# A Rapid Development Approach for Signal Strength Based Location Systems*

Uzair Ahmed, Andrey Gavrilov, Sungyoung Lee, Young-Koo Lee

## Abstract

*Location systems are core technologies for enabling pervasive computing smart spaces. Signal Strength based location estimation offers economical viability and sufficient accuracy for numerous location based services. Despite extensive research being carried out in this positioning method, tedious and lengthy development life cycle prohibits wide scale deployment of these systems. We present a new approach based on online machine learning paradigm which significantly reduces the development time. Besides rapid development of location systems this approach shows competitive location accuracy and allows incremental expansion of location system.*

## 1 Introduction

Positioning systems are on the verge of becoming common services in modern mobile and ubiquitous computing spaces [7],[8],[11]. Satellite signal based GPS technology globally provides pervasive location awareness but suffers from degraded accuracy in indoor environments. Indoor positioning systems have been subject to costly infrastructure and special hardware devices mounted on the objects of interest Active Badge [12],Cricket [15],Active Bat [14] and Ubisense [13]. 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 [6],[9],[10],[16],[18] and [21]. RSS based location awareness applications include, but 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. 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. RSS based location estimation is classification problem in the sense that location of device is estimated based on RSS feature vectors received by the target machine. Fundamental assumption behind such systems is that RSS values exhibit distinguishable features at different locations. These patterns are collected, in site calibration phase, and stored in Radio Map feature space. Radio Map plays pivotal role of training pattern classification machines which are then used to estimation location on the basis of received signal strength patterns reported by mobile devices.

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## 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 for example RADAR [6] and [9]. Nearest Neighbor and its variants require a database of sample RSS, so called Radio map, read-

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ings at the estimation time for pattern matching. As the area and number of target locations grow, size of this database dramatically increases and face with scalability issues.

Some researches have also employed GPS like triangulation method for location estimation with lower accuracy than other methods. Asim et al [17] 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 like bayesian networks based solutions have also been employed for this problem but are computationally exhaustive and difficult to scale. Andrew et al [10] reported 1.5 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 complexity of Bayesian structures grows and become computationally expensive.

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[16]. 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 [18]. A 'Modular Multi Layer Perceptron' approach is presented in [21] that further improves accuracy and scalability of RSS based location estimation by incorporating prior knowledge about signal availability in the area into classifier design.

## 3 Rapid Development Approach

Until now long development time of signal strength based location systems is not particularly addressed from machine learning stand point. Most of the research is focused on fast and efficient sensor data collection in order to reduce the required labor and time [19], [20]. Fig. 1 shows a general schematic of development life cycle which is commonly followed by all signal strength based location systems. In this development life cycle, the Site Calibration Phase and the Training Phase are *offline* development phases. By offline phases, we refer to the tedious and time consuming tasks which are required to be carried out prior to actually start using a positioning system online. In this paper we present a novel *online* and *incremental* machine learning approach to rapidly develop a location system. Unlike classic location system development methodology, this approach requires no off line or lab time Training Phase to train the classifier. Online learning of RSS patterns and corresponding locations enables rapid location system development because this approach removes site calibration phase and off line training phase from development life cycle as shown in Fig. 2. Our approach is based on Fuzzy ArtMap neural network system which can learn classification problems online in real time. Fuzzy ArtMap is a more general ArtMap [3] to handle analog input patterns and perform online, incremental supervised learning of pattern-class pairs presented in arbitrary order. In addition to short development time, our location system development methodology delivers other desirable features which cannot be realized using previous methods. i) Flexible and incremental expansion of location system is easy and straight forward in our approach. By expanding location system flexibly and dynamically we mean incrementally learning new location in real time thus increasing area by including more target locations. In order to achieve this purpose, using previous approaches, Radio Map feature space is required to be extended to include training RSS pattern-location mapping and then retraining of classifier with extended radio map is required. In case of retraining with new feature space, most of 'off line training' based classifiers face with the '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

