Hybrid RFID System-based Pedestrian Localization: A Case Study

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***Abstract*— Localization systems using RFID – especially passive RFID – are coming increasingly under the spotlight. Passive RFID has a relatively small sensing range compared to other radio-frequency-based localization techniques. Therefore in practice the deployed tags may not cover the whole scene of interest. Additionally, in the area of pedestrian localization, the unpredictable movement of pedestrians makes a complete RFID tag coverage extremely difficult. This paper introduces a hybrid RFID localization system used for indoor pedestrians to overcome the coverage shortfall associated with passive RFID tags. Two extra sources are used to assist the RFID system: local INS sensors and ZigBee nodes. A particle filter serves as a fusion framework. A test scenario was built with 220 RFID tags and 8 ZigBee nodes deployed in a museum. Different algorithms were evaluated in this deployment. The results show that the hybrid approach produces robust localization even with a low number of tags.**

***Index Terms* - RFID, hybrid localization, fingerprinting, dead reckoning, particle filter**

I. Introduction

Localization based on passive RFID technology offers great potential for commercial use due to the extensive installation of passive RFID tags, the low cost of tags, and the effortless maintenance required. RFID localization is a viable alternative compared to other localization techniques in indoor scenarios where the GPS signal is undetectable. The stability of RFID localization is better than other radio-based localization systems, such as WLAN or GSM localization, due to the relatively small reading range.

Localization techniques have been used for a long time on pedestrians. However, indoors, making the system accurate enough to fulfil the needs of many applications still poses a challenge. Pedestrian localization has some unique characteristics compared to other applications. First, the pedestrian typically has unpredictable in-body movements. These movements cause noise on measurement equipment installed on pedestrian's bodies. Second, any part of a pedestrian's body can block the line-of-sight of microwaves and which makes it hard to properly apply propagation theory.

UWB systems, compared to other indoor localization techniques, benefit good accuracy and stability. However, the UWB system typically has a short sensing range and is relatively power-hungry [1]. Due to these drawbacks UWB nodes are difficult to be deployed universally indoors.

A key advantage of the passive RFID technique over the UWB system is the ease of installing great numbers of RFID tags in an indoor area. A vast deployment of passive tags costs significantly less than other localization systems of comparable scale and size. It is therefore reasonable to consider passive RFID as an attractive solution for indoor pedestrian localization.

Passive RFID localization – with its obvious advantages – still needs to overcome a number of obstacles, especially with regard to pedestrians. Designing a portable passive UHF reader is difficult due to its much more power consumption compared to active communication systems. Moreover, passive RFID system characteristics restrict the reader reading angle. This literally becomes a pivotal issue in pedestrian localization. The walker can turn around at any time – and then previously read tags are lost. More seriously the user can stay in a place where no tag is read for a long time.

In this paper, we focus the discussion on the use of other techniques to enhance the viability of RFID localization. We use two extra sources: a local INS sensor and ZigBee nodes. Both are widely used for localization so that the additional outlay for these devices is low. Particle filter is used as the fusion framework, as similar in [2].

The other parts of the paper are organized as follows: section II reviews some related works on similar topics; section III describes in detail the proposed fusion algorithm; section IV introduces the hardware/software platform, the experimental setup and the test results; finally section V contains our conclusions and a research road map going forward.

II. Related Works

Passive RFID localization has been intensively researched recently. [1] gives a thorough overview of the ranging techniques based on RFID which are fundamental in many localization algorithms. [3,4,5] survey different RFID localization algorithms.

Passive RFID localization can be further classified into reader localization and tag localization. TABLE I briefly describes typical passive RFID localization applications. The pedestrian – in the intended application scenario proposed in this paper – carries the reader and is self-localized: this is the only way to deploy massive numbers of tags. The wide deployment of readers in existing infrastructure in many museums and exhibit halls is impracticable anyway. In our survey, therefore, we focus on localization with a moving reader and fixed tags.

