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Platform and Algorithm Development for a RFID-Based Indoor Positioning System

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In recent years, developing Indoor Positioning System (IPS) has become an attractive research topic due to the increasing demands on Location-Based Service (LBS) in indoor environment. Several advantages of Radio Frequency Identification (RFID) Technology, such as anti-interference, small, light and portable size of RFID tags, and its unique identification of different objects, make it superior to other wireless communication technologies for indoor positioning. However, certain drawbacks of existing RFID-based IPSs, such as high cost of RFID readers and active tags, as well as heavy dependence on the density of reference tags to provide the LBS, largely limit the application of RFID-based IPS. In order to overcome these drawbacks, we develop a cost-efficient RFID-based IPS by using cheaper active RFID tags and sensors. Furthermore, we also proposed three localization algorithms: Weighted Path Loss (WPL), Extreme Learning Machine (ELM) and integrated WPL-ELM. WPL is a centralized model-based approach which does not require any reference tags and provides accurate location estimation of the target effectively. ELM is a machine learning fingerprinting-based localization algorithm which can provide higher localization accuracy than other existing fingerprinting-based approaches. The integrated WPL-ELM approach combines the fast estimation of WPL and the high localization accuracy of ELM. Based on the experimental results, this integrated approach provides a higher localization efficiency and accuracy than existing approaches, e.g., the LANDMARC approach and the support vector machine for regression (SVR) approach.

Keywords: Indoor positioning system; RFID; Weighted Path Loss (WPL); Extreme Learning Machine (ELM).

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1. Introduction

Nowadays, the popularity of social networks and the widespread usage of mobile devices stimulate the huge demands on Location-Based Service (LBS) in both indoor and outdoor environment. Global Positioning System (GPS) provides marvelous LBS in outdoor environment. However, due to the lack of line-of-sight (LoS) transmission channels between a satellite and a receiver, and the attenuation and scattering of microwave signals [1], GPS is not capable of providing positioning service with sufficient localization accuracy in indoor environment. Hence, developing an Indoor Positioning System (IPS) to provide reliable and precise indoor positioning and navigation becomes a hot research topic recently. It is worth noticing that a lot of problems, such as multipath effect of signal reflection from walls and furniture, physical layout changes of furniture and signal scattering due to large density of obstacles, make positioning and navigation in indoor environment much more complicated and challenging than in outdoor environment.

Various wireless communication technologies have been proposed and developed in order to provide indoor positioning and navigation, including Infrared, Bluetooth, ultrasound, Wireless Local Area Network (WLAN), Ultra-Wideband (UWB) and Radio Frequency Identification (RFID) [2–4]. Active Badge is an IPS making use of diffuse infrared technology to realize indoor localization [5]. The major disadvantages of Infrared-based IPSs such as Active Badge come from the requirements of LoS and short-range transmission of infrared signal. Due to the compatibility of Bluetooth tags and

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readers with the majority of mobile devices, Bluetooth-based IPS has also been proposed recently [6]. However, the communication range of Bluetooth is usually shorter than 10 m, thus largely limiting its application for indoor positioning. IPSs by adopting ultrasound technology such as Cricket [7] and Active Bat [8] have been proposed over the recent decades. Time-of-flight measurement techniques are leveraged by these IPSs to provide indoor location information. The involved huge cost and large scalability of these systems' infrastructure requirements make them inaccessible for common indoor localization applications. With the rise of wireless communication, WLAN has also been exploited to estimate the indoor location of a mobile target for years. By reusing the existing WLAN infrastructure, WLAN-based IPSs (RADAR [9], Ekahau [10]) requires only little deployment cost. However, the current optimal localization accuracy of WLAN-based IPS can only reach 3 m, which fails to meet the positioning precision requirements in some circumstances. In contrast, UWB-based IPS can provide a higher localization accuracy. For instance, the optimal localization accuracy of Ubisense [12] can reach 30 cm. Nevertheless, the interference of metallic and liquid materials can largely affect its performance. In addition, the high manufacturing cost of UWB readers also limits its application [4].

Compared with other technologies, RFID technology has several advantages, such as no requirement of LoS, anti-interference, and the fact that RFID tags are small and light and most importantly, it can uniquely identify different objects. It has been widely used in asset tracking, industrial automation and medical care. The application of RFID technology in developing IPS has become a hot research topic in recent years. RFID-based IPSs such as SpotON [13] and LANDMARC [14] can uniquely identify, localize and track equipment and persons successfully.

However, several drawbacks hinder the further development of existing RFID-based IPSs. One is the high cost of RFID readers and the active RFID tags. In order to overcome this, we develop a cost-efficient RFID-based IPS by using cheaper active RFID tags and sensors. Unlike LANDMARC, the signal strengths emitted from RFID tags in our system are picked up by RFID sensors instead of RFID readers.

Another drawback of existing RFID-based IPS is that its localization accuracy largely depends on the density of reference tags. Too many reference tags may result in increased RF interferences. We proposed the Weighted Path Loss (WPL) localization algorithm which does not require any reference tags for real-time indoor localization in [15] in order to address this problem. The WPL approach can be classified as a centralized model-based localization algorithm and it works as follows. The distance between the tracking tag and each sensor is calculated based on a modified International Telecommunication Union (ITU) indoor path loss (PL) model in the first place. Then the estimated location of the tracking tag is obtained as the summation of each sensor's weighting factor (reciprocal of the distance between the tracking tag and each sensor) multiplied by its physical location, provided all the physical locations of the sensors are known. Based on the experimental results shown in [15], the WPL approach can provide a higher localization accuracy than existing RFID-based IPSs. In this paper, we analyze the performance of WPL more comprehensively in terms of both localization accuracy and robustness under different scenarios.

In order to further enhance the localization accuracy of our RFID-based IPS, another fingerprinting-based localization algorithm: Extreme Learning Machine (ELM) was proposed in [15]. It consists of two phases: offline phase and online phase. During the offline phase, some RFID tags are adopted as reference tags. We record the historical Received Signal Strength (RSS) of these reference tags received at each sensor as well as their physical locations. The RSS vector and the corresponding location vector of these reference tags are adopted as the inputs and the training targets of ELM, respectively. Then, after the training process of ELM, we can obtain an ELM model. During the online phase, unlike the LANDMARC system, the reference tags are not required anymore. After feeding the RSS vector of the tracking tag into the ELM model, the output given by ELM is the estimated location of the tracking tag. Since ELM can be classified as a machine learning fingerprinting-based localization algorithm, we further compare the performance of ELM with other machine learning localization algorithms to obtain an overall performance evaluation of ELM in this paper.