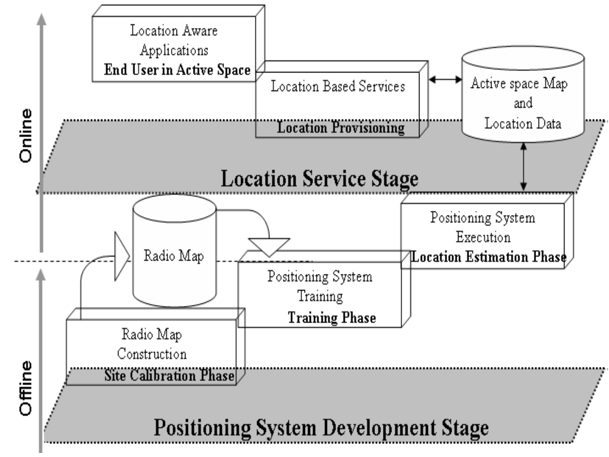


**Figure 1. Development Life Cycle in Previous Approaches**

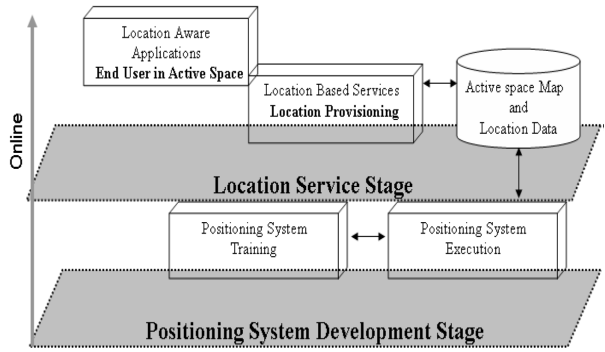


**Figure 2. Rapid Development Life Cycle**

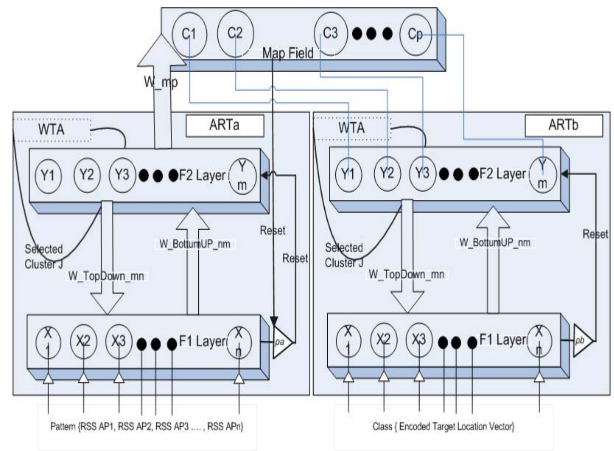


**Figure 3. Fuzzy ArtMap Network Topology**

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.

ii) Learning Rare Events is very common issue that RSS based location classifiers face. Very nature of radio wave propagation in indoor environments cause imbalanced classes. It 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 based on a single exposure to an event, and does not show the catastrophic forgetting of rare events that other classification methods do. Moreover inside the building radio wave propagation follows a complex model and produce non stationary feature values in RSS vectors. Fuzzy ArtMap exhibits remarkable ability to classify non stationary data sequences.

### 3.1 Fuzzy ArtMap Overview

Fuzzy ArtMap is Adaptive Resonance Theory (ART) based Self organizing neural network for real time autonomous learning environments. Fuzzy ArtMap network is composed of a pair of Fuzzy ART networks (Fuzzy $\text{ART}_a$ and Fuzzy $\text{ART}_b$) which employ combination of fuzzy logic and Adaptive Resonance Theory [4] to establish stable recognition categories in response to temporal stream of analog RSS input patterns. Rigorous characterization of Fuzzy ART and Fuzzy ArtMap neural networks can be found in [2] and [3]. Fig. 3 shows topological structure of Fuzzy ArtMap neural network. Fuzzy ART modules $\text{ART}_a$ and $\text{ART}_b$ 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 $\text{ART}_a$ recognition categories to $\text{ART}_b$ recognition categories. This is achieved by connecting $\text{F}_2$ Layer, so called ${\text{F}_2}^b$, neurons of $\text{ART}_b$ to Map Field nodes with on-to-one, non-adaptive links in both ways. On the other hand each $\text{F}_2$ layer, so called ${\text{F}_2}^a$, neuron of $\text{ART}_a$ 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 referred to as $\text{F}^{ab}$. 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 $\text{ART}_a$ category and $\text{ART}_b$ category then system increases vigilance parameter of $\text{ART}_a$ so that $\text{ART}_a$ can categorize this pattern in different category or can create new category for this pattern that matches $\text{ART}_b$ class category. This mechanism allows network to capture novel features that can be incorporated through learning new $\text{ART}_a$ recognition category. Activation of Map Field results in output signal from each $\text{F}^{ab}$ 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 $\text{F}^{ab}$ 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 $\text{ART}_a$ and also allow very different RSS inputs to form categories that make same location estimation. 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.

