Self-scalable Fuzzy ArtMap for Received Signal Strength Based Location Systems

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Abstract. Indoor Location Systems have several demanding applications but requirement of costly infrastructure prohibits large scale deployment of this technology. Received Signal Strength (RSS) based location systems can provide high resolution, up to 3 meters, while keeping the solution economically viable. Although extensive research has been carried out in this area still tedious sensor data collection, so called site calibration, lengthens location system development life cycle. We present a new approach based on Fuzzy ArtMap neural network that significantly reduces development time. Besides shortening development time of location systems, our technique allows dynamic expansion of location aware site which is not possible in previous systems. Moreover, location estimation results show competitive performance in comparison with other methods.

Keywords: Indoor Location Systems, Received Signal Strength, Pattern Recognition, Online Learning, Location Aware Computing

1 Introduction

Indoor location systems are on the verge of becoming common services in modern mobile and ubiquitous computing environments [10],[11],[14]. Satellite signal based Global Positioning System (GPS) technology provides globally pervasive location awareness but suffers from degraded accuracy in indoor environments. Indoor location systems have been subject to costly infrastructure and require special hardware sensing devices mounted on the objects of interest e.g. Active Badge [15],Cricket [18],Active Bat [17] and Ubisense [16]. Received Signal Strength based positioning technology offers viable solution to ever increasing users of hand held devices, e.g. PDAs and note books connected through pervasive deployments of Wireless LAN infrastructure. Since signal strength measurements must be reported by the wireless network interface card ,built into these devices, as part of standard compliance; positioning using received signal strength (RSS) is both feasible and economical. [9],[12], [13],[19],[21], [24]. RSS based location systems can enable a wide range of applications such as automatic call forwarding to user's location; robotic global localization, exploration and navigation tasks; Finder, Guiding and Escorting systems; first hop communication partners; liaison appli-

cations; location based advertisement and positioning of entities in large warehouses.
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”. Process of capturing signal strength patterns at particular locations is called ’site calibration’, as shown in Fig. 1.

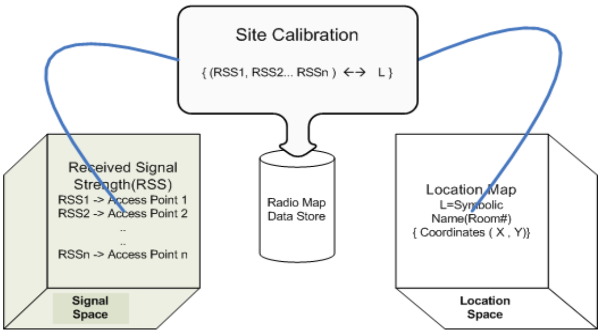

Figure 1: Site Calibration Phase

Later, when some devices report similar patterns the location of target object can be estimated using pattern recognition techniques. RSS based location estimation is, intrinsically, a pattern recognition problem in the sense that location of target machine, such as PDA, is estimated based on RSS feature vectors received on it.

2 Related Work

Received Signal Strength based location estimation has acquired a lot of interest from research community. Nearest Neighbors based pattern recognition technique and its derivates have been used by pioneering works on RSS based location estimation [9] and [12]. Nearest Neighbor and its variants require a reference database of sample RSS, so called Radio map, readings at the estimation time for pattern matching. Size of Radio Map dramatically increases, producing scalability issues, as the area and number of target locations grow.

Some researches have also employed GPS like triangulation method for location estimation. Asim et al [20] achieved 4.5 meter location estimation error in area of 60 square meters target. Triangulation methods work on assumption that signal strength decays only as function of distance of receiver device from sender access points. Radio Signal strength decay is function of several factors of indoor environments that affect the validity of this assumption. This fact severely limits the accuracy of such methods for indoor location estimation.

Probabilistic approaches, such as bayesian networks, have also been employed. Andrew et al [13] reported 1.5 square meter distance error but only for 30 square meter area test bed. As the number of target locations and wireless access points increase, the complexity of Bayesian structures grows and become computationally expensive creating scalability issues.

Neural network have been widely employed in pattern recognition problems due to their remarkable ability to tolerate noise and to generalize to patterns unseen at training time. Ogawa et al employed Learning Vector Quantization networks to develop location estimation system for 350 square meter area using 5 access points[19]. Battiti et al have reported their research on using feed forward back propagation network on small scale (624 square meter area using 3 access points) location estimation system [21]. A ’Modular Multi Layer Perceptron’ approach is presented in [24] that improves accuracy and scalability of RSS based location estimation. Support Vector Machines (SVM) have been employed by Xuanlong et al for localization in densely distributed sensor networks [23]. Battiti et al [22] reported RSS location system based on SVM in a relatively small area (750 meters) with 5 access points.

3 Rapid Location System Development Approach

In this paper we present a novel location system based on self-scalable Fuzzy ArtMap neural network. Fuzzy ArtMap is generalized ArtMap (also called Predictive Art)[4] network which can handle analog input patterns and performs online and incremental learning of pattern-class pairs presented in arbitrary order. Our location system offers several desirable features which cannot be realized using previous methods. Until now, rapid development of RSS based location systems is major issue that keeps this technology from becoming widely deployed.

