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Context-aware, self-scaling Fuzzy ArtMap for received signal strength based location systems

Uzair Ahmad · Andrey V. Gavrilov · Young-Koo Lee · Sungyoung Lee

Abstract Location awareness is the key capability of mobile computing applications. Despite high demand, indoor location technologies have not become truly ubiquitous mainly due to their requirements of costly infrastructure and dedicated hardware components. Received signal strength (RSS) based location systems are poised to realize economical ubiquity as well as sufficient accuracy for variety of applications. Nevertheless high resolution RSS based location awareness requires tedious sensor data collection and training of classifier which lengthens location system development life cycle. We present a rapid development approach based on *online* and *incremental* learning method which significantly reduces development time while providing competitive accuracy in comparison with other methods. ConSelFAM (**Con**text-aware, **Sel**f-scaling **F**uzzy **A**rt**M**ap) extends the Fuzzy ArtMap neural network system. It enables *on the fly* expansion and reconstruction of location systems which is not possible in previous systems.

Keywords Online incremental learning · Indoor location systems · Signal strength · Self-scalability · Context aware classifier

1 Introduction

Received signal strength (RSS) based location systems can enable a wide range of mobile computing, context-aware applications. Especially for indoor environments, where satellite signal based Global positioning system does not work well, this location technology offers promising solution to ever increasing users of hand held devices connected through pervasive deployments of IEEE 802.11 standard, so called WiFi, networks. This is mainly because all WiFi devices should report received signal strengths as part of standard compliance. Several researchers have reported encouraging results on developing location systems using RSS establishing its feasibility and economic viability (Bahl et al. 2000; Pehlavan et al. 2002; Andrew et al. 2002; Ogawa et al. 2003; Battiti et al. 2002; Ahmad et al. 2006).

WiFi location systems attracted a lot of attention from research community. From *resolution* aspect they can be categorized in two classes; *coarse-grained* and *fine-grained*. Intel's Place-Lab (LaMarca et al. 2005) location system is often quoted example of radio beacon based location systems. RADAR positioning system (Bahl et al. 2000) is pioneering work in fine grained positioning systems which employ a detailed *Radio Map*. Both methods differ in two aspects, *resolution* of target location and *coverage* area that they provide. Radio beacon based systems focus on greater coverage, such as campus wide, and provide coarse granularity of location information, up to 25 m. On the other hand *Radio Map* based systems provide fine-grained location resolution, up to 3 m, and cover relatively smaller and covered environments such as hospitals and super markets. This paper focuses on the issues that *Radio Map* based location systems face but our method is also beneficial for beacon based systems.

An end-to-end development life cycle of RSS based location system can be divided into two major stages and five different phases. Figure 1 shows general schematic of development life cycle. It comprises two stages, in bottom-up direction, containing different development phases and respective subsystems. A vertical line is shown which again divides the subsystems into two modes of development. *Offline* mode subsystems require lab time for data collection,

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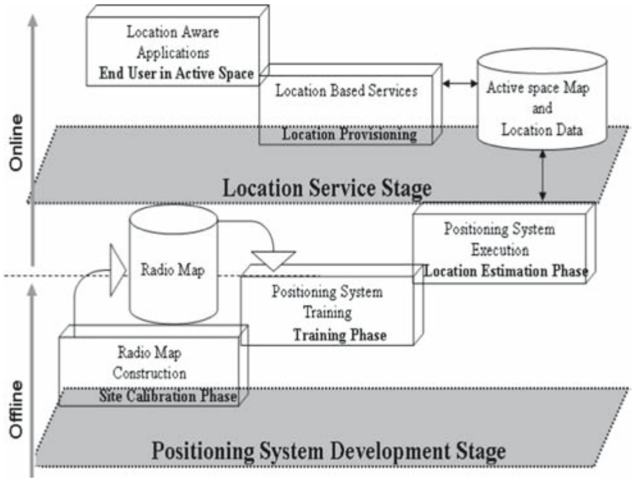

Fig. 1 Typical development life cycle of location systems

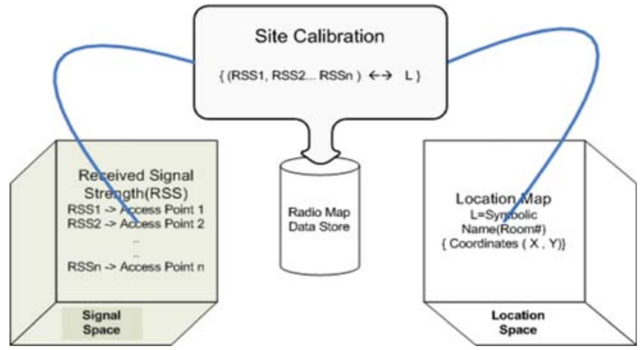

Fig. 2 Site calibration: Radio Map creation process

preprocessing, classifier training and optimization etc. Whereas *online* mode means that subsystems can be made with plug in components as described in Iqbal et al. (2005), Nasir et al. (2005) and Ahmad (2007).

WiFi signal strength based location systems fundamentally assume that signal strength of different signal sources, access points, exhibit recognizable patterns, so called fingerprints, which are distinguishable at different locations. These patterns are captured at each target location and stored in a database namely *Radio Map*. Suppose that d access points form an d-dimensional signal space RSS^d covering a location space A then this association can be represented mathematically as

$$F : RSS^d \rightarrow A \tag{1}$$

More specifically, suppose there are n target locations covered by d access points there exist associations between rss patterns and the ith location which can be modeled as mapping f

$$(a^n_{i=1}) = f(rss^d) \tag{2}$$

where $(a^n_{i=1}) \in A$ and $rss^d \in RSS^d$. Typically the j_{th} signal strength vector rss^d_j is an ordered sequence tuple with respect to access points

$$rss^d_j = (ss_{AP1}, ss_{AP2}, ss_{AP3} \dots ss_{APd}) \tag{3}$$

in which each signal strength component represents a feature.

Creation of Radio Map, also called *Site Calibration*, involves capturing this information and storing observed signal strengths vectors in a data store as shown in Fig. 2.

The *Radio Map* provides input data along with location IDs, or class labels, for training classification machines. In Sect. 2 we offer a brief study of several researches on using different classification methods to achieve high accuracies. Later, when some devices report similar patterns the location of target object can be estimated using trained pattern classifier.

One of the major draw backs of existing approaches is that it requires extensive and laborious sensor data collection or *Site Calibration*. Partly due to this problem, existing systems focus on evaluating classification methods on small scale location systems while, as discussed by Ahmad et al. (2006), development of large scale location system presents certain challenges which degrades the accuracy of classifier. These issues are not particularly addressed in previous work. In Sect. 3 we identify and discuss these limitations in detail.

The design goals of an ideal approach should address these issues as discussed in Sect. 4. In our work the efficacy of online incremental learning approach is demonstrated through proof of concept implementations in real environment. Main contribution of this paper is to provide succinct analysis of issues, lay down the design and implementation of our approach for *rapid*ly developing *large scale* and incrementally *extensible* location systems and extensively evaluate it in comparison with previous approaches. Primary motivation of this work is to exploit 'fuzzy arithmetic' and 'adaptive resonance theory' based *online and incremental* learning systems, Fuzzy Art (Carpenter et al. 1991) and Fuzzy ArtMap (Carpenter et al. 1992), for achieving our design goals. An overview of their learning dynamics is given in Sect. 5. We identify certain limitations of these system and present a **Con**text-aware, **Sel**f-scaling **F**uzzy **A**rt**M**ap system in Sect. 6. The experimental design and test setup technical details are elaborate in Sects. 7 and 7.4 presents comparative results analysis.