Since the model-based approaches can provide a location estimation of a target in a short time and fingerprinting-based approaches can provide a higher localization accuracy in general, following this idea, we proposed another localization algorithm: WPL-ELM in [16], which integrates the fast estimation of WPL and the high localization accuracy of ELM together. During the offline phase, the indoor environment is divided into small zones first and an ELM model is developed for each zone. During the online phase, the WPL approach is used to determine the zone of the target primarily, then the ELM model of that zone is deployed to provide the final estimated location of the target. We evaluate and present a more elaborate performance assessment of WPL-ELM in terms of average localization accuracy, distance error distribution and cumulative percentile of error distance in this paper.

The rest of the paper is organized as follows. The state-of-the-art of RFID-based IPSs and indoor localization algorithms are investigated in Sec. 2. In Sec. 3, the background knowledge for this paper is provided. Section 4 demonstrates a system overview of our RFID-based IPS first, followed by the algorithm formulation of the three proposed localization algorithms. In Sec. 5, we present the experimental results and evaluation of the proposed algorithms. The conclusion and future work are given in Sec. 6.

2. Related Work

2.1. *RFID-based IPS*

A typical RFID-based IPS consists of three basic components: RFID readers, RFID tags and the interconnecting communication network. Both RFID readers and tags use a predefined RF frequency and protocol to transmit and receive data. The RFID reader is able to read the data emitted from RFID tags. RFID tags can be classified into two categories: passive and active tags.

Passive RFID tags operate without a battery and are mainly used to replace the traditional barcode technology. A variety of RFID-based IPSs by adopting passive RFID tags have been proposed in recent two decades [17,18]. Although they are lighter and less expensive than active tags, the range of the passive RFID tags is limited to approximately 1 to 2 m which largely restricts the coverage area of their system [19].

Active RFID tags are small transceivers equipped with button-cell batteries. They can actively transmit their ID and additional information to RFID readers. In contrast to passive RFID tags, a typical active RFID tag enables long transmission range of 30 m or more with the help of an onboard radio and a small antenna, rendering it quite suitable for identifying and tracking high-unit-value products or persons in complex indoor environments. RFID-based IPSs which use active RFID tags such as SpotON [13] and LANDMARC [14] have been proposed in recent decades. SpotON is a fine-grained IPS based on RFID signal strength. SpotON tags are custom devices that operate standalone or potentially as a plug in card enabling larger devices to take advantage of location-sensing technology. It can provide 3D location information of the tag. LANDMARC is one of the earliest and most famous IPSs by using active RFID tags and readers. In order to increase accuracy without placing more readers, extra fixed location reference tags are introduced in LANDMARC to facilitate location calibration. By collecting the RSS from each tag to readers, an RSS radio map is built. The system receives the RSS data from both reference tags and tracking tags in real time. After comparing the RSSs of the tracking tags with those of reference tags, the weighted *k*-nearest neighbor algorithm is adopted to estimate the locations of the tracking tags. It is reported that the localization accuracy of LANDMARC is around 1.5–2 m with 50% probability. An enhanced LANDMARC approach has been proposed in [20] aiming to make the calculated coordinate of the tracking tags closer to the real-time measurements without extra readers and reference tags.

2.2. *Indoor localization algorithms*

With the booming development of leveraging various wireless communication technologies to provide indoor positioning and navigation, indoor localization algorithms have been extensively studied and numbers of approaches have been proposed over the past two decades [3,4]. In general, indoor localization algorithms can be classified into two categories: model-based approaches and fingerprinting-based approaches.

Model-based approaches. This type of localization algorithms calculates the location of mobile targets based on geometrical models. For instance, the log-distance PL model is used to establish the relationship between the measured RSS and the Radio Frequency (RF) propagation distance [21,22]. Several model-based approaches employing radio propagation models have been investigated in [23]. The average localization accuracy of these IPSs is around 5 m.

Besides the RSS related model, other geometric models have been utilized to characterize the relationship between signal transmitters and receivers. For example, PinPoint [24] is based on Time of Arrival (ToA), Cricket [7] on Time Difference of Arrival (TDoA), and VOR [25] on Angle of Arrival (AoA). In general, model-based approaches consume less time than fingerprinting-based approaches to estimate the location of a mobile target.

The WPL approach we propose in this paper can be classified as a model-based approach, since its location estimation process involves the modified ITU indoor PL model.

Fingerprinting-based approaches. Another type of localization approaches adopt fingerprint matching as the basic scheme. They usually involve two phases: an offline training phase and an online localization phase. During the offline training phase, a site survey dedicated to measuring the RSS fingerprints at some known locations is performed in the indoor environment and consequently, a RSS fingerprint database is built up. During the online localization phase, when a user sends a location query containing his or her current RSS fingerprint, the location of the user will be estimated by matching the measured fingerprint with the fingerprints stored in the database, and the location associated with the matching fingerprint will be returned as his or her location estimate.

A majority of these approaches leverages RF signals for RSS fingerprinting. To name a few, RADAR [9] and Horus [11] are based on WiFi signal, while LANDMARC [14] utilizes RFID signal; FM radio [26], geomagnetism [27] and GSM signals [28] are also adopted as fingerprints for indoor localization. Although fingerprinting-based approaches require a site survey to build up a fingerprint database during the offline phase, they can provide a higher localization accuracy than model-based approaches generally.

The ELM approach we propose in this paper is classified as a machine learning fingerprinting-based approach. The integrated WPL-ELM approach we propose combines the advantages of both approaches.

3. Background Knowledge

3.1. *Indoor PL model*

The most commonly used PL model for indoor environments is the ITU Indoor Propagation Model [29]. It provides a relation between the total path loss PL (dBm) and distance d (m) as:

$$\mathrm{PL} = 20\log(f) + 10\alpha\log(d) + c(k,f) + X_\sigma, \tag{1}$$

where f (MHz) is the radio frequency, c is an empirical floor loss penetration factor, k is the number of floors between transmitter and receiver, α is the pass loss exponent, and X_σ normally represents a Gaussian random noise with standard deviation σ. The signal propagation conditions depend on different indoor environments due to multipath fading and shadow fading. Therefore, the pass loss exponent α which ranges from 2 to 4 dependent on the layout of indoor environment should be determined empirically.

