Non-intrusive Localization of Passive RFID Tagged Objects in an Indoor Workplace

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***Abstract*—This paper presents our work on localizing a passive UHF RFID tagged object in an indoor workplace. We focus on uncontrolled settings with random orientations of the target object, dynamically moving people in the environment and cluttered rooms with many furniture items. Multiple fixed antennas are used to handle random tag orientations and human body effects. The antennas are placed in a way to minimize the obstruction for human activities and the effect of human presence and movement on the localization system. We use zone-based and exact localization methods incorporating probabilistic and deterministic machine learning techniques. We also propose a combined coarse-to-fine approach to improve accuracy and increase speed. Experimental results show that our system is able to localize an object with an error of 37 cm for exact localization and with an accuracy of 92% for zone-based classification. Experiments in challenging conditions showed that our overall design is robust to human body effects, even exploits the destructive effects of human body on UHF RFID sensing.**

I. INTRODUCTION

In the last decade, Radio Frequency Identification (RFID) has become a prominent identification technology, because it is cost-effective, operates without line-of-sight and minimizes human intervention. It is becoming pervasive in many areas, from supply-chain management and asset tracking to context-aware systems and robotics.

Although primarily designed for identification, RFID technology also provides useful information about mobility status (by analyzing fluctuations) and coarse-grained location (by correlating detection events with proximity to a reader). Currently, many commercially available UHF RFID readers provide the Received Signal Strength Indicator (RSSI) value along with the detection information. Finer-grained location estimates can be obtained by calculating the tag-reader distance using the RSSI and the RF propagation model [1]. However, this model is designed for free space and not directly applicable to indoor environments. Moreover, RSSI values are more unpredictable in case of passive sensors [2], [3], [4].

In this work, our aim is to localize a passive UHF RFID tagged object in an indoor workplace, such as an office, a garage (mechanic) or a hospital room. Workplaces are cluttered settings due to furniture-like objects and human motion in the environment. To illustrate, consider an emergency room with large objects such as cabinets, benches, drawers, trolleys and a patient bed. Medical personnel are moving in the free space to perform the required tasks for patient care. In addition to the effects of human presence/motion and environmental objects in general indoor scenarios, workplaces introduce other constraints which might affect the localization performance. As an example, RFID readers and antennas must be placed in a non-intrusive way not to interfere with human motion. Sensors on objects must satisfy the size and cost requirements (i.e. small and inexpensive objects require small and cheap sensors). In addition, the overall system must be robust to human occlusion and movement.

We designed our localization system based on the aforementioned constraints. Because our aim is to localize small and inexpensive objects in a non-intrusive way, we preferred using passive UHF RFID technology due to its battery-less and long-range operability. We used multiple antennas to reduce the effect of noisy RSSI readings and handle random orientations of the target object. Most of the antennas were ceiling mounted and the remaining ones were installed in a way not to obstruct human motion, as well as to minimize human body effects (occlusion, attenuation, reflection) on localization accuracy. We setup the experimental environment and scenarios to match an example workplace. The environment was occupied with many furniture items which affect the RF propagation by causing reflection and absorption. We designed the experimental scenarios to create a typical human workplace environment by introducing (i) human presence (standing still and occluding the tag) (ii) continuous human movement and (iii) presence of multiple tags. Each of these conditions represent additional challenges for RFID-based localization algorithms.

Two types of localization strategies were employed in this work. In *zone-based localization*, the aim is to find the two-dimensional region containing the tag. For some applications, exact coordinates may not be required and a coarse-grained zone information may be sufficient. As an example, consider an operating room. Detecting that the blood pressure cuff is on the patient bed (not on the counter) is a strong indicator that the patient's blood pressure is being measured. The second approach is *exact localization*, where we aim to estimate the two-dimensional coordinates of object location relative to some reference point. We also propose a coarse-to-fine combination of the zone-based and exact localization techniques, *coarse-to-fine cascaded localization*. In this method, the zone containing the object is determined first. Next, the exact location is estimated given that the object is in

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that particular zone. Although this approach is efficient in terms of speed, inaccurate classification in the first step may cause high localization errors. To reduce the effects of wrong classification, we defined a confidence score and compared it to an empirically identified threshold between the two steps.

