An Online Sequential Extreme Learning Machine Approach to WiFi Based Indoor Positioning

Han Zou, Hao Jiang, Xiaoxuan Lu and Lihua Xie
EXQUISITUS, Centre for E-City, School of Electrical and Electronics Engineering
Nanyang Technological University
Singapore, 639798
Email: $\{zouh0005, jiangh, xlu010, elhxie\}$@ntu.edu.sg

***Abstract*—Developing Indoor Positioning System (IPS) has become an attractive research topic due to the increasing demands on Location Based Service (LBS) in indoor environment recently. WiFi technology has been studied and explored to provide indoor positioning service for years since existing WiFi infrastructures in indoor environment can be used to greatly reduce the deployment costs. A large body of WiFi based IPSs adopt the fingerprinting approach as the localization algorithm. However, these WiFi based IPSs suffer from two major problems: the intensive costs on manpower and time for offline site survey and the inflexibility to environmental dynamics. In this paper, we propose an indoor localization algorithm based on online sequential extreme learning machine (OS-ELM) to address these problems accordingly. The fast learning speed of OS-ELM can reduce the time and manpower costs for the offline site survey, and more importantly, its online sequential learning ability enables the proposed localization algorithm to automatically and timely adapt to the environmental dynamics. The experimental results show that the proposed localization algorithm can provide higher localization accuracy than traditional approaches due to its fast adaptation to various environmental changes.**

I. 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. Since GPS is not capable of providing reliable and precise positioning services in indoor environment due to the lack of line of sight (LoS) transmission channels between a satellite and a receiver, wireless indoor localization has been extensively studied and a number of solutions have been proposed in the past two decades [1]. IEEE 802.11 (WiFi) is the most commonly used technology for indoor positioning because the existing WiFi infrastructures, such as WiFi routers, are widely available in large numbers of commercial and residential buildings, and nearly every mobile device now is equipped with a WiFi receiver. As such, it is low-cost and practical to develop a WiFi based indoor positioning system (IPS) to provide LBS in indoor environment. Some proposed WiFi based IPSs can achieve meter-level localization accuracy [1] [2].

A large body of existing WiFI based IPSs leverage fingerprinting-based approach as the localization algorithm. Fingerprinting-based approach consists of two phases: an offline training phase and an online localization phase. During the offline training phase, WiFi received signal strength (RSS) from various WiFi access points (APs) are recorded at known locations to build up a WiFi RSS fingerprint database. During the online localization phase, when a user sends a location query containing the current WiFi 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 the location estimate.

However, the existing WiFi based IPSs adopting the fingerprinting-based approach suffer from two major problems. One is that the site survey involves intensive costs on both time and manpower during the offline calibration phase. The other problem is that the fingerprinting-based approach is not robust to environmental dynamics. Since the WiFi RSS fingerprint database is built during the offline phase, it cannot nicely reflect the real-time radio map of the WiFi signals once the environment is altered during the online phase. Various environmental factors can interfere the propagation of WiFi signals severely [2]. It will greatly reduce the localization accuracy of the entire system.

In this paper, we propose an indoor localization algorithm based on online sequential extreme learning machine (OS-ELM) which can not only reduce the time and the manpower costs for the offline site survey, but also take the environmental dynamics into account during the online localization phase. Originating from the batch learning extreme learning machine (ELM), OS-ELM inherits the advantage of ELM which can provide good generalization performance at an extremely fast learning speed [3]. In [4] and [5], an RFID based IPS utilizing ELM as a fingerprinting localization algorithm has been verified to give a competitive performance in terms of both the efficiency and the localization accuracy. In addition, OS-ELM has the online sequential learning ability which does not require retraining when new data are received [6]. Differently from other online sequential learning algorithms such as SGBP [7] and GAP-RBF [8] which require specific types of hidden nodes, OS-ELM is able to adapt to various types of hidden nodes. Therefore using OS-ELM as a localization algorithm can address the two challenging problems of the existing WiFi based IPS to a great extent. Its fast learning speed greatly reduces the time consumptions and the manpower costs for the offline site survey. In the meanwhile, the online sequential learning ability of OS-ELM permits the entire system to provide sufficient localization accuracy even under the environmental changes.