The operating frequency of our RFID IPS is 2.4 GHz and k is 1 in our case since all the RFID sensors and tags are put on the same floor. After calculating the related terms $20\log(f)$ and $c(k,f)$ in (1), and summing with the constant term, the indoor PL model can be further expressed as:

$$\mathrm{PL}(d) = \mathrm{PL}_0 + 10\alpha\log(d) + X_\sigma. \tag{2}$$

With PL_0 as the reference pass loss coefficient.

3.2. *Extreme learning machine (ELM)*

ELM is a kind of machine learning algorithm based on a Single-hidden Layer Feedforward neural Network (SLFN) architecture. It has been proved to provide good generalization performance at an extremely fast learning speed [30]. In [31], WLAN IPS by using the ELM approach has been provided to give a better performance in terms of both the efficiency and the localization accuracy.

The outputs with L hidden nodes in SLFNs can be represented as:

$$\mathbf{y}_N(\mathbf{x}) = \sum_{i=1}^{L} \beta_{\mathbf{i}} g_i(\mathbf{x}) = \sum_{i=1}^{L} \beta_i G(\mathbf{a_i}, b_i, \mathbf{x}), \tag{3}$$

where a_i, b_i are the weights and bias connecting the input nodes and the ith hidden node, β_i are the output weights connecting the ith hidden node and the output nodes, and $G(a_i, b_i, x)$ is the activation function which gives the output of the ith hidden node with respect to the input vector x.

In order to widen the application range of ELM, [32] shows that a SLFN with atmost N hidden nodes and with almost any nonlinear activation function can exactly learn N distinct observations. Given N arbitrary distinct training samples $(\mathbf{x}_j, \mathbf{t}_j), j = 1, 2, \ldots, N$, by substituting $\mathbf{x}$ with $\mathbf{x}_j$ in (3) we obtain

$$\mathbf{H}\beta = \mathbf{T}, \tag{4}$$

where

$$\mathbf{H} = \begin{bmatrix} G(\mathbf{a}_1, b_1, \mathbf{x}_1) & \ldots & G(\mathbf{a}_L, b_L, \mathbf{x}_1) \\ \vdots & \ldots & \vdots \\ G(\mathbf{a}_1, b_1, \mathbf{x}_N) & \ldots & G(\mathbf{a}_L, b_L, \mathbf{x}_N) \end{bmatrix}_{N\times L}, \tag{5}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L\times m} \quad \text{and} \quad \mathbf{T} = \begin{bmatrix} \mathbf{t}_1^T \\ \vdots \\ \mathbf{t}_N^T \end{bmatrix}_{N\times m}. \tag{6}$$

In the above, H is the hidden layer output matrix of ELM; the ith column of H is the ith hidden node's output vector with respect to inputs $x_1, x_2, \ldots, x_N$, and the jth row of H is the output vector of the hidden layer respect to the input vector of x_j.

Unlike the traditional training algorithms for neural networks which need to adjust the input weights and hidden layer biases, [30] has proved that the parameters of SLFN can be randomly assigned provided that the activation function is infinitely differentiable. Therefore, the hidden layer output matrix H remains unchanged once these parameters are randomly initialized. To train a SLFN is simply equivalent to finding an optimal solution β_{LS} of (4) as:

$$||\beta_{LS} - T|| = \min_{\beta} ||H\beta - T||. \tag{7}$$

The optimal solution of the above equation can be found as $\beta_{LS} = H^{\dagger}T$, where $H^{\dagger}$ is the Moor–Penrose generalized inverse of H.

4. Proposed Approaches

4.1. *System overview*

The main components of the RFID IPS developed on our own consists of numbers of RFID sensors, active RFID tags, a wireless sensor network that enables the communication between these devices, a RFID coordinator and a location server. Unlike the LANDMARC system, the signal strengths emitted from tags are picked up by RFID sensors instead of RFID readers in our system, due to the high price of RFID readers. The RFID coordinator in our IPS is modified from a RFID sensor to collect the Received Signal Strength Indication (RSSI) data from all RFID sensors. All the RFID sensors, tags and coordinator use TICC2530 as the wireless module. The manufacturing cost of each RFID sensor is only \$15, much less than the cost of a typical commercial RFID reader. By using the 3 V coin cell, the battery life of each tag is around one month. Figures 1(a)–1(c) shows a typical RFID sensor, a RFID tag and a RFID coordinator developed by us respectively. The system communication protocol is based on ZigBee 2.4 GHz. Before system operation, each active RFID tag is preprogrammed with a unique 4-character ID for identification by sensors. In addition, we found that the value of RSS obtained by the same sensor from different tags at an identical location may be different, possibly due to the variation of the chips and circuits. Therefore, we made some adjustments to ensure that the emitted powers of all tags in our system are in a similar level. The following is a brief operation procedure of our system.

First of all, RFID tags broadcast their unique ID signal every second in the indoor environment. Then, RFID sensors pick up the signal strength of each tag. With external power supply, these sensors are able to send RSS information of all tracking tags to the RFID coordinator continuously through the wireless sensor network. The RSSI data from all RFID sensors are received at the RFID coordinator which is connected to the location server. In our experiment, it is enough to use one RFID coordinator to cover a 100 m^2 indoor environment. After that, the location server calculates the estimated location of each tracking tag by using the proposed localization algorithms.

