2006 International Joint Conference on Neural Networks
Sheraton Vancouver Wall Centre Hotel, Vancouver, BC, Canada
July 16-21, 2006

Modular Multilayer Perceptron For WLAN Based Localization

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Abstract- **Location Awareness is key capability of Context-Aware Ubiquitous environments. Received Signal Strength (RSS) based localization is increasingly popular choice especially for in-building scenarios after pervasive adoption of IEEE 802.11 Wireless LAN. Fundamental requirement of such localization systems is to estimate location from RSS at a particular location. Multipath propagation effects make RSS to fluctuate in unpredictable manner, introducing uncertainty in location estimation. Moreover, in real life situations RSS values are not available at some locations all the time making the problem more difficult. We employ Modular Multi Layer Perceptron (MMLP) approach to effectively reduce the uncertainty in location estimation system. It provides better location estimation results than other approaches and systematically caters for unavailable signals at estimation time.**

Key Words: Artificial Neural Networks, Pattern Recognition, Location Aware Computing

I. INTRODUCTION

Location information is an integral and crucial component of ubiquitous computing applications [1] [2] [3] [4] [5] [7]. In building localization has been subject to costly infrastructure and special hardware devices mounted on the objects of interest [17]. Pervasive adoption of IEEE802.11 (a, b, g) Wireless LAN (WiFi) has increased the potential of Location-Awareness technology to become a common service. Since signal strength measurements must be reported by the wireless network interface card as part of standard compliance, Positioning using Wireless LAN received signal strength (RSS) is both feasible and economical.

WiFi RSS based location awareness applications include, but are not limited to, a wide range of services to the end user like automatic call forwarding to user's location, robotic global localization, exploration and navigation tasks, Finder, Guiding and Escorting systems, first hop communication partners, liaison applications, location based advertisement and positioning of entities in large warehouses. We are developing Location awareness capability for ubiquitous computing middleware CAMUS [14]. We define Location Awareness system development life cycle as having three distinct phases; Calibration phase, Training phase an Estimation phase. Basic concept behind WiFi RSS based location awareness is that received signal strengths, from different Access Points (APs), follow certain patterns, so called fingerprints, at a particular location. These patterns are captured at each location and stored in a database namely "Radio Map". Let l be the set of target locations and s signal strength patterns. Let A_i set of access points where i indexes over set of APs visible at particular location l . Calibration phase captures this information and stores observation vectors $o = \langle s, A_i, l \rangle$ in Radio Map data store. Result of calibration phase is a mapping function represented as $l = f(s)$. Later when some device reports the same pattern, it is matched with previously captured patterns and location of that device can be estimated. Process of capturing the RSS at particular locations in a site is called 'site calibration'. Fig 1 shows the methodology of calibration process.

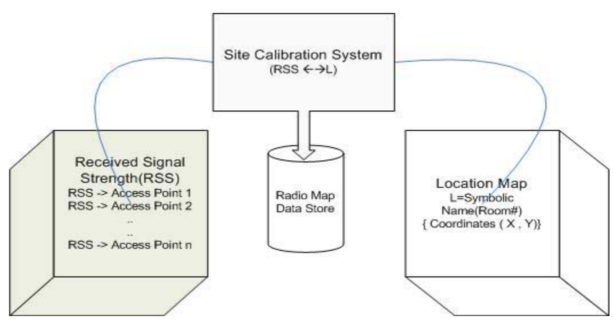

Fig 1: Site calibration: basic concept

Once a Radio Map is built, it is used to develop a mapping function between target locations and respective RSS values. This function is later employed to estimate location of a device given RSS values.

IEEE 802.11 (a and b, g) standards complying WLAN operates in two publicly available radio frequency spectrums, 5 and 2.4 Mhz respectively. In building radio wave propagation follows a complex model due to Non Line of Sight (NLOS) multi-path effects because of the building geometry, human body absorption, neighboring devices and dynamic nature of environments. Due to these limitations, in building location estimation becomes a complex problem difficult to be engineered using classical mathematical methods. Neural networks provide massive parallelism, fault tolerance and adaptation to changing circumstances. Previously we implemented a neural network based localization system on small scale, 300 square meters, with three access points [19]. With encouraging results we extended our problem scale to 1240 square meter building involving 8 access points for implementing localization. In this paper we present our extended experiments to develop artificial neural networks based location estimation system. Next section provides an overview of the previous work. In section III, our Modular Multi Layer Perceptron approach is presented. Section IV describes Design and Implementation details of the system. Results of experiments are presented in section V.

