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Han, Zou

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An RFID Indoor Positioning System by Using Weighted Path Loss and Extreme Learning Machine

Han Zou[1], Hengtao Wang[2], Lihua Xie[1], and Qing-Shan Jia[2,3]
1. EXQUISITUS, Centre for E-City, School of Electrical and Electronics Engineering
Nanyang Technological University
Singapore, 639798
Email: {zouh0005, elhxie}@ntu.edu.sg
2. Center for Intelligent and Networked Systems, Department of Automation, TNLIST
Tsinghua University
Beijing 100084, China
Email: {wangt07@mails., jiaqs@}tsinghua.edu.cn
3. Laboratory for Information and Decision Systems
Massachusetts Institute of Technology
77 Massachusetts Avenue, Cambridge, MA 02139, USA

***Abstract*—Radio Frequency Identification (RFID) technology has been widely used in many application domains. How to apply RFID technology to develop an Indoor Positioning System (IPS) has become a hot research topic in recent years. LANDMARC approach is one of the first IPSs by using active RFID tags and readers to provide location based service in indoor environment. However, major drawbacks of the LANDMARC approach are that its localization accuracy largely depends on the density of reference tags and the high cost of RFID readers. In order to overcome these drawbacks, two localization algorithms, namely weighted path loss (WPL) and extreme learning machine (ELM), are proposed in this paper. These two approaches are tested on a novel cost-efficient active RFID IPS. Based on our experimental results, both WPL and ELM can provide higher localization accuracy and robustness than existing ones.**

I. Introduction

The demands on Indoor Positioning System (IPS) have increased a lot in recent years. The GPS based outdoor location service has been widely used, however GPS cannot provide positioning service with sufficient localization accuracy in indoor environments due to the lack of line of sight (LoS) transmission channel between the satellite and the receiver. In addition, a lot of other problems make positioning and navigation in indoor environment much more complicated and challenging than in outdoor environment, such as physical layout changes of furniture, signal scattering due to large density of obstacles, multipath effect of signal reflection from walls and furniture and even momentary changes of human movements or opening and closing of doors.

Various approaches based on different technologies such as Infrared, Wireless Local Area Network (WLAN), Ultra-Wideband (UWB) and Radio Frequency Identification (RFID) have been proposed and developed in order to provide positioning and navigation in indoor environment [1] [2] [3]. RFID technology has been widely used in many application domains such as asset tracking, industrial automation and medical care. How to apply RFID technology to develop IPS has become a hot research topic in recent years. RFID has several advantages, such as no requirement of LoS, RFID tags are small and light and most importantly, it can uniquely identify different equipment and persons. The basic components of an RFID IPS include RFID readers, RFID tags and the communication network between them. The RFID reader is able to read the data emitted from RFID tags. Both RFID readers and tags use a predefined RF frequency and protocol to transmit and receive data. Passive RFID tags operate without a battery and they are mainly used to replace the traditional barcode technology. Active RFID tags are small transceivers with button-cell batteries to power the transceivers. They can actively transmit their ID and additional information to RFID readers. They are quite suitable for identifying and tracking high-unit-value products or persons in complex indoor environments.

A well-known IPS using the RFID technology is LANDMARC [4]. It utilizes the concept of reference RFID tags. The Received Signal Strength Indicator (RSSI) from these reference tags that is received by the receiver is used as the realtime training data. It is reported that the localization accuracy of LANDMARC is around 1.5-2m with 50 percent probability. An enhanced LANDMARC approach has been proposed in [5]. This improved scheme aims to make the calculated coordinate of the tracking tags closer to the real time measurements without extra readers and reference tags.

However, one drawback in these RFID IPSs is the high cost of RFID readers and the active tags. Another issue is that when the number of tracking tags increases in the system, the event of RSS data package loss occurs more frequently due to the limitation of RF data transmission channel or signal collision. It affects and reduces the localization accuracy of the system severely. Based on our evaluation, the percentage of perfect RSSI samples (sample without any RSS data package loss) is around 48% of the total number of RSSI samples we collected in our experiment. If the RSS vector in one RSSI sample contains too many RSSs that are out of the reasonable range due to signal collision or long distance between reader and tag, both the LANDMARC approach and the enhanced LANDMARC approach cannot provide an estimated location close to the real physical location of the tracking tag.

