An Integrative Weighted Path Loss and Extreme Learning Machine Approach to RFID based Indoor Positioning

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***Abstract*—In recent years, applying RFID technology to develop an Indoor Positioning System (IPS) has become a hot research topic. The most prominent advantage of active RFID IPS comes from its unique identification of different objects in indoor environment. However, certain drawbacks of existing RFID 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 location based service, largely limit the applications of active RFID IPS. In order to overcome these drawbacks, we develop a cost-efficient RFID IPS by using cheaper active RFID tags, sensors and reader. In addition, one localization algorithm: integrated Weighted Path Loss (WPL) - Extreme Learning Machine (ELM) which combines the fast estimation of WPL and the high localization accuracy of ELM is proposed. According to the algorithm, an indoor environment is divided into small zones firstly and an ELM model is developed for each zone during the offline phase. 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. Based on our experimental result, this integrated algorithm provides a higher localization efficiency and accuracy than existing approaches.**

I. Introduction

In recent years, with the widespread usage of mobile devices and the increasing popularity of social networks, the demands of Location Based Service (LBS) have increased a lot in both indoor and outdoor circumstance. GPS can provide excellent LBS in outdoor environment. However, due to the lack of line of sight (LoS) transmission channel between the satellite and the receiver, GPS is not capable of providing positioning service with sufficient localization accuracy in indoor environment. Developing an Indoor Positioning System (IPS) to provide reliable and precision 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.

A number of wireless communication technologies have been proposed and developed in order to provide indoor positioning and navigation, including Infrared, Bluetooth, Ultra-Wideband (UWB), Radio Frequency Identification (RFID) and Wireless Local Area Network (WLAN) [1] [2]. 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 been studied and explored in recent years.

LANDMARC is one of the earliest and most famous IPSs by using active RFID tags and RFID readers [3] . In order to increase accuracy without placing more readers, extra fixed location reference tags are introduced in LANDMARC to facilitate location calibration. 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 [4]. 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.

One drawback of these RFID IPSs is the high cost of RFID readers and the active RFID tags. In order to overcome this, we develop a cost-efficient RFID IPS by using cheaper active RFID tags, sensors and readers in this paper. Unlike the LANDMARC system, the signal strengths emitted from RFID tags are picked up by low-cost RFID sensors instead of RFID readers in our system. Another drawback is that the localization accuracy of these RFID IPSs largely depends on the density of reference tags. Too many reference tags may result in increased RF interferences. In [5], two localization algorithms: Weighted Path Loss (WPL) and Extreme Learning Machine (ELM) are proposed to overcome this drawback.

The WPL approach is a centralized model-based localization algorithm and the ELM approach is a machine learning fingerprinting localization algorithm.

Based on the experimental results shown in [5], WPL can provide a faster estimation while ELM can provide a higher localization accuracy. On the other hand, WPL cannot provide very high localization accuracy like ELM and the drawback of ELM is the tedious testing time during the online phase. In order to integrate the advantages of these two approaches and overcome the drawbacks of them as well, a novel localization algorithm: WPL-ELM is proposed in this paper. During the offline phase, an indoor environment is divided into small zones firstly and an ELM model is developed for each zone during the offline phase. 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. Based on our experimental results, WPL-ELM can not only provide higher localization accuracy, but also perform a more efficient way compared with existing ones.

The rest of the paper is organized as follows. In Section II, the background knowledge for this paper is provided. Section III introduces our RFID IPS and the algorithm formulation of the proposed localization algorithm. In Section IV, we present the experimental results and performance evaluation of the proposed algorithm. The conclusion is given in Section V.

II. Background Knowledge

A. 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 [4], the signal strength s_{ij} can be expressed as:

$$s_{ij} = PL(d_{ij}) = PL_0 + 10\alpha log(d_{ij}) \tag{1}$$

where PL_0 is the reference pass loss coefficient and α is the pass loss exponent. Based on (2), the distance between the jth tracking tag and the ith sensor can be calculated by:

$$d_{ij} = 10^{\frac{s_{ij}-PL_0}{10\alpha}} \tag{2}$$

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

$$w_{ij} = \frac{\frac{1}{d_{ij}}}{\sum_{i=1}^{A}\frac{1}{d_{ij}}} \tag{3}$$

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

$$(u_j, v_j) = \sum_{i=1}^{A} w_{ij}(x_i, y_i) \tag{4}$$

B. Methodology of 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 [6]. ELM can be adopted to solve 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 vectors RSS_{pq}, $p = 1, 2, ..., P$, $q = 1, 2, ..., Q$ 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 (hardlim) function $G(a, b, x) = hardlim(ax + b)$ is chosen as the activation function in this paper. The training process of ELM is introduced in [6]. 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:

$$\beta = H^{\dagger}L \tag{5}$$

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.