2 Related works

Nearest neighbors based pattern recognition technique and its variants have been used by pioneering works estimation of Bahl et al. (2000) and Pehlavan et al. (2002). These methods 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, resulting in scalability issues, as the area and number of target locations grow.

Some researchers have also employed GPS like triangulation method for location estimation. Smailagic et al. (2001) achieved 4.5 m location estimation error in area of $60\,\text{m}^2$ 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. (2002) reported $1.5\,\text{m}^2$ distance error but only for $30\,\text{m}^2$ 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 networks 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. (2003) employed learning vector quantization networks to develop location estimation system for $350\,\text{m}^2$ area using five access points. Battiti et al. (2002) have reported their research on using feed forward back propagation network on small scale ($624\,\text{m}^2$ area using three access points) location estimation system. Modular neural networks approach is presented in Ahmad et al. (2006) that improves accuracy and scalability of RSS based location estimation. Support vector machines (SVM) have been employed by Xuanlong et al. (2005) for localization in densely distributed sensor networks.

3 Limitations of previous approaches

Despite several research results have proved the feasibility of RSS based location systems, there are still some issues which prohibit wide scale availability of this technology. This section offers a discussion of these issues and limitations in previous approaches.

3.1 Laborious development and reconstruction

Developing a location system fundamentally amounts to *Site Calibration* and *Classifier Training* phases, as can be seen in Fig 1, but special nature of indoor radio wave poses *reconstruction* problem as well. Such environments as super markets and hospitals might experience restructuring, even though not frequently, which most likely changes signal strength distributions. This can potentially render a location system ineffective and require reconstruction of classifier even if only a small part of building is affected. Thus both *development* and *reconstruction* of location system become a laborious task.

RSS based location estimation is a multi-class classification problem which requires extensive sensor data collection in order to create *Radio Map* which provides training data for classification machines to learn signal to location relationship. It has been reported by several researchers that detailed Radio Map, in terms of number of samples per location, is crucial component for finer granularity and higher accuracy. Recently some researchers have proposed statistical interpolation of RSS data to reduce the effort and time required for constructing Radio Map. Radial basis functions have been employed by John et al. (2003) to interpolate the missing data of un-calibrated locations. Li et al. (2005) proposed a method of using unlabeled samples for reducing the sampling rate at each location and number of locations. It should be noticed that even if the actual calibration points are reduced, these techniques still need to calibrate the area. Despite an extensive research being put into enhancing calibration speed, construction of Radio Map has been a major hurdle in wide acceptability for this technology.

As the number of locations increase, pattern classification task becomes harder due to overlapping classes and imbalance in class data. Mostly, it takes several training and parameter tuning sessions in order to make a classifier to yield sufficient accuracy. Same time is required to retrain the classifier in case of *reconstruction* as changes in signal distribution in a small area require retraining whole classifier. Modular classifier approach tries to localize this problem by portioning the location space into subspaces and train several redundant as well as sperate modules for each subspace (Ahmad et al. 2006). Although this approach localizes the problem area and *reconstruct* only affected part but we propose to further reduce training time to a great extent by using *online* learning methods as explained in Sect. 5.

3.2 Increasing the scope of location system

Location systems might be required to recognize new target locations. We refer to this requirement as "increasing the scope of location system" which involves two aspects of (i) *extensibility* and (ii) *expansibility*. Before we describe these concepts in the context of location estimation, a formal definition of *range* and *scope* of location system is required. Radio wave obeys inverse-square law in free space which states that

$$\text{signal strength} \approx 1/r^2$$

where r is distance between transmitter and receiver. Indoor environment further impose several environmental factors which collectively reduce signal strength outside a certain region to be undetectable by the receivers. This physical property of radio signals ultimately defines the range of a location system. Assume that a classifier is trained to learn association between signal space S and location space A, as shown in Eq. 1, where S is composed of n access points. *Range* of this system can be formalized as

$$S \supseteq (AP_1, AP_2, AP_3, \ldots, AP_n) \tag{4}$$

whereas $S \rightarrow A$.

Similarly, pattern classifier that categorizes RSS input vectors into a set of n target locations $(a_1, a_2, a_3 \ldots a_n)$, the *scope* of a location system is an area A such that

$$A^S \supseteq (a_1, a_2, a_3, \ldots a_n) \tag{5}$$

Definition 1 Extending means to increase the *scope* of location system without changing its *range*.

According to this definition there could be a new set of m locations $(a'_1, a'_2, a'_3 \ldots a'_m)$ to be recognized by the classifier which was already trained using same dimensions, Eq. 3, of input space for area A.

$$A^S \supseteq (a_1, a_2, a_3 \ldots a_n) \cup (a'_1, a'_2, a'_3 \ldots a'_m) \tag{6}$$

Definition 2 Expanding means to increase the *range* of location system in order to increase its *scope*. This implies that there could be a new set of p locations $(b_1, b_2, b_3 \ldots b_p)$ that a location system should learn to recognize in addition to already learned A. Whereas these locations may or may not be within the *range*, Eq. 4, of location system. Let S' denote a new set of access points

$$S' \supseteq (AP_{n+1}, AP_{n+2}, AP_{n+3}, \ldots AP_m)$$

required to form additional signal space which includes these locations. Then a range increment can be represented as

$$A^{S \cup S'} \supseteq (a_1, a_2 \ldots a_n) \cup (a'_1, a'_2 \ldots a'_m) \cup (b_1, b_2 \ldots b_p) \tag{7}$$

Notice that increasing the range necessarily increase the scope of system but not otherwise.

Although this requirement seems to be very basic capability that location systems should posses but, so far, no such capability is improvised by previous systems. In order to achieve this scalability, using previous approaches, Radio Map feature space is required to be extended to include training RSS pattern–location data and then retraining of classifier with extended Radio Map. In case of retraining with new feature space, most of the *offline* training based classifiers face the *Stability-plasticity dilemma* which states that learning new pattern–class mappings causes erosion of previous knowledge acquired by classifier during early training. Another method to overcome this problem is to retrain classifier with whole Radio Map (that includes both old and new training data) which is tedious and cumbersome.

3.3 Visibility issue

From location estimation stand point, one important aspect of indoor radio wave propagation is that not all access points are available at all target locations all the time, especially in case of a large scale location system. We refer to signal availability of a particular access point at a given location as its *visibility*. Large scale application of RSS based location estimation faces visibility phenomena which can be modeled as a priori probability of signal source visibility at a particular location. Let v denote the event when a signal is detected at a given location a.

$$P_V(v_a) = \frac{\text{Number of times when signal detected}}{\text{Total number of scans}}$$

A priori probabilities of signal visibility at all locations can thus be computed during sensor data collection. In order to further explain this problem we present visual explanation of *visibility* issue in a real environment. The probability mass function of each access point[1] is shown in Fig. 3 using eight circular radar graphs where individual locations are listed on the edges of each circle. Visibility probability is shown starting from center of circle, which represents zero, and ending at the edge which represents one. These Access Points are deployed in Department of Computer Engineering building, third Floor, which is shown in Fig. 12 map.

As it is obvious from these graphs, every access point is visible on a subset of locations, shown as filled circles in Fig. 12. This is because radio signals face several attenuation and fading factors which cause intermittent or permanent non-availability of access point at a given location. Since a particular access point constitutes a distinguishing feature for pattern recognition machine, this implies that non-availability of a particular Access Point signal at given location can have adverse affect on location estimation.

Previously modular pattern classifiers were employed to effectively cope with this issue (Ahmad et al. 2006) but that approach further contributes towards complex design and laborious training of several classifiers.

4 Online and incremental learning approach

In this paper we present a novel approach for building location systems based on ConSelFAM neural network. Fuzzy ArtMap is a generalized ArtMap (also called Predictive Art) (Carpenter et al. 1992) network which can handle analog input patterns and performs *online* and *incremental* learning of pattern–class pairs presented in any arbitrary order. We demonstrate that this approach effectively overcome the

[1] We identify each access point using last four digits of its MAC address e.g. AP5659.