We implemented all localization methods based on the RSSI information. We also experimented with read rate (number readings per second — RR) and compared the effectiveness of the two information types. Our contributions in this work can be summarized as follows:

- We propose design strategies for the placement of sensory equipment, such that interference with human activities and effects of human presence on localization algorithms is minimized.
- We compare the effectiveness of RRSI and RR information both in zone-based and exact localization tasks.
- We propose a combined coarse-to-fine approach to improve localization accuracy and reduce localization time.
- We evaluate the system in realistic settings with human movement, occlusion and multiple tags, in addition to the ideal setting.

This paper is organized as follows. In Section II, we present a summary of the related work. In Section III, we describe the methodology: optimum placement of the sensory equipment and localization algorithms. Experimental results are presented in Section IV and conclusions are drawn in Section V.

II. Related Work

RFID technology has become popular in the last decade for both localization of tags [2] [5], [6], [7], [8], [9], [10] and readers [11], [12]. For tag localization, earlier works concentrated on the active RFID technology [9], [10]. Below, we present an overview focusing on the passive RFID tag localization.

In [2] and [5], algorithms were developed for localization and indexing of nomadic objects (which change locations infrequently) in a room-like environment. While the first algorithm depends on a user carrying a camera-equipped RFID reader, the second one relies on steerable antennas. As the user or antenna moves, the object is detected from different vantage points and more precise location is estimated by finding the intersection of detection ranges. The algorithm in [2] was able to localize 90% of a hundred objects to an area 0.8 meters a side (in an office with dimensions 4.9 m by 3.4 m). However, a rough scan of the whole room was reported to take about 1 minute, which might be long for some applications.

A Bayesian approach for localizing passive RFID tags was presented in [8], which is also based on rotatable reader antennas. The algorithm first generates detection maps for different transmitting power levels of the reader. Assuming that all reading events (for each reader, each power level and each rotation angle) are independent, position of the tag is determined by maximizing the posterior probability. Localization error was reported as 0.6 meters with four readers in a 5 m by 4 m environment.

We aim to use multiple fixed antennas to approach the steerable/rotatable antenna setup explained in [2], [5], [8]. The information type used in these works was RR, obtained at different attenuation levels. We use the RSSI information for faster localization, because the total time of an event is 15-30 minutes for our target application.

In [7], extensions were proposed to the nearest neighbors algorithm in [10], which was originally developed for active tags. Tag discrepancies were handled by pre-processing the signal strength values and reference tags were selected based on the read rate as well as the distance in RSSI. By including these extensions, mean localization error decreased from 33.15 cm to 20.89 cm in a one-dimensional setup.

A two-layer localization algorithm was proposed in [6], where an SVM classifier is used for coarse localization first and the traditional particle-filtering algorithm is used for finer-grained localization next. Active RFID tags were used to localize people wearing the tags. In our work, we followed a similar approach for passive tags, and also incorporated a confidence score between the two layers.

III. Methodology

In this section, we describe our methodology for designing the experimental setup, scenarios and algorithms for localization. Design choices were made considering a hospital operating room, which is a challenging workplace environment with many objects and dynamically moving people. Nonetheless, our methodology, as well as results, can be generalized to other workplace environments.

A. Experimental Setting

1) Room Layout and Antenna Placement: The experimental setting (Figure 1) was designed to match a typical operating room, where a patient bed sits at the center; cabinets, benches and small tables stand next to the walls. Medical tools are usually located on/in these furniture items or close to patient bed, when in-use. People move in the free area between the center object and the edge furniture. In our experimental setup (Figure 1), a table ($75 \times 25 \times 75$ cm) was positioned at the center of the experimental area. Three small tables ($50 \times 75 \times 85$ cm) were placed at the three sides of the table (right, left and head — foot is usually left free). Items on these smaller tables are representatives for items on counters, trolleys, as well as items taken out from the cabinets. The main experimental area was surrounded with many furniture items such as desks and cabinets (Figure 1). These objects are sources for multipath and other adverse conditions affecting the RF propagation.