In order to overcome the above drawbacks, in this paper, we develop a cost-efficient RFID IPS by using cheaper active RFID tags, sensors and readers. Unlike the LANDMARC system, the signal strengths emitted from RFID tags are picked up by RFID sensors instead of RFID readers in our system. The manufacturing cost of each RFID sensor is much less than the cost of a typical RFID reader. Two localization algorithms: Weighted Path Loss (WPL) and Extreme Learning Machine (ELM) which can provide higher localization accuracy and robustness than existing ones are also proposed in this paper. The WPL approach can be classified as a centralized model-based localization algorithm. The distance between the tracking tag and each sensor is calculated based on a modified International Telecommunication Union (ITU) indoor path loss 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. The ELM approach is a machine learning fingerprinting algorithm. It consists of offline and online phases. During the offline phase, some RFID tags are adopted as reference tags. We record the historical RSSs of these reference tags which are received at each sensor and also 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. We can obtain an ELM model after the offline training process. During the online phase, 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.

The rest of the paper is organized as follows. In Section II, the background knowledge for this paper is provided. Section III introduces the proposed localization algorithms. In Section IV, we present the experimental results and evaluation of the proposed algorithms. The conclusion and future work are given in Section V.

II. Background Knowledge

A. Indoor Path Loss Model

The most commonly used path loss model for indoor environments is the ITU Indoor Propagation Model [6]. It provides a relation between the total path loss PL (dBm) and distance d (m) as:

$$PL = 20log(f) + 10\alpha log(d) + c(k, f) - 28 \tag{1}$$

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 and α is the pass loss exponent. The signal propagation conditions are dynamic in different indoor environments due to multipath fading and shadow fading. Therefore, the pass loss exponent α should be determined empirically and ranges from 2 to 4 dependent on the layout of indoor environment.

The operating frequency of our RFID IPS is 2.4GHz and k is 1 in our case since all the RFID readers and tags are put on the same floor. After calculating the related terms $20log(f)$ and $c(k, f)$ in (1), we can sum all these terms together as PL_0. Therefore, the indoor path loss model can be further expressed as:

$$PL(d) = PL_0 + 10\alpha log(d) \tag{2}$$

where PL_0 is the reference pass loss coefficient and α is the pass loss exponent.

B. 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 [7]. In [8], WLAN IPS by using the ELM approach has been proved 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 enlarge the application range of ELM, [9] shows that a SLFN with at most N hidden nodes and with almost any nonlinear activation function can exactly learn N distinct observations. Suppose there are N arbitrary distinct training samples $(x_j, t_j), j = 1, 2, \ldots, N$, we can represent the SLFN for each sample as:

$$\mathbf{y}_N(\mathbf{x_j}) = \sum_{i=1}^{L} \beta_i G(\mathbf{a_i}, b_i, \mathbf{x_j}), j = 1, 2, \ldots, N. \tag{4}$$

Now the above N equations can be written as:

$$\mathbf{H}\beta = \mathbf{T} \tag{5}$$

where

$$\mathbf{H} = \begin{bmatrix} G(\mathbf{a}_1, b_1, \mathbf{x}_1) & \ldots & G(\mathbf{a}_L, b_L, \mathbf{x}_1) \\ \vdots & \ldots & \vdots \\ G(\mathbf{a}_1, b_1, \mathbf{x}_N) & \ldots & G(\mathbf{a}_L, b_L, \mathbf{x}_N) \end{bmatrix}_{N \times L}, \tag{6}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L \times m} \text{ and } \mathbf{T} = \begin{bmatrix} \mathbf{t}_1^T \\ \vdots \\ \mathbf{t}_N^T \end{bmatrix}_{N \times m}. \tag{7}$$

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, [7] has proved that these parameters of SLFN can be randomly assigned if only the activation function is infinitely differentiable. Therefore, the hidden layer output matrix H remains to be unchanged once these parameters are randomly initialized. To train a SLFN is simply equivalent to finding an optimal solution β_{LS} of (5) as:

$$||\beta_{LS} - T|| = \min_{\beta} ||H\beta - T||. \tag{8}$$

The smallest least square solution of (5) becomes $\beta_{LS} = H^{\dagger}T$, where $H^{\dagger}$ is the Moor-Penrose generalized inverse of H.