4.2. *Methodology of WPL*

Suppose we have A RFID sensors and B tracking tags. Each sensor can pick up the signal strengths of all B tracking tags. In order to calculate the estimated location of each tracking tag, we define the signal strength of the jth tracking tag received at the ith sensor as s_{ij}, where $i \in [1, A]$, $j \in [1, B]$. The real position of the ith sensor is defined as (x_i, y_i). Based on the PL Model defined in Sec. 2, the signal strength s_{ij} can be expressed as:

$$s_{ij} = \mathrm{PL}(d_{ij}) = \mathrm{PL}_0 + 10\alpha \log(d_{ij}) + X_\sigma. \tag{8}$$

Therefore, based on (8), the distance between the jth tracking tag and the ith sensor can be calculated by:

$$d_{ij} = 10^{\frac{s_{ij} - \mathrm{PL}_0 - X_\sigma}{10\alpha}}. \tag{9}$$

The distances between these A RFID sensors and the jth tracking tag can be expressed as a d vector, given by $\mathbf{d}_j = (d_{1j}, d_{2j}, \ldots, d_{Aj})^T$. The weighting factor of the ith sensor with respect to the jth tracking tag is defined as:

$$w_{ij} = \frac{\frac{1}{d_{ij}}}{\sum_{i=1}^{A} \frac{1}{d_{ij}}}. \tag{10}$$

The unknown location coordinate (u_j, v_j) of the jth tracking tag is obtained by:

$$(u_j, v_j) = \sum_{i=1}^{A} w_{ij}(x_i, y_i). \tag{11}$$

4.3. *Methodology of ELM*

The ELM approach considers the localization problem as a regression problem. It consists of an offline phase and an

(a) (b) (c)

Fig. 1. RFID IPS mean components. (a) RFID sensor, (b) RFID tag and (c) RFID coordinator.

online phase. During the offline phase, some RFID tags are adopted as reference tags in order to build up an empirical database. P reference tags will be used and Q historical RSSI samples will be collected for each tag. Moreover, each RSSI sample is denoted as $((X_{pq}, Y_{pq}), \mathrm{RSS}_{pq})$, $p \in (1, P)$, $q \in (1, Q)$. The vectors RSS_{pq}, $p = 1, 2, \ldots, P$, $q = 1, 2, \ldots, Q$ are the inputs of the ELM and the corresponding location vectors (X_{pq}, Y_{pq}) are the training targets of ELM. The hard-limit transfer function is chosen as the activation function. The training process of ELM is introduced in Sec. 2. It can be conducted in the following three main steps:

Step 1: Randomly assign values to hidden node parameters.
Step 2: Calculate the hidden layer output matrix H.
Step 3: Calculate the output weight β by:

$$\beta = H^{\dagger} L, \tag{12}$$

where $H^{\dagger}$ is the Moor–Penrose generalized inverse of H.

During the online phase, the only thing we need to do is to feed the RSS vector which is contained in the RSSI sample of the tracking tag into the ELM model. The output given by ELM is the estimated location of the tracking tag.

4.4. *Methodology of integrated WPL-ELM*

The model-based approaches can provide an location estimation of a target in a short time since they do not require any site survey during the offline phase [4]. On the other hand, fingerprinting-based approaches can provide a higher localization accuracy than the model-based approaches, with an extra offline calibration [3,4]. Since WPL and ELM can be classified as a centralized model-based approach and a fingerprinting-based approach, respectively, it is brilliant if we can make use of both the fast estimation of WPL and the high localization accuracy of ELM together for indoor localization. Following this thought, another localization algorithm: WPL-ELM integrating the advantages of both WPL and ELM is proposed. The process of WPL-ELM is shown in Fig. 2.

During the offline phase, big indoor space is divided into multiple small zones according to the distribution of the RFID sensors. Then, an ELM model for each zone is developed.

During the online phase, the WPL approach is used to determine the zone of the tracking tag primarily in the first step. After we know the tracking tag is in which zone, the ELM model of that zone is deployed in the second step to provide the final estimated location of the target.

Fig. 2. Flowchart of integrated WPL-ELM approach.

5. Experimental Results and Performance Evaluation

In order to evaluate the performance of the proposed approaches, extensive experiments have been conducted. The test-bed is the Internet of Things Laboratory in School of Electrical and Electronic Engineering, Nanyang Technological University. The area of the test-bed is around $110\,\mathrm{m}^2 (6.4\,\mathrm{m} \times 17.1\,\mathrm{m})$. As shown in Fig. 3, there are 19 RFID sensors installed in the room. The positions of nine tracking tags and the RFID coordinator are also shown in Fig. 3.

Before the performance evaluation, we define the reasonable range of received signal strength the RFID sensor can pick up from RFID tags first. We put one tag directly besides one sensor in order to estimate the maximum signal strength a sensor can receive from a tag. After collecting 3600 RSSI samples in one hour, we find that the average signal strength received by the sensor is around -42 dBm with the standard deviation of 2.8 dBm. We also put one tag at the right lower corner and one sensor at the left upper corner of the room (as shown in Fig. 3) in order to estimate the minimum signal strength a sensor can pick up from a tag. The average signal strength received by the sensor is around -98 dBm with the standard deviation of 5.6 dBm. Therefore, we define the reasonable range of received signal strength to be from -40 to -100 dBm for our system.

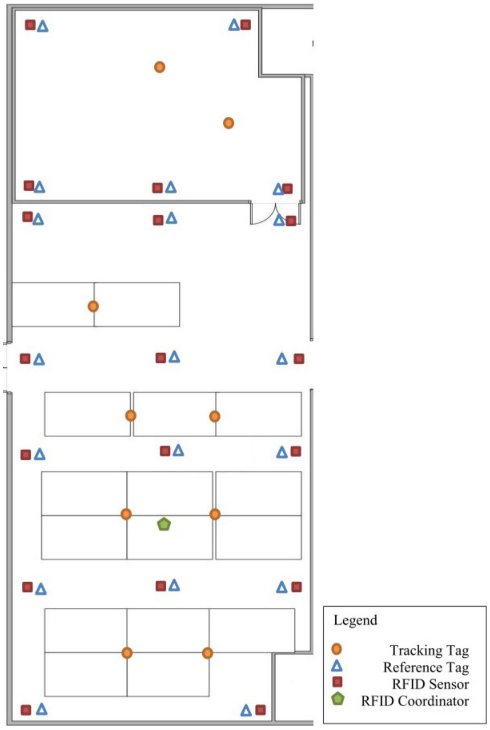


Fig. 3. Placement of RFID reference tags, tracking tags, sensors and coordinator in experiment I.

The distance error is used to measure the localization accuracy of the system. We define the location estimation error e to be the distance between the real location coordinates (x_0, y_0) and the system estimated location coordinates (x, y), as:

$$e = \sqrt{(x - x_0)^2 + (y - y_0)^2}. \tag{13}$$

During experiment I, as shown Fig. 3, 19 reference tags are distributed in the room. The main purpose of experiment I is to build up the historical RSSI sample database for ELM offline training. We keep collecting data of the signal strength of the 19 reference tags from the 19 RFID sensors for 10 days. We obtain 637,000 RSSI samples for each tag in this experiment. We put these samples with their corresponding real location coordinates into the ELM training process and built up the ELM model in each zone for real-time localization during the online phase.