Placement of the antennas must be made to cover the central points, as well as the points close to edges of the workspace. While it is possible to scan the central zone in a number of ways, covering the edge points is challenging. Placement to the adjacent wall is not an option because in order to cover the edge zone, the antenna must be very inclined to the floor (approaching a ceiling-mounted antenna). Placement on another wall, on the other hand, is susceptible to be affected by

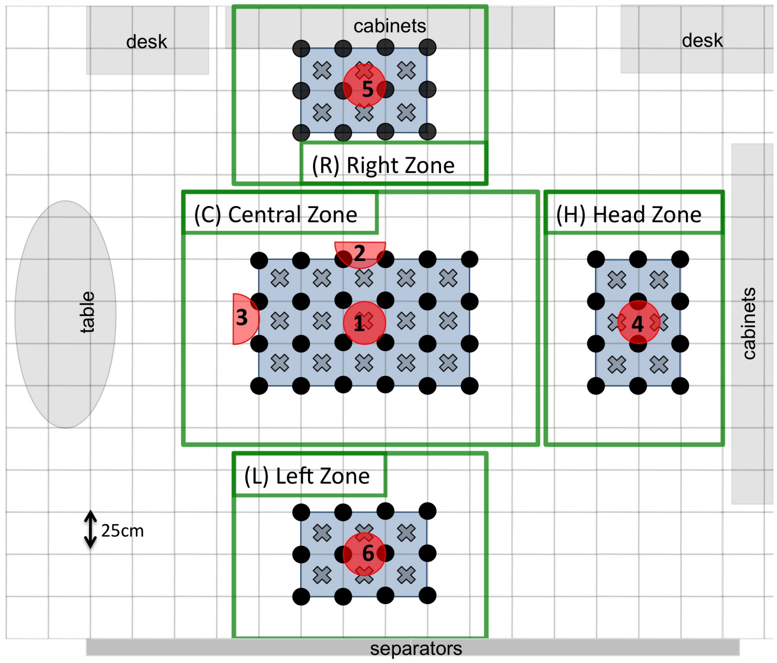

Fig. 1. Room Layout. Black dots: fingerprint locations. Crosses: test locations. Red full circles: Ceiling mounted antennas. Red half circles: Angled antennas. The room is separated into four zones: Central, Head, Left and Right.

human occlusion or motion. As a result, we preferred to place an antenna at the top of each zone, mounted at the ceiling, facing the floor (Antennas #4, #5, #6 in Figure 1).

Central zone was also scanned by a ceiling mounted antenna (Antenna #1 in Figure 1). In addition, two angled antennas were placed to improve localization accuracy (Antennas #2 and #3 in Figure 1). These antennas were positioned facing the central area, making a 45 degrees-angle with the floor and 2 m. above the floor to avoid obstructing human motion. Overall placement of the antennas is shown in Figure 1. Full circles represent the ceiling mounted antennas (2.7 meters above floor directly facing the floor). Half circles represent the 45 degrees-angled antennas. Note that this placement is realistic, completely applicable to a real world scenario.

2) RFID Equipment and Reader Coordination: Two RFID readers from Alien Technology (ALR-9900 (Four Antenna / Gen 2 / 902-928 MHz)) were used in the experiments. Readers operated in the Dense Reader Mode, which prevents the interference between readers in close proximity and is the best performing mode when tag-reader distance is higher than 1.5 meters [13]. In addition, 5dB of attenuation was applied on the 1 watt transmission power to reduce the interference further. Readers operated autonomously and an application on a host computer was set up to listen for notification messages from the reader containing any tag data that it has read.

Three circularly polarized antennas (ALR-9611-CR) were connected to each reader. The antennas have a balloon shaped radiation pattern and are less sensitive to tag orientation compared to linearly polarized antennae. Squiggle ALN-9540 type passive RFID tags, attached on foam and cartoon, were used in the experiments.

Although the RFID readers can operate simultaneously, each reader needs to cycle through the active antenna ports in a round-robin fashion. In our experiments, each reader visited the three ports in sequence and transmitted for 1 second through each port. The reader-antenna connections were assigned to minimize the interference: Antennas #1,#2 and #3 were connected to 1st, 2nd and 3rd ports of Reader 1 and antennas #4, #5 and #6 were connected to 1st, 2nd and 3rd ports of Reader 2 respectively. Therefore antennas were active sequentially in pairs 1-4, 2-5 and 3-6 (Figure 1). Note that, three antennas scanning the central region were never active at the same time.