TABLE I
TYPICAL APPLICATIONS OF PASSIVE RFID LOCALIZATION

	Fixed Object	Moving Object
Reader localization	The persons take the tag and "search" for the object with reader (autokey…)	Self-positioning of reader, tags are usually fixed (museum, exhibits…)
Tag localization	The reader usually has another localization source and scans for tag's position (working sites…)	Readers are usually fixed, objects take the tag and get itself localized (warehouse…)

[6] describes a self-localization system based on RFID. The reader is attached to a mobile robotic system. The location is estimated using a Bayesian estimator with a presumed sensor model of the RFID reader. [7] extended the idea into the RFID reader with RSSI measurement. Another statistical-based RFID localization algorithm is described in [8]: the authors investigated tag detection using multiple powered readers.

A proximity-based RFID localization framework for building sites is introduced in [9]. The reader is equipped with a GPS receiver, whose output is a reference to localize tags in unknown locations.

Passive RFID localization has also been applied in industry. RFID key entry has been introduced by some automobile companies [10]. Construction sites are another area of application: where tools can be found using RFID-based localization technology [11].

Many previous works have dealt with the hybridization of dead reckoning with other techniques. [12,2,13] discuss the fusion of dead reckoning with radio-based localization. Furthermore, [14] describes how dead reckoning can be fused with ultrasonic localization. The basic idea is usually a framework based on a Kalman or particle filter which will also be followed in this paper.

Some works have investigated the hybridization of RFID with other techniques. A system that fuses RFID localization with dead reckoning in emergencies was introduced in [15]. Although the RFID reader was simulated in this research, it illustrates the viability of this type of hybrid system.

III. HYBRID RFID LOCALIZATION

A. RFID localization

RFID localization techniques can be classified into: multilateration, scene analysis and proximity – as concluded in [3,4,5]. Multilateration and scene analysis methods typically need hardware support (for example, to measure signal strength or accurate time of fight). The RFID module in our scenario is compact as it needs to fit in portable devices and often lacks the hardware needed to implement localization algorithms.

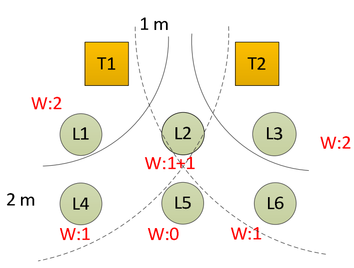

Fig- 1 Principle of proximity-based RFID localization

To get around this we designed a proximity-based localization algorithm which is similar to the approach presented in [9]. The basic principle is to assume that the object (pedestrian with reader) is located in the overlapping areas of the sensing ranges of different tags, as depicted in Fig- 1.

After reading tags in a time period T, the algorithm calculates a weight for each candidate cell i.e. each potential position of the pedestrian. The improvement compared to [9] is that the influence of the distance on the tag reading probability is considered. Supposing tag A_n is detected in T, the weight of each candidate cells is defined as:

$$w_{k,t}^{n}=\begin{cases}2, & D(L_k,L_{A_n})<1\text{ m}\\ 1, & 1\text{ m}<=D(L_k,L_{A_n})<=2\text{ m}\\ 0, & D(L_k,L_{A_n})>2\text{ m}\end{cases}$$
$$w_{k,t}=\sum_{i=1}^{n}w_{k,t}^{n} \quad (1)$$

where D indicates the distance between cell k and the tag A_n. The weights from all detected tags are summed up. Finally, cells with the highest weight form an estimation zone E (cells 1, 2 and 3 in Fig- 1). The algorithm assumes the pedestrian's location to be the average location in the estimation zone:

$$E=\arg\max_{k}(w_k);\quad \hat{l}=\overline{\sum_{k\in E}L_k} \quad (2)$$

This localization has the advantage that unreadable nearby tags don't influence the weights. Such things can happen because of damage or shielding by furniture or humans.

B. Particle Filter and Dead Reckoning

In areas not covered by the RFID tag, the algorithm either stays with the latest location generated by the RFID localization system or relies on alternative sources of information.

One way to supplement and augment the RFID localization algorithm is to leverage the local INS sensor for approximating the step length and estimating the walking direction. An algorithm is proposed in [15] and tested in the simulator. It uses the extended Kalman filter to fuse the output of INS sensors (steps and orientations) with the RFID.