Fig. 2 shows general schematic of development life cycle of previous approaches. It comprises two stages (in bottom up sequence) in which different development phases produce subsystems, in step-wise fashion, in order to realize location system and location based services. At *Positioning System Development Stage*, ’Calibration Phase’ and ’Training Phase’ take place in lab time or *off line*. A trained classifier is then employed for actual location estimation in real time or *online*. At *Location Service Stage*, location based services and end user applications are hosted using distributed component models such as [25]. Unlike previous approaches, our approach does not require *off line* (or lab time) training phase. Online learning of RSS patterns

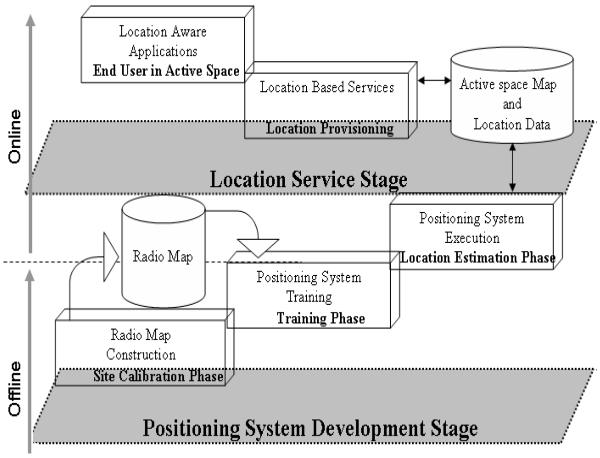

Figure 2: Development Life Cycle in Previous Approaches

and corresponding locations shortens development time by removing 'Calibration Phase' and *off line* 'Training Phase' from development life cycle. Fig. 3 shows how rapid location system development is realized in our approach.

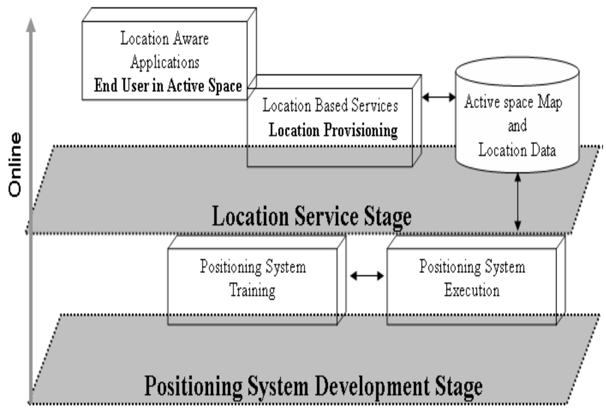

Figure 3: Rapid Development Approach

Flexible and Dynamic expansion of location system is easy and straight forward in our approach. Expanding location system flexibly and dynamically requires incremental learning of new location thus increasing area by including more target locations. Previously, in order to achieve this objective, Radio Map feature space is required to be extended to include new training RSS pattern-location mappings and then classifier needs to be retrained with extended radio map. In case of retraining with new feature space, most *off line* training based classifiers face *stability plasticity dilemma*. That means learning new pattern-class mappings causes erosion of previous knowledge acquired by classifier during early training. Other techniques overcome this problem by retraining classifier with whole Radio Map (that includes both old and new training data). Fuzzy ArtMap is capable of incremental learning and ensures stable learning of categories while exposed to new set of pattern-class pairs [4]. This capability allows flexible learning of new locations without requiring retraining with whole new feature space.

Original Fuzzy ArtMap specification requires that capacity of network, in terms of number of categories (locations in our case) that network can learn, need to be fixed prior to learning. Prior fixation, of number of categories that network can learn, means that once RSS patterns of a *fixed* number of locations, with respect to the capacity of network, are learned by network then more locations can not be incorporated or learned by that network. This limits the application of original Fuzzy ArtMap in terms of dynamically expanding the location system. We extend original Fuzzy ArtMap system such that it does not require prior fixation of capacity of network thus allowing network to self-scale itself as new categories are presented to it. This solution is explained in more detail in next section.

Lastly, learning Rare Events is very common issue that RSS based location classifiers face. Very nature of radio wave propagation in indoor environments causes imbalanced classes. Which means that there may be some locations where size of RSS training patterns is far less than other locations. Fuzzy ArtMap is capable of learning even single exposure to rare events and does not show the catastrophic forgetting of rare events, as is the case with other classification methods.

4 Fuzzy Art and Fuzzy ArtMap

Fuzzy ArtMap is Adaptive Resonance Theory based self organizing neural network for real time autonomous learning environments. It is composed of a pair of Fuzzy ART neural networks (so called Fuzzy ART_a and Fuzzy ART_b) therefore we briefly, and sequentially, explain Fuzzy Art system first and then Fuzzy ArtMap system in this section.