B. Data Collection and Experimental Scenarios

The dataset consists of the RFID readings and location labels (both zone-based and exact location). An RFID reading has the following format:

$$< timestamp, readerID, antennaID, tagID, RSSI >$$

Readings were captured while the item was positioned at:

- Reference points: shown with black dots in Figure 1. (24 in central region, 12 in each side region: 60 in total)
- Test points: shown with crosses ("×") in Figure 1. (15 in central region, 6 in each side region: 33 in total)

Because the target object does not have a fixed orientation, the tag can be in any orientation as well. Therefore, we captured the RFID readings for three orientations of the tag: (i) facing the separators, (ii) facing the oval table and (iii) facing the ceiling (Figure 1). Duration for each recording was limited to 30 seconds, which ensures that sufficient data is recorded for localization (<10 seconds) and allows for performing localization several times through the recording. There was nobody in the room during the experiments except the experimenter, who stayed away from the RFID equipment unless otherwise stated.

The dataset includes RFID recordings in several scenarios designed to imitate a typical workplace environment:

- Scenario #1: (Ideal Scenario) There is neither human presence/movement nor additional tags (other than the target tag) in the vicinity of the experimental area.
- Scenario #2: (Human Walking Scenario) A person is walking in the free space between the center table and side tables with a regular walking speed (≈1m/s). Only the target tag was present in the experimental area.
- Scenario #3: (Human Standing Scenario) A person is standing immediately next to the tag to create occlusion. Only the target tag was present in the experimental area.
- Scenario #4: (Multiple Tag Scenario) There is no human presence/movement in the vicinity of the experimental area. However two additional non-target tags were placed in each zone (total of 8).

The total data amount is approximately 4 hours (Train: 1.5 hours Test: 2.5 hours). Training samples were collected only in the ideal scenario (Scenario #1) whereas test samples were collected in all four scenarios.

C. Algorithms for Localization

Location of the RFID tagged object was estimated by first extracting the useful statistics within a sliding window (of length 3 seconds) and next applying classification and/or filtering algorithms on these features. We experimented with two types of features: mean RSSI and Read Rate (RR — the number of readings per second). During feature extraction, readings were grouped according to antenna ID and mean RSSI (or RR) is computed for each antenna. Next, these values were concatenated to obtain the final six-dimensional feature vector.

Mapping of the feature sequence to location information can be performed in several ways. We now explain our methods and propose a cascaded strategy, which is efficient both in terms of speed and accuracy.

1) Zone-based Localization: In zone-based localization, we are interested in estimating the zone which the tag currently lies in, given observations up to the current time instant. The experimental area is split into four zones: central, head, left and right (Figure 1). Estimation of the posterior probability density over zone-based location is a Bayesian Filtering problem and can be computed recursively using prediction and update steps [11], [14].

For the prediction step, position of the object at the next time instant is predicted based on the current position of the object using a motion model. We defined a simple and generalizable motion model based on the expected duration in a zone and the size of the zone. Because an object does not frequently change place, zone transition matrix was defined with high probability of self-transitions and low probability of out-transitions. To handle the non-uniformly splitted zones (Figure 1) out-transitions were adjusted proportional to zone sizes, such that an out-transition into a larger zone has more probability than an out-transition into a smaller zone ($P(central|head) > P(right|head)$).

In the update step, an observation model is used to incorporate the sensor measurement into the posterior density estimation over location. Observation likelihood is often represented with a Gaussian probability density function (pdf), where the parameters of the pdf are estimated using the training data. However a single Gaussian pdf can represent only a unimodal density. In case of passive RFID sensing, even the tag is very close to the reader (in the high RSSI region) the tag may not be detected at all, resulting in zero RSSI. Level of multipath and reflections may increase at particular locations causing variations in RSSI. Consequently, it may not be possible to make a parametric estimate for observation likelihood. To handle this situation, we also used the Kernel Density Estimation method [15], which is a non-parametric way of estimating the probability density function of a random variable.

2) Exact Localization: In exact localization, the aim is to estimate the 2-D coordinates of tag location. Radio signals have temporal stability (signal strength from the same source at the same location is stable in time) and spatial variability (signal strength from the same source at different locations differs). Relying on this fact, location of an object can be determined by comparing the signal descriptors from an object at unknown location to a previously constructed radio map or fingerprints. We used the Weighted k-Nearest Neighbors algorithm (w-kNN), where we find the most similar fingerprints and compute a weighted average of their 2-D positions to estimate the unknown tag location [7], [10].