Our approach follows a similar model as described in [2], using particle filter as the fusion mechanism. Here the estimated state is the real position of pedestrian. The output from absolute localization mechanisms, such as RFID and ZigBee, are assumed to be a Gaussian distribution around the real location. The movement model is considered as:

$$\begin{pmatrix}x_t^{\{i\}}\\ y_t^{\{i\}}\end{pmatrix}=\begin{pmatrix}x_{t-1}^{\{i\}}+\cos(\theta_t)\cdot d_t\\ y_{t-1}^{\{i\}}+\sin(\theta_t)\cdot d_t\end{pmatrix}+\begin{pmatrix}\cos(\theta_t+\Delta\theta_t)\cdot\Delta d_t\\ \sin(\theta_t+\Delta\theta_t)\cdot\Delta d_t\end{pmatrix} \quad (3)$$

Here, θ_t and d_t indicate the estimated walking direction and the distance from INS sensor, respectively; $\Delta\theta_t$ and Δd_t are the assumed measurement error. The estimation follows the same method as described in [2].

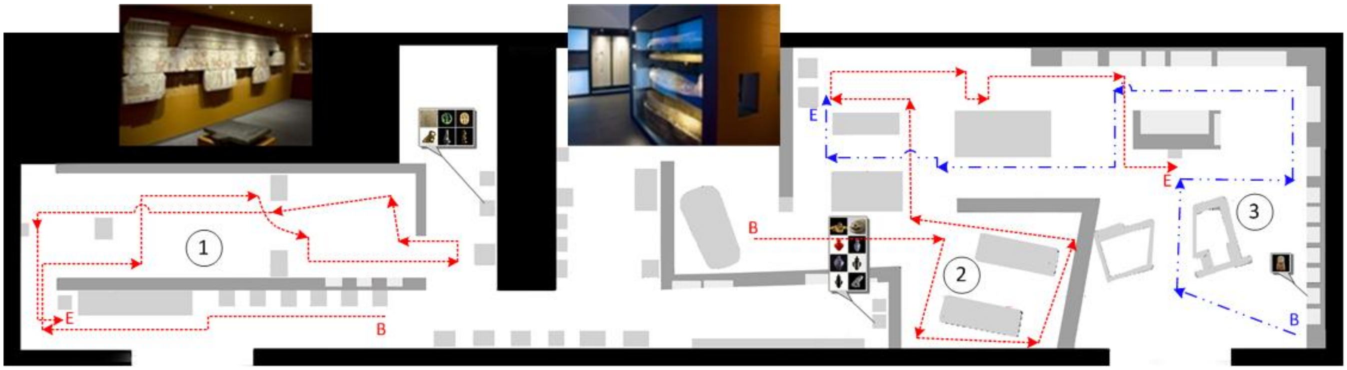

Fig- 2 Walking trajectories in Roemer-Pelizaeus-Museum Hildesheim used for evaluation

The measurement model of particle filter is modeled as:

$$w_t^{\{i\}} = w_{t-1}^{\{i\}} \cdot p(r_t \mid l_t^{\{i\}}); \quad l_t^{\{i\}} = [x_t^{\{i\}}, y_t^{\{i\}}]$$
$$p(z_t \mid l_t^{\{i\}}) = \frac{1}{\sqrt{2\pi\sigma_{rfid}}^2} \exp\left(\frac{(x_t^{\{i\}} - x_{rfid,t})^2 + (y_t^{\{i\}} - y_{rfid,t})^2}{2\sigma_{rfid}^2}\right) \tag{4}$$

Here, *i*, l_t and w_t indicate the index of each single particle, the location of objects at time *t* and the weight of particle at time *t*, respectively; and $[x_{rfid}, y_{rfid}]$ is the estimated location from RFID localization as described in III-A.

C. *ZigBee localization and "Multi-Way" method*

The aforementioned RFID localization algorithm can be migrated easily on a ZigBee node in a tag-free zone by simply exchanging $[x_{rfid}, y_{rfid}]$ to $[x_{zb}, y_{zb}]$ and σ_{rfid} to σ_{zb} :

$$w_t^{\{i\}} = w_{t-1}^{\{i\}} \cdot p(r_t \mid l_t^{\{i\}}); \quad l_t^{\{i\}} = [x_t^{\{i\}}, y_t^{\{i\}}]$$
$$p(z_t \mid l_t^{\{i\}}) = \frac{1}{\sqrt{2\pi\sigma_{zb}}^2} \exp\left(\frac{(x_t^{\{i\}} - x_{zb,t})^2 + (y_t^{\{i\}} - y_{zb,t})^2}{2\sigma_{zb}^2}\right) \tag{5}$$