Fuzzy Art incorporates combination of Fuzzy Set theory and Adaptive Resonance Theory (ART) [4] to accomplish unsupervised, incremental and online learning of analog valued input vectors presented to system in arbitrary order. Fig. 4 shows topological structure of Fuzzy Art neural network. It consists of two processing layers F_1 and F_2. Each neuron of F_1 layer is linked, through bottom up synaptic connections, to all neurons of F_2 layer and vice versa. Adaptive weights of bottom up and top down synaptic connection bear same value in Fuzzy Art systems. F_1 layer neurons evaluate a 'choice function' and F_2 layer neurons represent learned categories in input space. Choice function produces ranking list based on component wise fuzzy distance between input pattern and bottom up connection weights and a choice parameter alpha. Output of choice function is adaptively fed into 'Winner Takes All' (WTA) filter and winner neuron is, tentatively, selected as category of this input pattern. Vigilance subsystem confirms, or dismisses, this decision based on externally adjustable resonance parameter ρ .

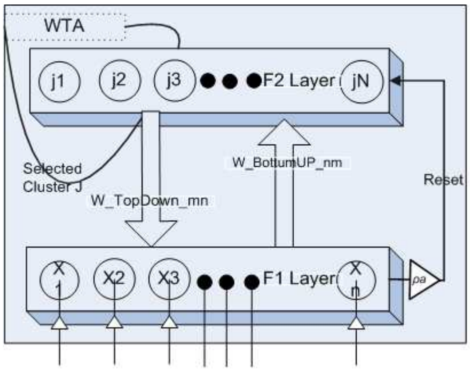

Figure 4: Fuzzy Art Network Topology

A comprehensive treatment of Fuzzy Art characteristics is given in [3]. Fig. 5 flow chart presents our implementation of original Fuzzy Art unsupervised learning algorithm for fast and stable categorization of analog input patterns. In original Fuzzy Art, learning capacity of network need to be determined before learning. Before learning starts all F_2 layer neurons are said to be 'uncommitted'. During learning as soon as a new category, which was not encountered until that point, is sensed by system an 'uncommitted' F_2 layer neuron becomes 'committed' in order to represent this category. This process goes on until learning capacity, total number of 'uncommitted' neurons, is reached. We extend Fuzzy Art learning and classification algorithm such that it can be dynamically scaled to additional input spaces while its learning capacity is reached. This capability is very crucial for dynamic extension of Location Systems as described in previous section.

Main differences in original Fuzzy Art and Self-scalable Fuzzy Art can be seen in network initialization method and dynamic incorporation of new F_2 layer neurons into system. Self-scalable Fuzzy Art algorithm initializes a network without any F_2 layer neurons and include new F_2 neurons when new categories are

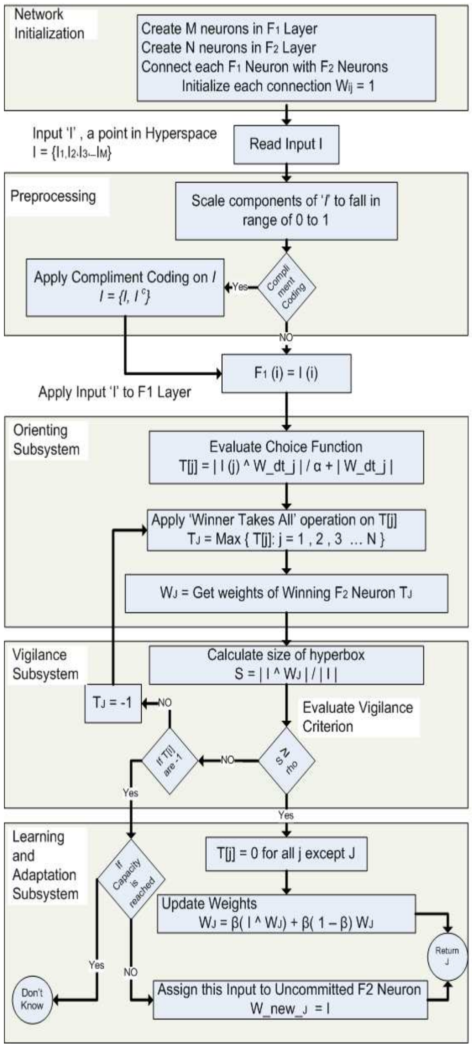

Figure 5: Flowchart of FuzzyART Online Clustering Algorithm

formed by network. This way Self-scalable Fuzzy Art do not divide F_2 neurons into 'uncommitted' and 'committed' neurons instead if capacity is reached a neuron is incorporated dynamically otherwise a 'don't know' response is given as output.

One of the distinguishing properties of Fuzzy Art neural network system is that it can output a 'don't know' response, which means that network do not assign an input pattern to any categories if pattern is very dissimilar to all categories. This capability is realized by means of learning capacity concept. When all F_2 layer neurons become committed and an input is encountered which does not qualify to be a member of any category then network outputs a 'don't know' response. Self-scalable Fuzzy Art preserves this property of original Fuzzy Art by allowing *capacity* parameter to

