Active RFID Reader clustering and neural networks for indoor positioning

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***Abstract* – Active RFID systems can be used as the foundations to deploy Indoor Real Time Location Systems (RTLS) and value-added context-aware and ambient intelligence services. In this work the feasibility of applying Clustering techniques and neural networks within an Active RFID system to develop an indoor location service is explained and evaluated. In previous works, a fingerprint technique and radiomap (collection of Received Signal Strength (RSS) measurements from the tags's beacons at the network of Readers) have been used to train a neural network and after that, to infer the tag position. In this research work we improve the accuracy of the location engine by means of the Cluster concept where the total area is divided in several zones which are associated to different set of Readers called Reader Cluster. Each Reader Cluster has associated a trained Multi-Layer Perceptron (MLP) which is specialized in estimating the target locations within that space region. By simulation, it is shown that the clustering approach improves the system accuracy, specializing several MLP in estimating target locations in bounded regions, while keeping the number of Readers and the size of the Radiomap (number of RSS training samples).**

I. INTRODUCTION

Active RFID can be used as a cost-effective and enabling technology of indoor positioning services. We propose using Active RFID at 2,4 GHz and a processing engine based on clusters of neural networks to infer the tag position. The only assumption is that the RFID Readers can measure the Received Signal Strength (RSS) from a tag beacon. Then a set of Readers, called cluster of Readers, are specialiced in positioning on a particular area of the target environment. The collection of RSS measurements from a cluster of Reader is processed by a particular neural network that estimates the tag's position. Our proposal can be used with any Active RFID system available on the market that complies with the previous assumption.

A positioning system calculates the position by means of measuring a signal generated between a tag (attached to a person or a mobile object) and the network of Readers; second, a location algorithm processes the gathered signals to estimate the position (x,y). There are several kind of measurements from a RF signal which are useful for a location algorithm: *Angle of Arrival* (AoA), *Time of Arrival* (ToA) y *Received Signal Strength* (RSS) [1]. All of them need a model of the wireless channel to be used.

The problem is that the wireless channel at 2,4GHz in indoor environments is rather complex to characterize and model due to its stochastic nature. There are challenging factors to take into account such as the common Non Line of Sight communication link between the tags and Reader because of the building geometry, obstacles like walls, furniture or even mobile objects or people; also the multipath and fading effects on the RF signal, etc. Therefore it is well known that the RSS measure does not follow an ideal deterministic model and its real behavior is environment dependant.

Positioning algorithms could be classified into distance based or pattern recognition problem. A distance based algorithm determines the distances between the tag and three or more reference points and locates tags by triangulation. Due to the random variability of an indoor wireless channel, a distance based algorithm suffers from high errors and it is not advisable for indoor positioning.

A positioning algorithm based on pattern recognition employs the gathered signals from known (x,y) points from a building (called the radiomap), like the Received Signal Strength, which conforms a particular pattern. This technique is called the fingerprint method based on RSS and it requires an intensive measurement campaign, called calibration phase, in order to build the radiomap of the target environment.

Once we have the radiomap database, during the online phase the matching algorithm compares the characteristics of the observed signal with the existing fingerprints in the radio map and chooses the reference point that matches best with the observed data and estimates the tags current position. The main advantage of the fingerprint method is that the radiomap characterizes and takes into account the random features and complexity of the indoor wireless channel. The main drawback of the fingerprint method is that it needs a big amount of data collection and manual labor for creating the radiomap. The positioning accuracy normally depends on the number of samples of the dataset.

In this paper we explain a novel clustering technique for pattern recognition and how to apply Multilayer Perceptrons as the positioning engine for a cluster of Readers. Moreover, by means of simulation we benchmark the mean error and accuracy between a one cluster of Reader and few clusters scenario within a typical indoor environment of $576m^2$.

The rest of the paper has the following content: Section II describes related works. Section III explains the indoor channel and physical model. In section IV the performance metrics to evaluate the Active RFID positioning system are defined. Then the basis of a multilayer perceptron positioning engine is presented. In section VI the proposed clustering technique is explained. Then it is justified the simulation assumptions and the working methodology. In section VIII the results are discussed and, finally section IX shows the conclusions.

II. RELATED WORK

There are several proposals for positioning pattern matching algorithms based on RSS fingerprint: LANDMARC [2] is an indoor Active RFID system that uses a network of Readers with a grid of reference tags (landmarks) that use the K-Nearest Neighbors (KNN) algorithm. It is the most basic algorithm which compares an observed RSS vector with all available fingerprints in the reference radiomap and finds a reference point from the radiomap with the smallest Euclidean distance. EKAHAU [3] is a commercial Active RFID system based on WiFi standard that uses probabilistic methods based on bayesian networks.