III. Proposed Approaches

A. System Overview

Our RFID IPS consists of a number of RFID sensors and tags, a wireless sensor network that enables the communication between these devices, a RFID reader and a location server. Unlike the LANDMARC system, the signal strength emitted from tags are picked up by RFID sensors instead of RFID readers in our system, due to the high price of RFID readers. Both RFID sensors and active RFID tags in our system use TICC2530 as the wireless module. The manufacturing cost of each RFID sensor is only $15, which is much less than the cost of a typical RFID reader. 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. One of reasons could be the variation of the chips and circuits. Therefore, we conducted some adjustments to make sure that the emitted powers of all tags in our system are in a similar level.

A brief operation procedure of our system is as follow. First of all, RFID tags broadcast their unique ID signal every second in the indoor environment. The battery life of each tag is around one month. 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 reader continuously through the wireless sensor network. The RSSI data from all RFID sensors are received at the RFID reader which is connected to the location server. Our experiment shows that one RFID reader is good enough to cover a $100m^2$ indoor environment. After that, the location server calculates the estimated location of each tracking tag by using the proposed localization algorithms.

B. 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 Path Loss Model defined in Section II, the signal strength s_{ij} can be expressed as:

$$s_{ij} = PL(d_{ij}) = PL_0 + 10\alpha log(d_{ij}) \tag{9}$$

Therefore, based on (9), the distance between the jth tracking tag and the ith sensor can be calculated by:

$$d_{ij} = 10^{\frac{s_{ij} - PL_0}{10\alpha}} \tag{10}$$

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

$$w_{ij} = \frac{\frac{1}{d_{ij}}}{\sum_{i=1}^{A} \frac{1}{d_{ij}}} \tag{11}$$

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

$$(u_j, v_j) = \sum_{i=1}^{A} w_{ij}(x_i, y_i) \tag{12}$$

C. Methodology of ELM

The ELM approach considers the localization problem as a regression problem. It consists of an offline phase and an 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 $((X_{pq}, Y_{pq}), RSS_{pq})$, $p \in (1, P)$, $q \in (1, Q)$. The vector RSS_{pq} are the inputs of the ELM and the corresponding location vector (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 Section II. 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:

$$\beta = H^{\dagger}L \tag{13}$$

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.

IV. Experimental Results and Performance Evaluation

We conduct a series of experiments to evaluate performance of the proposed localization algorithms. The testbed is the Postgraduate Room in Sensor Network Lab of School of Electrical and Electronic Engineering, Nanyang Technological University. The size of the test-bed is approximately

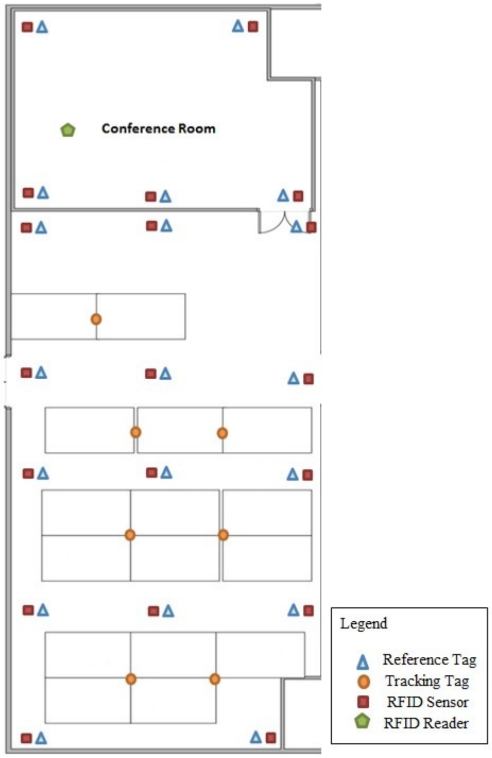


Fig. 1. Placement of RIFD reference tags, tracking tags, sensors and reader

$6.4m \times 17.1m$. As shown in Figure 1, there are 19 RFID sensors distributed in the room. The distance between adjacent sensors is around $3m$. 19 reference tags are put directly under each sensor in order to collect RSSI samples for ELM offline training. The positions of 7 tracking tags are also shown in Figure 1. One RFID reader is put in the conference room to collect data from all RFID sensors.