III. Proposed Approach

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 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. Both RFID sensors and active RFID tags in our system use TICC2530 as the wireless module. The battery life of each tag is around one month. 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 the identification by sensors. 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 reader continuously through the wireless sensor network. The RSSI data from all RFID sensors are received at the RFID reader which is connected to a location server. In our experiment, one RFID reader is good enough

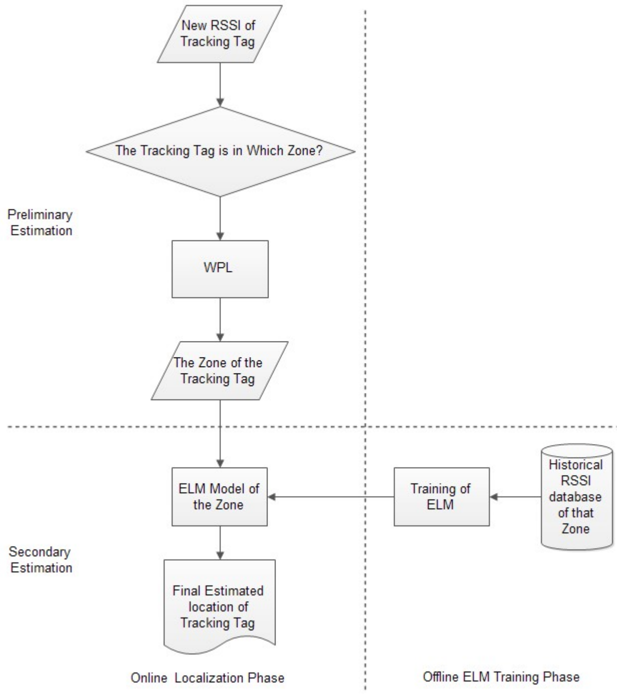

Fig. 1. Flowchart of Integrated WPL-ELM Approach

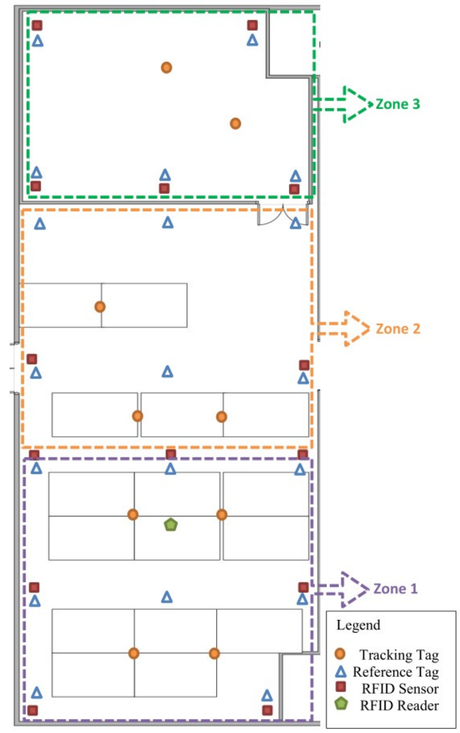

Fig. 2. Placement of RIFD tracking tags, sensors and reader

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 algorithm.

B. Methodology of integrated WPL-ELM

Based on the experimental results in [5], the advantage of WPL is its faster estimation and relative better localization accuracy compared with existing model-based localization algorithms. It usually uses less than 0.2s to test a new RSSI sample with 1.65m localization accuracy. ELM can provide a higher localization accuracy, but there is a tradeoff between the localization accuracy and the testing time. The testing time increases if a higher localization accuracy is required. In order to combine the faster estimation of WPL and the higher localization accuracy of ELM, a novel localization algorithm: WPL-ELM integrating both approaches is proposed. The process of this proposed localization algorithm is shown in Figure 1.

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.

IV. Experimental Results and Performance Evaluation

Series of experiments have been conducted to evaluate the performance of the proposed localization algorithm. The test-bed is the Postgraduate Room in the Internet of Things Laboratory in School of Electrical and Electronic Engineering, Nanyang Technological University. The size of the test-bed is approximately $110m^2$ $(6.4m \times 17.1m)$. 14 RFID sensors are deployed in the room. The positions of these RFID sensors and the RFID reader are shown in Figure 2. As shown in Figure 2, the entire room has been divided into three small zones in order to evaluate the localization performance of the proposed integrated WPL-ELM approach. Zone 1 contains 7 sensors and 4 tracking tags. Zone 2 contains 8 sensors and 3 tracking tags. There are 5 sensors and 2 tracking tags in Zone 3.

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:

$$e = \sqrt{(x - x_0)^2 + (y - y_0)^2} \tag{6}$$

Since the WPL approach is adopted as the preliminary estimation in the integrated WPL-ELM approach and its localization accuracy depends on the path loss exponent α, we conduct an experiment and use a curve fitting method to construct the relationship between RSSI and distance, as:

$$PL(d_i) = -52.40 - 10 \times 3.58 \times log(d_i) \tag{7}$$

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.