The rest of the paper is organized as follows. A review of OS-ELM is provided in Section II. Section III formulates the proposed localization algorithm. The simulation results and evaluation of OS-ELM are presented in Section IV. In Section V, a system overview of our WiFi Based IPS is provided firstly, and followed by the experimental results and performance evaluation of the proposed localization algorithm. We conclude the work in Section VI.

II. Review of OS-ELM

ELM is a kind of machine learning algorithm based on a Single-hidden Layer Feedforward neural Network (SLFN) architecture. OS-ELM on the basis of ELM was developed for SLFNs with additive hidden nodes [6]. Assume there are N arbitrary distinct training samples $(\mathbf{x}_i, \mathbf{t}_i) \in \mathbf{R}^n \times \mathbf{R}^m$, where $\mathbf{x}$ are the training inputs and $\mathbf{t}$ are the training targets . If a SLFN with L hidden nodes can approximate these N samples with zero error, there exist β_i, $\mathbf{a}_i$ and b_i such that

$$f_L(\mathbf{x}_j) = \sum_{i=1}^{L} \beta_i G(\mathbf{a_i}, b_i, \mathbf{x}_j) = \mathbf{t}_j, j = 1, 2, \ldots, N, \quad (1)$$

where $\mathbf{a}_i$ and b_i are the learning parameters of the hidden nodes, β_i is the output weight, and $G(\mathbf{a_i}, b_i, \mathbf{x}_j)$ is the activation function which gives the output of the ith hidden node with respect to the input $\mathbf{x}_j$. If the hidden node is additive, $G(\mathbf{a_i}, b_i, \mathbf{x}_j) = g(\mathbf{a_i} \cdot \mathbf{x}_j + b_i), b_i \in R$, where $\mathbf{a}_i$ is the input weight vector, b_i is the bias of the ith hidden node, and $\mathbf{a_i} \cdot \mathbf{x}_j$ denotes the inner product of the two.

OS-ELM algorithm contains two phases: an initialization phase and a sequential learning phase. Suppose the network has L hidden nodes and the data $\aleph = \{(\mathbf{x_i}, \mathbf{t}_i) | \mathbf{x}_i \in \mathbf{R}^n, \mathbf{t}_i \in \mathbf{R}^m, i = 1, \ldots, N.\}$ are presented to the network sequentially. In the initialization phase, $rank(\mathbf{H}_0) = L$ is required to ensure that OS-ELM can achieve the same learning performance as ELM, where $\mathbf{H}_0$ denotes the hidden output matrix for the initialization phase. The number of training data required in the initialization phase, N_0, has to be equal to or greater than L, i.e. $N_0 \geq L$.

Initialization phase: a small chunk of training data $\aleph_0$ is used to initialize the learning, where $\aleph_0 = \{\mathbf{x}_i, \mathbf{t}_i\}_{i=1}^{N_0} \subseteq \aleph$ and $N_0 \geq L$.

Step 1: Randomly assign the input parameters: input weights $\mathbf{a}_i$ and bias b_i, $i = 1, \ldots, L$.

