1.0; higher is better). This metric measures how many members of a class are assigned to the same cluster. In our case, all RFID tags located on one panel should be assigned to the same cluster. As homogeneity and completeness are opposing metrics which can widely differ from each other, we also calculate the validity score (v-score v), which is defined as the harmonic mean of homogeneity h and completeness c (i.e., $v = \frac{2 \cdot c \cdot h}{c+h}$) and has the same boundaries as the two other metrics.

For calculating the Pearson correlation coefficient between our ground truth and the estimated RFID tag locations we first set the coordinates of each RFID tag in our ground truth to the center of its corresponding panel. Then, we calculate and set the coordinates of each RFID tag to the mean estimated coordinates of the RFID tags on the same panel, which we have obtained via k-Means. Finally, we use the Euclidean distances between all RFID tags of our ground truth and our estimation to calculate the Pearson correlation coefficient.

B. Results & Discussion

Due to the more complex setup and the underlying mechanisms of how our approach works—essentially inferring distances based on temporal differences without anchors to the actually traversed paths—we expect multi-dimensional scaling to yield results of limited utility for this case study.

As can be seen in Figure 6c, the inferred locations of the RFID tags only marginally represent the ground truth depicted in Figure 6b. Specifically, without additional information, multidimensional scaling can not reconstruct structural obstacles and complex path traversals as only the elapsed times between RSSI peaks of RFID tags are considered for distance estimation. In general, most of the RFID tags are located along a distinguishable line, indicating the timely differences of when the actual panels were read in time. However, some RFID tags are located in the center of the visualization, indicating similar distances to several other clusters. Note that the wall depicted in Figure 6b is not shielded, meaning that bleed-through reads are possible. In fact, after manual inspection of our data, we find that several bleed-through, as well as stray reads occurred when reading RFID tags along the wall, which are responsible for the estimated locations of the RFID tags in the center of our visualization (see Figure 7).

While we can't use absolute distances for RFID tag localization, the calculated median (max) Pearson correlation coefficient of $r = 0.62$ (0.67) for Session 0 and $r = 0.64$ (0.83) for Session 1 indicate that we can still use relative distances between RFID tags/panels to realize several real-world use-cases. For example, optimizing picking paths of retail staff when replenishing articles on the salesfloor (i.e., smart picking lists) or identifying misplaced items due to item neighborhoods, or guiding store staff towards a specific RFID tag by using the mobile RFID reader as "radar", leveraging the relative distance information of the RFID tags.

Some of the mentioned real-world applications depend on properly detecting "stacks of items" (i.e., clusters in the form of a single panel in our case study) in addition to relative distances between RFID tags. Hence, to evaluate the utility of our results for said applications, we apply k-Means to the obtained RFID tag coordinates with a predefined set of $k = 27$ clusters (i.e., the number of panels we used in our case study). We receive clusters that are rather homogeneous (homogeneity score of $h = 0.55$) and complete (completeness