During experiment I, as shown Figure 2, 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 14 RFID sensors for 10 days. We obtain 637000 RSSI samples for each tag in this experiment. We put these samples with their corresponding real location coordinates into the ELM training process and build 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 both 9 tracking tags from the 14 RFID sensors for 5 days. The main purpose of experiment II is to evaluate the localization accuracy of the integrated WPL-ELM approach. We obtain 325000 RSSI samples for each tag in this experiment.

We evaluate the performance of WPL-ELM based on the RSSI samples of 9 tracking tags from the experiment II database. Since WPL is adopted as the preliminary estimation of the tracking tag, we first analyze the reliability of WPL in classifying the tracking tags into the correct zone. Based on the experimental results, WPL can determine the zone of the tracking tag with a 97.8% accuracy. With 0.15s fast estimation and 1.782m 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 Back-propagation (BP) algorithm, support vector machine for regression (SVR) algorithm, ELM and WPL-ELM is shown in Figure 3 and Figure 4. As shown in Figure 3, the distance error distribution of WPL-ELM ranges mainly within 2.3m which is the best among the four approaches.

Table I demonstrates the performance comparison among the four approaches in terms of the training time, the average testing time and the average localization accuracy. As observed in Table I, the overall average localization accuracy of WPL-ELM is 0.799m, 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 greatly reduces both the training time during the offline phase and the testing time during the online phase as compared with ELM. The overall training time of WPL-ELM is 147.089s which saves 41% less time than ELM. The average testing time of WPL-ELM is 0.432s which is 4.22 times faster than ELM. Therefore, WPL-ELM can overcome the drawback of ELM which is the tedious testing time during the online phase.

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

TABLE I
COMPARISON BETWEEN WPL-ELM AND ELM

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
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**

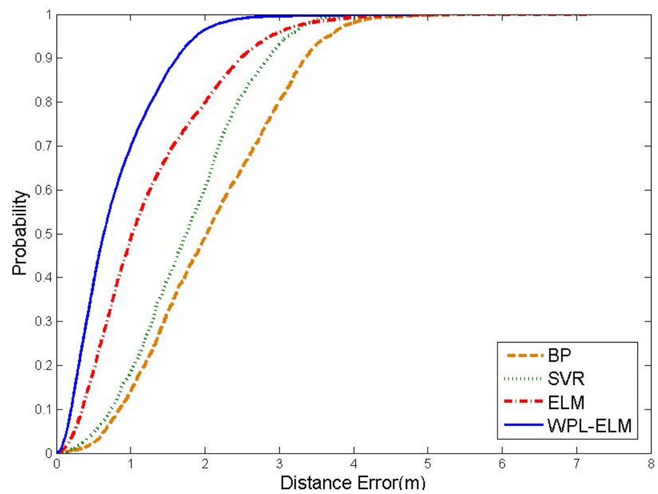

Fig. 4. Cumulative percentile of error distance for different methods

V. CONCLUSION

In this paper, we proposed a cost-efficient RFID IPS by using cheaper active RFID tags, sensors and reader. Furthermore, considering the fast estimation of WPL and the high localization accuracy of ELM, a novel localization algorithm: WPL-ELM which integrates the advantages of both approaches was proposed. Based on the experimental results, the training time and the testing time of WPL-ELM are 1.69 times and 4.22 times faster than ELM. In addition, 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, it also can greatly reduce the deployment cost of the entire system because it requires less number of RFID sensors than WPL to maintain the same localization accuracy.

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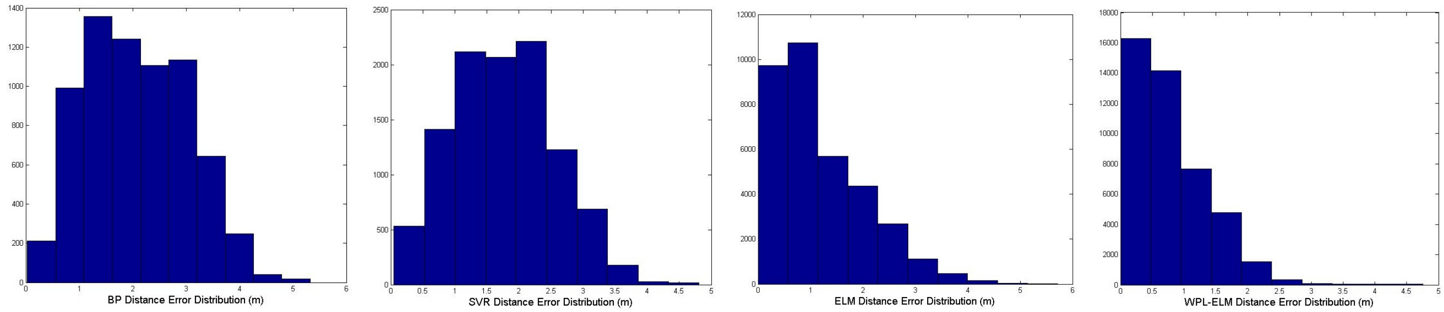

(a) BP (b) SVR (c) ELM (d) WPL-ELM

Fig. 3. Comparison of Distance Error Distribution for different methods

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