During experiment II, we keep collecting data of the signal strength of nine tracking tags from the 14 RFID sensors for five days. The main purpose of experiment II is to evaluate the localization accuracy of WPL approach, ELM approach and the integrated WPL-ELM approach. We obtain 325,000 RSSI samples for each tag in this experiment. The detailed experimental results are presented in 5.2, 5.3, and 5.4.

5.1. *Estimation of the PL exponent α in WPL*

The WPL approach largely depends on the PL exponent α. Therefore, an experiment is conducted to measure the RSSI values of different distances from a RFID sensor in order to find out the relationship between RSSI and distance. As shown in Fig. 3, seven reference tags located on the left side and the RFID sensor at the left upper corner of the test-bed are selected in this experiment, since there are relatively clearer LoS between the sensor and these tags. We measure the signal strength at 1.50, 3.45, 5.06, 7.64, 10.64, 13.54 and 17.09 m. At each location, 3000 RSSI samples are collected in 1 day. Figure 4 shows the average signal strength of the collected RSSI data at various locations.

Based on the data, we use a curve fitting method to construct the relationship between RSSI and distance, as:

$$\mathrm{PL}(d_i) = -52.40 - 10 \times 3.58 \times \log(d_i), \tag{14}$$

i.e., the pass loss exponent α is taken as 3.58 and the reference pass loss coefficient PL_0 as -52.40 dBm. We assume that α and PL_0 remain unchanged in the entire test period.

5.2. *Performance evaluation of WPL*

5.2.1. *Localization accuracy*

We keep collecting data of the signal strength of the nine tracking tags from the 19 RFID sensors for seven days in

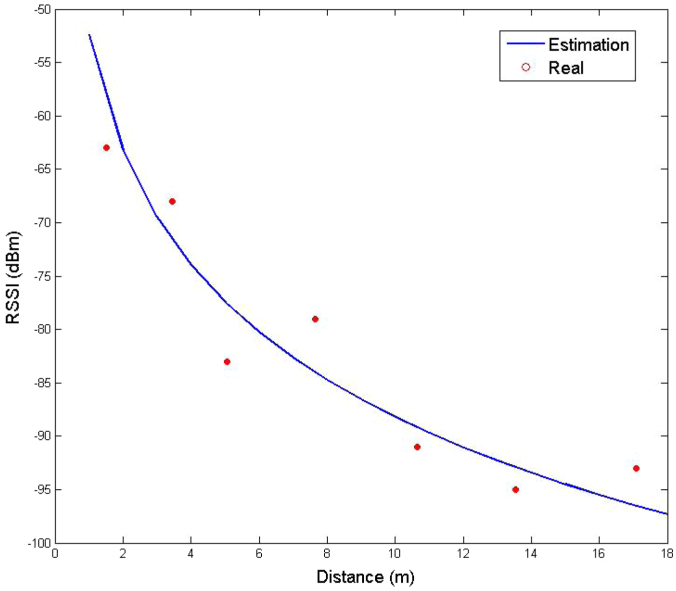


Fig. 4. Relationship between RSSI and distance.

Table 1. Localization accuracy statistics.

Approach	Average localization accuracy (m)
LANDMARC	2.642
Enhanced LANDMARC	1.990
WPL	**1.651**

experiment I in order to evaluate the localization accuracy of the WPL approach. Since WPL is classified as model-based approaches, the performances of LANDMARC [14] and enhanced LANDMARC [20] are chosen to be compared with WPL. Furthermore, LANDMARC and enhanced LANDMARC use the weighted *k*-nearest neighbor algorithm to estimate the location of the tracking tags, we choose *k* equal to the maximum number of reference tags in order to optimize the localization accuracy of these methods.

Based on the RSSI samples of all the tracking tags, we collected during experiment I, the localization performance comparison between LANDMARC, enhanced LANDMARC and WPL are presented in Table 1 and Fig. 5. As shown in Table 1, the average localization accuracy by using LANDMARC, enhanced LANDMARC and WPL is respectively 2.642, 1.990 and 1.651 m. WPL enhances the precision of localization accuracy by 38% over LANDMARC and 17% overenhanced LANDMARC. To conclude, WPL provides the highest localization accuracy among the three approaches.

5.2.2. *Robustness*

In order to evaluate the robustness of WPL when the number of RFID sensors is reduced, we turned off five RFID

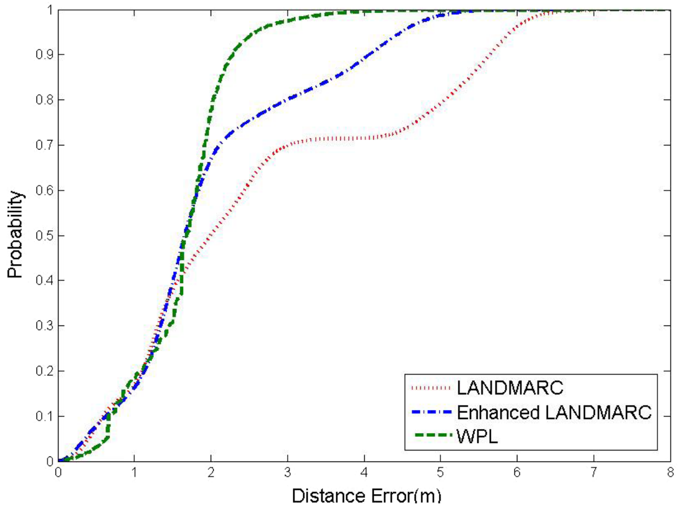


Fig. 5. Cumulative percentile of error distance for different methods.