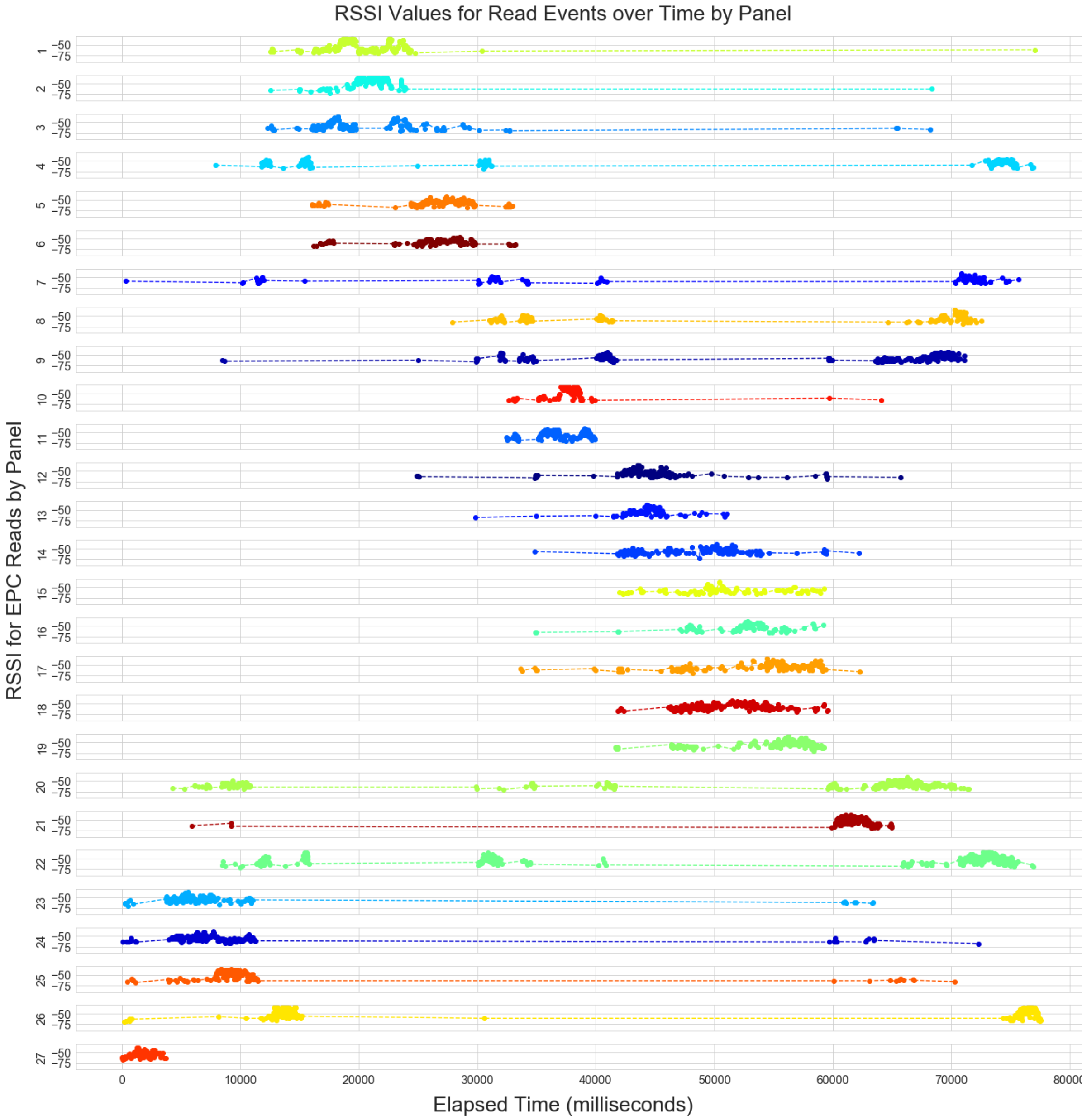


Fig. 7: **RSSI Read Events by Panel over Time.** For our case study we depict the RSSI read events per EPC for each panel for an exemplary experiment. Due to the irregular walking pattern as well as increased walking distances we set the segment separation threshold to $\Delta = 15,000$ milliseconds.

score of $c = 0.56$), resulting in a v-score of $v = 0.55$. For baseline comparison we randomly assign clusters and obtain a v-score of $v = 0.13$ (with homogeneity and completeness both 0.13).

These results indicate that we can potentially use our cluster assignments and the distances between the clusters to identify outliers, which translates into the identification of misplaced articles in a retail environment.

VI. Conclusions & Future Work

In this paper we have demonstrated a novel methodology to infer relative distances between RFID tags leveraging time-based differences in read events. Specifically, our results indicate that, depending on the layout of our experiments, we can infer positions of RFID tags with an MAE of up to 28.36 cm and a correlation coefficient of up to $r = 0.95$ for our controlled lab experiments. Further, we have shown that we are able to detect groups of RFID tags, which are put in close proximity to each other in our ground truth (i.e., the different panels). When adding RSSI values to reduce stray reads, we were able to achieve similar, for certain setups even better results than when only considering temporal distances.

Finally, we conduct a case study with a larger number of RFID tags and additional structural complexity, where we tasked three participants to read as many RFID tags as possible.

We find that our suggested approach yields promising results, warranting further investigations to evaluate its performance in real-world retail applications. Specifically, we could optimize picking paths of retail staff when replenishing articles or identify misplaced items due to item neighborhoods (i.e., clusters).

For Future Work we intend to evaluate our approach in a real-world scenario, which we expect to be more challenging due to an even larger number of RFID tags. Moreover, we additionally plan on including relative differences between RSSI values of simultaneously read RFID tags to better reflect depth information. Further, we are interested in incorporating additional data of sensors, such as accelerometer or gyroscope, available in the mobile handhelds into the calculation of temporal distances.

We strongly believe that the methodology and dataset[3] presented in this paper will build the foundation for an array of novel RFID tag localization techniques, all based on temporal distances.

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