II. Related Work

There have been several efforts to develop Location Aware system based on RSS. Bayesian classification and filtering [4] [8], Statistical learning theory [6], *K*-Nearest Neighbors [1][2][9], GPS like triangulation [18] and Kalman Filtering [10] have been employed for solving this problem. Indoor wireless signal propagation is so complicated and elusive that it is still hard to achieve and maintain reasonable accuracy level for indoor location estimation systems. Nearest Neighbors based pattern recognition technique and its derivates have been used traditionally by many researchers. RADAR system reported 2.65 square meter distance error. K. Pehlavan *et al* also used KNN technique and achieved 2.8 meter distance error [9]. Nearest Neighbor and its variants require a database of sample RSS readings at the estimation time for pattern matching. As the area and number of target locations grow, this size of the database dramatically increased and it becomes impractical to achieve sufficient scalability. On the other hand GPS like triangulation methods provide poor performance due to multi-path propagation effects in indoor environments. Asim *et al* [18] achieved accuracy with 4.5 meter distance error in an area of 60 square meters. Probabilistic approaches like Bayesian networks based solutions achieve better performance but they are computationally exhaustive and difficult to scale. Andrew *et al* reported 1.5 square meter distance error but only for 30 square meter area test bed. As the area and number of target locations and wireless access points increase, the computational complexity of Bayesian structures grows and become computationally hard. Only Battiti *et al* [11] have employed neural networks for this problem. They used feed forward back propagation network that takes RSS of 3 Wireless Access Points (AP) to cover 624 square meter area. 200 samples were used to train neural network for each target location. They reported median estimation distance error of 1.75 meter. This model assumes that all the inputs are available at every location all the time. Practically, this approach has limited applicability because in real life scenario some AP may not be visible (not in range) at all the locations for all the time. We employ a modular approach that perfectly caters for this situation.

III. Our Approach

Contrary to previous approaches, we provide architectural support for unavailability of signals at estimation time. The problem of constantly fluctuating RSS and even absence of wireless signal introduces uncertainty in location estimation. Radio map based localization is directly affected by the fact that how closely sample signal data represent the real life radio signal propagation. We managed to collect a 100 RSS samples at each target location at 42 target locations (Refer to section IV). Multi Layer Perceptron (MLP) has been employed by many researches for pattern recognition problem [6] [7]. But same approach is not sufficed to our problem due to unpredictable absence of signal in real life. For empirical data collection an Hp iPAQ pocket PC equipped with integrated Intel wireless network interface card was used to build the radio map of the environment. IEEE 802.11 (a, b, g) standard specifies that signal strength measurement must be reported by the network interface card (NIC) as part of standard compliance [15]. The RSSI is measured in dBm and normal values for the RSSI value are between -10 and -100 [16].We propose a modular approach to cope with this uncertainty effectively. Details of our architecture are given in next section.

A. Modular Multi Layer Perceptron (MMLP)

Fundamental assumption of radio map based localization is that signal strength of all access points in the target area is available all the time. This assumption does not cater for a subtle nature of radio wave propagation specially inside the buildings e.g. all access points are not visible at all target locations all the time. This implies that non-availability of a particular access point at given location can have adverse affect on location estimation. We refer to signal availability of a particular access point at a given location as 'visibility'. Fig 2 shows radar graphs for visibility ratio of individual six access point at 42 target locations. All target locations IDs are listed around the graph and visibility of each access point is shown as line connecting these points.

We use last four digits of access point's MAC (Media Access Control) address in order to identify each AP. Figure 2 shows visibility graphs of 6 access points in our target area.