This method works fine in most situations. In the real test, however, it is noticed that simple switching between RFID and ZigBee localization will give the user a negative feeling. For a "smoother" shift from RFID to ZigBee we propose a *Multi-Way (MW)* method for ZigBee localization. The MW algorithm starts from a presumed location – the last estimated location from the RFID localization algorithm – and evaluates all possible walking trajectories. Each time a transition is made from one cell to another, this trace is rated by summing the rating from the previous cell and the new rating of this transition calculated from the current RSSI measurement. If there are multiple ways to reach a cell, the algorithm takes only the highest rate:

$$G_{x,t} = G_{x,t-1} + \max(R_k) \quad \text{if } D(k->x) = 1 \tag{6}$$

Please note that the MW algorithm "grows" from one point to the whole map ($G_{x,0} = 0$), the user will then notice smoother shifts from RFID to ZigBee localization.

The rate calculation follows the following equation:

$$R_k = \frac{1}{(d_{\max} - d_{\min})} \cdot (-d_k + d_{\max}) \tag{7}$$

where d_k is the Euclidean distance between the fingerprint of one candidate cell to the measured RSSI values. $d_{\max}$ and $d_{\min}$ are the largest and smallest Euclidean distances of all candidate cells to the measured RSSI, respectively.

IV. MEASUREMENT AND EVALUATION

A. *Hardware and software*

We built a portable hybrid RFID localization system to evaluate the system in a live scenario. There were only a few suitable modules available when we were building the system. Our choice was restricted by several requirements: 1) it had to be a passive UHF reader with 2) at least 2 m sensing range and 3) a small size for integrating it in the portable device and 4) moderate power consumption and battery powered. In the end we went for an M10 UHF RFID module from SkyeTek. However, the M10 module does not provide signal strength or phase measurement.

Fig- 3 Structure of the hardware and outward looking

The system structure and the physical appearance of the device are depicted in Fig- 3. The sensor device comprises the M10 RFID reader with antenna, MCU, ZigBee, HMC6343 INS module and the battery. The MCU on the sensor board runs ContikiOS in order to coordinate different tasks. A PDA running Android communicates with the sensor device via Bluetooth, which is responsible for running different localization algorithms and providing the interactive GUI.

The sensor device delivers collected data to the PDA for further treatments: the RFID reader outputs the scanned tag ID at 2 Hz; the ZigBee outputs measured signal strength (RSSI) at 5 Hz and the INS sensor outputs measured magnetic field and acceleration in 3 dimensions at 10 Hz. We call the period of calculating a new position *evaluation round*, which is 500 ms in our tests.

B. Measurement setup

The algorithms have been tested in a real scenario located in the *Römer-Pelizaeus-Museum* in Hildesheim, Germany. The exhibit room *Der Tod in der Wüste* is about 40 meter long and 12 meter deep. The map of the test room and the three walking trajectories are shown in Fig- 2. In each test, the tester taking the hardware mimicked a normal visitor in the room: stopped, watched at exhibits and sometimes looked at the PDA for information. Each test took about 1 to 2 minutes.

Totally ca. 220 RFID tags and 8 ZigBee nodes were deployed. Most RFID tags were installed inside the vitrines; some were installed behind the wall. The ZigBee nodes were installed under the roof.

To test the hybrid localization algorithms in both dense and sparse RFID environments, the scanned RFID tags are post-processed by manually reducing the number of read tags in the test. We reduced the number of tags by 50%, 70% and 90% for all three walking trajectories tested by randomly skipping read tags. A total of 12 different test cases were evaluated. The *tag coverage* (TC, the percentage of evaluation rounds when at least one RFID tag is read) for each test case is shown in TABLE II.

TABLE II
LIST OF TEST CASES AND THEIR TAG COVERAGE

Walking trajectories	Tag reduction	Tag coverage (TC)
1	0%	54.2%
	50%	37.7%
	70%	26.9%
	90%	9.9%
2	0%	56.3%
	50%	48.3%
	70%	41.1%
	90%	13.2%
3	0%	68.5%
	50%	54.9%
	70%	41.8%
	90%	16.4%

For the purpose of analysis, the raw data are stored on a local database during the test and later processed by computer. In order to guarantee the correctness of the results, the Matlab scripts call the Java classes – used in the live scenario – directly.

