RIL – Reliable RFID based Indoor Localization for Pedestrians

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Abstract: Various approaches based on different wireless technologies have been proposed for indoor localization; however RFID technology remained the key focus of research in recent years compared to other technologies available on the market. RFID localization solutions are based either on tag detection count or signal attenuation, yet their reliability are not consistent. In this paper, we propose a novel approach that guarantees a reliable solution for indoor localization. Our localization algorithm confines the user's location by a combination of tag detection and RSSI measurement. The results are refined by the use of filtering algorithm.

1. INTRODUCTION

Localization and navigation in a non GPS environment is based on technologies such as WLAN, ZigBee, Bluetooth, RFID and UWB in recent years. However most of these technologies are not reliable and some of them are less scalable and are not flexible. Inadditon some fail to be cost efficient.

Radio frequency identification (RFID) technology has fascinated society in terms of economic and scientific scenario and is employed to a large extent in commercial areas such as healthcare, automotive and chemical industries for various applications. Features such as user-friendly, hands free, low power consumption, high security are other vital attributes that RFID technology inherits.

In recent years, RFID has been exploited much for self localization and navigation. RFID dominates other wireless technologies concerned with indoor localization as it pledges supremacy with its precise positioning ability. Today's indoor localization for pedestrians based on RFID technology lacks reliability. To overcome this we aim to attain a Reliable Indoor Localization using RFID (RIL) in order to provide scalable, reliable and accurate localization of the pedestrians which the other technology fails to provide.

This paper is structured as follows: In Section 2, we review state of art technologies using RFID for localization function and illustrate the benefits and advantages of our approach. In section 3, we explain the characteristic features of RFID sensors in general and portray the features of sensor that we employed in our approach. In section 4, we describe our RIL approach that features the sensor models based on tag detection and we present a localization algorithm that confines the user's location. In section 5, we evaluate our experimental results performed indoors and in section 6, we conclude our paper.

2. STATE OF THE ART

Indoor positioning using RFID technology has been studied to a great extent especially for robots and pedestrians.

In one approach using RFID, Decentralized slam (DSLAM) algorithm is employed for sharing information between pedestrians in an altruistic manner [1]. Also in this approach, the PDR (Pedestrian Dead Reckoning) method is used to track automatically the position of each pedestrian from acceleration patterns. In a nutshell, based on shared information history, RFID provides optimization to accelerometer values for tracking individual's path.

Another approach utilizes super-distributed smart-entity infrastructures for tracking objects in indoors [2]. The prototype reveals that the positioning service provides an average accuracy of approx. ±15 cm at a meticulous walking speed with a tag density of 39 tags/m^2.

Wilson illustrates that received signal strength information between the reader and the tagged item need not be a factor to localize the objects, whereby they designed a method that maps the tag count percentage to the database of tag count patterns at various attenuation levels and distances from the base station reader [3].

SpotON [4] is a well-known location sensing system that makes use of received signal strength indication (RSSI) to estimate the distance between the active RFID tags and thereby localizing the user with the help of inter-tag distance. The radios used in this approach can handle hardware variability, hence increases estimation accuracy.

The LANDMARC [5] approach utilizes reference tags to localize an object indoors. However LANDMARC has drawbacks such as i. Ample scanning time to scan all the power levels. ii. Accuracy depends on tags behavior and iii. Long latency for every update as computation is executed in a server.

Hähnel attained indoor localization using RFID and laser scans [6]. In his approach, a probabilistic sensor model was used to compute the likelihood of tag detections. Using a highly accurate Fast SLAM algorithm, maps were generated for laser range scans. The downside of this approach is that it does not work independently without the input from the laser scans.

The Snapshot approach uses the idea of vision based localization and the tag detection for localization [7]. The algorithm features a particle filter for localization, utilizing the detection rate of tags obtained from snapshots and the odometer data from the robot. An accuracy of 40 cm is

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achieved after few executions of the particle filter. The drawback of this approach is the time-consuming training phase as it requires several snapshots to be done earlier, and accurate self-localization is possible if there are reference snapshots.