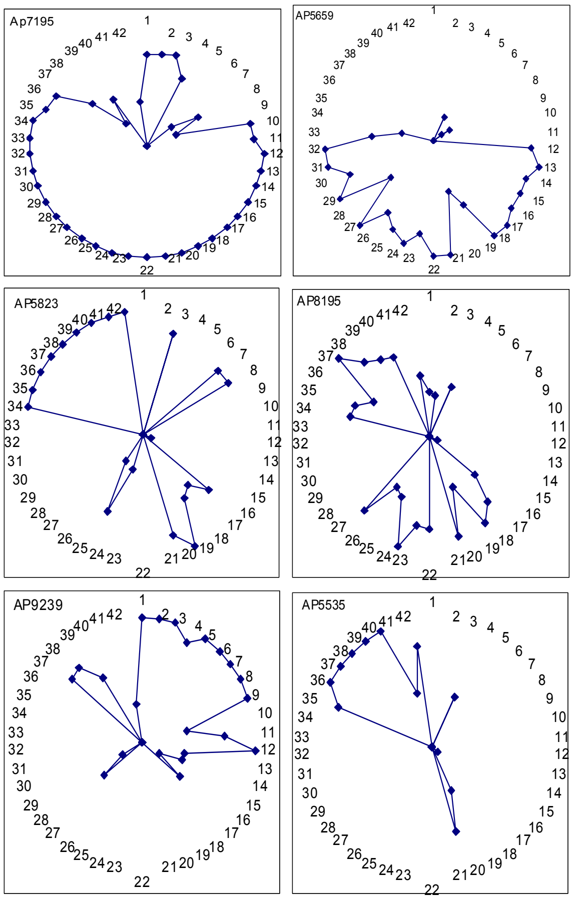

Fig 2: Visibility ratio of individual access point at different locations

We summarize this information in a visibility matrix table as shown in Table 1.

TABLE 1. Visibility Matrix

Access Points	***Location IDs***
AP7195,AP5823,AP9235;	19,16,17,18,20,24,25,26,34,35;
AP7195,AP9235,AP5659;	13,17,18,21,22,27,29,31,32,12,14,15,16,19, 20,23,24,25,26,28,30,33,34;
AP7195,AP9239,AP9235;	12,10,13,14,16,28;
AP5823,AP5535,AP8195;	37,19,20,35,36,38,39,40,42;

A close observation of radio map gives important clues for using MMLP. Visibility of a signal allows filtering out possibility of unlikely locations and vice versa. Therefore for each set of available signal we employ a separate MLP neural network with best results. The overall architecture includes a rule based component at the beginning of estimation. All the Access Points (AP) in range at a particular location are presented to this module. Based on this input it selects the next appropriate Neural Network Module. The criterion of selection is visibility (Accessibility) of AP at a particular location. For our experimental setup this selection criteria is summarized in Table 2.

TABLE 2. Visibility Matrix Decision Rules

AP 5535	AP 8195	AP 9239	AP 5659	AP 7195	AP 5823	AP 9235	Module
0	0	0	0	1	1	1	A
0	0	0	1	1	0	1	B
1	1	0	0	0	1	0	C
0	0	1	0	1	0	1	D

In table 2, value 1 stands for signal availability and 0 for non availability. Four neural networks, with RSS of different APs on the input layer, are employed to estimate the location. Modular Multi Layer Perceptron architecture is shown in Fig 3. Our experiments were conducted with many different variants of MMLP architecture. Fig 2 is a particular instance of MMLP only to convey the basic idea.