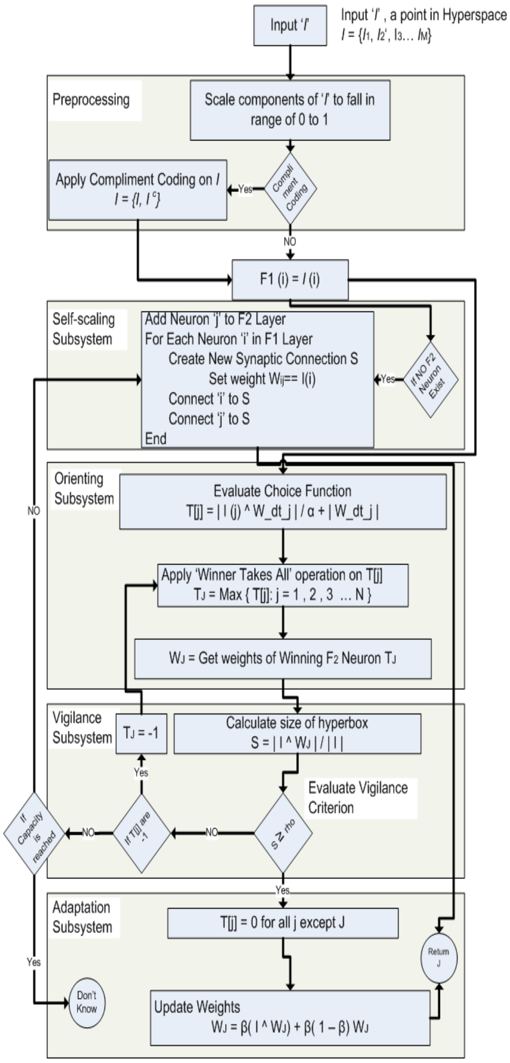

Figure 6: Flowchart of Self Scalable FuzzyART Online Clustering Algorithm

be externally adjustable. *capacity* is increment only parameter that can be adjusted as a network is required to learn more categories than its previous capacity. Fig. 6 shows Self-scalable Fuzzy Art learning algorithm.

Now we briefly describe learning dynamics of Fuzzy ArtMap. Topological structure of Fuzzy ArtMap neural network is presented in Fig. 7. Fuzzy ART modules ART_a and ART_b self-organize category grouping for separate input sets v (feature RSS vector reported by mobile device) and e (encoded location information). Map Field is inter-ART module that controls the learning of an associative map from ART_a recognition categories to ART_b recognition categories. This is achieved by connecting F_2 Layer, so called ${\text{F}_2}^b$, neurons of ART_b to Map Field nodes with one-to-one non-adaptive links in both ways. On the other hand each F_2 layer, re-

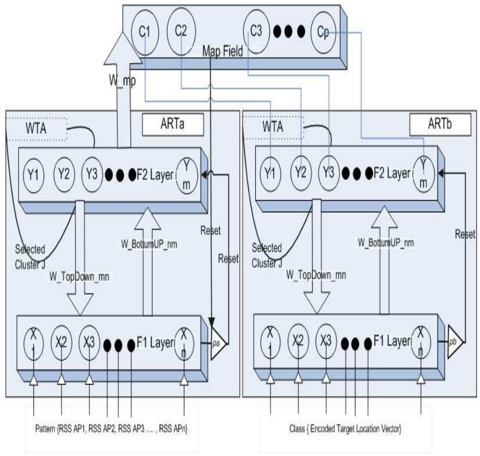

Figure 7: Fuzzy ArtMap Network Topology

ferred to as ${\text{F}_2}^a$, neuron of ART_a is connected to all Map Field nodes via adaptive links. Since Map Field represents a mapping from both ${\text{F}_2}^a$ and ${\text{F}_2}^b$, it is denoted as F^{ab}. This map does not directly associate feature vectors with encoded class labels but rather associate the compressed codes of groups of v and e. During learning pattern-class pairs, if a mismatch occurs at Map Field between ART_a category and ART_b category then system increases vigilance parameter of ART_a so that ART_a can categorize this pattern in different category or can create new category for this pattern that matches ART_b class category. This mechanism allows network to capture novel features that can be incorporated through learning new ART_a recognition category. Activation of Map Field results in output signal from each F^{ab} node, a vector corresponding to target location, that eventually becomes out put of Fuzzy ArtMap network. Learning RSS-location pair occurs if Fuzzy ArtMap network is presented with both RSS input vector and target location vector. In Location estimation occurs in case only RSS input vector is presented to network. Activation of F^{ab} occurs both in case of learning mode and estimation modes. Match tracking and orienting subsystem allows Fuzzy ArtMap network to establish different categories for similar RSS inputs at ART_a as well as allows very different RSS inputs to form categories that belong to same location. This is achieved by activating orienting subsystem only when ART_a makes a location estimate that does not confirm with actual location provided to ART_b. This condition starts match tracking by adjusting ART_a vigilance parameter in such a way that estimation error is removed.

We adapt a simplified version of Fuzzy ArtMap, presented in [8], which employs only one Fuzzy Art network instead of two and optimized for hardware implementation of Fuzzy ArtMap network. Simplified Fuzzy

ArtMap exhibits same learning and recall performance as original Fuzzy ArtMap and its learning algorithm is shown in Fig. 8.