A series of videos was also recorded during the test to give reference locations (real world locations). All results were compared against the reference locations extracted from the videos.

TABLE III summarizes the algorithms tested: they will be described in detail in later sections. Due to the randomness of the particle, the algorithms using a particle filter were executed 20 times and the average estimation error at each second was calculated.

TABLE III
LIST OF EXPERIMENTED LOCALIZATION ALGORITHMS

Abbreviations	Full Name	Description
RFID-PR	RFID Proximity	Proximity-based RFID localization
PF-RFID	Particle filter with RFID only	Particle filter (random walk) using RFID localization as the only estimation source
PF-RFID-KNN	Particle filter with RFID and KNN	Particle filter (random walk) using RFID localization and KNN localization (ZigBee) as estimation sources
PF-RFID-MW	Particle filter with RFID and MW	Particle filter (random walk) using RFID localization and MW algorithm as estimation sources
PF-RFID-DR	Particle filter with RFID and Dead-Reckoning	Particle filter applying a walking model and using RFID localization as the only estimation source
PF-RFID-ALL	Particle filter with RFID, MW and Dead-Reckoning	Particle filter applying a walking model and using RFID localization and MW algorithm as estimation sources

C. RFID localization without fusion

First we tested the RFID localization on its own, specifically, the RFID-PR and PF-RFID algorithms in TABLE III. The size of this article does not allow us to publish the results for each test case with all different tag coverage (TC) in detail. Thus, we present in the following the average results of the three test cases for two scenarios, high TC (> 50% coverage) and low TC (< 15% coverage).

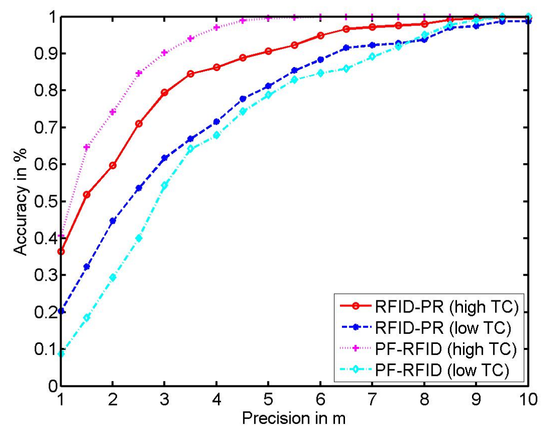

Fig- 4 Accuracy vs. precision for non-fused RFID localization

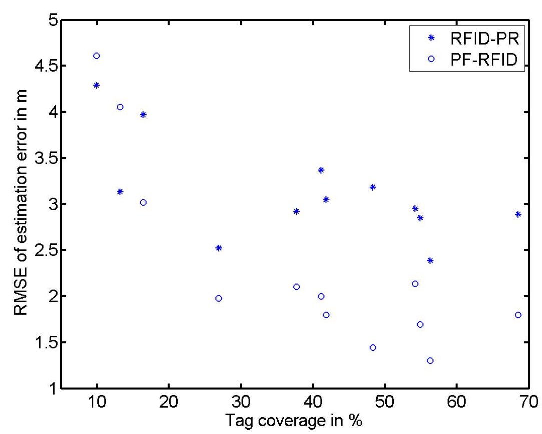

Fig- 5 RMSE of estimation error of non-fused RFID localization algorithms with different tag coverage

The result as shown in Fig- 4 illustrates first of all that the particle filter works well with RFID localization – it smooths the RFID localization output by reducing the noise error. Both with high TC and low TC the PF supported versions run clearly better.

Fig-5 shows that the performance of the RFID localization algorithm without hybridization is relatively stable with tag coverage between 25 % and 70 %. However, the performance drops radically when the tag coverage is below 20 %.

Fig-5 also demonstrates that the particle filter doesn't help much in zones sparsely covered with tags. Once the tag coverage is near 10 %, it even reduces the performance. In such case, another absolute localization technique is helpful.

D. Hybrid localization with ZigBee

In the second group of tests, we compared the RFID localization approach with hybrid localization with ZigBee (both with a particle filter for output smoothing). The major goal to integrate ZigBee localization is to improve the quality of location estimation for situations where no RFID tag was read.

