In-building Localization using Neural Networks

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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 indoor 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. Multi-path 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, Location Aware Computing, Wireless LAN

1 INTRODUCTION

Location information is an integral and crucial component of ubiquitous computing applications [1] [2] [3] [4] [5] [12]. In building localization has been subject to costly infrastructure and special hardware devices mounted on the objects of interest [24]. 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* [21]. 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". 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.

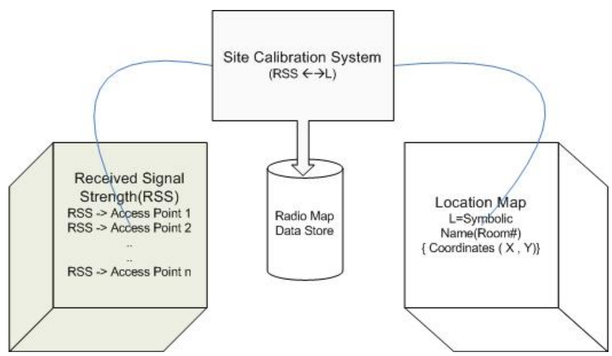

Fig 1: Site calibration: basic concept

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, b, g) standard complying WLAN operates in two publicly available radio frequency spectrums, 5 and 2.4 Mhz. In-building radio wave propagation follows a complex model due to Non Line of Sight (NLOS) multi-path effects due to 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

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mathematical methods. Neural networks provide massive parallelism, fault tolerance and adaptation to changing circumstances. In this paper we present our experiments to develop artificial neural networks based location estimation system. Next section provides an overview of the previous work. In section 3, our Modular Multi Layer Perceptron approach is presented. Section 4 describes Design and Implementation details of the system. Results of experiments are presented in section 5.

2 RELATED WORK

There have been several efforts to develop Location Aware system based on RSS. Bayesian classification and filtering [4], *K*-Nearest Neighbors [2] [14] [15], GPS like triangulation [25] and Kalman Filtering [15] 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. Table 1 summarizes the results of previous researches. We considered four aspects of work that should be of interest to the readers.

Table 1: Results of previous researches

Technique		AC†	AP‡	SMP§	Err**
Neural Net (Trento) [16]		624	3	200	1.91
Triangulation (CMU) [25]		60	3	17	1.524~
Bayesian Net (Rice) [4]		30	9	100	1.5
Kernels (HKU) [18]		100	3	100	3
KNN	RADAR [2]	980	3	40	2.65
	Oulu [14]	65	4		2.4
KNN + Kalman Filter	UNM [15]		5	20	3.2

Nearest Neighbors based pattern recognition technique and its derivates have been used traditionally by many researchers. This method requires 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. Probabilistic approaches like Bayesian networks based solutions achieve better performance but they are computationally exhaustive and difficult to scale. 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* [16] have employed neural networks for this problem. 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.

† Area Covered in Square Meters
‡ Number of Access Points used
§ Number of Samples used per location
** Accuracy measure in Average Euclidean distance error

3 OUR APPROACH

Since all target locations are available, in addition to RSS values at each location during calibration, supervised learning is used to recognize signal patterns. The problem of constantly fluctuating RSS and even absence of wireless signal introduces very unreliable location estimations. Estimation reliability is directly affected by how good sample wireless signal data at target locations represent the real life situations. Therefore, we managed to collect a large number of RSS samples at each target location, contrary to the previous approaches, after a detailed site calibration. Particulars of site and its radio map are given in section 4.1. 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. We propose a modular approach to cope with this uncertainty effectively. Details of our architecture are given in next section.

3.1 Modular Multi Layer Perceptron (MMLP)

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 visibility matrix and current 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

AP-1	AP-2	AP-3	Module
1	1	1	123
1	1	0	12
0	1	1	23

Three 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 2. Our experiments were conducted with many different variants of MMLP architecture. Fig 2 is a particular instance of MMLP concept only to convey the basic idea.

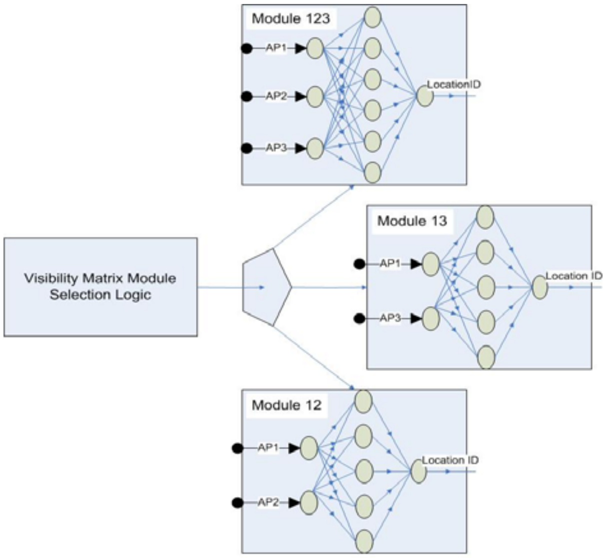

Fig 2: Modular Multi Layer Perceptron (MMLP) Architecture

4 Design And Implementation

We conducted experiments in 3rd floor of Engineering Building. Fig 3 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.