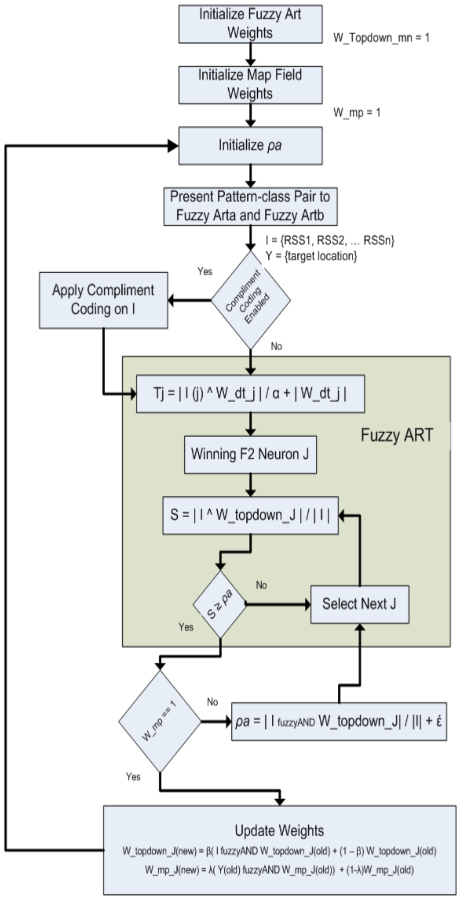

Figure 8: Flowchart of Simplified FuzzyArtMap Online Learning Algorithm

Simplified Fuzzy ArtMap incorporates original Fuzzy Art network (to establish categories in input space) and a Map Field (to associate categories to target classes). We replace original Fuzzy Art with Self-scalable Fuzzy Art in order to enable Fuzzy ArtMap network to learn new RSS patterns as they appear as well as to learn new location incrementally and dynamically. Learning dynamics of Self-scalable Fuzzy ArtMap are shown in Fig. 9. Our implementation of self-scalable Fuzzy Art and Fuzzy ArtMap networks is available in as open source [25].

5 Model Training and Experimental Design

We conducted extensive experiments in 1240 square meter area of Computer Engineering Department build-

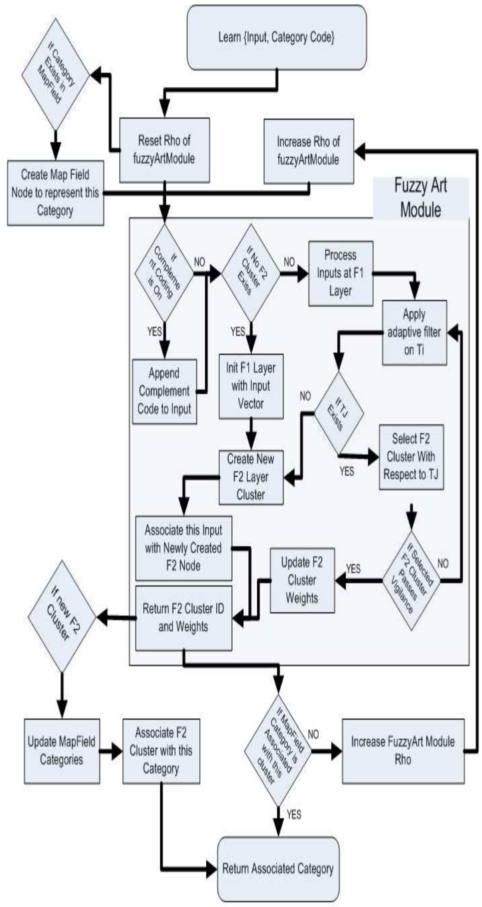

Figure 9: Self-Scalable FuzzyArtMap Learning Algorithm: Flow Chart

ing. Map of target site is shown in Fig. 10 and target locations are indicated as filled circles. Target locations are represented as a unique identification number at application level while, during training, presented to classifiers in a binary encoded form. We used pocket pc (HP iPaq 1450 model with built in WLAN card) devices to capture signal strength vectors.

Fuzzy ArtMap neural network was trained online as RSS patterns were being collected and same data set was used to train other models. We tested location estimation performance with RSS vectors which were collected on different days and time from training data. Inputs are presented as predefined ordered sequence of received signal strengths of a set of access points deployed in target area. Fuzzy ArtMap network suffers from category proliferation problem as characterized by Moore [1]. In order to overcome this problem a normalization technique, namely Complement Coding, is proposed by Carpenter et al in [3]. This normalization technique allows network to reduce effect of presentation frequency of an input pattern as well as order

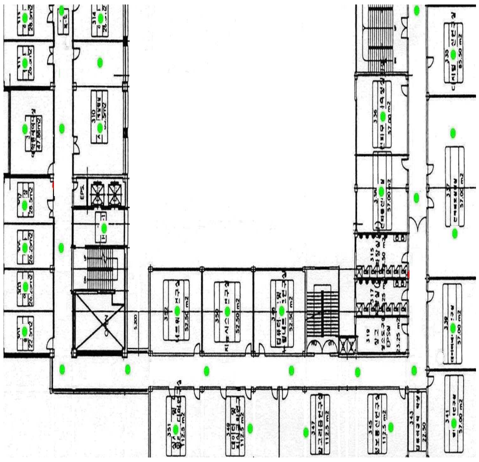

Figure 10: Map of Target Site

of presenting input patterns to Fuzzy ArtMap, as explained in [4]. We developed Fuzzy ArtMap models with and without complement coding in order to evaluate its efficacy in location estimation problem. Complement coding requires input pattern values to fall in range of 0 to 1 but actual RSS values range between -10 dBm to -100 dBm. We apply scaling normalization on raw RSS input vector such that all values are transformed in range of 0 to 1.