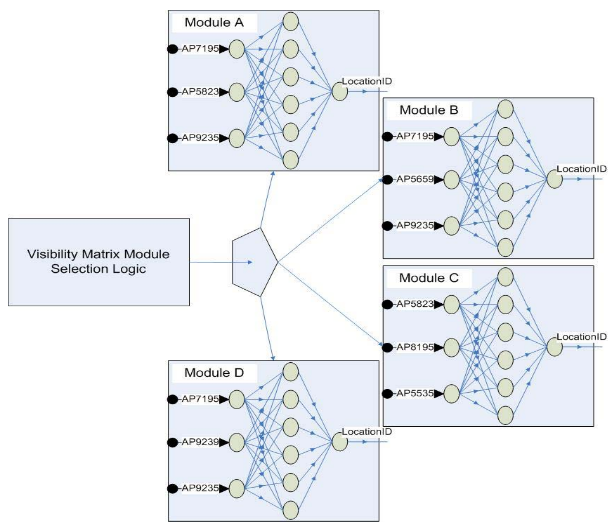

Fig 3: Modular Multi Layer Perceptron (MMLP) Architecture

IV. DESIGN AND IMPLEMENTATION

We conducted experiments in 3rd floor of Engineering Building. Fig 4 shows the map, target locations and location of wireless Access Points. We divided all target locations into three regions. Corridor 1 is horizontal corridor with 10 target points. All point in corridor 1 region are given IDs from 11~20 from right to left. Corridor 2 is right vertical corridor with 6 target points. All points in corridor 2 region are numbered as 21~26.

Similarly Corridor 3 is left vertical corridor with 6 target points. All points in corridor 3 region are numbered as 31~36. Two corner locations are termed as zero points as shown in Fig 3. Total area covered by these points is 286 square meter.

A. Calibration Phase

We collected 300 samples of RSS from all three Access Points at each location in calibration phase. Three IEEE802.11 (a, b, g) 3COM Access Points have been deployed in three corridors, as shown in Fig 4. We developed a device driver interface to capture the signal strength based on NDIS specification. NDIS protocol driver acts as a "relay" between an application and the NDIS miniport driver. Signal strengths recorded at each location are stored in a database called "Radio Map". Later this radio map is used to provide training samples for different neural network modules.

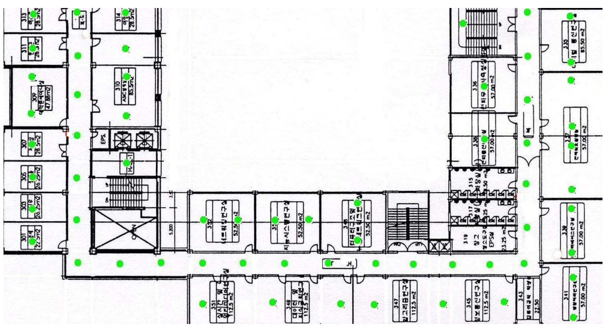

Fig 4: Location Map, Target Locations

Graph shown in Fig 5 is made of a subset of the radio map. Location IDs are listed on x-axis and RSS values on y-axis.

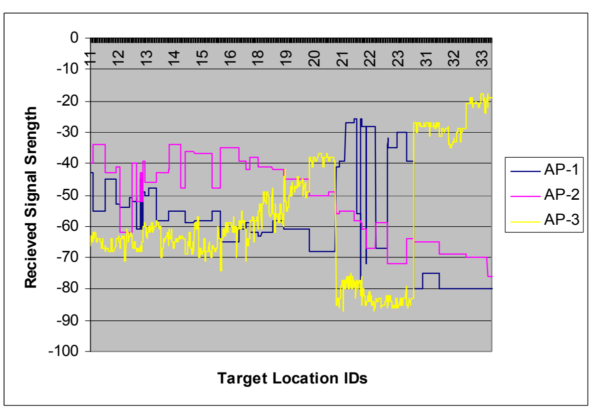

Fig 5: Points where all APs are accessible

Appendix A graph shows some locations where signal of only a subset of access points can be received. Purpose of presenting radio map here is to emphasize the incompleteness and dynamic nature of RSS data at different locations. Moreover, Device at two different locations can sometimes report same RSS readings, and can report very different readings while at the same location. This dilemma is main obstacle for getting absolute correct performance with the techniques mentioned in section 2.

B. Training Phase

Training phase is used to train different neural networks and analyze their comparative performance. Fig 6 shows system components that are involved in training phase.