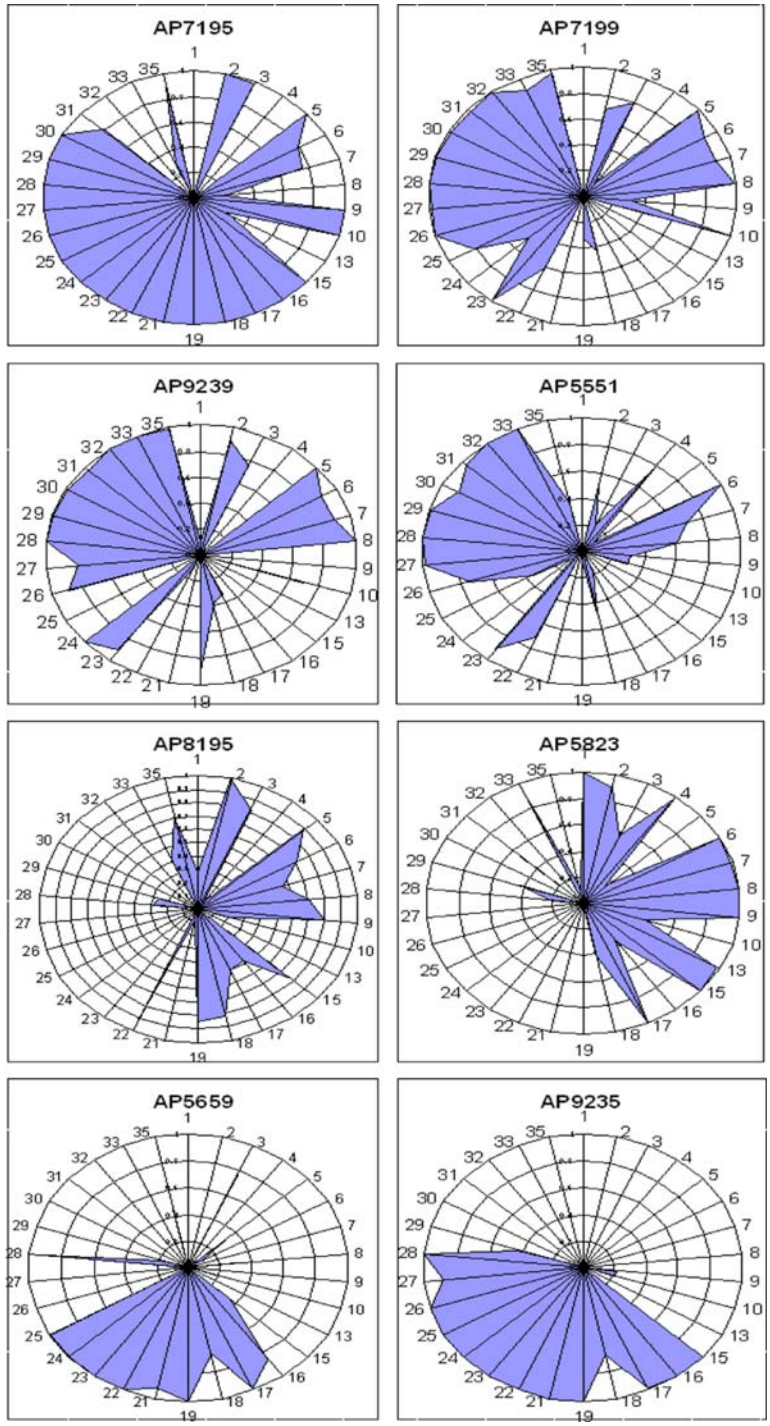

Fig. 3 Visibility graphs of eight access points at 35 locations in target area

limitation, presented in Sect. 3, as well as offers several desirable features which cannot be realized using previous methods. Unlike previous approaches, our approach does not require calibration phase and *offline* (or lab time) training phase by means of online learning which shortens development time dramatically. Figure 4 shows how our approach transforms location system development life cycle.

In the following subsections we explain how our approach meet the design goals such as reducing excessive development and training time, increasing system *scope* and addressing the *visibility* problem.

4.1 Rapid development via online learning

Fuzzy ArtMap classification system learns pattern class pairs *online*, which implies that *Radio Map* feature space need not be created prior to model training. This property enables such

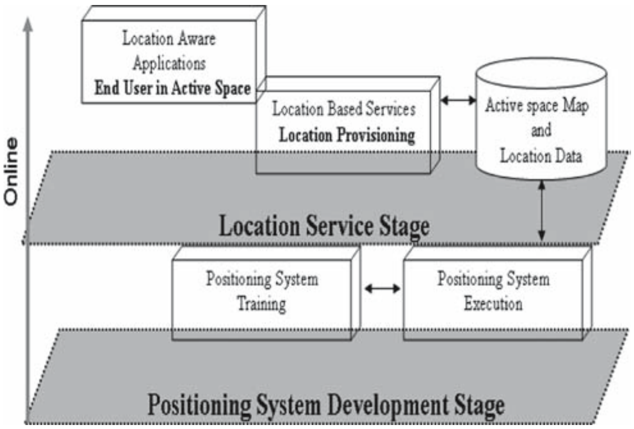

Fig. 4 Rapid development approach

location systems that can be built without calibration phase and *offline* model training phase. Previous approaches are based on *offline* training based pattern recognition methods which incurs long site calibration phase and training phase onto development life cycle as shown in Fig. 1. We demonstrate that by virtue of online learning capability of Fuzzy ArtMap both phases can be removed from development life cycle, as shown in Fig. 4, and rapid location system development can be realized.

4.2 Extensibility and expansibility via incremental learning

Flexible and dynamic expansion of location system is easy and straight forward in our approach. As discussed in Sect. 3.2, by expanding location system flexibly and dynamically we mean to incorporate new locations thus increasing the *scope*, Eqs. 4, 5, of location system. Fuzzy ArtMap is capable of *incremental* learning and demonstrates stable learning of classes when exposed to a new set of pattern–class pairs (Carpenter et al. 1992). This capability allows flexible learning of new locations without requiring retraining with old and new feature space as is the case with previous systems. Nevertheless Fuzzy Art 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 a network then more locations can not be incorporated or learned by that network. This limits the application of Fuzzy ArtMap in terms of dynamically expanding a pattern classification problem or, in this case, location system. We extend 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 Sect. 6.1 in more detail.

Table 1 Visibility matrix based modular approach

7195	7199	9239	5551	5823	5659	9235	Module
1	1	1	0	1	0	0	M1
0	1	1	0	0	1	1	M2
1	0	1	1	1	0	0	M3
1	0	0	0	1	1	1	M4
1	0	1	0	0	1	1	M5

4.3 Visibility awareness

Previous researches have shown that *visibility matrix* based approach of *modular classifiers* improves location accuracy. This method partitions input space as well as output space based on visibility probability of a set of access points over a cluster of locations. Then separate classifiers, called modules, are trained for each partition as shown in Table 1. In this table, column heading shows identifier of a particular access point and corresponding rows show either 0 or 1 based on its visibility status. Last column shows corresponding classifier modules. A module is defined such that a certain number of access point must have visibility status 1 for cluster of locations. Thus each module is trained for a particular set of access points who have visibility status 1 in the same row. Notice that the last column characterizes the output space partitioning while other columns determine input space. Refer to Ahmad et al. (2006) for more detailed treatment of visibility matrix based modular classifier approach.

Although modular approach improves overall accuracy but, obviously, this method increases complexity and might take longer periods of training. We propose to improvise visibility information as *context* and enable the classifier to recognize RSS patterns based on it. Comparative results show that this context-awareness achieves comparable accuracy to modular approach and greatly simplifies the visibility-aware learning. The learning dynamics of context-awareness are explained in Sect. 6.2.