Step 2: Calculate the initial hidden layer output matrix $\mathbf{H}_0 =$

$$\begin{bmatrix} G(\mathbf{a}_1, b_1, \mathbf{x}_1) & \ldots & G(\mathbf{a}_L, b_L, \mathbf{x}_1) \\ \vdots & \ldots & \vdots \\ G(\mathbf{a}_1, b_1, \mathbf{x}_{N_0}) & \ldots & G(\mathbf{a}_L, b_L, \mathbf{x}_{N_0}) \end{bmatrix}_{N_0 \times L} \quad (2)$$

Step 3: Estimate the initial output weight $\beta^{(0)}$. Since $\mathbf{T}_0 = [\mathbf{t}_1, \ldots, \mathbf{t}_{N_0}]^T_{N_0 \times m}$, the problem is equivalent to minimizing $\|\mathbf{H}_0 \beta - \mathbf{T}_0\|$. Noticing that $\mathbf{H}^\dagger = (\mathbf{H}^T\mathbf{H})^{-1}\mathbf{H}^T$ [3], the optimal solution is given by $\beta^{(0)} = \mathbf{P}_0 \mathbf{H}_0^T \mathbf{T}_0$, where $\mathbf{P}_0 = (\mathbf{H}_0^T \mathbf{H}_0)^{-1}$, and $\mathbf{K}_0 = \mathbf{P}_0^{-1} = \mathbf{H}_0^T \mathbf{H}_0$.

Step 4: Set $k = 0$, where k is a parameter indicating the number of chunks of data that is presented to the network.

Sequential learning phase: present the $(k+1)$th chunk of new observations $\aleph_{k+1} = \{(\mathbf{x}_i, \mathbf{t}_i)\}_{i=(\Sigma_{j=0}^k N_j)+1}^{\Sigma_{j=0}^{k+1} N_j}$, where N_{k+1} denotes the number of observations in the $(k+1)$th chunk.

Step 1: Compute the partial hidden layer output matrix $\mathbf{H}_{k+1} =$

$$\begin{bmatrix} G(\mathbf{a}_1, b_1, \mathbf{x}_{(\Sigma_{j=0}^k N_j)+1}) & \ldots & G(\mathbf{a}_L, b_L, \mathbf{x}_{(\Sigma_{j=0}^k N_j)+1}) \\ \vdots & \ldots & \vdots \\ G(\mathbf{a}_1, b_1, \mathbf{x}_{\Sigma_{j=0}^{k+1} N_j}) & \ldots & G(\mathbf{a}_L, b_L, \mathbf{x}_{\Sigma_{j=0}^{k+1} N_j}) \end{bmatrix}_{N_{k+1} \times L} \quad (3)$$

Step 2: Calculate the output weight $\beta^{(k+1)}$. We have $\mathbf{T}_{k+1} = [\mathbf{t}_{(\Sigma_{j=0}^k N_j)+1}, \ldots, \mathbf{t}_{\Sigma_{j=0}^{k+1} N_j}]^T_{N_{k+1} \times m}$. Moreover,

$$\mathbf{K}_{k+1} = \mathbf{K}_k + \mathbf{H}_{k+1}^T \mathbf{H}_{k+1} \quad (4)$$

$$\beta^{(k+1)} = \beta^{(k)} + \mathbf{K}_{k+1}^{-1} \mathbf{H}_{k+1}^T (\mathbf{T}_{k+1} - \mathbf{H}_{k+1} \beta^{(k)}) \quad (5)$$

In order to avoid inverting matrices such as $\mathbf{K}_{k+1}^{-1}$ in Eq. (5) in the recursive process, the Woodbury formula [9] is applied to transform the equations as follows

$$\mathbf{K}_{k+1}^{-1} = \mathbf{K}_k^{-1} - \mathbf{K}_k^{-1} \mathbf{H}_{k+1}^T (\mathbf{I} + \mathbf{H}_{k+1} \mathbf{K}_k^{-1} \mathbf{H}_{k+1}^T)^{-1} \mathbf{H}_{k+1} \mathbf{K}_k^{-1} \quad (6)$$

Since $\mathbf{P}_{k+1} = \mathbf{K}_{k+1}^{-1}$,

$$\mathbf{P}_{k+1} = \mathbf{P}_k - \mathbf{P}_k \mathbf{H}_{k+1}^T (\mathbf{I} + \mathbf{H}_{k+1} \mathbf{P}_k \mathbf{H}_{k+1}^T)^{-1} \mathbf{H}_{k+1} \mathbf{P}_k \quad (7)$$

$$\beta^{(k+1)} = \beta^{(k)} + \mathbf{P}_{k+1} \mathbf{H}_{k+1}^T (\mathbf{T}_{k+1} - \mathbf{H}_{k+1} \beta^{(k)}) \quad (8)$$

Step 3: Set $k = k+1$. Go to Step 2 in this online sequential learning phase.