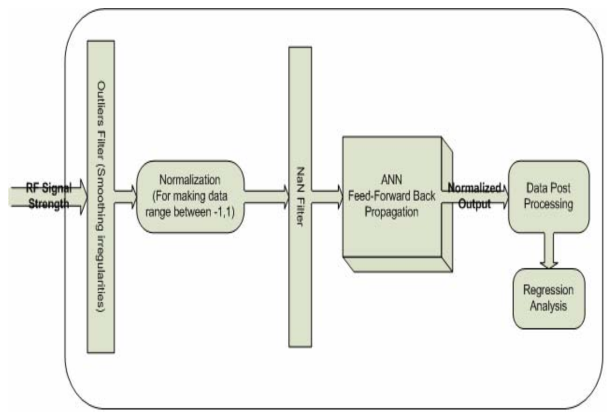

Fig 6: Neural Network Training System

Radio Map generated in Calibration phase is not used exactly. During calibration we observe certain RSS behaviors and apply statistical learning techniques to characterize signal strength properties at a particular location. Based on those characteristics, we implemented smoothing filters to remove outliers from RSS patterns. Fig 7 shows spikes (outliers) in received signal strength observations in real life. Such spikes have very little influence over learning and estimation of location because they appear for very shot time. In order to filter out such timely non-regular patterns from training data, we propose a histogram technique. This technique provides mapping that counts the number of observations that fall into various disjoint categories (bins), Let N denote the total number of observations and n be the total number of bins, the histogram is defined as:

$$N = \sum_{k=1}^{n} f_k$$

Where f_k is the frequency of occurrence of the RSS value in the k th bin. Let the variable r denote the RSS value. Then, r_{max} is defined as the largest RSS value such that all RSS values less than it have zero r_{min} is defined similarly. The size of the bins, b, is then defined as:

$$|b| = \frac{|r_{max}| - |r_{min}|}{\sigma}$$

Where σ is the standard deviation of RSS values at a given location. Next we define a threshold frequency f_{thres} such that all frequencies below this frequency are assigned zero values. We then have a new set of frequencies $\{f_i \mid f_i \geq f_{thres}\}$ of size $m \leq n$, with the corresponding bins denoted by b_i.

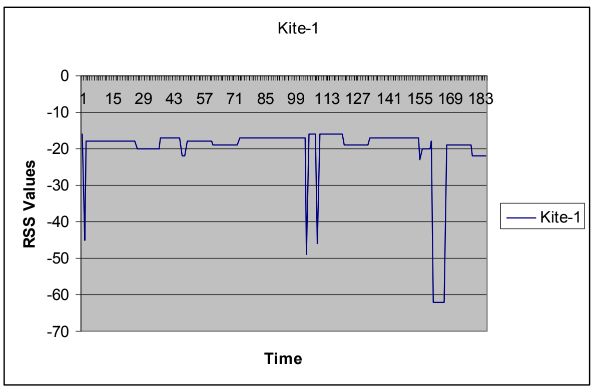

Fig 7: Spikes in RSS Graph

After this we perform normalization on this new set of bins and get the normalized bin values. Next component normalizes the data and targets by scaling. After normalization some RSS values become too small to be effective in neural network learning. Such values are filtered by NaN (Not a Number) filter component. Then training sets are presented to neural network for binding of the patterns of RSS with respective Location IDs by learning. After learning is complete, data post processing component converts results back into un-normalized vectors. Regression analysis component is implemented to analyze the results. All neural network modules take received signal strengths of visible access points as input and generate location id as output. We employed several configurations for finding the best location estimation accuracy. It is observed that choice of transfer functions; number of neurons at hidden layers and training algorithm affect the training error. Combination of log-sigmoid transfer function at hidden layer neurons and tan-sigmoid at output neuron were found to be producing comparatively good results. Summarization of different training configurations is given in table 3.