We measure location estimation error in two aspects. i) Absolute deviation of location estimate from actual location. Absolute deviation is measured as Mean Absolute Error (MAE), ratio of *unclassified* RSS vectors and ratio of *miss-classified* RSS vectors over all test vectors. ii) Deviation of location estimate, denoted as 'e', relative to some *thresh-hold*. Relative error is measured as percentage of deviation, relative to a *thresh-hold* value, among total number of test patterns. Table 1 presents training results of Fuzzy ArtMap network with and without complement coding. Fuzzy ArtMap model trained with complement coding is denoted as FAM-CC and FAM represents model trained without compliment coding.

Table 1: Fuzzy ArtMap Results on Training Radio Map

	FAM-CC	FAM
Clusters	36	167
MAE	.066	.018
Unclassified	0	11
Miss classified	.02	.006
$e \leq 1$	.02	.006
$e \leq 2$	.02	.006
$e \leq 3$	0	0

Training results show that complement coding controls category proliferation problem and classifies all RSS vectors successfully but classification performance is slightly affected. Training Fuzzy ArtMap without complement coding, un-normalized input vectors, results in higher accuracy but increases indecisiveness, in terms of unclassified RSS patterns, as well. This problem aggravates during testing phase as results suggest in next section.

In order to compare location estimation performance of Fuzzy ArtMap with *off line* training based classification methods we developed three other classification methods as suggested in previous work. Since these methods require a complete feature space, in this problem Radio Map , to be in place before training starts. Therefore, we collected two sets, for training and testing, of RSS patterns at each target location over a period of five days.

i) Multi Layer Perceptron (MLP) [21]
ii) Learning Vector Quantization (LVQ) [19]
iii) Support Vector Machines (SVM) [22].

We conducted several experiments, with different training parameters, for each of these methods in order to discover best location estimation performance on both training and test Radio Map. Here we describe only the best performing parameters for each method. Multi Layer Perceptron network was trained using Levenberg Marquardt algorithm [5] with one hidden layer of 70 neurons and one output layer of 35 neurons. It took 2000 epochs to achieve 0.021 Mean Absolute Error. Learning Vector Quantization network was trained with 'lvq1' algorithm presented in [6]. LVQ network structure contained 100 neurons at competitive layer and 35 neurons at linear transformation layer. This network achieved 0.018 Mean Absolute Error in 50 epochs. Support Vector Machines, presented in [7], were trained with different kernel functions. Polynomial kernel of degree 2 and Radial Basis Function (RBF) produced 0 Mean Absolute Error. Table 2 presents comparative results of different classifiers during training. Both polynomial kernel and RBF kernel are denoted as (P) and (R) respectively in results.

Table 2: Comparative Results on Training Radio Map

Method	Unclsfd	MAE	$e \leq 1$	$e \leq 2$	$e \leq 3$
FAM-CC	0	0.06	74	82	91
FAM	11	0.02	99.55	99.55	100
SVM (P)	0	0	100	100	100
SVM (R)	0	0	100	100	100
MLP	0	0.021	75	79	91
LVQ	0	0.018	56	69	80

6 Location Estimation Performance Comparison

In order to compare location estimation performance of Fuzzy ArtMap with other methods we conducted rigorous test experiments. Unlike previous approaches, test data were collected on different days and time of the day than training data were collected. Table 3 presents comparative testing results of different classifiers which were trained for location estimation using same Radio Map. Unlike training phase, performance of Fuzzy ArtMap (FAM) with no complement coding severely degraded in testing phase. Nevertheless with complement coding (FAM-CC) the results were significantly better than Learning Vector Quantization (LVQ) classifier and similar to Multi Layer Perceptron (MLP) classifier. Support Vector Machine classifier outperformed other classification methods.

Table 3: Comparative Results on Testing Radio Map

Method	Unclsfd	MAE	e ≤1	e ≤2	e ≤3
FAM-CC	0	1.06	75	81	92
FAM	389	0.64	78	85	96
SVM (P)	0	0.65	78	84	96
SVM (R)	0	0.71	75	84	96
MLP	0	1.03	75	79	91
LVQ	0	2.60	55	69	80

Location estimation performance of different classification methods , using test Radio Map, is shown in graphs of Fig. 11, 12, 13, 14 and 15. These line graphs show number of test RSS patterns on X-axis and both target location ID and location estimate by respective method on Y-axis. All methods were tested with same RSS patterns and estimation performance at individual locations is shown in these graphs.

As Fig. 14 results suggest, Fuzzy ArtMap model without complement coding produces very high location accuracy on individual locations but with the disadvantage of *unclassified* RSS patterns. As explained in previous section, un-normalized inputs introduce indecisiveness in network, during test phase only 160, out of 540, test patterns could be mapped to target location.