5 Fuzzy Art and Fuzzy ArtMap

Fuzzy Art is adaptive resonance theory based self organizing neural network for real time autonomous learning environments. Fuzzy ArtMap is composed of a pair of Fuzzy ART neural networks denoted as Fuzzy ART_a and Fuzzy ART_b. We briefly, and sequentially, explain Fuzzy Art system first and then Fuzzy ArtMap system in this section. Fuzzy Art combines of fuzzy set theory and adaptive resonance theory (ART) (Carpenter et al. 1992) to accomplish unsupervised, incremental and online learning of analog valued input vectors presented to system in arbitrary order.

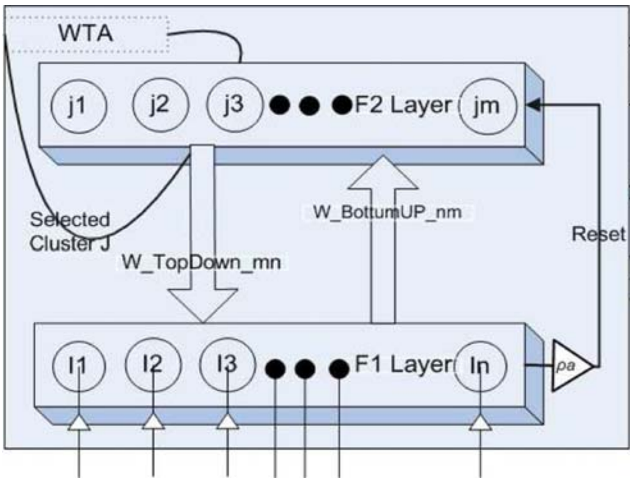

Fig. 5 Fuzzy Art network structure

5.1 Fuzzy Art

Here we describe learning dynamics and our implementation of of Fuzzy Art neural network system. A comprehensive treatment of Fuzzy Art characteristics can be found in Carpenter et al. (1991). Figure 5 shows topological structure of Fuzzy Art.

It consists of two processing layers F_1 and F_2. Each neuron of F_1 layer is linked, through bottom up synaptic connections W_BottomUp_nm, to all neurons of F_2 layer and vice versa. Adaptive weights of bottom up and top down synaptic connection, denoted as W_TopDown_mn, bear same value in Fuzzy Art systems. F_2 layer neurons represent learned categories in input space. Each F_2 neuron is refereed to as *committed* (if it already represents a category) or *uncommitted* (it it is not representing any category). Fuzzy Art learning is governed by a *choice* parameter α, a *vigilance* parameter ρ and and learning rate parameter β. Figure 6 shows learning dynamics of Fuzzy Art unsupervised learning algorithm for fast and stable categorization of analog input patterns. Network initialization creates n and m neurons in F_1 and F_2 layers respectively and synaptic connections get initialized. ART systems can employ a special preprocessing method, so called *complement coding*, to input vector I. Orienting subsystem determines system choice of m F_2 layer categories for this input vector. This is achieved by evaluating a *choice function* by F_1 layer neurons. For every input vector $I = (I_1, I_2, I_3 \ldots I_M)$, this function produces a ranking list based on component wise fuzzy distance $T(j)$, between input pattern and synaptic connection weights, and a choice parameter α.

$$T(j)_{j=1}^{n} = |I(j)| \wedge W(j)/\alpha + |W(j)|$$

$T(j)$ ranking list is adaptively fed into a Winner Takes All (WTA) filter and resulting winner neuron is, tentatively,

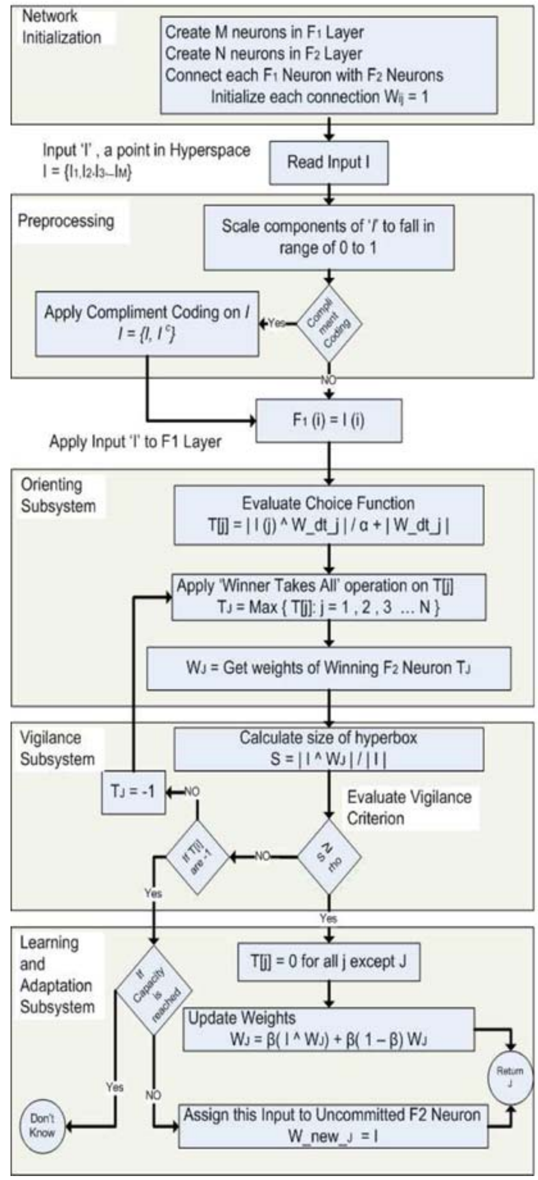

Fig. 6 Learning dynamics of FuzzyART online clustering algorithm

selected as category of current input pattern. Vigilance subsystem confirms, or dismisses, this decision based on externally adjustable vigilance parameter ρ. In case of dismissal relearning continues by reevaluating the ranking list until a satisfactory category is found or learning capacity, denoted here as n, of system is reached. Learning ensues once a category choice satisfies vigilance subsystem. All weights that belong to confirmed category J neuron are updated as following.

$$W_J = \beta(I \wedge W_J) + \beta(1-\beta)W_J$$

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

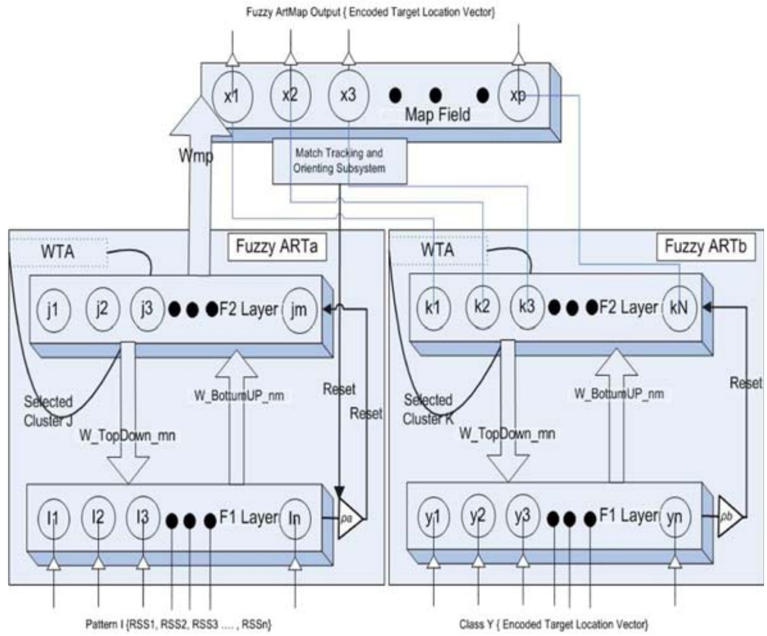

Fig. 7 Fuzzy ArtMap network structure

any categories if it 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.