3) Cascaded Coarse-to-Fine Localization: The idea behind combined coarse-to-fine localization is to incorporate the zone-based location information into the exact localization process. This combination can be achieved by means of a cascade, where zone-based localization finds the most likely zone along with a confidence score. If the confidence score is greater than some threshold (means that we are confident about the zone-based localization result), w-kNN algorithm is run over the fingerprints only in that zone. Otherwise, w-kNN algorithm is run over all fingerprint points. We used the posterior probability of the zone, given observations up to the current time instant, as the confidence score. The threshold was empirically set as 0.8.

IV. Experimental Results

In this section, we present the experimental results. First we explore to what extent each antenna contributes to localization performance. Next we evaluate the zone-based and exact localization approaches in the ideal setting (Scenario #1). Finally, experimental results in human presence/movement and multiple tags (Scenarios #2, #3, #4) are reported.

Zone-based localization performance was evaluated with the *classification accuracy*, which is defined as :

$$\text{Accuracy}_{\text{zone}} = \frac{\text{true positive} + \text{true negative}}{\text{total \# of test samples}} \quad (1)$$

Exact localization results are reported in terms of *mean localization error*, which is defined as:

$$\text{Error} = \text{mean}\{\sqrt{(x_e - x_g)^2 + (y_e - y_g)^2}\} \quad (2)$$

where, (x_g, y_g) and (x_e, y_e) denote the actual and estimated locations respectively.

A. Individual Contribution of the Antennas

In this experiment, we aim to explore the degree of contribution of each antenna to the localization performance. This analysis is essential to evaluate the necessity of an antenna, as well as the efficiency of antenna placement and positioning.

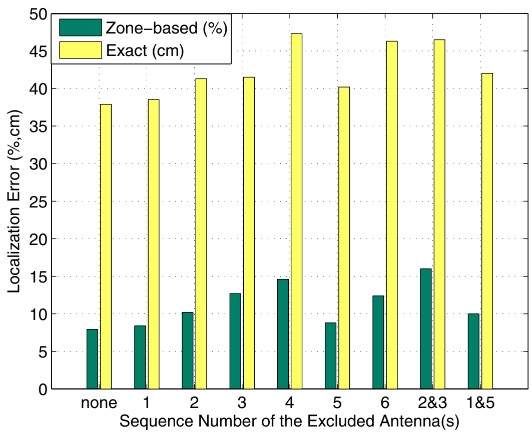

Fig. 2. Zone-based and exact localization errors when the indicated antennas are excluded.

Figure 2 depicts the localization error for several antenna combinations (Sequence number of the excluded antenna(s) are shown in x-axis). Lowest error rates were achieved when all antennas were active, indicating that all antennas contributed to localization accuracy. However contributions of the 1st and 5th antennas were the smallest. The 1st antenna had little effect because its main coverage area was scanned also by the 2nd and 3rd antennas. Moreover, these two antennas provided more discriminative information because they scanned through *x* and *y* dimensions and possible tag locations lie in the *x*-*y* plane (Figure 1). Analyzing the behavior of the 5th antenna, we observed that it's measurement model gives less information about location, because the observation likelihood $(\text{P}(\text{observation}|\text{location}))$ has higher standard deviation. Because all antennas were identical, different behavior of the 5th antenna can be attributed to the environmental factors. Our further experiments justified that the metal cabinets in the right zone (Figure 1) cause reflections and unanticipated behavior of RSSI readings captured by Antenna #5.

When both 1st and 5th antennas are excluded, zone-based classification accuracy dropped from 92% to 90% and exact localization error increased from 37.9 to 42.0 cm. Considering that the reader used in our experiments was a 4-port one, this result suggests that using 1 reader and 4 antennas, instead of 2 readers and 6 antennas, might be more cost and time efficient. However, because the reader needs to traverse four ports, the latency will be longer (2 seconds, instead of 1.5 seconds).

B. Zone-based Localization

In this experiment, we aim to find the location of the tagged object as one of the four zones shown in Figure 1. Classification into zones was performed using Bayesian Filtering with a Gaussian measurement model and with a KDE-based measurement model. We also calculated the classification scores obtained with other machine learning algorithms: Support Vector Machines (SVMs) and LogitBoost [15]. Although SVM and LogitBoost are known to be more powerful classifiers, they do not take the temporal information into account. In addition to the results obtained with RSSI, we provide scores obtained with read rate (RR).