Overall estimation performance comparison results are presented in Fig. 16 bar graph and Fig. 17. Results show that Fuzzy ArtMap, with complement coding, produces smallest Mean Absolute Error during testing phase. In terms of relative error, Fig. 17, results indicate competitive location estimation accuracy of Fuzzy ArtMap and Support Vector Machines provide slightly

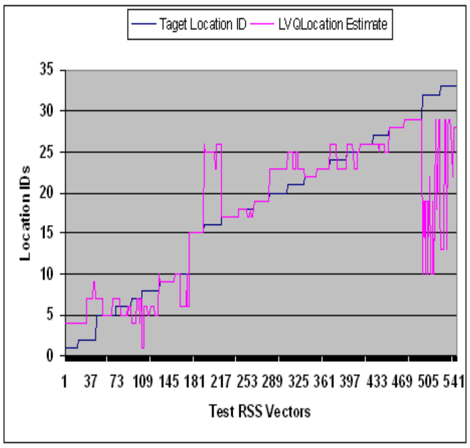

Figure 11: Learning Vector Quantization Location Estimation Results for Individual Location

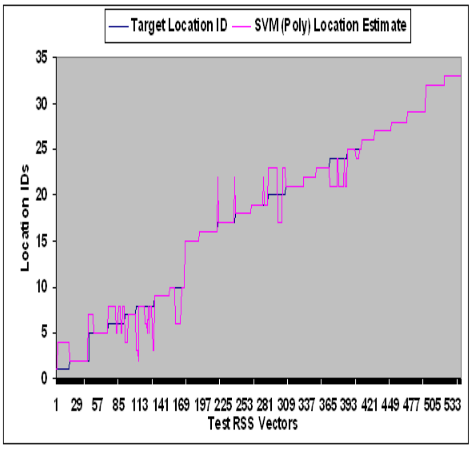

Figure 12: Support Vector Machines Location Estimation Results for Individual Location

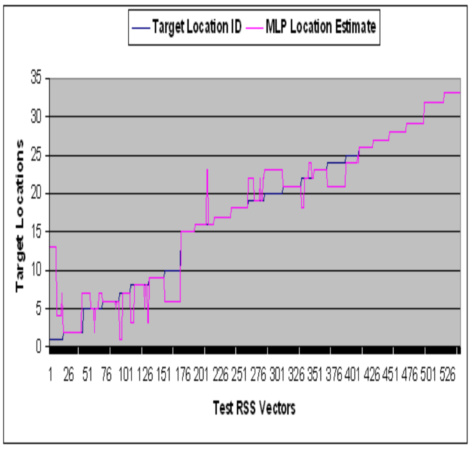

Figure 13: Multi Layer Perceptron Location Estimation Results for Individual Location

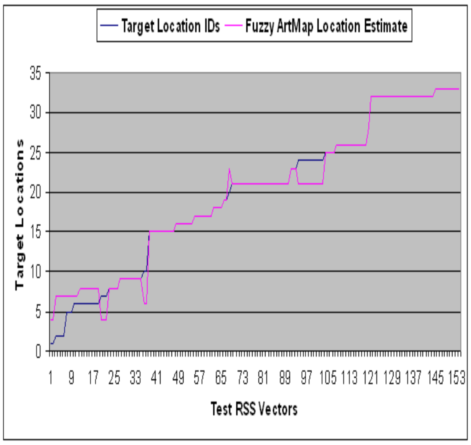

Figure 14: Fuzzy ArtMap (without Complement Coding) Location Estimation Results for Individual Location

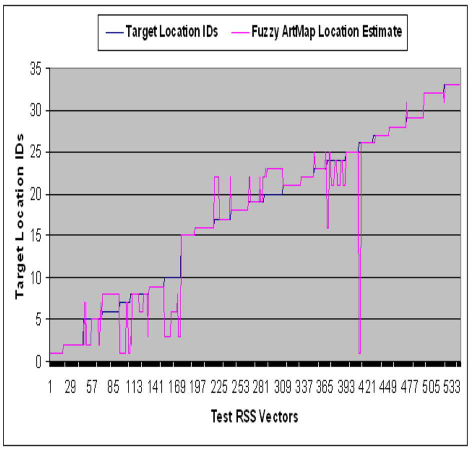

Figure 15: Fuzzy ArtMap Location Estimation Results for Individual Location

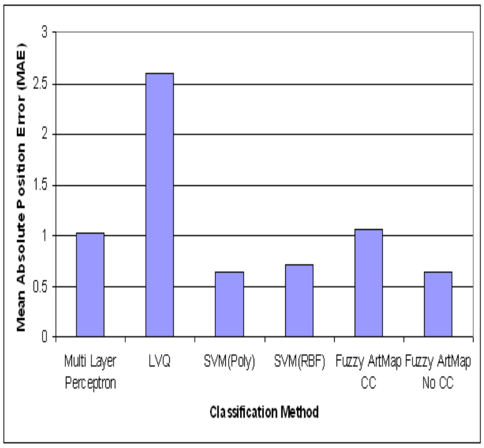

Figure 16: Comparison of Mean Absolute Position Error

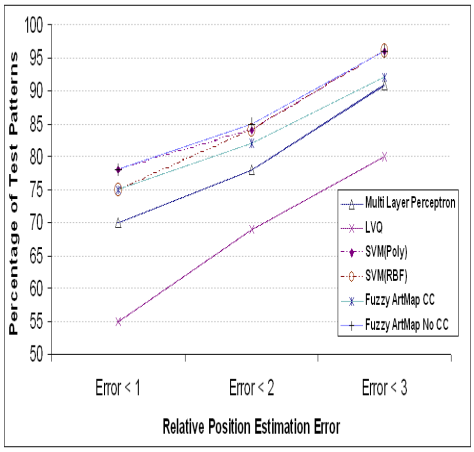

Figure 17: Comparative Performance Results

better accuracy while MLP and LVQ models give lower accuracy.