The comparison given in Fig- 6 to Fig- 8 shows that, with high tag coverage, ZigBee localization offers little help or even reduces system accuracy. However, in the zone with sparse tag coverage, ZigBee localization can be useful for adjusting the RFID localization algorithm even with a very noisy RSSI measurement (mean error over 4 meters with ZigBee-only algorithm).

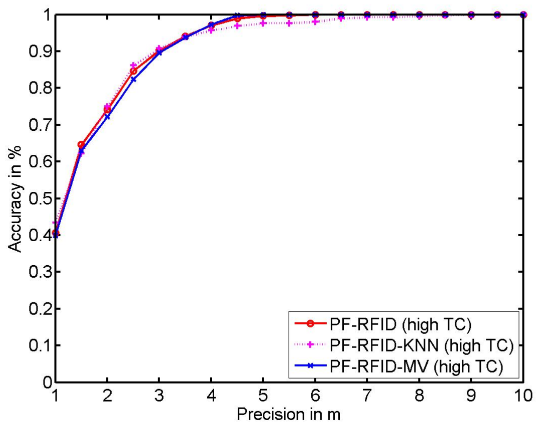

Fig- 6 Accuracy vs. precision for ZigBee-supported RFID localization (high tag coverage)

Typically, the MW algorithm works better than KNN; in some cases it can improve the RMSE over 0.3 meters. Nonetheless, the improvement is trivial. The reason is – we believe – that the particle filter smoothed the output so that the MW algorithm does not improve it much further.

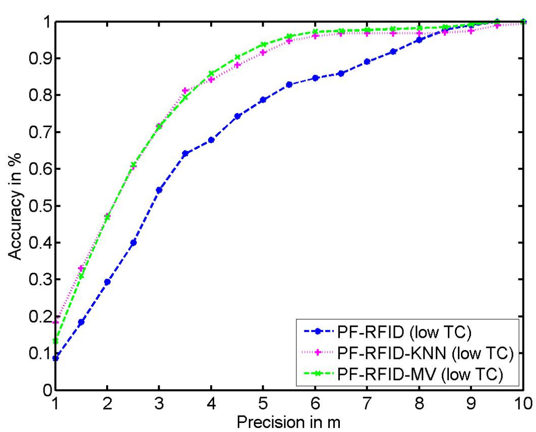

Fig- 7 Accuracy vs. precision for ZigBee-supported RFID localization (low tag coverage)

E. Hybrid localization with INS sensor

The last group of tests will show how the INS sensor can support RFID localization. A fundamental difference to the previously tested algorithms is that using the INS sensor the movements of the particles in the estimation phase of the particle filter is controlled with the model introduced in Section-III. We will compare the PF-RFID-MW algorithm – the best algorithm in the previous tests – with the PF-RFID-DR and, finally, the PF-RFID-ALL algorithm.

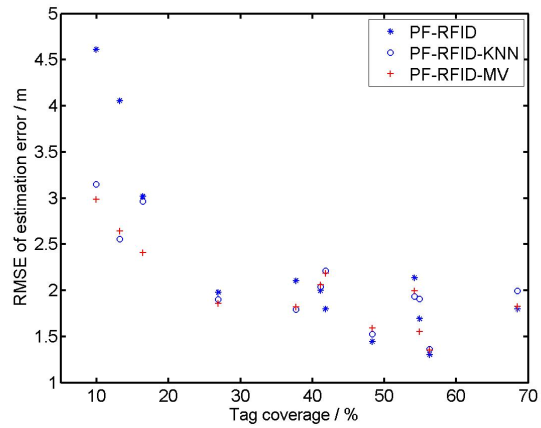

Fig- 8 RMSE of estimation error of ZigBee-supported RFID localization algorithms with different tag coverage

The results as shown in Fig- 9 to Fig- 11 demonstrate that if fused with dead reckoning (step detection and compass) only, it improves the performance considerably with high tag coverage but falls short with low tag coverage. The logical explanation is that the INS-supported algorithm has a better movement model so that each particle moves more accurately than in a random walk. However, as a relative position estimation technique the accuracy of dead reckoning degenerates with time. This means that when the RFID localization algorithm makes no correction over a long time period, there will quickly be a significant deviation from the actual real world location.