In order to evaluate the performance of the proposed localization algorithms, 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:

$$e = \sqrt{(x - x_0)^2 + (y - y_0)^2} \tag{14}$$

Based on our experimental results, we define the reasonable range of RSS the RFID sensor can pick up from RFID tags to be from -40 to -100dBm for our system. If all signal strengths contained in a RSSI sample are within in this range, it is defined as a perfect RSSI sample. Otherwise, if a RSSI sample contains more than one signal strength that is beyond the reasonable range, it is defined as a defect RSSI sample. The robustness of a localization algorithm can be measured by the difference between the real physical location of the tracking tag and the estimated location when the localization algorithm uses defect RSSI samples.

During experiment I, we keep collecting data of the signal strength of the 19 reference tags from the 19 RFID sensors for 12 days. The main purpose of experiment I is to build up the historical RSSI sample database for ELM offline training. We obtain 763600 RSSI samples for each tag in this experiment. In these RSSI samples, 45.11% of them are perfect RSSI samples. During experiment II, we keep collecting data of the signal strength of both 7 tracking tags and 19 reference tags from the 19 RFID sensors for 7 days. The main purpose of experiment II is to evaluate the localization accuracy of both the WPL approach and the ELM approach. We obtain 458640 RSSI samples for each tag in this experiment. In these RSSI samples, 47.73% of them are perfect RSSI samples. The detail experimental results are presented in Part B and C.

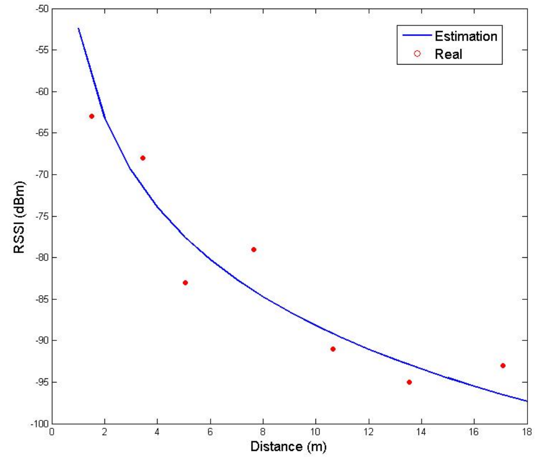


Fig. 2. Relationship between RSSI and distance

A. Selection of the path loss exponent α in WPL

The WPL approach largely depends on the path loss exponent α. Therefore, we conduct an experiment 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 Figure 1, 7 reference tags put at the left side and the RFID sensor at the left upper corner of the test-bed are selected in this experiment, since there are relative clearer line of sight between the sensor and these tags. We measure the signal strength at 1.50m, 3.45m, 5.06m, 7.64m, 10.64m, 13.54m and 17.09m. At each location, 3000 RSSI samples are collected in 1 day. Figure 2 shows the average signal strength of collected RSSI data at various locations.

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

$$PL(d_i) = -52.40 - 10 \times 3.58 \times log(d_i) \tag{15}$$

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

B. Localization Accuracy

1) Comparison between WPL and ELM: 5000 RSSI samples of each reference tag are randomly chosen as training samples from experiment I and experiment II database for ELM offline training process. Another 5000 perfect RSSI samples of each tracking tags are chosen separately as testing

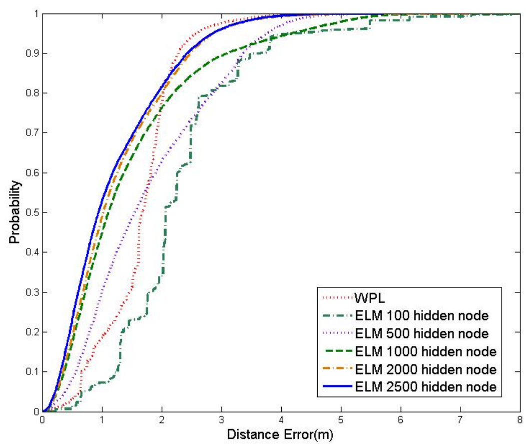


Fig. 3. Cumulative percentile of error distance of WPL and ELM with different number of hidden nodes