4.1 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 3. Our system is implemented to cover 300 Square Meters 'U' shaped Area (see Fig 3). 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. A laptop 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 [22]. The RSSI is measured in dBm and normal values for the RSSI value are between

-10 and -100 [23]. 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 3: Location Map, Target Locations and location of Wireless Access Points

Graph shown in Fig 4 is made of a subset of the radio map. Location IDs are listed on x-axis and RSS values on y-axis in Fig 4, 5. Signals from all three Access Point can be received on these points.

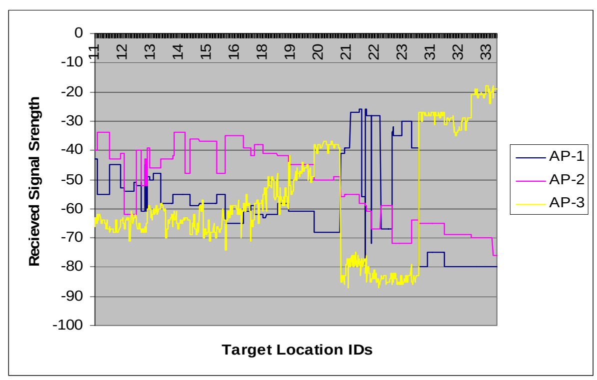

Fig 4: Points where all APs are accessible

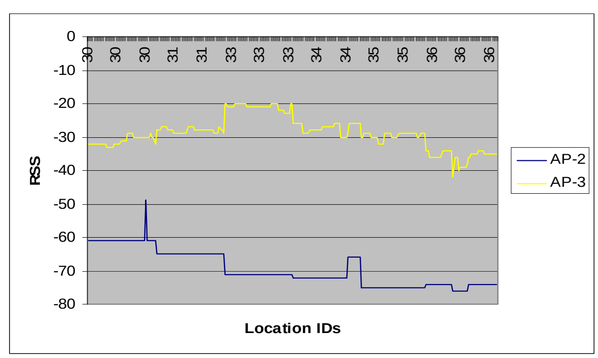

Fig 5: Points where only AP-2 and AP-3 are accessible.

Fig 5 graph shows some locations where signal of only two 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. 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.

4.2 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.