### 3.2 Simplified Self-Scalable Fuzzy ArtMap

We adapt a simplified version of Fuzzy ArtMap, presented in [5], which employs only one Fuzzy Art network instead of two with same learning and recall performance as original Fuzzy ArtMap. Simplified architecture is optimized for hardware implementation of Fuzzy ArtMap network. The learning dynamics of Fuzzy Art and Fuzzy ArtMap networks are respectively shown in Fig. 4.

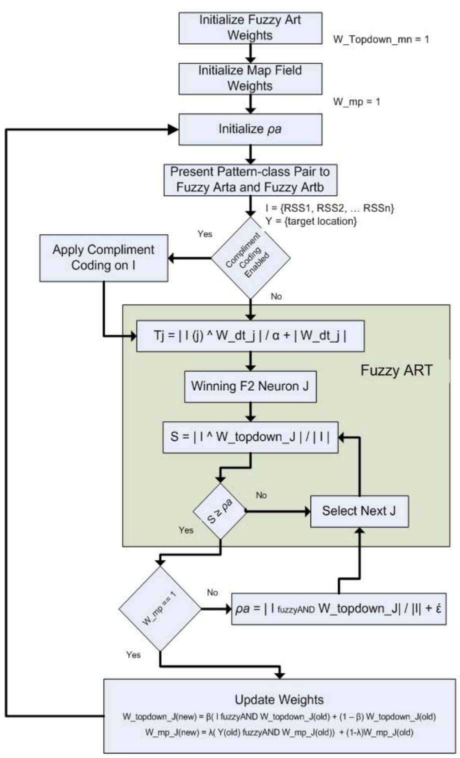


**Figure 4. FuzzyARTMAP Learning Algorithm**

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 cannot be learned (or incorporated) into that network. This limits the application of original Fuzzy ArtMap in terms of dynamically expanding the location system. We adapt original Fuzzy ArtMap in our implementation such that it do not require capacity of network to be fixed prior to learning and allows network to self-scale itself as new categories (locations) are presented to it. Our implementation of our self-scalable fuzzy ArtMap network is available as open source [22].

## 4 Experimental Design and Implementation

We conducted our experiments in 1240 square meter area of Computer Engineering Department Building as shown in Fig. 5. Filled circles indicate target locations. used pocket pc (HP iPaq 1450 model) and laptop device (Toshiba satellite model) for getting received signal strength vectors from 9 wireless access points.

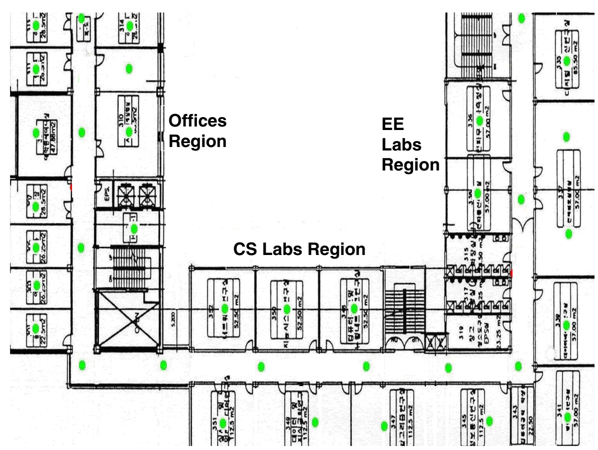


**Figure 5. Experimental site map for location system development**

### 4.1 RSS Inputs and Target Location Encoding

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 [2]. This normalization technique allows network to reduce effect of presentation frequency of an input pattern and order of presenting input patterns as explained in [3]. Since our aim is

to develop location estimation system without off line training, complement coding enables fast online learning of RSS pattern and corresponding location pairs. Therefore we apply complement coding normalization to RSS patterns at learning and estimation time. Complement coding requires input pattern values to be 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.
Target locations are represented as ID (a number that uniquely identifies a location from others). Inside network target locations are represented as binary encoded form.

