Estimating Relative Tag Locations based on Time-Differences in Read Events

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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 (i) inferring tag locations for different experimental setups and (ii) comparing our results to ground truth data. 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.

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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. We present two approaches to determine relative locations of RFID tags, based on the timestamps and RSSI values of read events. Specifically, we use temporal distances between read events, which we map to estimated geometrical distances using MDS. 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 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. [8] 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) [9], [10], or received signal strength [9], [11]. 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 [12].

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.

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

Song et al. [13], 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 [14] and He et al. [15].

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 [16] 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* [17]), ultrasound (*Active Bat* [18] and *Cricket* [19]), and computer vision (*Easy Living* [20]).

RFID-based Location Systems. The *SpotON* system proposed by Hightower et al. [21] 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. [22] 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], [23], [24].

The LANDMARC system [25] 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 [26] 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 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. [27] 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

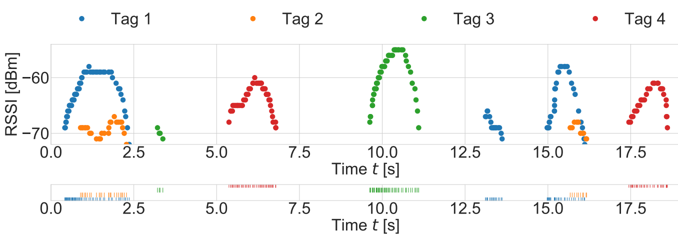


Fig. 1: **Temporal Distances Illustration.** This figure illustrates the calculation of temporal distances for RFID tag read events. **Bottom:** We have highlighted the read events of 4 different RFID tags (vertical bars) over time (x-axis), which is the foundation for our *Temporal Distances* approach. 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 where consecutive reads are not longer apart than $1,000$ 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 filtering (i.e., each segment has to contain at least 5 read events to minimize the impact of stray reads), 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.

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. [27] 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 [28] 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 [29], which potentially affects reading performance and thus, the overall quality of the obtained results.

III. Methodology

A. Data Collection & Preprocessing

During 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.

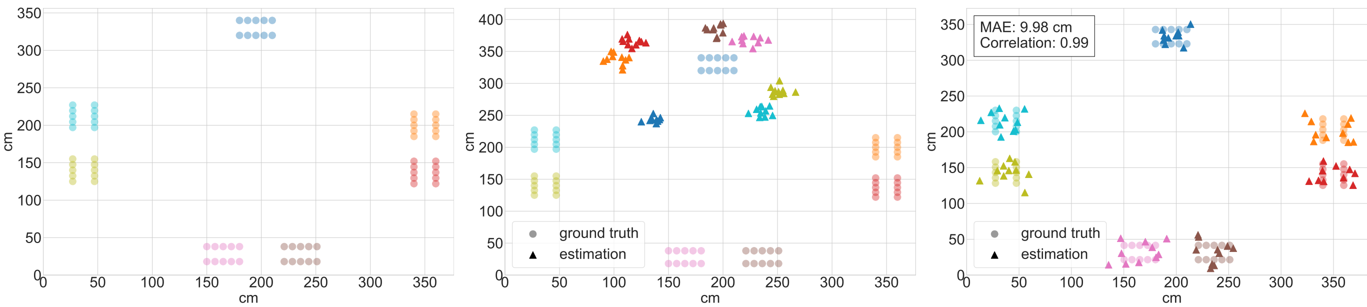
B. Estimating Relative Tag Distances

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.
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, we first partition the RSSI sequences for each RFID tag by time-differences larger than $1,000$ milliseconds between read events. Note that we set our partition threshold so that only roughly 5% of all observed time-differences introduce a new partition.

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. Further, we remove segments with fewer than 5 read events

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



(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. Additionally, we calculate correlation between the estimated temporal and empirical distances of our RFID tags.

to minimize noise in our data (i.e., stray reads). Note that our approach is subject to multipath propagation [29] and results might suffer from noisy RSSI values. At this point, we leave further investigations into noise minimization open for future work.