III. Proposed OS-ELM Localization Algorithm

The proposed OS-ELM approach considers the localization problem as a regression problem. During the offline calibration phase, an initial OS-ELM model will be built up. OS-ELM only requires a relative sparse radio map of WiFi RSS to construct the model because of its fast learning speed. It can greatly reduce the time consumption and manpower costs for the offline site survey. During the online phase, by leveraging the online learning ability of OS-ELM, new WiFi RSS fingerprints which are collected at some known locations will be integrated with the initial OS-ELM model to update and generate a revised OS-ELM model, in order to reflect the environmental dynamics.

A. Offline Calibration Phase

Suppose $\aleph_0$ WiFi RSS fingerprints are collected at some known locations during the offline calibration phase. These WiFi RSS fingerprints and their corresponding physical locations are adopted as the training inputs $\mathbf{x}$ and the training targets $\mathbf{t}$ respectively for OS-ELM offline training. Similarly to the initialization phase of OS-ELM, the initial OS-ELM model will be trained as mentioned in Section II. The detailed steps are illustrated below:

Step 1: Randomly assign the input parameters: input weights $\mathbf{a}_i$ and input bias b_i.

Step 2: Calculate the initial hidden layer output matrix $\mathbf{H}_0$.

Step 3: Estimate the initial output weight $\beta^{(0)}$.

Step 4: Set $k = 0$, where k indicates the number of updating times of WiFi RSS fingerprints that are collected during the online calibration phase.

B. Online Sequential Learning Phase

During the online sequential learning phase, WiFi RSS fingerprints are collected at some known locations. These WiFi RSS fingerprints and their corresponding physical locations will be adopted as online training samples, and they will be updated to revise the initial OS-ELM model. The revised OS-ELM model will be able to adapt to various environmental changes.

Suppose $\aleph_{k+1}$ WiFi RSS fingerprints have been collected during the $(k+1)$th online calibration, the revised OS-ELM model will be obtained by the following steps:

Step 1: Calculate the partial hidden layer output matrix H_{k+1}.

Step 2: Calculate the output weight $\beta^{(k+1)}$.

Step 3: Set $k = k + 1$ for the next online calibration.

C. Online Adaptive Localization Phase

Before any WiFi RSS fingerprints are collected at any known locations during the online phase, the initial OS-ELM model will be leveraged to calculated the users' locations based on their real-time WiFi RSS fingerprints. After some WiFi RSS fingerprints are collected at some known locations during the online phase, the latest revised OS-ELM model will be used to provide the estimated location of the user.

IV. Simulation Results and Evaluation

We develop a simulation environment using Matlab R2013a in order to evaluate the performance of the proposed OS-ELM approach before any experiment is conducted. We assume a $20m \times 20m$ room where 4 WiFi routers are installed at the four corners of the room. The most commonly used path loss model for indoor environment is the ITU Indoor Propagation Model [10]. Since it provides a relation between the total path loss PL (dBm) and distance d (m), it is adopted to simulate the WiFi signal generated from each WiFi router. The indoor path loss model can be expressed as:

$$PL(d) = PL_0 - 10\alpha log(d) + X_\sigma \tag{9}$$

where PL_0 is the pass loss coefficient and it is set to be -40dBm in our simulation. X_σ represents a zero-mean Normal random noise with standard deviation $\sigma = 0.5$, and α is the path loss exponent.