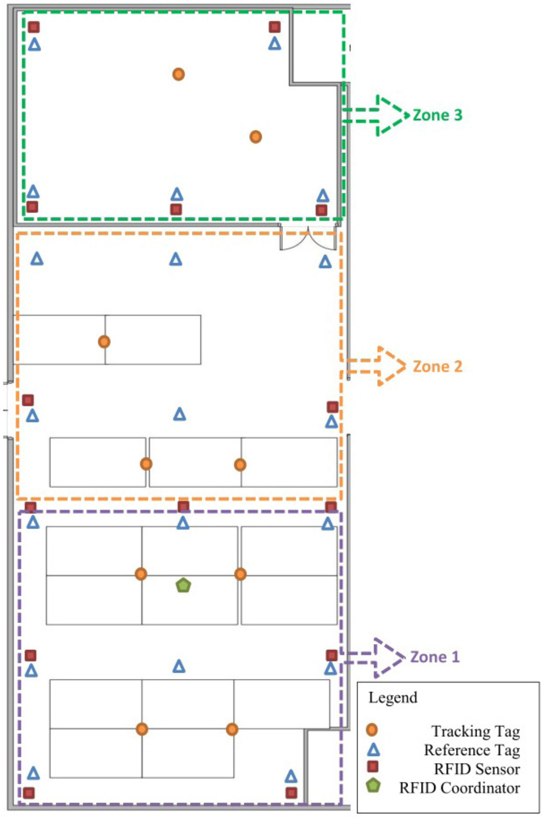


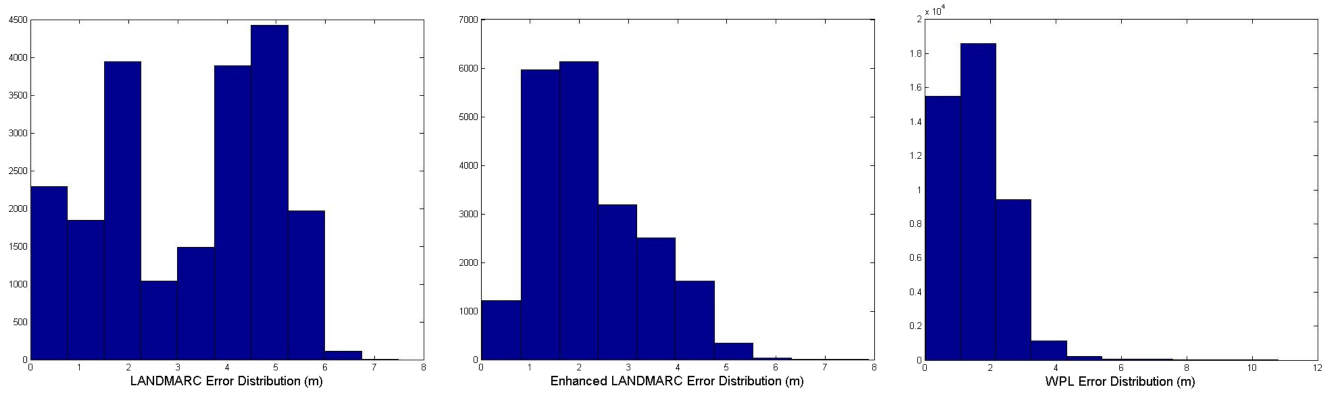
Fig. 6. Placement of RFID reference tags, tracking tags, sensors and coordinator in experiments II and III.

sensors in the test-bed during experiment II. As shown in Fig. 6, we keep collecting data of the signal strength of the nine tracking tags from the 14 RFID sensors for seven days in this experiment. Then we compare the performance of LANDMARC, enhanced LANDMARC and WPL using 14 sensors with experiment I database, where 19 sensors are used.

The mean and variance of the location estimation error of the three approaches with different number of RFID sensors are presented in Table 2. Figure 7 demonstrates the distance error distribution of the three approaches.

Table 2. Comparison between WPL and other methods.

No. of RFID sensor	19		14	
Approach	Average	Variance	Average	Variance
LANDMARC	2.642	0.108	2.973	0.191
Enhanced LANDMARC	1.990	0.192	2.214	0.420
WPL	**1.651**	0.290	**1.782**	0.337



(a) (b) (c)

Fig. 7. Comparison of distance error distribution for different methods. (a) LANDMARC, (b) Enhanced LANDMARC and (c) WPL.

As shown in Table 2, the localization performances of all the three approaches become worse with lower density of RFID sensors. However, it can be observed that the localization accuracy of WPL still remains the best among the three approaches when five RFID sensors are removed from the test-bed. Under this circumstance, WPL still enhances the precision of localization accuracy by 40% over LANDMARC and 19% over enhanced LANDMARC. Compared with the results when 19 sensors are used, the localization accuracy of LANDMARC, enhanced LANDMARC and WPL decreases to 13%, 11% and 8%, respectively. The performance decay of WPL is the smallest. As shown in Fig. 7, the distance error distribution of LANDMARC in Fig. 7(a) and enhanced LANDMARC in Fig. 7(b) are much more scattered, while that of WPL is mainly limited within 2.7 m as shown in Fig. 7(c).

Thus we can safely conclude that WPL remains more reliable and robust when the number of RFID sensors is reduced.

5.3. *Performance evaluation of ELM*

Since ELM is a fingerprinting-based localization algorithm, we build up a historical RSSI fingerprints database for ELM offline training during experiment II in the first place. As shown in Fig. 6, we keep collecting data of the signal strength of the 19 reference tags and the nine testing tags from the 14 RFID sensors for five days during the offline phase. 318,500 RSSI samples for each tags are obtained in this experiment.

For each of 19 reference tags, 5000 RSSI samples are randomly chosen as training fingerprints from the experiment II database. Here we choose 5000 RSSI samples of each reference tag for ELM offline training process, considering the limitation of the number of input variables in ELM. When the number of input variables is too large, unnecessary hidden nodes parameters will be introduced and cause ELM to be unstable and overfitted easily. In our system, we found that 5000 input variables (RSSI samples in our case) is appropriate for ELM training.

Besides the number of input variables, another parameter that could affect the localization accuracy of ELM is the number of hidden nodes in the ELM hidden layer. The localization accuracy of ELM can be improved with the increase of the number of hidden nodes in the ELM hidden layer. However, both training time and testing time also increase. For instance, the ELM approach with 2500 hidden nodes enhances the precision of localization accuracy by 33% over WPL but the testing time is as long as 1.937s, which is too long for real-time localization. Thus, there is a tradeoff between the localization accuracy and the testing time when applying the ELM approach. Based on our evaluation, we choose 2000 hidden nodes in the ELM hidden layer for ELM in our system.