Zone-based localization results are presented in Table I. In spite of the very noisy nature of RSSI, it still provides more helpful information compared to RR in our setup. Bayesian Filtering outperform the other classification methods because history and prior information are incorporated in Bayesian Filtering, whereas SVM and LogitBoost do not consider the temporal structure of the data. We also observe that, while the RSSI is well modeled with a Gaussian pdf, read rate is better modeled with non-parametric Kernel Density Estimator (KDE). Therefore, considering non-parametric approaches can be helpful when working with readers that do not provide RSSI (or under strict time constraints such that RSSI providing capability is not used).

TABLE I
ZONE-BASED LOCALIZATION ACCURACY SCORES (%) FOR VARIOUS INFORMATION TYPES AND CLASSIFICATION METHODS

	Information Type	
Classifier	RSSI	RR
Bayes. Filt. Gaussian	92.5	81.3
Bayes. Filt. KDE	91.6	85.5
SVM	88.5	83.5
LogitBoost	87.7	83.7

The confusion matrix[1] shows that, most of the confusion is between central and left zones (Table II). Although being symmetric in the experimental area, less confusion is observed between central and right zones due to the different object placement in the outer area (Figure 1).

C. Exact and Cascaded Localization

In this experiment, we aim to estimate the exact location of a tagged object with the k-NN algorithm. We used k=15 considering that the tag can be in any orientation. Exact localization errors are presented in Table III, for both the single level k-NN and the combined strategy with a zone-based

[1]A visualization of classifier accuracy where each column represents the instances in a predicted class and each row represents the instances in an actual class.

TABLE II
CONFUSION MATRIX FOR BAYESIAN FILTERING WITH RSSI

classified as →	Central	Left	Head	Right
Central	**1110**	118	13	19
Left	28	**476**	0	0
Head	0	0	**504**	0
Right	0	0	30	**474**

classification step first. The combined approach improves localization accuracy, in addition to reducing the search space. First, zones can be modeled better because of higher data amount. Fingerprints from unrelated locations can be similar because of environmental effects and can be included in the nearest neighbor set misleading the estimate. By first classifying into the zones, we implicitly make use of neighboring fingerprints. Figure 3 shows the CDF of localization error for both methods. With the hybrid method, 50% of the time the error is smaller than 30 cm and 90% of the time the error is smaller than 67 cm.

TABLE III
EXACT AND CASCADED LOCALIZATION ERRORS (CM) OBTAINED WITH RSSI AND RR

	Information Type	
Classifier	RSSI	RR
kNN	44.5	52.0
cascaded	37.4	50.3

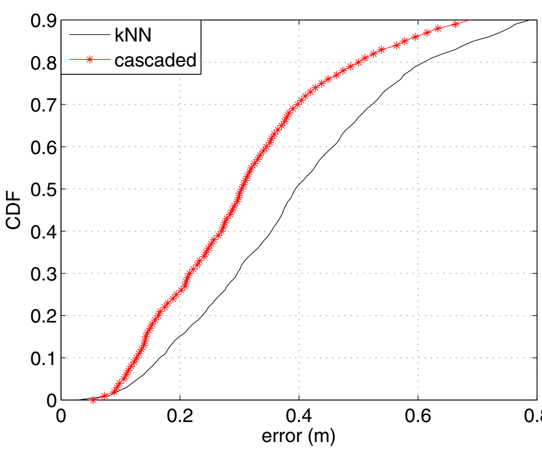

Fig. 3. CDF of localization error for kNN (exact) and cascaded localization methods

D. Scenarios #2, #3: Effect of Human Movement and Occlusion

In this experiment, we evaluate the performance of localization methods in case of human occlusion and movement (Scenarios #2 and #3) and compare with the ideal setting (Scenario #1). Results are presented in Table IV. Human movement causes a slight decrease in zone-based localization accuracy and does not affect the exact localization performance. Human occlusion, on the other hand, improves both

TABLE IV
LOCALIZATION PERFORMANCE IN SEVERAL SCENARIOS

Scenario #	Zone-based Loc. Acc. (%)	Cascaded Loc. Error (cm.)
1 (ideal)	92.0	37.9
2 (hum. mov.)	90.4	37.9
3 (hum. occ.)	97.0	34.4
4 (multitag)	86.5	42.1

zone-based and exact localization scores. The reason can be explained as follows. Human body functions as a barrier between zones and blocks the propagation of waves to the other zones. Multipath effects are minimized because some part of the reflected signals is absorbed by human body. Therefore zone-based localization accuracy is considerably improved. Cascaded localization error also decreases due to the better zone prediction in the first step. The error for single-stage exact localization was measured to be 40 cm.