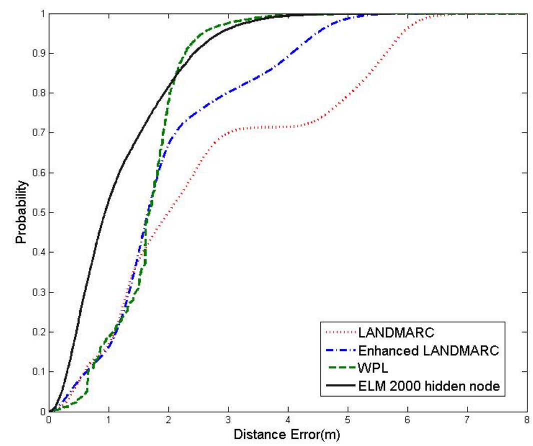


Fig. 4. Cumulative percentile of error distance for different methods

samples from experiment II database to evaluate the performance of both the ELM approach and the WPL approach.

The reason we choose 5000 RSSI samples of each reference tag for ELM offline training process is that there is an upper bound for the number of input variables in ELM. If the number of input variables is too large, it will introduce unnecessary hidden nodes parameters which will cause ELM to be unstable and overfitted easily. We found that 5000 input variables (RSSI samples in our case) is appropriate for ELM training in our system.

Besides the number of input variables, another parameter that could affect the localization accuracy of ELM is the number of hidden nodes in ELM hidden layer. Figure 3 demonstrates the performance comparison result between W-PL and ELM with different number of hidden nodes. It can be seen from the Figure 3 that as the number of hidden nodes in ELM hidden layer increases, the localization accuracy of ELM improves. Based on our test, when the number of hidden nodes increases to 1000, the localization accuracy of ELM is 1.476m which becomes better than the performance of WPL (1.651m). However, we also notice that the ELM approach requires more time to test a new RSSI sample when the number of hidden nodes increases. The WPL approach usually uses less than 0.2s to test a new RSSI sample. In contrast, the ELM approach with 2500 hidden nodes requires 1.937s, although it enhances the precision of localization accuracy by 33% over WPL. Thus, there is a tradeoff between the localization accuracy and the testing time if we want to use the ELM approach.

In summary, ELM with proper number of hidden nodes provides higher localization accuracy than WPL.

2) Comparison between WPL, ELM and other methods: The localization accuracy of WPL and ELM are compared against LANDMARC [4] and enhanced LANDMARC [5]. 5000 perfect RSSI samples of each tracking tag are randomly chosen from experiment II for this evaluation. The performance of the ELM approach with 2000 hidden nodes is chosen in this comparison. Since LANDMARC and enhanced LANDMARC use weighted k-nearest neighbour algorithm to estimate the location of the tracking tags, we choose k to be the maximum number of reference tags in order to optimize the localization accuracy of these methods.

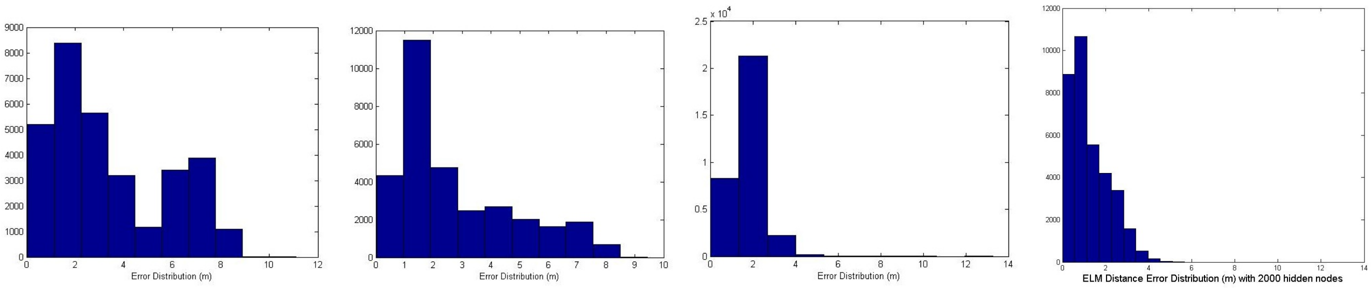
The performance comparison result between the four approaches is presented in Figure 4. Figure 5 demonstrates the distance error distribution of the four different approaches. The average localization accuracy of all 7 tracking tags by using LANDMARC, enhanced LANDMARC, WPL and ELM is respectively 2.642m, 1.990m, 1.651m and 1.198m. The reduction in estimation error for WPL is 38% over LANDMARC and 17% over enhanced LANDMARC. ELM enhances the precision of localization accuracy by 55% over LANDMARC, 40% over enhanced LANDMARC and 27% over WPL respectively. The distance error distribution of WPL as shown in Figure 5(c) ranges mainly within 2.5m and ELM as shown in Figure 5(d) ranges mainly within 2m. In contrast, the distance error distribution of LANDMARC and enhanced LANDMARC are much more scattered.