TABLE 3 Training Performance of different Configurations

Algori thm	Perfor mance	Goal	Epoc- hs	Struc ture	Transfer Func Hidden Layer	Output Layer
RP*	0.01338	0.01	10000	381	Tan	Lin
SCG†	0.01371	0.01	10000	381	Tan	Lin
CGB‡	0.01599	0.01	3000	381	Tan	Lin
LM§	0.01328	0.01	1000	381	Tan	Lin
LM	0.01080	0.01	5000	381	Log	Lin
LM	0.00999	0.01	398	3881	Log	Lin
LM	0.00866	0.001	5000	3881	Log	Lin
LM	0.00866	0.0001	3700	3881	Log	Tan

As shown in table 3, different configurations for feed-forward back-propagation neural networks were considered; e.g. training properties in terms of error goal, performance and required epochs, neural network structure, training algorithms and transfer functions are listed. All of the employed training algorithms use gradient of the performance function to adjust the weights. The gradient is determined using a technique called back-propagation, which involves performing computations backwards through the network. The back-propagation computation is derived using the chain rule of calculus and is described in Chapter 11 of [7]. Four training algorithms were chosen based upon literature review on supervised learning for pattern recognition with feed forward back propagation neural networks. In order to avoid over fitting problem of neural networks early stopping method was used. Mean Square Error (MSE) performance function was employed to measure the network errors. We performed our experiments using MATLAB neural network tool box [18]. As Table 3 suggests, Levenberg-Marquardt algorithm performed best in terms of faster pattern learning and goal achievement.

C. Estimation Phase

After training phase live data from the environment need to be tested with trained neural networks. In estimation phase RSS captured on mobile device is presented to the input layer of neural network. After the number of accessible AP is determined, different preprocessing components are implemented to filter, scale and normalize data. Fig 8 shows all the components involved in execution phase.

Outliers filter component is implemented to remove spikes from RSS data at run time. Normalization component is responsible to scale the inputs in a given range. Once normalized, RSS readings are presented to

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* Resilient Propagation

† Scaled Conjugate Gradient

‡ CGB: Conjugant Gradient Powell/Beale Restarts

§ LM: Levenberg-Marquardt

the appropriate Neural Network module. Out put of neural network is post processed (De-normalized) to get the Location ID estimate. In next section we shall present performance some results.

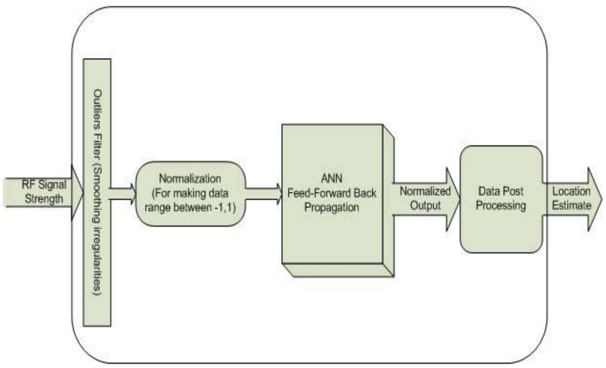

Fig 8: Execution of Location Estimation System

V. EXPERIMENTAL RESULTS

Results are presented as estimation error in terms of meters. We employ Manhattan distance between estimated and actual location to represent error.

TABLE 4: Execution Performance of different Network configurations

Structure	Transfer Func		Training Algo	Error (Meter)		
	Hidden Layer	Output Layer		Max Error	Avg Error	Median Error
381	Tansig	Linear	CGF	1.9884	0.3501	0.143
381	Tansig	Linear	RP	1.8392	0.2863	0.1114
381	Tansig	Linear	SCG	1.5867	0.2740	0.0713
381	Tansig	Linear	LM	1.6263	0.2833	0.1001
381	Logsig	Linear	LM	1.8311	0.1724	0.008
3881	Logsig	Linear	LM	2.1667	0.1258	0
3881	Logsig	Tan	LM	2.1667	0.1258	0

Table 4 summarizes all the network configurations that we tested for one module (with no missing inputs). 3881 architecture with Levenberg-Marquardt Algorithm training algorithm produced best average performance with 0.1258 meter error in estimation. But this network produced the maximum error of 2.1667 meters at the same time.

In order to analyze the performance of location estimation system, it is needed to employ a comprehensive model that can balance the performance measure among all aspects of accuracy. We applied a comprehensive model for evaluation of location estimation techniques. It covers the all performance aspects. This evaluation model provides both qualitative and quantitative insight into performance of location estimation system.