Two classical machine learning algorithms, Back-propagation (BP) algorithm and support vector machine for regression (SVR) algorithm, are chosen in comparison with ELM. After building up the ELM model, we evaluate the performance of these three approaches based on the RSSI samples of the nine tracking tags from the experiment II database. The cumulative percentile of error distance for the three approaches is shown in Fig. 8. Table 3 demonstrates the performance comparison between the three approaches in terms of the training time, testing time and average localization accuracy of the samples.

As observed from Table 3, ELM has an enormous advantage in training time and learning speed. It learns up to 391.94 times and 5.66 times faster than BP and SVR, respectively. On the other hand, BP and SVR obtain shorter testing time than ELM. The testing time of 1.825s is really a drawback of ELM because it will introduce certain delay in real-time localization of the tracking tags. It can be seen in Table 3, the average localization accuracy of all nine

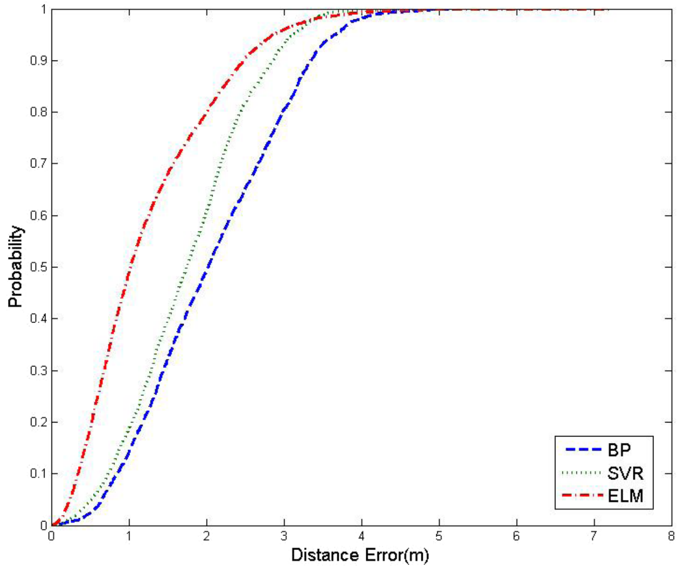


Fig. 8. Cumulative percentile of error distance for different methods.

Table 3. Comparison between ELM and other methods.

Approach	Training time (s)	Testing time (s)	Accuracy (m)
BP	97200	**0.007**	2.084
SVR	1402.887	0.013	1.769
ELM	**248.026**	1.825	**1.198**

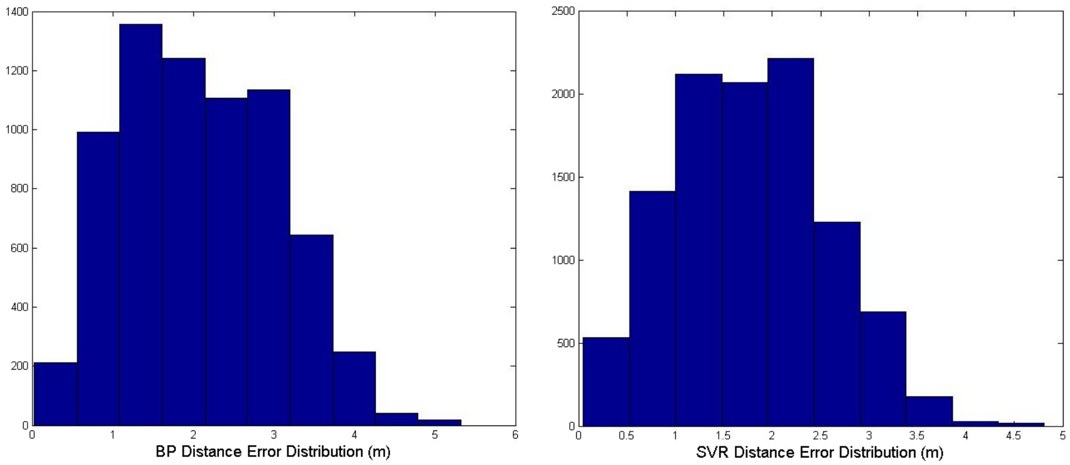
tracking tags by using BP, SVR and ELM is 2.084, 1.769 and 1.198 m. ELM enhances the precision of localization accuracy by 43% over BP and 32% over SVR, respectively. Figure 9 demonstrates the distance error distribution of the three different approaches. The distance error distribution of ELM as shown in Fig. 9(c) ranges mainly within 3 m. In contrast, the distance error distribution of BP in Fig. 9(a) and SVR in Fig. 9(b) are much more scattered.

To conclude, ELM has a tremendous advantage in offline training time and online localization accuracy compared with other approaches.

5.4. *Performance evaluation of WPL-ELM*

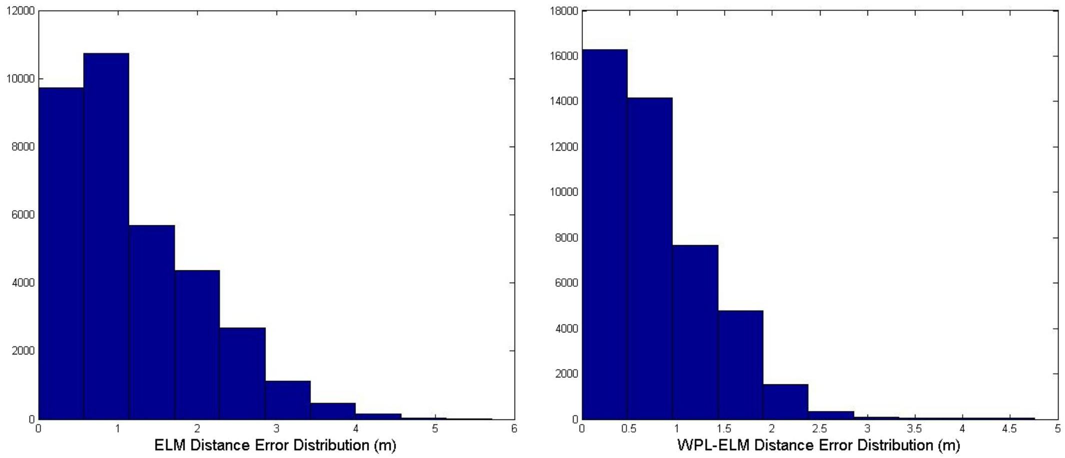
We conduct experiment III to evaluate the performance of the integrated WPL-ELM approach. During the offline phase, As shown in Fig. 6, the entire room is divided into three small zones first. Zone 1 contains seven sensors, eight reference tags and four tracking tags. Zone 2 contains eight sensors, nine reference tags and three tracking tags. There are five sensors, five reference tags and two tracking tags in Zone 3. We keep collecting data of the signal strength of the 19 reference tags and the nine testing tags from the 14 RFID sensors for five days during the offline phase. 318,500 RSSI samples for each tag are obtained in this experiment. After that, for each of 19 reference tags, 5000 RSSI samples are randomly chosen as training fingerprints from the experiment III database. These RSSI samples with their corresponding physical location coordinates are put into the ELM training process and are adopted to build up the ELM model in each zone for real-time localization.