In our design, we used the likelihood of tag detection as in Hähnel's approach. However by using only parameter tag count we cannot achieve reliable indoor localization as it lead to false positive results. We also cannot rely on attenuation all times. Unlike from the reviewed approaches [3] to [7], our design takes into account the tag RSSI as well as tag detection rate that yields accuracy of 35 cm in the worst case. Moreover a training phase as in approach [7] is not necessary that consumes ample time. We attained an efficient localization outcome even when we used reduced distribution of tags (15/m^2) compared to a distribution of 39 tags/m^2 as discussed in approach [2]. Overall, using our design one can obtain an efficient, reliable, scalable, cost-effective indoor localization system.

3. CHARACTERISTIC OF RFID

A basic RFID system comprises of three parts: a RFID reader, an antenna and a RFID tag. The vital role of an RFID reader device is to interrogate an RFID tag. An antenna in the reader emits radio signals that in turn activate the tag, enabling the reader to incorporate data to an tag.

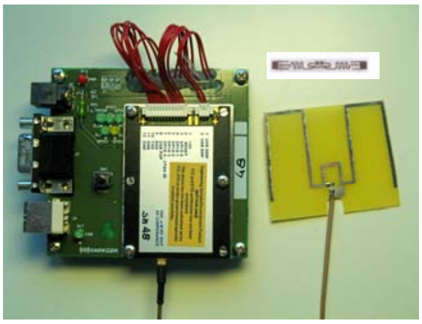

Fig 1: CAEN'S A528 OEM UHF RFID reader and ALIEN'S Higgs Tag

For our experimental design, we used a short range device, CAEN'S A528 OEM UHF RFID reader and ALIEN'S Higgs Tag [Fig. 1]. The characteristic feature of our reader is compactness, multiregional support, EPC Class1 Gen2 protocol based, programmable output power (up to 500mW in eight steps), with USB and UART support. We employed a compact bent dipole linearly polarized antenna WANTENNAX008 in our RFID reader that supports the European UHF RFID band. The A528 reader used in our design provides wideband, narrowband and tag RSSI values. The wideband RSSI is a measure of the total signal level seen by the ADC at the first stage of receiving path, whereas the narrowband RSSI value is derived after digital filtering and has information only on the signal level inside the channel bandwidth. Narrowband and wideband RSSI measurements are internally used in A528 firmware to administer the accurate behavior of the R1000 transceiver in the reader. By issuing a single low level communication codes, the reader detects multiple transponders and this procedure is termed as inventory. As a result one gets a sequence of byte streams that contains a message ID, source name, inventoried tag IDs, respective timestamps and tag RSSI values, as well as the result code indicating success or failure for the inventory.

4. RIL APPROACH

The RIL infrastructure shown in Figure 2 comprises of RFID tags (1) for tracking the position of user, a RFID reader (2) to interrogate and retrieve the tag ID and the tag RSSI values and a mobile (3) that acts as a graphical user interface for the user.