Fig 9, 10, 11 and 12 show the error in estimation at every target location of the site. On x-axis of each graph, test patterns are listed and on y-axis location ID and estimation is plotted as a line graph. This shows location specific performance of different networks. It is obvious from these graphs that location estimation error is divided in two aspects i) over all error in the area ii) location specific error. Although Module B produces highest error at one location still it provides best accuracy in overall aspect. This fact is obvious when a closer observation is made on to the location specific results of each candidate neural network.

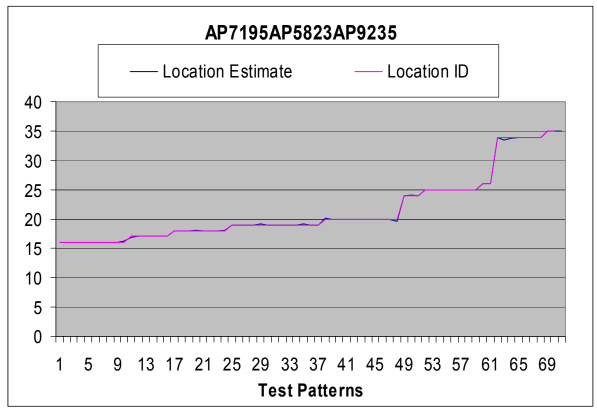

Fig 9: Estimation Accuracy graph of Module A

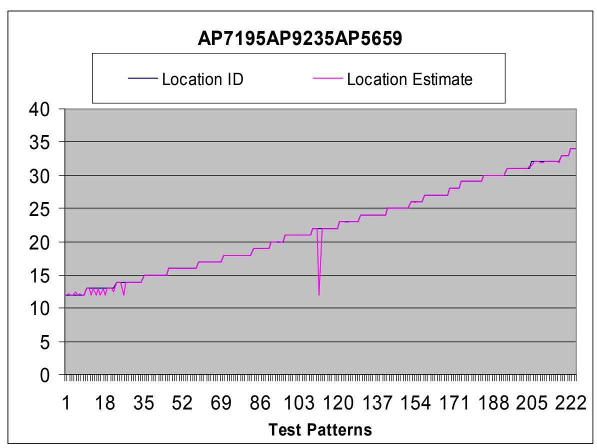

Fig 10: Estimation Accuracy graph of Module B

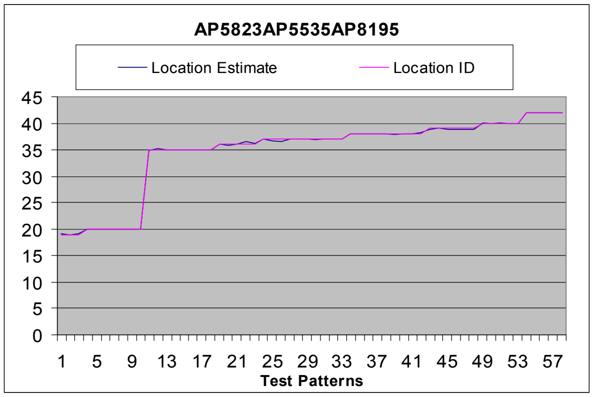

Fig 11: Estimation Accuracy graph of Module C

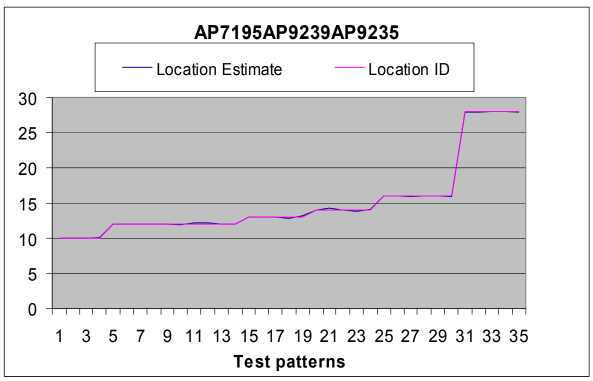

Fig 12: Estimation Accuracy graph of Module D.