C. Evaluation

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 [30], [31] 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 [32] to determine the required rotation which minimizes the error to the ground truth. Finally, we apply the ground truth scaling factors on all coordinates, which allows us to calculate Mean Absolute Error (MAE) in Euclidean distance (see Figure 2c). For n tags, we calculate the MAE of the coordinates as follows:

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

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.

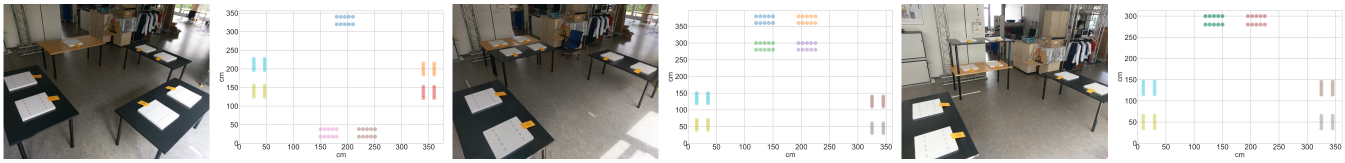
IV. Experimental Setup

A. RFID Hardware

We use the *ZEBRA RFD8500 handheld* mobile RFID reader for our experiments. We configure the device to use *Session 0* in *AB flip* mode. Further, we set the power level of the reader to the maximum value of 30.0 dBm, which equals 1W, for all our experiments. We connect a mobile device running Android to the reader via Bluetooth to collect timestamps, RSSI values, and the corresponding EPCs for each read event, and store the collected data on the phones internal storage. We use 70 or 80 RFID tags, depending on the experiment (see Section IV-C), of the model *UPM Web 208_3*, which is commonly used in retail applications.

B. Facilities

We conduct all experiments in a large room containing work tables, toolboxes, racks, and several additional RFID tags. Note that the room also contained several metal constructions (see Figure 3), such as a conveyor belt, highlighting that our test facility largely represents a real-world setting with high potential for noisy reads.



(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.

C. Layout of Experiments

For our experiments, we use wooden tables that we arrange in different layouts. We attach RFID tags in groups of ten on polystyrene panels, where each panel simulates a group of products of the same class. 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 arranged 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 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.

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%)

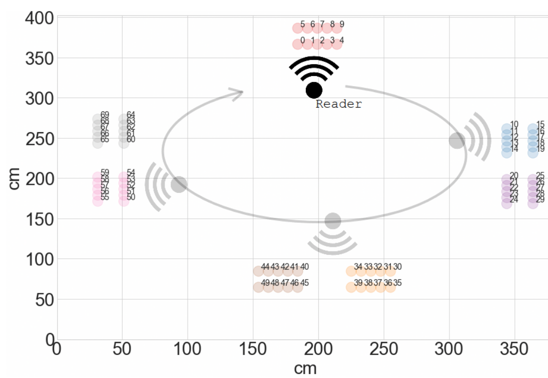
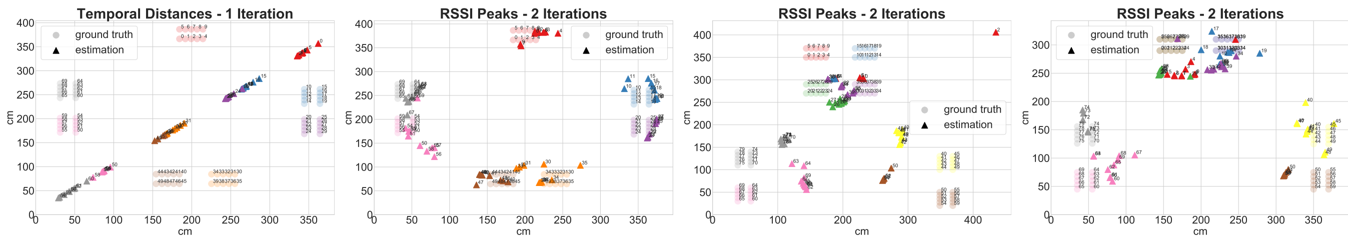


Fig. 4: **Circular Walk Reading Pattern.** For every different layout (i.e., 2D, Asymmetric 2D and 3D), we try to read RFID tags following always the same circular path (see arrow) for multiple repititions (i.e., iterations).