7 Conclusions

Received Signal Strength based location systems can enable several location based applications but, due to lengthy development life cycle, wide scale deployment of this technology faces development and scalability issues. We propose a rapid development approach based on online learning classifier, Fuzzy ArtMap, which significantly shortens the development time as well as enables dynamic scalability of location systems. Original Fuzzy ArtMap specification has learning capacity feature which gives network the capability of producing 'don't know' response when confronted with very different input patterns than previous experience of network. But this feature prohibits dynamic expansion of pattern recognition system, location systems in this case. We tailored original Fuzzy ArtMap, to make it self-scalable, in order to overcome this limitation while still retaining the previous capability. Self-scalable Fuzzy ArtMap neural network for RSS based location system is developed in real life environment. We compared location estimation performance with other classification methods such as 'Multi Layer Perceptron', 'Learning Vector Quantization' and 'Support Vector Machines'. On the basis of extensive experimental results we conclude that Self-scalable Fuzzy ArtMap provides competitive location estimation accuracy as well as leverages novel features, i) *Rapid system development* ii) *Flexible and dynamic expansion* of system, which can not be realized using previous methods.

References

[1] Moore. B ,”ART and pattern clustering”. In Proceedings of the 1988 connectionist models summer school, pp. 174-183, 1988

[2] Carpenter, G.A., Grossberg, S., ”Adaptive Resonance Theory”, The Handbook of Brain Theory and Neural Networks, Second Edition. Cambridge, MIT Press, pp. 87-90, 2003

[3] Carpenter, G. A., Grossberg, S., and Rosen, D. B. ”Fuzzy ART: Fast stable learning and categorization of analog patterns by an adaptive resonance system”, Neural Networks, Vol. 4, pp. 759-771, 1991

[4] Carpenter, G.A., Grossberg, et al, ”Fuzzy ARTMAP: A neural network architecture for incremental supervised learning of analog multidimensional maps”, IEEE Transactions on Neural Networks, Vol. 3, pp. 698-713, 1992

[5] Hagan, M. T., and M. Menhaj, ”Training feedforward networks with the Marquardt algorithm,” IEEE Transactions on Neural Networks, vol. 5, no. 6, pp. 989-993, 1994.

[6] T. Kohonen. ”Learning vector quantization”, The Handbook of Brain Theory and Neural Networks, pages 537-540. MIT Press, 1995

[7] V. Vapnik, ”The true nature of statistical learning”, Springer, 1995

[8] M. Teresa Serrano-Gotarredona , Bernabe Linares-Berranco, Andreas, G. Andreaou, ”Adaptive resonance theory microchips-Circuit Design Techniques”, Springer 1st edition, May 5, 2005

[9] P. Bahl, et al. ”RADAR: An in-building RF-based user location and tracking system.” In IEEE INFOCOM 2000, pp. 775-784, March 2000

[10] R. Want and B. Schilit, ”Expanding the horizons of location-aware computing”, IEEE Computer, pp. 31-34, August 2001.

[11] Cynthia et al, ”Challenges in Location-Aware Computing” Published by IEEE ComSoc, 2003

[12] K. Pehlavan et al, ”Indoor Geolocation Science and Technology”, IEEE Communications Magazine, 2002

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

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

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

[16] UbiSense, ”Local position system and sentient computing.” `http://www.ubisense.net/`

[17] Andy Ward et al, ”A New Location Technique for the Active Office”. IEEE Personal Communications, Vol. 4, No. 5, pp. 42-47, October 1997

[18] N.B. Priyantha et al, ”The Cricket Location-Support System,” Proc. 6th Ann. Int’l Conf. Mobile Computing and Networking, ACM Press, New York, pp. 32-43, 2000

[19] Tomoaki Ogawa, Shuichi Yoshino, and Masashi Shimizu, ”Location Determination Method for Wireless Systems Based on Learning Vector Quantization”,NTT Network Innovation Laboratories, Vol 1. No. 9. Japan

[20] Asim Smailagic et al, ”Location Sensing and Privacy in a Context Aware Computing Environment”, Pervasive Computing, 2001.

[21] Roberto 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

[22] Roberto Battiti, et al, ”Statistical Learning Theory for Location Fingerprinting in Wireless LANs”, Technical Report DIT-02-0086, University of Trento Italy, October, 2002

[23] Xuanlong et al, ”A Kernel-Based Learning Approach to AdHoc Sensor Network Localization”, ACM Transactions on Sensor Networks (TOSN) Volume 1 , Issue 1, pp. 134-152, ISSN:1550-4859, August 2005

[24] Uzair Ahmad et al, ”Modular Multilayer Perceptron for WLAN Based Localization”, IEEE International Joint Conference on Neural Networks, Vancouver, Canada, July 2006

[25] CompoNet, Componentization of Neural Networks, `http://sourceforge.net/projects/componet/`