In summary, WPL and ELM can provide higher localization accuracy than LANDMARC and enhanced LANDMARC.

C. Robustness Comparison between WPL, ELM and Other Methods

The event of RSS data package loss occurs frequently in IPS due to the limitation of the RF data transmission channel and signal collision. Sometimes, it is possible that all the RSSI samples we receive are samples that contain one or more signal strengths that are out of the reasonable RSS range.

In order to evaluate the robustness of WPL and ELM, 5000 defect RSSI samples of each tracking tag are randomly chosen from experiment II database. The performance of ELM approach with 2500 hidden nodes is chosen in this comparison. The robustness comparison between WPL, ELM, LANDMARC and enhanced LANDMARC is presented in Figure 6. The average localization accuracy of all 7 tracking tags by using LANDMARC, enhanced LANDMARC, WPL and ELM is 3.503m, 3.407m, 1.671m and 1.137m. It can be seen in Figure 6, even by using the RSSI samples that contain some signal strengths that are beyond the reasonable RSS range, both WPL and ELM can still provide relative



(a) LANDMARC (b) Enhanced LANDMARC (c) WPL (d) ELM

Fig. 5. Comparison of Distance Error Distribution for different methods

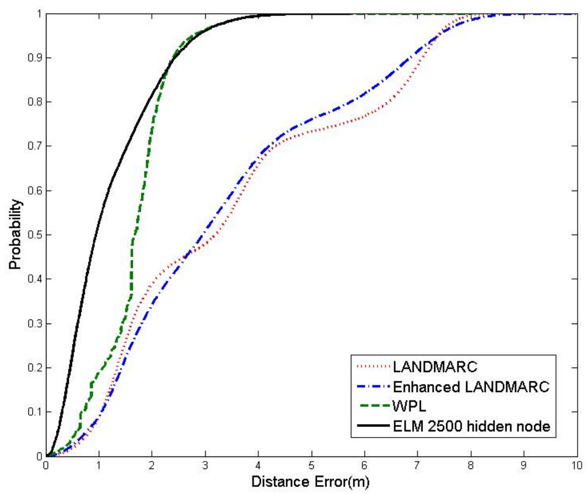


Fig. 6. Cumulative percentile of error distance for different methods

higher localization accuracy than LANDMARC and enhanced LANDMARC. In this case, ELM enhances the precision of localization accuracy by 68% over LANDMARC, 67% over enhanced LANDMARC and 32% over WPL respectively. We can conclude that ELM is more robust than WPL and other methods.

V. Conclusion and Future Work

In this paper we proposed a cost-efficient RFID IPS by using cheaper active RFID tags, sensors and reader. Two localization algorithms: WPL and ELM were also proposed in this paper. Our experimental results show that the WPL approach enhances the precision of indoor localization by 38% and 17% over the LANDMARC approach and the enhanced LANDMARC approach respectively. The ELM approach enhances the precision of indoor localization by 55% over the LANDMARC approach and 40% over the enhanced LANDMARC approach. In addition, ELM can provide relative higher localization accuracy than WPL when RSSI samples contain some signal strengths that are beyond the reasonable range due to signal collision, demonstrating that ELM is more robust than WPL when there are more tracking targets in the system. The advantage of WPL is that it can provide an estimated location of the tracking tag faster than ELM. The reason is that ELM needs to increase the number of hidden nodes to achieve higher localization accuracy, and the system requires more time to provide an estimated location.

Considering the advantages of WPL and ELM, the future work can be focused on how to integrate these two approaches in order to provide a more accurate estimated location of the tracking tag.

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