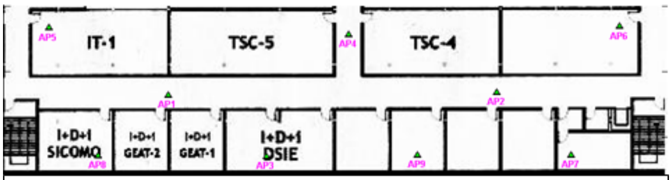

FIGURE 1 – FLOOR PLAN OF THE TARGET ENVIRONMET ($576\,m^2$) AT THE POLYTECHNIC UNIVERSITY OF CARTAGENA. 9 ACCESS POINT (AP1-AP9)

Aeroscout [4] is another commercial Active RFID system, based on WiFi with RTLS services, which employs the RSS fingerprint method.

Battiti *et. al.* [5] was the first proposal to employ a neural network for location estimation using an only cluster of WiFi Access Points and mobile devices WiFi-enable in an indoor environment. In [6] and [7] are used an only cluster of WiFi Access Points and one neural network for indoor location estimation.

In [8] we studied and evaluated a Multilayer Perceptron (MLP) neural network as the positioning engine; it is analyzed the influence of the number of deployed Readers on the mean error and precision but related to a single cluster of Readers and one neural network.

III. Channel and Environment Model

In Fig.1 the 2D layout of the simulated environment is depicted. It is an area of *576m²* of teaching labs from the Polytechnic University of Cartagena composed of a main corridor and several rooms at both sides of the corridor. In [9] an intensive measurement campaign at 2,4 GHz in our target environment was described and it was shown that a path-loss shadowing model that takes into account signal attenuation due to walls and obstacles [10] characterizes the wireless channel behavior with high precision. In equation (1) the main expresion of this model is represented, where L(d) is the signal attenuation (expressed in decibels), at a distance d between the emitter and the receiver.

$$L(d) = L_0 + \sum L_{obs} + 10\alpha \ \log_{10}(d) + X \qquad (1)$$

IV. Metrics for Positioning Performance Characterization

For the performance evaluation of the location service we define three figures of merit: Mean Absolute Error, Root Mean Square Error, and Precision.

Mean Absolute Error (MAE) is defined as the mean Euclidean Distance between the true (X, Y) position and the estimated (X´, Y´) position taking into account a collection of points test. MAE is calculated once the MLP has been trained.

Root Mean Square Error (RMSE) is related to the variance of the error. For example, if a high RMSE is achieved but with a low MAE, it is because there are areas where the positioning engine has a poor precision than other areas where the system gets better precision.

Precision (or Accuracy) is related to the cumulative distribution function of the random variable error. If the positioning engine gets a precision of E meters with P probability, it means that any estimated (X´, Y´) position will be within a disc of center (X, Y) and radius E with probability P.

V. Positioning Estimation Engine

Artificial neural networks are self-learning techniques which, starting from an environment radiomap, are effective for the localization of problems, since they act as universal interpolators. One of their main characteristics is that no prior knowledge about environment geometry (position of rooms, walls and obstacles) is needed. Knowledge about propagation channel and Reader positions is not necessary either. In our system, different Readers use the RSS measurements from a given tag to determine its location within the work area.

The Multilayer Perceptron is a kind of artificial neural network very useful to solve function approximation problems. This network can achieve a good interpolation and is able to extrapolate values of the function for function inputs never shown before.

This property is called generalization ability and it is what makes these mathematical tools very useful.

Therefore, it starts from the previous knowledge of certain points of the function one wants to interpolate. In this case, from the radiomap of the environment, which provides the relationship between the RSS measured by different Readers and the location (x,y) from where the beacons were sent.

The architecture of the MLP is made of input layers, hidden layers and output layer. Each layer is made of units or processing neurons, where the outputs from the previous layer are multiplied by its respective weights *wij* and added and then fed to a transfer function. In short, it is a network of internal weights *w* which, given the fact that they are appropriately chosen, is able to approximate the function that relates the inputs of the input layer with the outputs of the output layer. The weights are computed during the training stage (offline phase). In that stage, a set of samples whose outputs are known are fed to the network so that the network can learn the relationships. By an iterative algorithm, the neuronal weights of each layer are evolving progessively and minimizing an error function.

After the training, the network will be able to estimate the position (x,y), with a given error, for any input vector (RSS1, RSS2, RSS3,...,RSSn), never previously seen in the training stage. The resulting error is called test error or generalization error.