During the offline calibration phase, α is set to be 2 in scenario I and simulated WiFi RSS fingerprints from the 4 WiFi routers are collected at 10 randomly selected offline calibration points for OS-ELM offline training, with 200 WiFi RSS fingerprints collected at each point. The hardlim function $G(a, b, x) = hardlim(ax + b)$ is chosen as the activation function and 380 hidden nodes are selected and put in the hidden layer during the offline training. The initial OS-ELM model is obtained after 0.219s training process. In order to imitate the environmental dynamics in the room, we set α to be 2.5 in scenario II and 3.5 in scenario III respectively. WiFi RSS fingerprints are collected at 5 online calibration points and 5 online testing points under each scenario. 200 WiFi RSS fingerprints are collected at each point and the positions of these points are distinct. The updated WiFi RSS fingerprints at the online calibration points are adopted as online training samples and leveraged to revise the initial OS-ELM model.

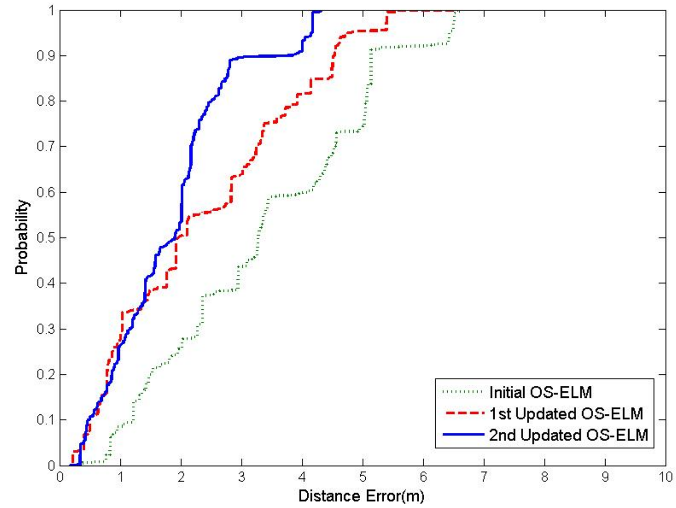

Fig. 1. Cumulative percentile of error distance

We evaluate the performance of OS-ELM with each online sequential learning update based on the WiFi RSS fingerprints collected at the 10 online testing points. The distance error is used to measure the localization accuracy of the proposed OS-ELM approach. 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), i.e.:

$$e = \sqrt{(x - x_0)^2 + (y - y_0)^2} \tag{10}$$

Table I illustrates the performance of OS-ELM with each online sequential learning update in terms of training time, testing time and average localization accuracy. The comparison of cumulative percentile of error distances between the initial OS-ELM and the two updated OS-ELM is presented in Figure 1. It can be easily spotted from Table I that the average localization accuracy of OS-ELM becomes better when more WiFi RSS fingerprints at various online calibration points have been learnt online. The latest updated OS-ELM can provide 1.794m , which enhances the precision of indoor localization by 42.18% over the performance of initial OS-ELM. Furthermore, the online sequential learning of OS-ELM is very efficient. It only spends 0.014s on average to calculate the output weights β for newly received 1000 WiFi RSS fingerprints in each online sequential learning update.

TABLE I
SIMULATION RESULTS OF OS-ELM

Number of Calibration Points (Offline + Online)	Training Time (s)	Testing Time (s)	Accuracy (m)
10 + 0	0.219	0.015	3.103
10 + 5	0.148	0.014	2.563
15 + 5	0.139	0.014	**1.794**

Based on the simulation results and evaluation, we can conclude that OS-ELM could provide higher localization accuracy due to its efficient online sequential learning ability when the indoor environment is altered during the online phase.

V. EXPERIMENTAL RESULTS AND PERFORMANCE EVALUATION

A. System Overview

In order to evaluate the performance of the proposed adaptive OS-ELM approach, 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 $580m^2$ $(35.1m \times 16.6m)$.