E. Scenario #4: Effect of Multiple Tags in the Environment

In this experiment, we investigate the effect of multiple tags in the environment. During the experiment, two tags were uniformly placed in each zone in addition to the target tag.

Both zone-based and cascaded localization scores deteriorated when multiple tags were present in the environment (Table IV). When the number of tags is increased, read rate per tag reduces because of the collision detection mechanism, therefore processing more data can be a potential solution. However, increasing the sliding window length, we observed only a slight improvement. Further analysis revealed that the increase in error was not uniformly distributed to all locations. While there was no difference for most of the locations, we observed a high increase for the rest. These locations mostly correspond to the edges of zones.

F. Effect of Orientation and Location

To investigate the dependence of localization performance on tag orientation, we calculated localization error in subsets of different orientations. No significant difference was observed between the localization results obtained at different orientations. Therefore we can deduce that, our antenna setup and localization methods are robust to the orientation changes of the target object. Because our object of interest was made of foam, fingerprinting in three orientations were sufficient. When the object of interest is made of another material (e.g. wood or plastic), one may need to collect fingerprints in all orientations (e.g. facing the cabinets in addition to the table and separators – Figure 1).

Next, we analyzed how the error is distributed in the experimental area. Figure 4 shows the cascaded localization error for each testing location (Section III-B) averaged over all scenarios. We observe that the error pattern based on location is highly complicated. Still it is clear that the average error is higher in the central zone, especially at points close to the head zone. On the other hand, zone confusions were mostly between central zone and right or left zones. Head zone was separable with high accuracy in all scenarios, even when multiple tags were present in the environment. These observations indicate that, even when the zones are separated with 75 cm of distance (Figure 1) and each zone is scanned with one or more antennas, confusion rate is still around 10%.

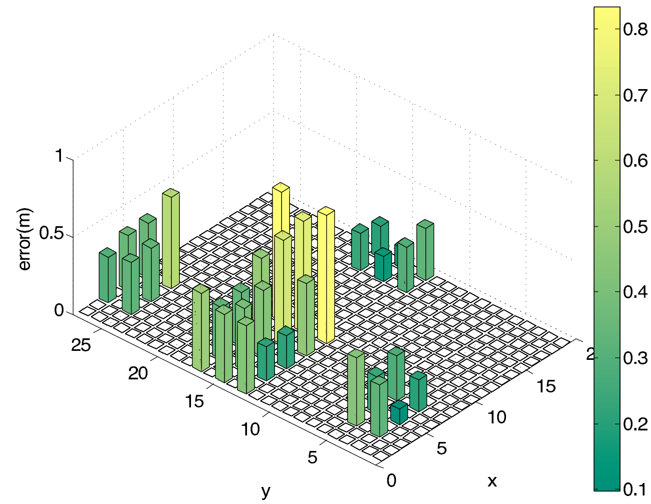

Fig. 4. Spatial distribution of the cascaded localization error (see Figure 1 for the room layout)

V. Conclusion

We developed passive RFID-based methods for localizing a small (and possibly inexpensive) object in an indoor workplace. Such environments are challenging for RFID applications because of random object orientations, human presence or motion and multiple target objects in the environment. We positioned the RFID antennas and configured the readers to minimize the obstruction for human activities and the effect of human presence and movement on the localization system. We experimented with both coarse-grained and fine-grained approaches and showed that a coarse-to-fine cascade yields the best location estimate. We conducted experiments introducing human presence, motion and multiple tags in the environment. Localization results show that it is possible to design UHF RFID-based context-aware systems robust to human body effects, which is a major concern for real applications. Future work includes developing methods for handling multiple tag scenarios, investigating the effect of object material variability and fusing the RSSI and RR information in an efficient way.

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