D. Circular Walk Reading Pattern

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).



(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.

V. Results & Discussion

A. *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.

B. *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.

C. Three-Dimensional Layout

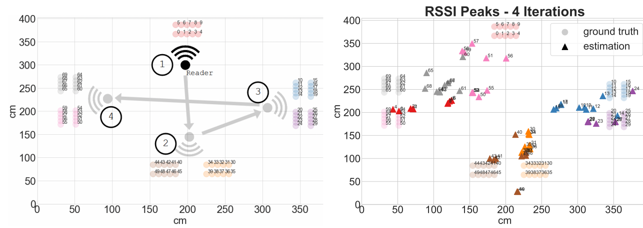
We achieve the best MAE (40.92 cm) and correlation coefficient ($r = 0.83$) for this layout after two iterations with the RSSI Peaks approach. As depicted in Figure 5d, we can detect the different RFID tag panels. As outlined in the description of this layout, there are two RFID tag panels (i.e., green 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.

D. Random Walk on Two-Dimensional Layout

In addition to the circular walk we also conduct first experiments following a random walk using our 2D Layout (see Figure 6a and Table III). Note that we follow the same path multiple times when conducting multiple iterations in this experiment. While our approaches can detect relative distances as well as the panels the RFID tags were put on (see Figure 6b), evident in the correlation coefficient of $r = 0.6$, they struggle to infer the correct positions of the tags. MAE, even after 4 iterations, remains at 114.35 cm, which is higher than for all other experiments (see Table IV).

TABLE III: **Random Walk Dataset.** For each layout we conduct several experiments (# iter, defining how often we follow the selected path). 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.

	# iter	# Events	# Events per Tag	Duration	Tags Read
	1	2,637	34	19s	65 (92%)
Random Walk	2	5,008	67	40s	69 (98%)
	4	5,808	86	80s	68 (97%)



(a) Schematic (b) Results

Fig. 6: **Random Walk on Two-Dimensional Layout Results.** We provide a schematic of the random walk approach for the 2D Layout in Figure 6a. Note that we follow the same random path (see Annotations 1 to 4) if we conduct more than one iteration in an experiment. While the error in terms of RFID tag positions is rather high, we can still easily distinguish the different RFID tag panels (see Figure 6b). Further, we can observe a similar problem, as for all experiments with only a single iteration. Distances between sequentially read panels are well estimated (e.g., (1) red, and (2) orange & brown), while the distances between further spread apart panels are influenced by stray reads, provoked by the random walk (e.g., (1) red, and (3) blue & green).

Discussion. As we only use timestamps of read events to infer distances between RFID tags, random walks represent a very challenging setup for our proposed methodology. In general, the results of our random walk experiment exhibit the worst MAE and correlation coefficient across all experiments. However, we can see that, with increasing iterations, MAE steadily decreases while the correlation coefficient increases, improving our results. We hypothesize that—in contrast to the circular walk—multiple iterations with different random walking paths can further improve our results. To verify this hypothesis more experiments are warranted which we leave open for future work at this point.

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

TABLE IV: **Random Walk Results.** In this Table we list MAE and the correlation coefficient r for our Random Walk experiments (# iter). 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.