As shown in Figure 2, 8 D-Link DIR-605L WiFi Cloud Routers are adopted as WiFi access points in the test-bed. One Android application is developed for collecting WiFi RSS fingerprints from each access point with the frequency of once per second. This Android application is installed on a Samsung I929 Galaxy SII mobile phone. All the WiFi RSS fingerprints at offline calibration points, online calibration points and online testing points are collected using this phone for performance evaluation. During the offline phase, as shown in Figure 2, 20 offline calibration points are selected and 1000 WiFi RSS fingerprints are collected at each point. These 20000 WiFi RSS fingerprints and their physical positions are adopted to establish the initial OS-ELM model. During the online phase, we continue to collect WiFi RSS fingerprints at several online calibration points and online testing points for five days. In each day, two distinct online calibration points and two distinct online testing points are selected in order to reflect the environmental dynamics. The positions of the 10 online calibration points and the 10 online testing points are also presented in Figure 2. Likewise, 1000 WiFi RSS fingerprints are collected at each point.

B. Comparison between OS-ELM and Batch ELM

It has been shown in [5] that the performance of batch ELM in terms of the offline training time, the online testing time and the average localization accuracy are better than classical machine learning algorithms such as Back-propagation (BP) algorithm and support vector machine for regression (SVR) algorithm. Therefore we choose the performance of batch ELM to be compared with the proposed OS-ELM.

Unlike OS-ELM which can update and revise the initial OS-ELM model sequentially during the online phase, batch ELM can only learn the WiFi RSS fingerprints with their corresponding locations during the offline phase. After the offline training process, a batch ELM model is obtained. During the online phase, after feeding the WiFi RSS fingerprint into the batch ELM model, this model will output the estimated location of the target. To make a fair comparison, we collect WiFi RSS fingerprints not only at the 20 offline calibration points but also at the 10 online calibration points during the offline calibration phase for batch ELM offline training. 1000 WiFi RSS fingerprints are collected at each point. Based on our experimental analysis, the hardlim function $G(a, b, x) = hardlim(ax + b)$ is chosen as the activation function for both batch ELM and OS-ELM. 620 hidden nodes are selected and put in the hidden layer for batch ELM offline training, which are the same for the initial OS-ELM offline training.

TABLE II
COMPARISON BETWEEN OS-ELM AND BATCH ELM

Number of Calibration Points (Offline + Online)	Training Time (s)	Testing Time (s)	Accuracy (m)
Batch ELM			
30 + 0	3.515	0.097	4.181
OS-ELM			
20 + 0	2.579	0.086	4.330
20 + 2	0.827	0.080	3.775
22 + 2	0.827	0.081	3.596
24 + 2	0.884	0.081	3.437
26 + 2	0.816	0.085	3.124
28 + 2	0.812	0.080	**2.928**

After building up the batch ELM model and the initial OS-ELM model, we evaluate the performance of these two approaches based on WiFi RSS fingerprints we collected at the 10 online testing points during the online localization phase. Table II demonstrates the performance comparison between batch ELM and OS-ELM in terms of the training time, the testing time and the average localization accuracy. As shown in Table II, although the localization accuracy of initial OS-ELM is slightly worse than that of batch ELM, the offline training time of OS-ELM is less than that of batch ELM. Initial OS-ELM saves 26.6% less time than batch ELM, which evidently reduces the time and manpower costs for offline site survey. The testing time of batch ELM and OS-ELM are almost the same.

For the online sequential learning phase, since we collected WiFi RSS fingerprints at two distinct online calibration points at each time, the performance of OS-ELM with each online sequential learning update is also presented in Table II. As observed from Table II, the average localization accuracy of OS-ELM becomes better when more WiFi RSS fingerprints at various online calibration points have been learnt online. In addition, another noteworthy point is that the online sequential learning time of OS-ELM is quite fast. It only spends 0.8332s on average to calculate the output weights β for newly received 2000 WiFi RSS fingerprints in each online sequential learning update.