5.2 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 I (feature RSS vector reported by mobile device) and Y (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 ${F_2}^b$, 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, referred to as ${F_2}^a$, neuron of ART_a is connected to all Map Field nodes via $W_m p$ adaptive links. Since Map Field represents a mapping from both ${F_2}^a$ and ${F_2}^b$, 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 I and Y.

During learning of 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. 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 I and target location vector Y. Location estimation occurs in case only RSS input vector is presented to the system. 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 Serrano-Gotarredona (2005), which employs only one Fuzzy Art optimized for hardware implementation of Fuzzy ArtMap system. Simplified Fuzzy ArtMap exhibits same learning and recall performance as original Fuzzy ArtMap and its learning algorithm is shown in Fig. 8.

6 ConSelFAM

Context-aware, self-scalable Fuzzy ArtMap extends original Fuzzy ArtMap neural network system in order to realize *on the fly* location system development and reconstruction which is aware of visibility clusters present in signal space. *On the fly* development essentially refers to capability of classifier to learn RSS to Location association at the time a signal is detected by mobile device.

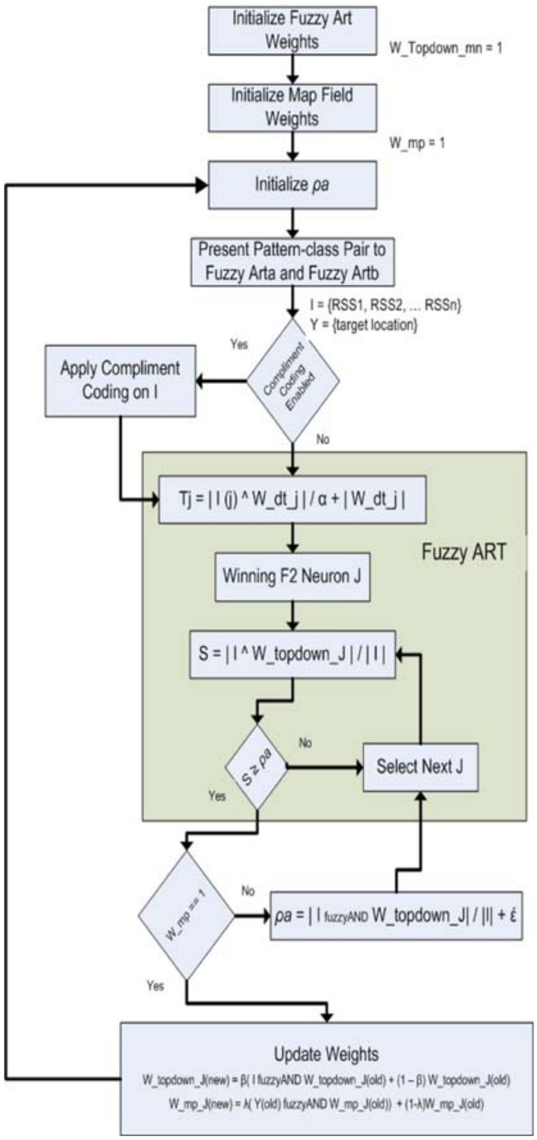

Fig. 8 Fuzzy ArtMap learning dynamics

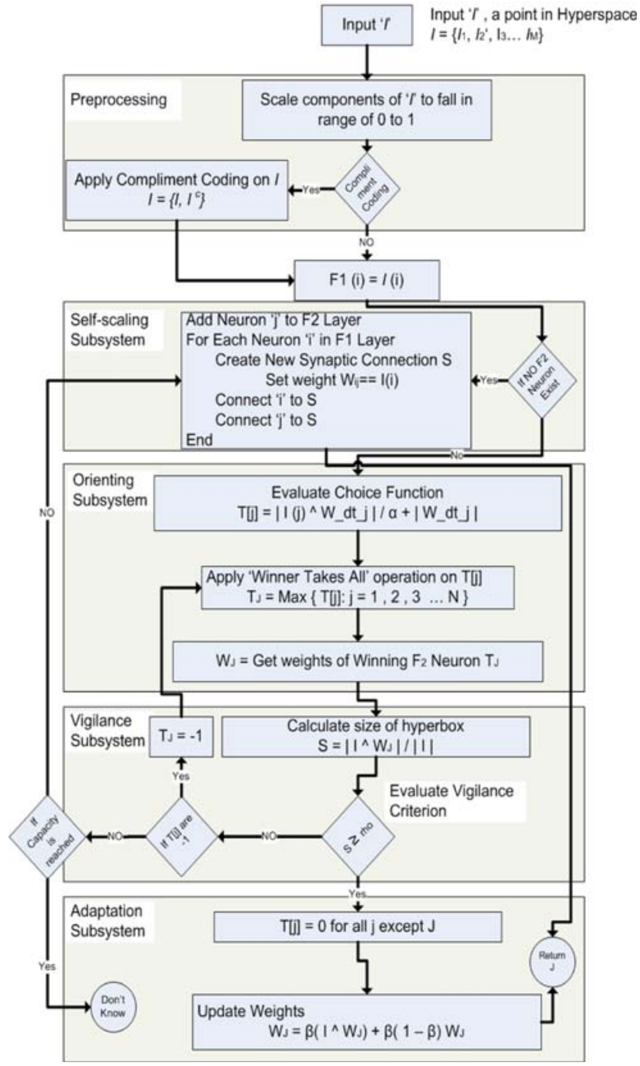

Fig. 9 Self-scaling Fuzzy ART learning dynamics

6.1 Self-scaling Fuzzy Art

In original Fuzzy Art, learning capacity of system need to be fixed in order to initialize a network. All F_2 layer neurons are said to be *uncommitted* before learning starts and as soon as a new input, which was not encountered until that point, is sensed by system an *uncommitted* F_2 layer neuron becomes *committed* to represent this category onwards. This process goes on until all patterns in input space are categorized or learning capacity is reached. As mentioned in Sect. 5.1, *don't know* response feature of Fuzzy Art systems is realized by means of fixed capacity. But, at the same time, fixed capacity puts *extensibility* limitation on Fuzzy Art which implies that system cannot learn beyond a certain number of categories. As discussed in Sect. 3.2, *extensibility* is very basic function that location estimation system should perform. We extend Fuzzy Art learning algorithm such that it can scale itself to additional input spaces when required. Fig. 9 shows self-scalable Fuzzy Art learning algorithm. This self-scaling variant preserves *don't know* response feature of original Fuzzy Art but in this scheme network capacity is externally adjustable, increment-only parameter that can be increased as a network is required to learn more categories. Main difference in original Fuzzy Art and self-scaling Fuzzy Art is in network initialization method. Self-scalable Fuzzy Art algorithm initializes a network without any F_2 layer neurons and include new F_2 neurons by means of self-scaling subsystem. This way if capacity is reached but more learning is required then a neuron is incorporated dynamically. 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 locations to achieve the *extensibility* defined by Eq. 6.