Until all the ELM models for each zone are established, we evaluate the performance of WPL-ELM based on the RSSI samples of nine tracking tags from the experiment III database. Since WPL is adopted as the preliminary estimation of the tracking tag, we first analyze the reliability



(a) BP (b) SVR

Fig. 9. Comparison of Distance Error Distribution for different methods.



(c) ELM

(d) WPL-ELM

Fig. 9. (*Continued*)

of WPL in classifying the tracking tags into the correct zone. By evaluating all the 318,500 RSSI samples for each tracking tags in experiment II, WPL can determine the zone of the tracking tag with a 97.8% accuracy. With fast estimation and 1.782 m localization accuracy of the tracking tag, WPL is fully capable of providing the correct zone of the tracking tag, or equally an estimate of its location.

After we get the preliminary location estimation of the tracking tag (tracking tag is in which zone), ELM is adopted to provide final estimated location of the target by using the ELM model of that zone which is developed during the offline phase. The performance comparison between ELM and WPL-ELM is shown in Fig. 10. The distance error distribution of WPL-ELM as shown in Fig. 9(d) ranges mainly within 2.3 m which is the best among the four approaches.

Table 4 demonstrates the performance comparison between ELM and WPL-ELM in terms of the training time, average testing time and average localization accuracy of the samples in each zone followed by the overall performance. As observed in Table 4, the overall average localization accuracy of WPL-ELM is 0.799 m, which enhances the precision of localization accuracy by 62% over BP, 55% over SVR and 33% over ELM, respectively. In addition, the more noteworthy point is that WPL-ELM largely reduces both training time during the offline phase and testing time during the online phase as compared with ELM. The overall training time of WPL-ELM is 147.089 s, saving 41% less time than ELM. The overall testing time of WPL-ELM is 0.432 s, 4.22 times faster than ELM. Therefore, WPL-ELM can overcome the drawback of ELM, namely the tedious testing time during the online phase.

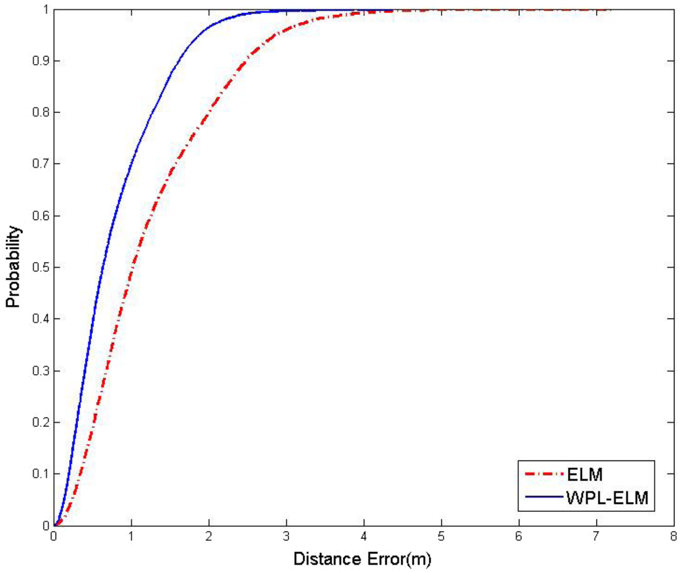


Fig. 10. Cumulative percentile of error distance for different methods.

Table 4. Comparison between WPL-ELM and ELM.

Approach	Training time (s)	Testing time (s)	Accuracy (m)
ELM	248.026	1.825	1.198
	WPL-ELM		
Zone 1	59.338	0.524	0.763
Zone 2	62.057	0.428	0.901
Zone 3	25.694	0.252	0.719
Overall	**147.089**	**0.432**	**0.799**
Improvement	**41%**	**76%**	**33%**

In summary, WPL-ELM can provide not only a higher localization accuracy than other approaches, but also a more efficient location estimation of the target than ELM.

6. Conclusion and Future Work

In this paper, we proposed a cost-efficient RFID IPS by using cheaper active RFID tags and sensors. In addition to the experimental results in [15,16] a more elaborate and comprehensive performance evaluation of the proposed three localization algorithms: WPL, ELM, WPL-ELM was demonstrated in this paper. Our experimental results show that the WPL approach enhances the precision of localization accuracy by 38% over LANDMARC and 17% over enhanced LANDMARC. In addition, WPL is more robust when the number of RFID sensors is reduced than existing approaches. The ELM approach has tremendous advantages in offline training time and online localization accuracy compared with other approaches. It improves the precision of indoor localization by 43% over BP and 32% over SVR, respectively.

Considering the fast estimation by WPL and the high localization accuracy by ELM, another localization algorithm: WPL-ELM which integrates the advantages of both approaches was also proposed in this paper. Based on our experimental results, the training time and testing time of WPL-ELM are 1.69 times and 4.22 times faster than ELM. Furthermore, it improves the precision of indoor localization by 62% over the BP approach, 55% over the SVR approach and 33% over the ELM approach, respectively. In conclusion, WPL-ELM can provide a higher localization accuracy of the target in a more efficient way than existing approaches. Moreover, WPL-ELM can greatly reduce the deployment cost of the entire system because it requires less RFID sensors than WPL to maintain the same localization accuracy.

Future work can be focused on the exploration and analysis of applying the WPL approach, the ELM approach and the WPL-ELM approach on other IPSs, such as Infrared-based IPS and WiFi-based IPS.

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