With online sequential learning of WiFi RSS fingerprints

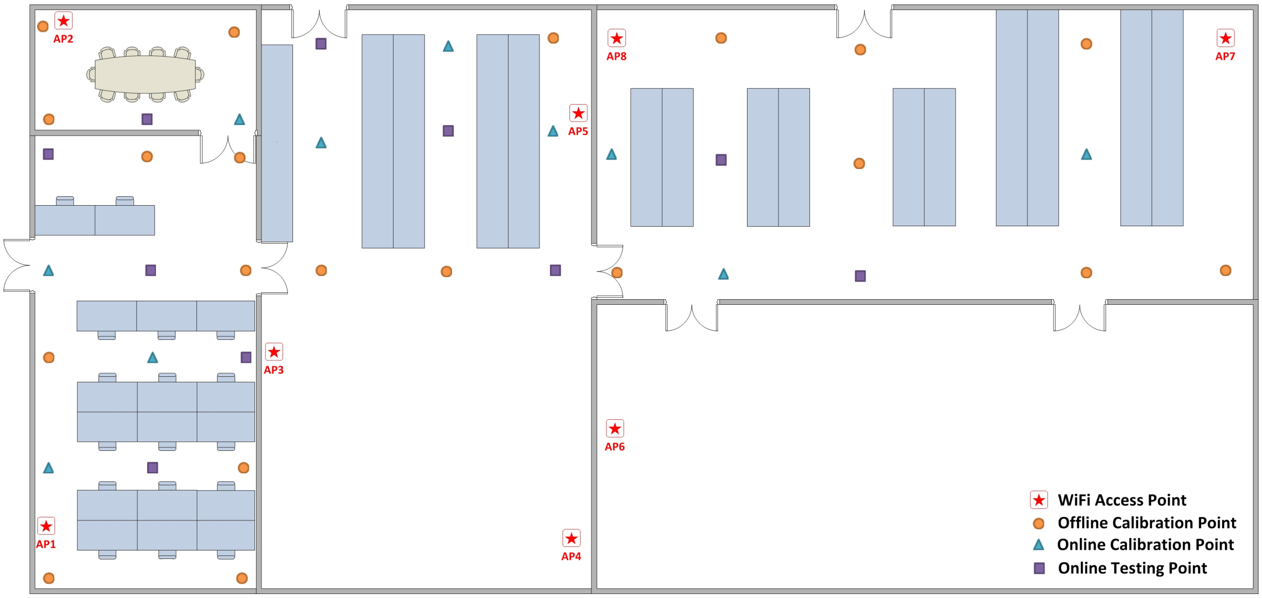

Fig. 2. Positions of the WiFi access points, offline calibration points, online calibration points and online testing points in the test-bed

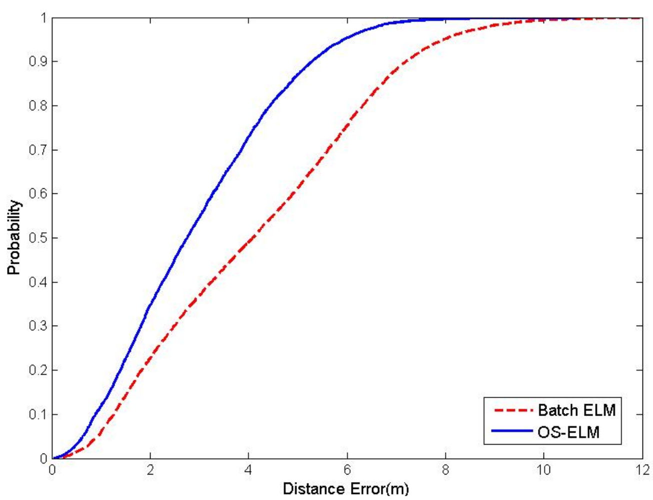

Fig. 3. Cumulative percentile of error distance for different methods

at 10 different online calibration points, OS-ELM can provide localization accuracy of 2.928m, which enhances the precision of indoor localization by 30% over batch ELM. The comparison of cumulative percentile of error distances between the latest updated OS-ELM and batch ELM is presented in Figure 3. Based on our experimental results, under the environmental changes such as the variation of occupancy distribution and the opening and closing of doors, OS-ELM is more robust and adaptive to the environmental dynamics than batch ELM.