6.2 Context-awareness

In order to achieve *expansibility* in scope, a classifier must be able to learn different input spaces without confusing different classes or locations as same due to similar patterns. Moreover, a signal input space might be partitioned into several subspaces due to physical properties of signals as described in Sect. 4.3. Therefore a particular subset M_i of total access points represents a subset of all locations, referred to as visibility cluster, where M_i is always visible. This implies that each set of access points in visibility matrix is important *context* that can improve pattern recognition capability. Therefore, instead of training a separate pattern recognition module for a each visibility cluster we incorporate this contextual information into one classifier thus making it *context-aware*. By context-awareness we mean to equip a classifier with specific domain knowledge such that it can differentiate among different input spaces. This capability is realized in Fuzzy ArtMap system by defining a mechanism to embed contextual knowledge, visibility cluster in our application, into classifier. A Context Field subsystem is introduced into Fuzzy ArtMap neural network as can be seen in Fig. 10 which enables system to distinguish between different contexts thus enhancing its learning as well as generalization capability. In this scheme two types of inputs are presented to network (a) classification context code (b) input pattern. Classification context code is defined by Eq. 5 as scope of a location system. Thus context-code in our application is visibility status of different access points. This information governs the further learning and recall operations of system. Learning dynamics of context-aware Fuzzy ArtMap are similar to original one except that it maintains contextual knowledge as a special hash table. As a particular set of access points, visibility cluster, is detected by the device a context-switching happens inside the network as shown in Fig 11. This switching directs the network to perform *choice function* and *vigilance check* on a particular set of F_2 nodes which belong to this context. Once a particular context is loaded next operations of learning or recall take place as described in Sect. 5.2 associative learning of Map Field connections ensues.

The implementation of self-scaling, context-aware Fuzzy Art and Fuzzy ArtMap networks is done in *C#* programming language and it is available as open source CompoNet.

7 Experimental design

7.1 Sensor data collection

Even though ConSelFAM do not require the *Radio Map* to be created in advance for training but in order to compare its performance with other methods we collected two sets, for training and testing, of RSS patterns at each target location. Furthermore, *context-awareness* requires prior knowledge of signal *visibility* in target site, therefore we created visibility matrix, as described in Ahmad et al. (2006), of access points while collecting signal strength patterns at target locations. Experimental site is $\bigcup$ shaped 1,240 m^2 area of Computer Engineering Department building as shown in Fig. 12 where and target locations are indicated as filled circles. This site contains lecture rooms, admin offices, labs as well as people and variety of computing devices. Since such indoor environments have high degree of interference which can cause temporal disturbances in signal strength patterns. Therefore,

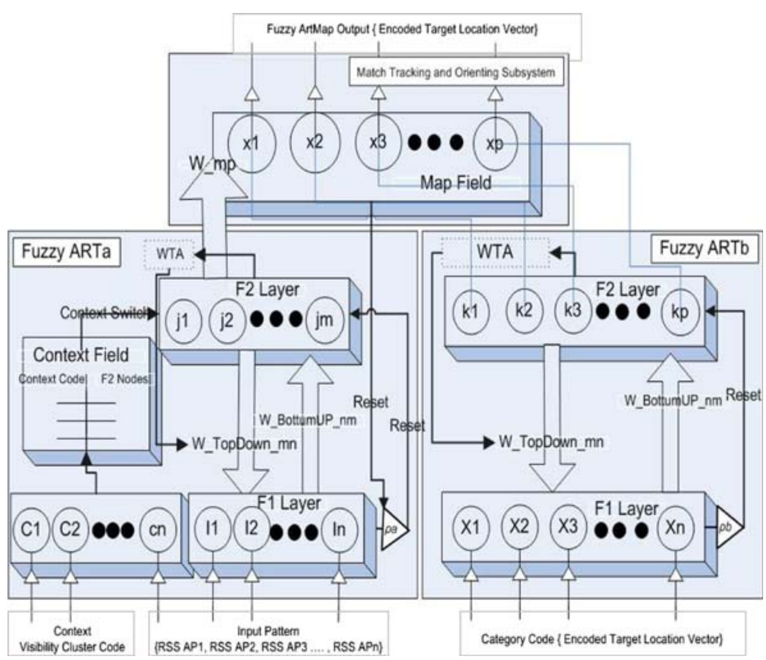

Fig. 10 Context-aware Fuzzy ArtMap network structure

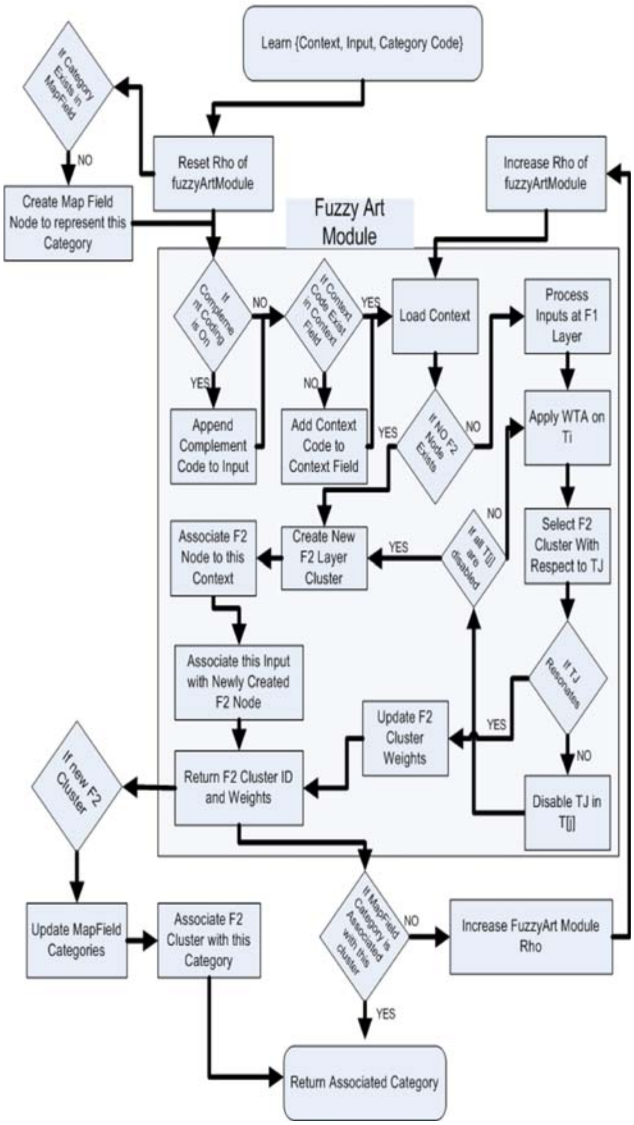

Fig. 11 ConSelFAM learning dynamics

unlike previous approaches, we did not collected sensor data in just one time. Rather, in order to enhance the representativeness of data, it was collected on a span of five days by different persons and devices. Moreover the data which were used to train classifier models belong to different days than test data. Target locations are represented as a unique identification number at application level while, during training, presented to classifiers in a binary encoded form. Pocket pc (HP iPaq 1450 model with built in WLAN card) devices were used to capture signal strength vectors.

7.2 Preprocessing

Adaptive resonance theory based learning systems suffers from category proliferation problem as characterized by

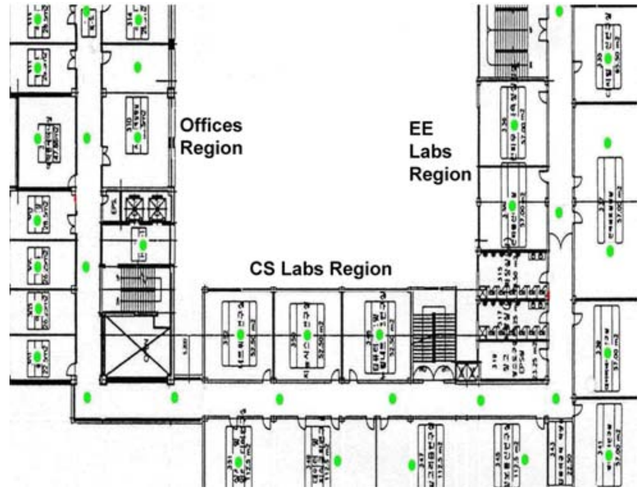

Fig. 12 Map of location system target site

Moore (1988). In order to overcome this problem a data preprocessing technique, namely Complement Coding, is proposed by Carpenter et al. (1991). Besides overcoming category proliferation problem, this technique allows network to reduce effect of presentation frequency of an input pattern as well as order of presenting input patterns to Fuzzy ArtMap, as explained in Carpenter et al. (1992). 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 to -100 dBm. A scaling normalization was applied on raw RSS input vector so that all values are transformed in range of 0–1. Same preprocessing is applied for multi layer perceptron location classifiers in both training and test phases.