### 4.2 Experimental Results

We measure location estimation error in terms of absolute deviation of location estimate from actual location and in terms of relative deviation. Absolute deviation is measured as Mean Absolute Error (MAE), ratio of unclassified RSS vectors (UC) and ratio of missclassified RSS vectors. Relative error is measured as ratio of estimate deviation less than a thresh hold value with total number of estimates. Table 1 presents training results of Fuzzy ArtMap network with and without complement coding(indicated as CC). In our experiments complement coding controls category proliferation problem and classifies all RSS vectors successfully but classification performance is slightly affected at the cost of five times more $F_2$ layer clusters and high ratio of unclassified patterns. Thus these results confirm the efficacy of Complement Coding technique for controlling the category proliferation problem and eliminating the 'don't know' responses from the classifier.

**Table 1. Fuzzy ArtMap Results on Training Radio Map**

| Clusters | CC | MAE | UC | e≤ 1 | e≤ 2 | e≤ 3 |
|---|---|---|---|---|---|---|
| 36 | Yes | .06 | 0 | .02 | .02 | 0 |
| 167 | No | .018 | .016 | .005 | .005 | 0 |

In parallel to Fuzzy ArtMap based location system we implemented two other neural network models for our location system i) multi layer perceptron (MLP) network ii) learning vector quantization (LVQ) network, in order to evaluate relative location estimation performance with previous approaches [16] and [18]. Table 2 presents comparative results of three classifiers during training.

**Table 2. Comparative Results on Training Radio Map**

| Classifier | UC | MAE | e≤1 | e≤2 | e≤3 |
|---|---|---|---|---|---|
| FMap-CC | 0 | 0.06 | 0.02 | 0.02 | 0 |
| FMap | 0.016 | 0.02 | 0.005 | 0.005 | 0 |
| MLP | 0 | 1.03 | 0.25 | 0.21 | 0.09 |
| LVQ | 0 | 2.60 | 0.45 | 0.31 | 0.20 |

We collected different set of data, to test all three classifiers estimation performance, on a different day and time than training data. Table 3 presents comparative testing results of three classifiers.Unlike training phase, performance of Fuzzy ArtMap with no complement coding severely degraded in testing phase. Nevertheless with complement coding the results were significantly better than other classifiers.

**Table 3. Comparative Results on Testing Radio Map**

| Classifier | UC | MAE | e≤1 | e≤2 | e≤3 |
|---|---|---|---|---|---|
| FMap- CC | 0 | 1.064 | 0.25 | 0.18 | 0.09 |
| FMap | .71 | 0.64 | 0.21 | 0.14 | 0.04 |
| MLP | 0 | 1.03 | 0.25 | 0.21 | 0.09 |
| LVQ | 0 | 2.60 | 0.45 | 0.31 | 0.20 |

## 5 Conclusions and Future Directions

We proposed a rapid development approach for developing signal strength based indoor location systems in short time. This approach employs online and incremental learning capabilities of Fuzzy ArtMap neural network system. Efficacy of this methodology is evaluated by developing positioning systems in real environment. The location estimation performance is compared with two other approaches based on Multi-layer Perceptron and Learning Vector Quantization classification methods. On the basis of experimental results we conclude that Fuzzy ArtMaps provides competitive location accuracy. In addition to that, our approach inculcates novel features in location systems that can not be realized using previous approaches. 1) Rapid system development 2) Flexible and incremental extension of system 3) Stable estimation performance. Current work faces limitations on effectively overcoming the problem of intermittent availability of signals at certain locations. Our future study shall investigate the potential benefits of incorporating prior knowledge about signal availability into the design of Fuzzy ArtMap.

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