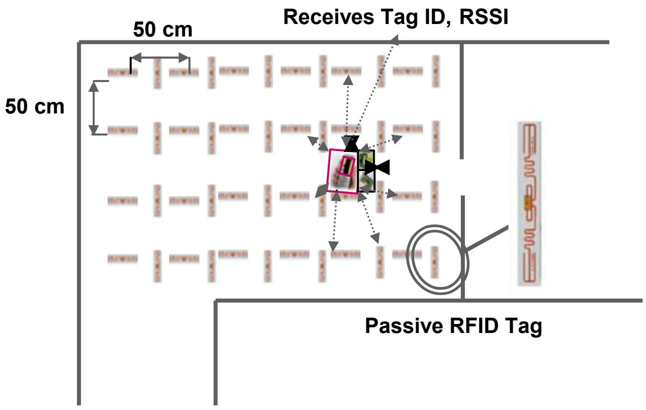

Fig 2: RIL Infrastructure

The maximum reading range of the A528 RFID reader is around 1.5 m. Tags were positioned horizontally and vertically on the floor to gain detection irrespective of the orientation of the antenna. As it should be worthwhile when implemented for a pedestrian purpose, we obtained readings by placing the reader at waist level (assuming that the user should either carry them in trouser pockets or in hand bags that are 50 cm above the pedestrian level). Each tag IDs location information is programmed in respective tags. Reader receives inventory byte stream commands from a mobile and confers back to mobile with tag info and their respective RSSI values. Cohering these RSSI measurements with detection counts, a mobile user's location is tracked with high precision.

In our RIL system we describe and compare three approaches for indoor localization .The three approaches are

i) Localization based on tag count described in 4.1
ii) Localization based on RSSI values described in 4.2
iii) Combination of tag count and RSSI values as described in 4.3.

The localization results are refined in all the three approaches with a particle filter described in 4.4.

4.1 Localization based on tag count probability

User localization by tag detection count has been widely described in literature; hence we implemented the same approach for the first step of our localization solution. For localizing the user a sensor model is used. First we overview our sensor model and then describe the localization algorithm that incorporates the sensor model.

Sensor model based on tag detection

In general, the tag detection depends on antenna orientation, power supply used by the reader and the object to which the tag is attached. We obtained a better detection irrespective of the antenna orientation, when tags being positioned horizontally and vertically. Usage of maximum power supply consistently resulted in better detection (see section 5.1). Tags that are far apart or more closer to the reader may endure different or inconsistent tag detection values. To overcome the above problem, we employ a probability model and the likelihood of tag detection over the period of time.

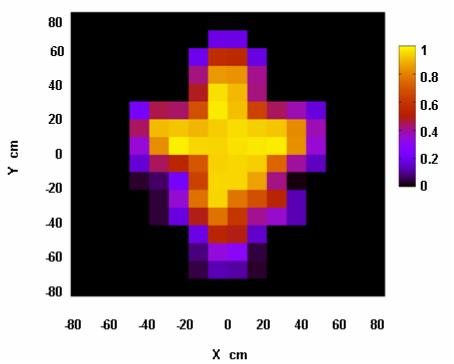

Fig 3: Probability based sensor model

The probability model is designed taking into account the probability of detection rate of tags over a particular period of time given the location *l*. According to Bayes' theorem in terms of likelihood, the posterior probability is directly proportional to the product of likelihood and prior probability. We associate it to our purpose as

$$P(T_d \mid z_{1:t}) \;\alpha\; L(T_d \mid z_t)\, P(T_d)$$

Here $P(T_d \mid z_{1:t})$ is the posterior probability of detecting tag T at location *l* given the data's collected from 1…t. $L(T_d \mid z_t)$ is the likelihood of detections T_d given the location *l* of the tag. Distance between tag and reader over time, posterior probability values, likelihood detection and tag detection were assigned to a lookup table and were used in localization algorithm. The sensor model depicted in Figure 3 shows the tag detection probabilities over a time of 40 seconds with the reader placed in position (0,0) at a height of 50 cm from the ground. This sensor model is used for our experiments.

Localization algorithm based on tag count probability

In the first step the reader does an inventory for a second. In this stipulated time, probability of each tag count is been calculated in the time steps 1…t. Each tag counts are superimposed on the lookup table of the sensor and posterior probability values were obtained. Based on the maximum posterior probability values, the distance between each tag to the reader was inferred. Finally, the position of the user was estimated by allocating the tag location and distance values to the particle filter (see section 4.4).