	# iter	Temporal Distance MAE	r	RSSI Peaks MAE	r
	1	122.52	0.50	119.40	0.51
Random Walk	2	121.05	0.53	117.67	0.54
	4	116.33	0.60	114.35	0.58

28.36 cm and a correlation coefficient of up to $r = 0.95$. 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) across all our experiments. 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 demonstrate preliminary results for reading tags while following a random path, which steadily improves performance with additional iterations. As demonstrated in this paper, our suggested approach yields promising first results, warranting further investigations to evaluate its performance in real-world retail applications. Particularly, closely examining article outliers could represent a first starting point for detecting misplaced items.

For Future Work we intend to evaluate our approach in a real-world scenario, which we expect to be more challenging due to larger numbers of tags that potentially affect the read performance. 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.

References

[1] D.-L. Wu, W. W. Ng, D. S. Yeung, and H.-L. Ding, "A brief survey on current rfid applications," in *Machine Learning and Cybernetics, 2009 International Conference on*, vol. 4. IEEE, 2009, pp. 2330–2335.

[2] R. Weinstein, "Rfid: a technical overview and its application to the enterprise," *IT professional*, vol. 7, no. 3, pp. 27–33, 2005.

[3] S. Garfinkel and B. Rosenberg, *RFID: Applications, security, and privacy*. Pearson Education India, 2006.

[4] K. Domdouzis, B. Kumar, and C. Anumba, "Radio-frequency identification (rfid) applications: A brief introduction," *Advanced Engineering Informatics*, vol. 21, no. 4, pp. 350–355, 2007.

[5] A. Raman, N. DeHoratius, and Z. Ton, "Execution: The missing link in retail operations," *California Management Review*, vol. 43, no. 3, pp. 136–152, 2001.

[6] C. Hekimian-Williams, B. Grant, X. Liu, Z. Zhang, and P. Kumar, "Accurate localization of rfid tags using phase difference," in *2010 IEEE International Conference on RFID (IEEE RFID 2010)*, April 2010, pp. 89–96.

[7] K. Curran and S. Norrby, "Rfid-enabled location determination within indoor environments," *International Journal of Ambient Computing and Intelligence (IJACI)*, vol. 1, no. 4, pp. 63–86, 2009.

[8] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 37, no. 6, pp. 1067–1080, Nov 2007.

[9] N. Patwari, A. O. Hero, M. Perkins, N. S. Correal, and R. J. O'dea, "Relative location estimation in wireless sensor networks," *IEEE Transactions on signal processing*, vol. 51, no. 8, pp. 2137–2148, 2003.

[10] A. Savvides, C.-C. Han, and M. B. Strivastava, "Dynamic fine-grained localization in ad-hoc networks of sensors," in *Proceedings of the 7th Annual International Conference on Mobile Computing and Networking*, ser. MobiCom '01. New York, NY, USA: ACM, 2001, pp. 166–179.

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

[11] J. Ash and L. Potter, "Sensor network localization via received signal strength measurements with directional antennas," in *Proceedings of the 2004 Allerton Conference on Communication, Control, and Computing*, 2004, pp. 1861–1870.

[12] D. Niculescu and B. Nath, "Ad hoc positioning system (aps) using aoa," in *INFOCOM 2003. Twenty-Second Annual Joint Conference of the IEEE Computer and Communications. IEEE Societies*, vol. 3. Ieee, 2003, pp. 1734–1743.

[13] J. Song, C. T. Haas, and C. H. Caldas, "A proximity-based method for locating rfid tagged objects," *Advanced Engineering Informatics*, vol. 21, no. 4, pp. 367–376, 2007.

[14] S. Simic and S. Sastry, "Distributed localization in wireless ad hoc networks," Technical Report UCB/ERL, Tech. Rep., 2002.

[15] T. He, C. Huang, B. M. Blum, J. A. Stankovic, and T. F. Abdelzaher, "Range-free localization and its impact on large scale sensor networks," *ACM Transactions on Embedded Computing Systems (TECS)*, vol. 4, no. 4, pp. 877–906, 2005.