VI. Conclusion

In this paper, we proposed an indoor localization algorithm based on OS-ELM to address the two challenging problems of the WiFi based IPS: the inflexibility to environmental dynamics and the intensive costs on manpower and time for offline site survey. Based on our experimental results, the fast learning speed of OS-ELM greatly reduced the time consumptions and manpower costs for the offline site survey. In the mean while, the online sequential learning ability of OS-ELM made it possible to reflect and adapt to the environmental changes quite well.

In summary, OS-ELM can provide higher localization accuracy with a fast online sequential learning speed to adjust to various environmental dynamics compared with the existing approaches.

Acknowledgement

This research is funded by the Republic of Singapore National Research Foundation through a grant to the Berkeley Education Alliance for Research in Singapore (BEARS) for the Singapore-Berkeley Building Efficiency and Sustainability in the Tropics (SinBerBEST) Program. BEARS has been established by the University of California, Berkeley as a center for intellectual excellence in research and education in Singapore.

References

[1] G. Deak, K. Curran, and J. Condell, ”A survey of active and passive indoor localisation systems,” Computer Communications, 2012.

[2] Y.-C. Chen, J.-R. Chiang, H.-h. Chu, P. Huang, and A. W. Tsui, ”Sensor-assisted wi-fi indoor location system for adapting to environmental dynamics,” in Proceedings of the 8th ACM international symposium on Modeling, analysis and simulation of wireless and mobile systems, pp. 118-125, 2005.

[3] G.-B. Huang, Q.-Y. Zhu, and C.-K. Siew, ”Extreme learning machine: theory and applications,” Neurocomputing, vol. 70, pp. 489-501, 2006.

[4] H. Zou, H. Wang, L. Xie, and Q.-S. Jia, ”An RFID indoor positioning system by using weighted path loss and extreme learning machine,” in Cyber-Physical Systems, Networks, and Applications (CPSNA), 2013 IEEE 1st International Conference on, pp. 66-71, 2013.

[5] H. Zou, L. Xie, Q.-S. Jia and H. Wang, ”An Integrative Weighted Path Loss and Extreme Learning Machine Approach to RFID based Indoor Positioning”, in Indoor Positioning and Indoor Navigation (IPIN), 2013 International Conference on, 2013.

[6] N.-Y. Liang, G.-B. Huang, P. Saratchandran, and N. Sundararajan, "A fast and accurate online sequential learning algorithm for feedforward networks," Neural Networks, IEEE Transactions on, vol. 17, pp. 1411-1423, 2006.

[7] Y. LeCun, L. Bottou, G. B. Orr, and K.-R. Mller,Efficient backprop, Lecture Notes Comput. Sci., vol. 1524, pp. 9-50, 1998.

[8] G.-B. Huang, P. Saratchandran, and N. Sundararajan,An efficient sequential learning algorithm for growing and pruning RBF (GAP-RBF) networks,IEEE Trans. Syst., Man, Cybern., B, Cybern., vol. 34, no. 6, pp. 2284-2292, Nov. 2004.

[9] G.H. Golub, C.F.V. Loan, Matrix Computations, third ed., The Johns Hopkins University Press, Baltimore, MD, 1996.

[10] T. Chrysikos, G. Georgopoulos, and S. Kotsopoulos, "Site-specific validation of ITU indoor path loss model at 2.4 GHz," in World of Wireless, Mobile and Multimedia Networks and Workshops, 2009. WoWMoM 2009. IEEE International Symposium on a, pp. 1-6, 2009.