7.3 Classifier training

ConSelFAM training was performed after visibility matrix creation but, for comparative analysis, original Fuzzy ArtMap based location classifier was trained *online* right at the time RSS patterns were being collected. Later same data set was used to train other models as described in Battiti et al. (2002), Ogawa et al. (2003), and Ahmad et al. (2006). 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. As shown in Eq. 3, inputs for a location classifier are modeled as predefined ordered sequence of received signal strengths of a set of access points deployed in target area. For each d dimensional rrs^d pattern, the classifier outputs an estimate of location. We measure location estimation error in two aspects.

Table 2 Fuzzy ArtMap results on training

	FAM-CC	FAM
F2 clusters	36	167
MAE	0.066	0.018
Unclassified	0	11
Miss classified	0.02	0.006
$e_r \leq 1$	0.02	0.006
$e_r \leq 2$	0.02	0.006
$e_r \leq 3$	0	0

Table 3 ContextAware Fuzzy ArtMap results

Context	F2 clusters	Epochs	Training MAE
5	20	3	0
4	27	3	0
3	36	3	0
2	29	3	0
1	26	3	0

Table 4 Multi-layer perceptron results (both modular and non-modular)

Module	Structure	Epochs	Training MAE
MLP	10-70-35	2, 000	0.021
mMLP1	5-40-8	100	0
mMLP2	4-80-8	100	0
mMLP3	4-50-25-10	100	0.0184
mMLP4	4-50-9	100	0.0047
mMLP5	4-30-15-6	100	0

(a) Absolute deviation: absolute deviation of location estimate from actual location is measured as mean absolute error (MAE)

$$|\text{MAE}| = \frac{1}{N}\sum_{i=1}^{N}\left|l_i - \hat{l}_i\right|$$

where N is total number of training or test patterns, l_i is location estimate of ith pattern and $\hat{l}_i$ is actual location.
(b) Relative deviation: this error of location estimate, denoted as e_r, is measured relative to some thresh hold value denoted as Γ . For N number of training or test patterns. Since n target locations are assigned IDs in a sequence from 1 n as they appear next to each other, relative error reflects severity of error in estimation. Which means that an estimate is less severe if it is relatively closer to actual location than the one which is farther away.

$$e_r = \frac{\sum_{i=1}^{N}\left[\left|l_i - \hat{l}_i\right| \leq \Gamma\right]}{N}$$

where thresh hold $\Gamma_{i=1}^{3}$ produces three severity of error values averaged over all location.

7.3.1 *Fuzzy ArtMap*

Table 2 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 without compliment coding is denoted as FAM.

Complement coding controls category proliferation problem and classifies all RSS vectors successfully but classification performance is slightly affected. Training Fuzzy ArtMap without complement coding results in higher accuracy but increases indecisiveness, *don't know* response in terms of unclassified RSS patterns, as well. During testing phase, This problem aggravated and FAM could not classify 389 patterns.

7.3.2 *ConSelFAM*

For context-aware, self-scalable Fuzzy ArtMap experiments we employed visibility matrix which was generated in data collection phase. Each tuple of this matrix represents a cluster of locations where a subset of access points are always visible as described in Sect. 4.3. Thus each cluster corresponds to separate classification *context*. Table 3 presents training results of for each context of classification.

Although ConSelFAM requires viability matrix to be known before learning starts, it requires less memory resources in terms of F_2 layer clusters than Fuzzy ArtMap. More importantly it does not require Radio Map creation and converges to optimal error in just three epochs, contrary to *offline* training based methods, which takes most of development time in previous approaches.

7.3.3 *Multi layer perceptron*

Multi layer perceptron (MLP) network was trained using Levenberg Marquardt algorithm (Hagan and Menhaj 1994) with one hidden layer of 70 neurons and one output layer of 35 neurons. It took 2,000 epochs to achieve 0.021 Mean Absolute Error. Network structure is denoted as *input layer-hidden layer-output layer*. Estimation performance of non-modular MLP network as well as visibility matrix based modular, indicated as mMLPx, on training Radio Map is given in Table 4.

7.3.4 *Learning vector quantization*

Learning vector quantization (LVQ) network was trained with $lvq1$ algorithm presented in Kohonen (1995). Non-modular LVQ network structure contained 100 neurons at competitive layer and 35 neurons at linear transformation

Table 5 Modular learning vector quantization results

Module	Structure	Epochs	Training MAE
LVQ	10-100-35	50	0.018
mLVQ1	5-30-8	100	0.03
mLVQ2	4-30-8	200	0.009
mLVQ3	4-40-10	100	0.027
mLVQ4	4-40-9	200	0.057
mLVQ5	4-40-6	100	0.048

Table 6 Comparative results on training Radio Map

Method	MAE	$e_r \leq 1$ (%)	$e_r \leq 2$ (%)	$e_r \leq 3$ (%)
FAM-CC	0.06	74	82	91
FAM	0.02	99.55	99.55	100
ConSelFAM	0	–	–	–
MLP	0.021	75	79	91
mMLP	0.002	–	–	–
LVQ	0.018	56	69	80
mLVQ	0.0342	–	–	–

Table 7 Comparison of prerequisites of different methods

Classifier	Radio Map	Visibility matrix
FAM	No	No
ConSelFAM	No	Yes
MLP	Yes	No
mMLP	Yes	Yes
LVQ	Yes	No
mLVQ	Yes	Yes

layer each corresponding to a particular location. This network achieved 0.018 mean absolute error in 50 epochs. Performance of non-modular LVQ network as well as modular LVQ classifiers, indicated as mLVQx, on training Radio Map is given in Table 5.

Table 6 presents summarized results of all methods. Modular classifier approach improves overall location accuracy but depends on visibility matrix to be established as prerequisite. Contrary to other methods Fuzzy ArtMap and ConSelFAM system takes only three epochs to achieve 0 MAE. Table 7 presents a comparison of prerequisites that each these methods depends on before learning.

7.4 Test results

Here we present comparative testing results of different classifiers using same test Radio Map. Both absolute and relative error measurements for each classifier are given in the following.

Table 8 shows performance of ConSelFAM for each visibility cluster or *context*. Tables 9 and 10 present same information for modular MLP and modular LVQ methods respectively. Notice that relative error performance of ConSelFAM is better than both mMLP and mLVQ which means that estimated location deviation from actual location is mostly limited to neighboring locations.

Table 8 ConSelFAM results

Context	Test MAE	$e_r \leq 1$ (%)	$e_r \leq 2$ (%)	$e_r \leq 3$ (%)
1	0.85	85	90	92
2	0.79	83	100	100
3	0.56	99	100	100
4	1	95	99	100
5	0.42	100	100	100

Table 9 Modular approach results: modular MLP

Module	Test MAE	$e_r \leq 1$ (%)	$e_r \leq 2$ (%)	$e_r \leq 3$ (%)
mMLP1	0.4140	85	90	91
mMLP2	0.7286	91	92	94
mMLP3	0.4957	81	95	96
mMLP4	0.556	91	92	99
mMLP5	0.9806	68	88	88

Table 10 Modular approach results: modular LVQ

Module	Test MAE	$e_r \leq 1$ (%)	$e_r \leq 2$	$e_r \leq 3$ (%)
mLVQ1	0.5571	87	91	91
mLVQ2	0.7214	91	91	92
mLVQ3	0.9760	66	92	93
mLVQ4	0.4087	93	95	95
mLVQ5	1.25	61	78	94

Summarized location estimation results of non-modular, modular and ConSelFAM are given in Table 11. MAE performance comparison is also shown in Fig. 13 and relative error performance in Fig 14. Modular MLP achieved best absolute error (MAE) performance. ConSelFAM showed best relative error performance which is consistent in training and test phases. Although LVQ benefits most significantly from *visibility* based modularity, overall performance of this method was lesser than other methods.