[16] J. Hightower and G. Borriello, "Location systems for ubiquitous computing," *Computer*, vol. 34, no. 8, pp. 57–66, 2001.

[17] R. Want, A. Hopper, V. Falcao, and J. Gibbons, "The active badge location system," *ACM Transactions on Information Systems (TOIS)*, vol. 10, no. 1, pp. 91–102, 1992.

[18] A. Harter, A. Hopper, P. Steggles, A. Ward, and P. Webster, "The anatomy of a context-aware application," *Wireless Networks*, vol. 8, no. 2/3, pp. 187–197, 2002.

[19] N. B. Priyantha, A. Chakraborty, and H. Balakrishnan, "The cricket location-support system," in *Proceedings of the 6th annual international conference on Mobile computing and networking*. ACM, 2000, pp. 32–43.

[20] J. Krumm, S. Harris, B. Meyers, B. Brumitt, M. Hale, and S. Shafer, "Multi-camera multi-person tracking for easyliving," in *Visual Surveillance, 2000. Proceedings. Third IEEE International Workshop on*. IEEE, 2000, pp. 3–10.

[21] J. Hightower, R. Want, and G. Borriello, "Spoton: An indoor 3d location sensing technology based on rf signal strength," 2000.

[22] C. Alippi, D. Cogliati, and G. Vanini, "A statistical approach to localize passive rfids," in *2006 IEEE International Symposium on Circuits and Systems*, May 2006, pp. 4 pp.–.

[23] A. A. Savochkin, Y. P. Mickhayluck, V. M. Iskiv, A. A. Schekaturin, A. V. Lukyanchikov, D. A. Savochkin, and E. A. Levin, "Passive rfid system for 2d indoor positioning," in *2014 20th International Conference on Microwaves, Radar and Wireless Communications (MIKON)*, June 2014, pp. 1–3.

[24] M. Bouet and G. Pujolle, "L-virt: Range-free 3-d localization of rfid tags based on topological constraints," *Computer Communications*, vol. 32, no. 13, pp. 1485 – 1494, 2009.

[25] L. M. Ni, Y. Liu, Y. C. Lau, and A. P. Patil, "Landmarc: indoor location sensing using active rfid," in *Pervasive Computing and Communications, 2003.(PerCom 2003). Proceedings of the First IEEE International Conference on*. IEEE, 2003, pp. 407–415.

[26] S. S. Saab and Z. S. Nakad, "A standalone rfid indoor positioning system using passive tags," *IEEE Transactions on Industrial Electronics*, vol. 58, no. 5, pp. 1961–1970, May 2011.

[27] D. Joho, C. Plagemann, and W. Burgard, "Modeling rfid signal strength and tag detection for localization and mapping," in *Robotics and Automation, 2009. ICRA'09. IEEE International Conference on*. IEEE, 2009, pp. 3160–3165.

[28] G. Grisetti, C. Stachniss, and W. Burgard, "Improved techniques for grid mapping with rao-blackwellized particle filters," *IEEE transactions on Robotics*, vol. 23, no. 1, pp. 34–46, 2007.

[29] S. Hinteregger, J. Kulmer, M. Goller, F. Galler, H. Arthaber, and K. Witrisal, "Uhf-rfid backscatter channel analysis for accurate wideband ranging," in *RFID (RFID), 2017 IEEE International Conference on*. IEEE, 2017, pp. 117–123.

[30] J. B. Kruskal, "Multidimensional scaling by optimizing goodness of fit to a nonmetric hypothesis," *Psychometrika*, vol. 29, no. 1, pp. 1–27, Mar 1964.

[31] I. Borg and P. J. Groenen, *Modern multidimensional scaling: Theory and applications*. Springer Science & Business Media, 2005.

[32] J. C. Gower, "Generalized procrustes analysis," *Psychometrika*, vol. 40, no. 1, pp. 33–51, 1975.