4.2 Localization based on RSSI measurements

Tag RSSI is the signal strength received by the user when a tag is interrogated. In our localization approach, tag RSSI values were collected when tags are detected. We then estimate the distance *d* from the signal strength using the formula.

$$d = 10^{(r \quad a)/b}$$

Here r is signal attenuation received when the tag is inventoried, a and b are attenuation coefficients (parameter for attenuation of the signal along its propagation path) assessed from prior measurement during the calibration phase. Finally, the position of the user was estimated by allocating the tag location and distance values to the particle filter (see section 4.4).

4.3 Localization based on cohered RSSI and tag count

A localization algorithm was developed that uses the tag detection count and RSSI to estimate the distance between the reader r and tag t. Signal strength and the tag count decreases with increasing distance, however at times probability of detection count of the tags will remain consistent or may provide false positive readings; therefore one cannot rely only on the tag count. The same is true for attenuation as well. These both factors lead to imprecise localization results when working in environment where tags are placed 50cms apart thus reducing the number of tags. Hence we developed a method that considers tag count and RSSI to confine the user's location by generating a probability to define the tag location. We carried out the localization method in 3 steps. In the first step (i) the

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detection probability P (t) was acquired. In the second step (ii), number of times that a tag receives the maximum RSSI value is accounted and a conditional probability is made for a value is accounted and a conditional probability is made for a detected tag with maximum RSSI value given the detection rates

$$\mathrm{P(r)} = P(T_{\max rssi} \mid d_t) = \frac{P(d_t \mid T_{\max rssi})\, P(T_{\max rssi})}{P(d_t)}$$

Here $P(d_t \mid T_{\max rssi})$ is the detection probability of the tag provided the tag posses a maximum RSSI value. We obtain the final probability by summing up probabilities obtained from (i) and (ii).

$$P(f) = P(t) + P(r)$$

The final step in our localization algorithm is confining the users location by data's obtained from previous steps. The final probability values are mapped on a lookup table (designed during a calibration phase) and corresponding distances are obtained. Finally the position of the user was estimated by allocating the tag location and distance values to the particle filter (see section 4.4).

4.4 Particle Filtering Algorithm

To apply the particle filter to position estimation the sensor models for tag detection P_{tc} (z | x), RSSI (P_{rssi} (z | x) and cohered RSSI and tag count ($P_{co\ (rssi+tc)}$ (z | x) are ascertained. In all the cases P (z | x) denotes the likelihood of the sensor observation z given the relative position x (to the reader).The particle filter algorithm consist of three steps:

1. Resampling: In this phase a new set of particles is drawn, assigning particle i, the weight w (i).
2. Prediction: The change of position is predicted by drawing for each sample a new sample according to the weight of the sample and according to the model.
3. Correction: In the correction phase the particle weights are updated. The weights of the particles in filter are proportional to the observation likelihood P (z | x).

The particles will congregate towards a point representing the position of user.

5. EXPERIMENTAL RESULTS

In all our experiments the reader was held at 50cm from the ground level. In order to test the efficiency of our designed RIL system, we carried out experiments in the pedestrian path of our campus. We carried out series of experiments to exploit the RFID sensor characteristics that we used in our experimental design. First we present results on the A528 RFID reader by varying the power in 8 steps.

a. **Read range obtained by stepping up /down the power**

The maximum power output of the reader is 500 mW. The reader can be programmed in 8 steps based on power output. We carried out experiments by stepping up and down the output power. The maximum readingrange that we obtained in each power state is summarized in Table 1.

Transmitting Power Tx in mW	Transmitting Power Tx in dBm	Read Range in cm
25	13.9	0
50	16.9	10
75	18.7	15
100	20	66
200	23	66
300	14.7	67
400	26	67
500	26.9	71

Table 1: Reading range depending on the transmitting power

As our goal is to obtain a reliable localization; it is obvious that the reader should be capable of detecting maximum number of tags. Therefore providing maximum power serves the above purpose.

b. **Error estimation with localization approaches**

We illustrated how localization works using our approach in comparison to the approach described in section 4.1 and 4.2. Tags are assigned 50cm apart both horizontally and vertically, however the distance between horizontal and vertical tags were 25cm. The tag distribution is shown in Figure 2.