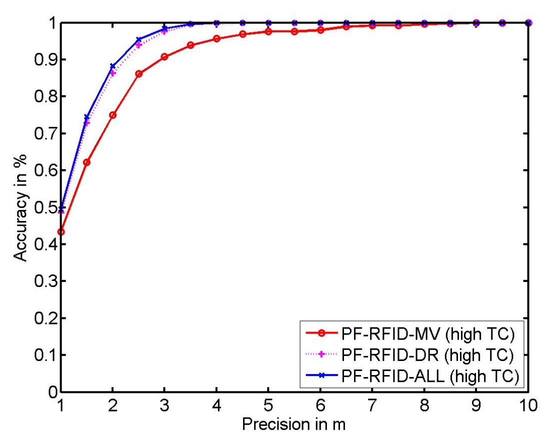

Fig- 9 Accuracy vs. precision for INS-supported RFID localization (high tag coverage)

The final test for the fusion with both ZigBee and INS sensor proved that both supporting mechanisms are critical: the INS sensor enhances RFID localization performance in the dense tag zone, and ZigBee comes more to bear in the sparsely tagged zone.

A few final words are called for here: 1) RFID localization works well independently in densely tagged zones only; 2) fusion with the INS sensor in a particle filter framework improves performance in densely tagged zones; 3) the use of another absolute positioning technique such as ZigBee or WLAN localization helps support and improve RFID localization in sparsely-covered zones.

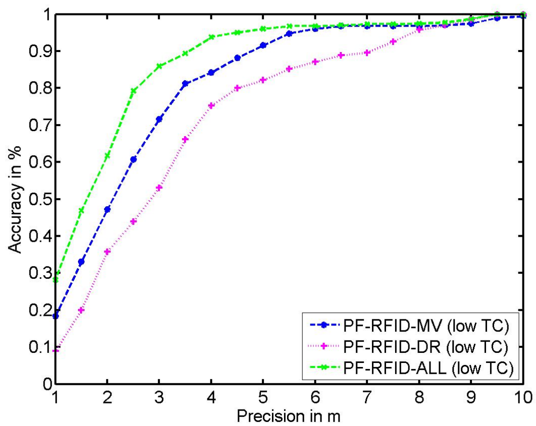

Fig- 10 Accuracy vs. precision for INS-supported RFID localization (low tag coverage)

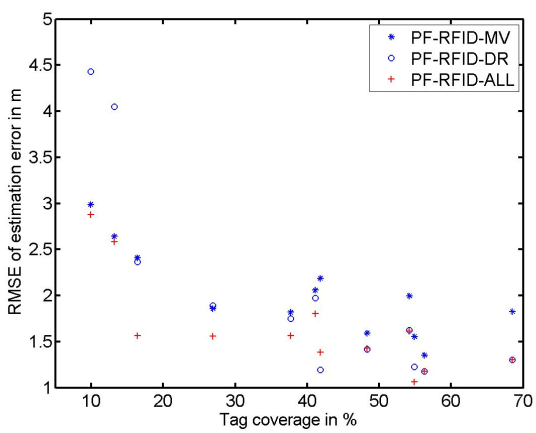

Fig- 11 RMSE of estimation error of INS-supported RFID localization algorithms with different tag coverage

V. Conclusion and Future Work

In this work we demonstrate a hybrid RFID localization system specially designed for indoor pedestrian navigation. The system is intended for use in real world environments, such as museums and exhibit halls. We also illustrated the hardware/software configuration for such a system.

We have proven the viability of such a system for use in very noisy and highly dynamic real world scenarios. We have also shown that, in areas with sparse tag coverage, overall system performance can be improved by the use of more sophisticated localization techniques.

Great value can be accrued, going forward, by improving the hardware design, especially the RFID reader, so it can accommodate more sophisticated localization algorithms, e.g. as presented in [16,17]. We believe that soon the hardware can be further reduced in size and be made sufficiently power-efficient for use in practice.

RFID localization accuracy can be further improved by applying sophisticated localization algorithms once the hardware is ready to offer more information. The impact of antenna angles (both on reader and tag) on reading range, signal strength as well as phase difference needs to be investigated as well.

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