VI. CONCLUSION AND FUTURE DIRECTIONS

Employing IEEE 802.11(a, b, g) Wireless LAN as infrastructure for indoor Location Awareness is prudent choice due to its low cost and pervasive coverage. Since all Wireless Network Interface Cards have to report Received Signal Strength as dBm, it is very practical to implement localization capability based on RSS values at a particular location. We employed a novel Modular Multilayer Perceptron architecture for Wireless LAN RSS based location estimation. This architecture provides robust mechanism for coping with unavailable information in real life situations. Experimental prototype was implemented for Engineering Building 3rd floor. We evaluate our location estimation system performance with both overall and location specific measures. Results show superior performance to previous approaches. Moreover our system does not require runtime searching of nearest neighbors in huge backend radio map database, as is the approach in previous work. This results in significant performance improvement and saves resources. In order to make this system available on demand for mobile end users, it is required to implement it as a software component. In future we plan to provide this system as a middleware service as explained in [12] [13].

ACKNOWLEDGEMENT

This research was supported by the Driving Force Project for the Next Generation of Gyeonggi Provincial Government in Republic of Korea.

REFERENCES

[1] P. Bahl, *et al.* "A software system for locating mobile users: Design, evaluation, and lessons", Microsoft Research, MSR-TR-2000-12, April 2000.

[2] P. Bahl, *et al.* "RADAR: An in-building RF-based user location and tracking system." In *IEEE INFOCOM 2000*, pages 775–784, March 2000

[3] Cynthia *et al,* "Challenges in Location-Aware Computing" Published by IEEE ComSoc 1536-1268/03/ 2003 IEEE

[4] Andrew *et al,* "Using Wireless Ethernet for Localization", 2002 IEEE/RSJ International Conference on Intelligent Robots and Systems

[5] Mike Hazas *et al,* "Location-Aware Computing Comes of Age," *Computer*, vol. 37, no. 2, pp. 95-97, February, 2004.

[6] Roberto Battiti *et al*, "Statistical Learning Theory For Location Fingerprinting In Wireless Lans", October 2002 Technical Report # DIT-02-0086 University of Trento Italy

[7] R. Want and B. Schilit, "Expanding the horizons of location-aware computing", *IEEE Computer*, 34(8):31–34, August 2001.

[8] Dieter *et al,"* Bayesian Filters for Location Estimation", *IEEE CS and IEEE ComSoc* 1536-1268/03

[9] K. Pehlavan *et al,* "Indoor Geolocation Science and Technology", IEEE Communications Magazine, 2002

[10] Guvenc *et al*, "Enhancements to RSS Based Indoor Tracking Systems Using Kalman Filters," GSPx & International Signal Processing Conference, Dallas, TX, March 31-April 3, 2003.

[11] R. Battiti *et al*, "Neural Network Model for intelligent networks: deriving the Location from signal patterns, The First Annual Symposium on Autonomous Intelligent Networks and Systems 2002

[12] Uzma Nasir *et al*, "On Building a Reflective Middleware Service for Location-Awareness", The 11 IEEE International Conference on Embedded and Real-Time Computing Systems and Application (RTCSA), Hong Kong, 17-19 August, 2005

[13]Mahrin Iqbal *et al*, "Reflective Middleware for Location-Aware Application Adaptation. ICCSA (2) 2005: 1045-1054

[14] Saad *et al,* "A Distributed Middleware Solution for Context Awareness in Ubiquitous Systems", 11th IEEE International Conference on Embedded and Real-Time Computing Systems and Applications (RTCSA'05) pp. 451-454

[15] Steve Pope, "Issues Related to RSSI Measurement", IEEE 802.11-02/520r0

[16] "IEEE 802.11 Network Adapter Design Guidelines for Windows XP", Microsoft, May 22, 2003 http://www.microsoft.com/whdc/ device/

[17] Roy *et al,* "The active badge location system**",** ACM Transactions on Information Systems (TOIS) Volume 10 , Issue 1 pp: 91 - 102

[18] Smailagic, *et al*, "Location Sensing and Privacy in a Context Aware Computing Environment", Pervasive Computing, 2001.

[19] Uzair *et al,* "In Building Localization using Neural Networks*",* IEEE International Conference on Engineering of Intelligent Systems, 22 April 2006.