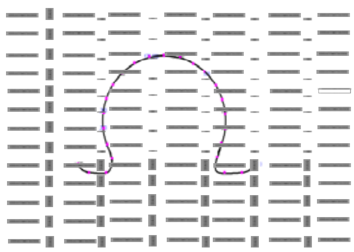

Fig 4: Trajectory in a grid of 300 *600 cm

We used a grid of 300 x 600 cm and created a trajectory over which spots are superimposed .The trajectory is shown in Figure 4.Readings were obtained over these spots when moved through the trajectory. Using the above obtained readings, approaches 4.1, 4.2, 4.3 were evaluated. In each of those described approaches, we run a particle filter several times considering the random nature of particles. Mean localization errors were determined over different time periods for each of those approaches. Mean localization means the average localization error by several measurements.

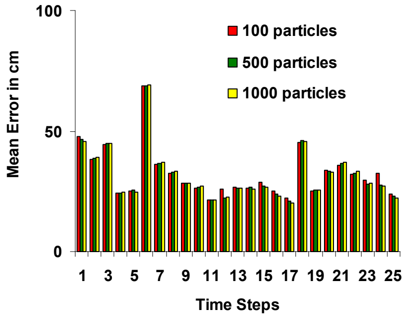

Fig 5: Localization error when executing approach 4.1 - Localization with tag count probability

The comparison of the all three approaches yielded estimation errors in its worst case of about 68 cm in approach 4.1 [Fig. 5], 64 cm in approach 4.2 [Fig. 6] and 35 cm in the approach 4.3 [Fig. 7].The results are summarized in Table 2.

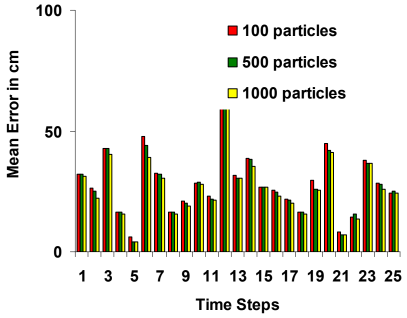

Fig 6: Localization error when executing approach 4.2 - Localization with RSSI

The results show that our cohered algorithm provides higher accuracy compared to the single solution based on tag count or RSSI values. Nevertheless, we tested the behaviour of the localization algorithm with changing number of particles in the particle filter that yielded no difference in estimation errors for 100, 500 or 1000 particles used.

	Measurement based on		
	Tag count	RSSI	RSSI + tag count
Worst Case	68 cm	61 cm	35 cm
Best Case	21 cm	6 cm	6 cm
Average	32 cm	27 cm	21 cm

Table 2: Mean localization error with filter using 100 particles

From our observations, usage of 100 particles is sufficient to obtain an optimum result. Without considering laser scan or odometry data as in Hähnel's [6] and snapshot [7] approaches respectively, our approach yields very low localization errors when compared. Runtime of particle filter remains almost same 7.3 ms, as in the snapshot approach however better than in Hähnel's approach.

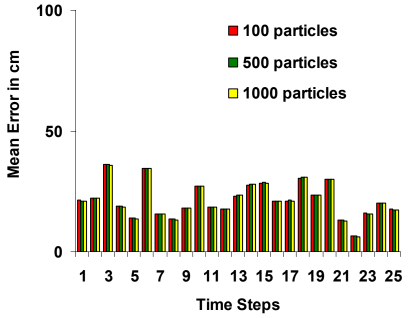

Fig 7: Localization error when executing approach 4.3 - Localization with combination of tag count and RSSI

6. CONCLUSION

Overall in this paper we illustrated and evaluated an accurate and reliable localization system based on RFID for pedestrians taking into account both tag count and the RSSI values. Also we compared our experimental design with various other approaches available in the localization field in recent years and we portrait and justify that our experimental design is scalable, accurate and reliable than other approaches in RFID localization.

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