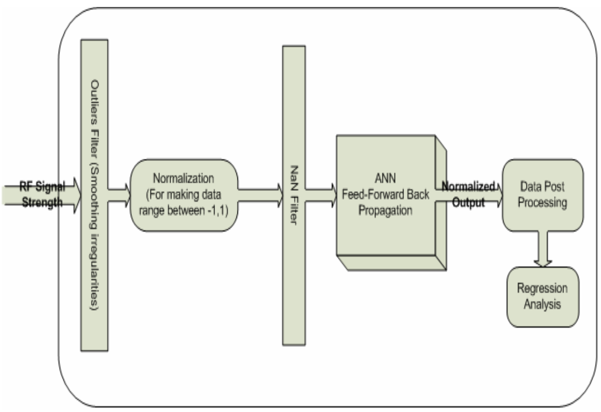

Fig 6: Neural Network Training System

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. Outliers are timely spikes 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. After filtering outliers we perform normalization on this new set of bins and get the normalized bin values. Next component normalize 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 convert results back into un-normalized vectors. Regression analysis component is implemented to analyze the results. We employed several configurations for finding the best location estimation accuracy. Our experiments cover different configurations of feed forward back propagation networks. Different learning algorithms have been employed to train the networks in best possible way. All of these algorithms use the gradient of the performance function to determine how to adjust the weights to minimize performance. 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 [7]. Four training algorithms were chosen based upon literature review on supervised learning for pattern recognition with feed forward back propagation neural networks. Resilient back-propagation uses only the sign of the derivative to determine the direction of the weight update; the magnitude of the derivative has no effect on the weight update. The purpose of the resilient back-propagation training algorithm is to eliminate harmful effects of the magnitudes of the partial derivatives. A complete description of the resilient back-propagation algorithm is given in [6]. In the conjugate gradient algorithms a search is performed along conjugate directions, which produces generally faster convergence than steepest descent directions. Discussion on conjugate gradient algorithms and their application to neural networks is given in [7]. The scaled conjugate gradient algorithm (SCG), developed by [11] was designed to avoid the time-consuming line search. For all conjugate gradient algorithms, the search direction will be periodically reset to the negative of the gradient. The standard reset point occurs when the number of iterations is equal to the number of network parameters (weights and biases), but there are other reset methods that can improve the efficiency of training. One such reset method was proposed by Powell [17], based on an earlier version proposed by Beale [10]. Levenberg-Marquardt (LM) algorithm appears to be the fastest method for training moderate-sized feed-forward neural networks (up to several hundred weights) [9]. The application of Levenberg-Marquardt to neural network training is described in [7]. 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. As Table 2 suggests, Levenberg-Marquardt algorithm performed best in terms of faster pattern learning and goal achievement. After adding one more hidden layer to network structure, the performance goal 0.001 was achieved met with this algorithm.

4.3 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 7 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 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.

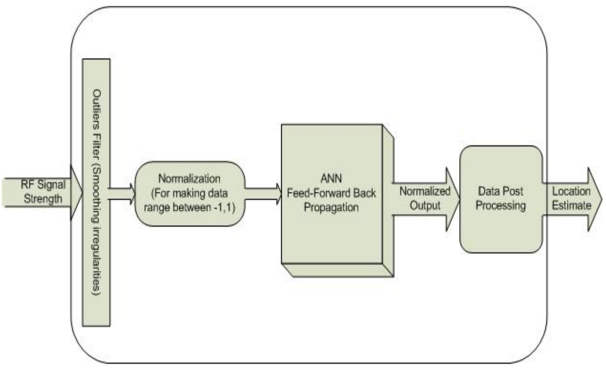

Fig 7: Execution of Location Estimation System

5 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 3

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 3 summarizes all the network configurations that we tested for one module (with complete 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 8 shows the error in estimation at every target location of the site. On x-axis of each graph, location ids are listed and on y-axis estimation error is plotted as a line graph. This shows location specific performance of different networks.

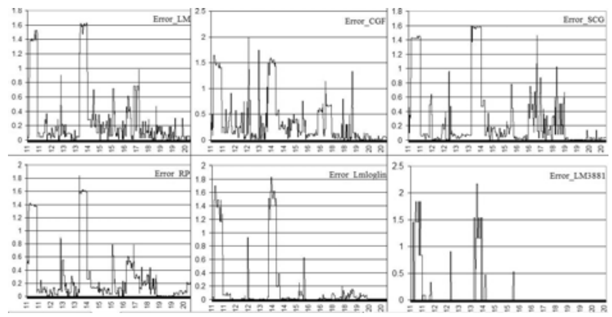

Fig 8: Estimation Error of different Neural Networks.

It is obvious from these graphs that location estimation error can be divided in two aspects i) over all error in the area ii) location specific error. Although 3881 structure produce highest error at two locations still it provides best accuracy overall aspect. This fact is obvious when a closer observation is made on to the location specific results of each candidate neural network. Fig 10 shows the estimation accuracy of 3881 neural network. Target Location IDs are listed on y-axis. 1800 Test samples are listed on x-axis. Fig 9 shows distance error of our system with 1800 test RSS patterns. Over all distance error is less than 1.18 meter.

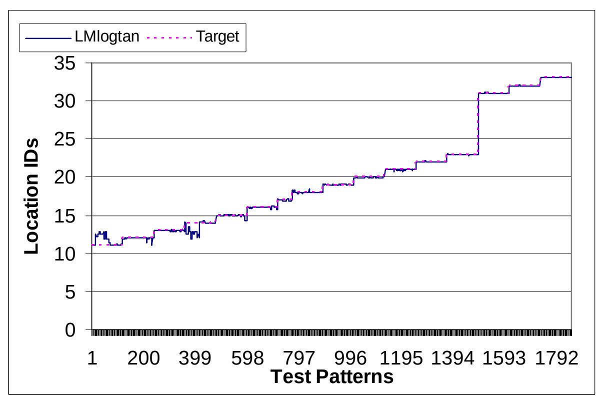

Fig 9: Estimation Accuracy graph of '3881' neural network.

6 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 part of standard compliance, localization capability can be made available to all WiFi enabled devices. 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 three corridors of 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 future this system shall be extended to cover larger area including rooms and laboratories. 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 [19] [20]. This location service is part of Context Aware Middleware for Ubiquitous Computing (CAMUS) project.

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