Table 11 Summarized comparative results on test Radio Maps

Method	MAE	$e_r \leq 1$ (%)	$e_r \leq 2$ (%)	$e_r \leq 3$ (%)
FAM-CC	1.06	75	81	92
ConSelFAM	0.72	92	97	98
MLP	1.03	75	79	91
mMLP	0.63	83	91	93
LVQ	2.60	55	69	80
mLVQ	0.79	79	89	93

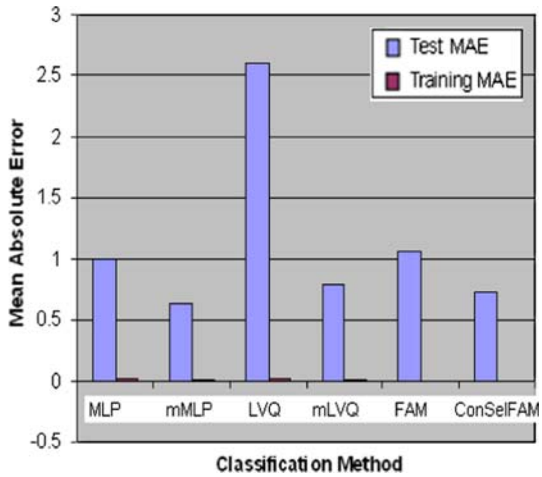

Fig. 13 Summarized comparative results of each method: mean absolute error

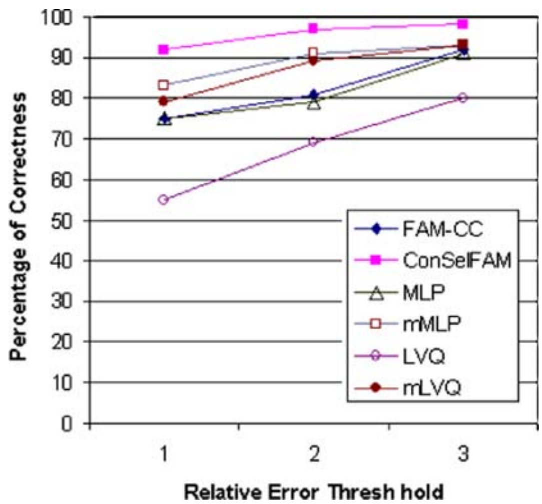

Fig. 14 Summarized comparative results of each method: relative estimation error

8 Conclusions and future work

On the fly extension in *scope* of pattern classification problems especially location systems is a desirable feature but it requires self-scalable classifier. Nevertheless only *self-scalability* can not help expand a classifier which means to learn new input spaces which are defined by different set of input features. In case of location systems, this issue is refereed to as increasing *range* of the system. Visibility matrix based approaches incorporate modular classifiers to achieve *extensibility* as well as *expansibility*. Furthermore, it is already known that visibility matrix of radio signals contains important information which can help improve classification performance.

Although modular classifier approach provides high accuracy and shorter training time still it requires both creation of Radio Map as well as visibility matrix of signal sources. ConSelFAM classifier design is inspired by modular classification but the only prior information it requires for learning is visibility matrix. It incorporate this prior information about visibility as classification *context*. A rapid development of classification systems can be realized driven by *online*, *incremental*,*self-scaling* and *context-aware* learning properties of ConSelFAM. *Extensibility* and *expansibility* are realized by introducing *Self-scaling* subsystem in Fuzzy Art and *Context Field* subsystem in Fuzzy ArtMap neural networks.

ConSelFAM is suitable for several classification problems which require context-awareness and scalability. An RSS based location system in real environment is developed to confirm the applicability of ConSelFAM pattern classification system. We compared location estimation performance with other classification methods such as multi layer perceptron, learning vector quantization and modular variants. On the basis of extensive experimental results we conclude that ConSelFAM provides competitive location estimation accuracy as well as leverages novel features which can not be realized using previous methods such as (1) *rapid system development and reconstruction* (2) *flexible and dynamic expansion of system*. In future we shall introduce enhancements to this system in order to automatically learn different classification *context*s such that no prior information about input spaces, e.g. visibility matrix, is required before learning.

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References

Ahmad U (2007) CompoNet: programmatically embedding neural networks into AI applications as software components. 19th IEEE international conference on tools with artificial intelligence, October 29–31, Patras, Greec

Ahmad U et al (2006) Modular multilayer perceptron for WLAN based localization. IEEE international joint conference on neural networks. Vancouver, Canada

Andrew et al. (2002) Using wireless ethernet for localization, IEEE/RSJ International Conference on Intelligent Robots and Systems

Bahl P et al (2000) RADAR: an in-building RF-based user location and tracking system. In: IEEE INFOCOM 2000, pp 775–784

Battiti R et al (2002) Neural network model for intelligent networks: deriving the location from signal patterns, the first annual symposium on autonomous intelligent networks and systems

Carpenter GA, Grossberg S, Rosen DB (1991) Fuzzy ART: fast stable learning and categorization of analog patterns by an adaptive resonance system. Neural Netw 4:759–771

Carpenter GA, Grossberg S et al (1992) Fuzzy ARTMAP: a neural network architecture for incremental supervised learning of analog multidimensional maps. IEEE Trans Neural Netw 3:698–713

CompoNet, Componentization of Neural Networks, http://sourceforge.net/projects/componet/
Hagan MT, Menhaj M (1994) Training feedforward networks with the Marquardt algorithm. IEEE Trans Neural Netw 5(6):989–993
Iqbal M et al (2005) Reflective middleware for location-aware application adaptation. Computational science and its applications (LNCS), pp 1045–1054
John K et al (2003) Minimizing calibration effort for an indoor 802.11 device location measurement system. Technical Report, MSR-TR-2003-82 Microsoft Research, November 13
Kohonen T (1995) Learning vector quantization, The handbook of brain theory and neural networks. MIT Press, Cambridge, pp 537–540
LaMarca A et al (2005) Place Lab: device positioning using radio beacons in the wild. Pervasive 3468:116–133
Li B et al (2005) Method for yielding a database of location fingerprints in WLAN. IEE Proc Commun 152(5):580–586
Moore B (1988) ART and pattern clustering. In: Proceedings of the 1988 connectionist models summer school, pp 174–183
Nasir U et al (2005) On building a reflective middleware service for location-awareness. In: Proceedings of the 11th IEEE international conference on embedded and real-time computing systems and applications, pp 439–442
Ogawa T, Yoshino S, Shimizu M (2003) Location determination method for wireless systems based on learning vector quantization. NTT Network Innovation Laboratories, vol 1, no. 9, Japan
Pehlavan K et al (2002) Indoor geolocation science and technology. IEEE Commun Mag 40(2):112–118
Serrano-Gotarredona MT, Linares-Berranco B, Andreaou AG (2005) Adaptive resonance theory microchips-circuit design techniques, 1st edn. Springer, Heidelberg
Smailagic A et al (2001) Location sensing and privacy in a context aware computing environment. Pervasive Comput. IEEE Wireless Communications, October 2002, vol 9(5). pp 10–17
Xuanlong N et al (2005) A kernel-based learning approach to AdHoc sensor network localization. ACM Trans Sensor Netw (TOSN) 1(1):134–152. ISSN:1550-4859