In our case, for the training and testing of the neural network, the Matlab Neural Network Toolbox has been used.

V. Clusters of Readers

In our system, a cluster is defined as a set of Readers which are associated with a particular area of the target environment (called a region space); i.e. a tag beacon placed in a region space will be matched with a particular cluster of Readers and the related MLP will be used to infer its position. Therefore the MLP of a cluster of Readers will be trained with radiomap points that belong to the corresponding region space. A collection of clusters of Readers must cover the whole area.

We seek the approach *divide and conquer;* instead of the whole area we divide into regions where the particular RSS pattern can be easily distinguised and, therefore, the MLP is able to better learn and achieve a high precision location estimation at this region.

In our first approach, we define manually the clusters of Readers and the rough area of the space region. However it is needed a method to classified a point (where a tag beacon is transmitted) into a cluster of Readers in order to choose the proper MLP to estimate the position. Due to the complex propagation effects, there are (x,y) points difficult to match to a cluster and there are edge points that can belong to several clusters of Readers.

Therefore a classification phase is needed. In our system, the KNN algorithm was used. To use this algorithm is necessary to add information about clustering in the Radiomap during the offline phase. Three steps were followed during the Radiomap generation process. First of all, we fixed the set of Readers to define the clusters we want to. Second, samples in which the bigger RSS measurements correspond to a cluster generated previously are associated to that cluster (or class). Thirdly, the samples which are not associated to any cluster, will be classified by means of the KNN algorithm, compared with the samples that were classiffied. This way, every sample is connected to at least one cluster, and there are no regions where the system cannot offer location service. This methodoly is explained in greater detail in the next sections.

VI. ASSUMPTIONS AND WORKING METHODOLOGY

4.1 Environment Characterization and Physical Parameters

A simulator tool with Matlab that employs its Neural Tool Box has been developed. This tool allows to characterize the digital map of a target scenario with enough detail: description of floors, rooms, walls, windows, doors, corridors, and so on.

In addition the simulator has a wireless channel module which accuracy depends on the propagation model. In our case, we use thet channel model from eq.(1) and it is enough to define the walls that separate each room, since our model does not take into account materials, but the number of walls traversed by the signal.

Second, there is a physical layer module where the transmission power of the tag and its antenna gain are configured. Moreover, the sensitivity and gain of the Readers are configured. In our simulations it was fixed a transmission power of 10 dBm, and a sensitivity of -110dBm. We assume that the antennas are isotropic. The gains of the antennas of Readers and tags are fixed to 5dBi and 0dBi respectively.

Finally, the Readers are positioned on the map. Nine Readers were positioned, avoiding shadow areas and selecting positions that provide good results as shown in Figure 1. It must be remarked that it is assumed that good coverage is available in all the area, otherwise it would affect negatively to the system, but these effects are out of the scope of the present work.

4.2 Selecting Channel Propagation Model

Several propagation models are available to be used: path-loss, free-space, path-loss doble slope, partition loss, etc. We have selected a path loss model with the parameters estimated in [9] for our environment.

4.3 Building the Radiomap

A 1.6m x 0.8m grid is set up. The coordinate system origin is stated in the left upper corner. All points have a prefixed height that simulates the average height of a tag carried by users. It was fixed to 1.5m. Once the physical layer has been modeled, the Radiomap is generated by the Simulator Tool; for each point of the grid is calculated and stored the point coordinates and the RSS vectors measured by the deployed Readers. The total size of the Radiomap is 335 samples.

4.4 Clustering and Associating Regions

In order to apply the clustering technique, the Radiomap needs to contain information about to what cluster belongs each RSS sample to. To do this the three steps mentioned above were followed. Once this is done, we get the datasets with the RSS samples which will be used in the training phase of the MLP associated to each cluster of Reader. From this Radiomap, the new testing samples will be classified by the KNN algorithm during the online phase before processing the corresponding MLP and estimating the new position.

4.5 Selecting and Trainging Neural Networks (MLP)

The next step is to select an architecture for the neural networks that will be trained to approximate the function that matches the RSS vectors and target position (X,Y). We needed to train as many MLPs as the number of clusters of Reader. The selected architecture was the same for all the neural networks:16-4-2. This architecture is powerful enough and provided good results in previous works [8]. The proposed architecture is made of two hidden layers with 16 and 4 neurons respectively and hyperbolic tangent as transfer function. The output layer is made of 2 neurons (estimated X‘ and Y‘) , which transfer function is the identity so as not to limit the output range. In the input layer we have as many units as Readers associated to cluster which is estimating the position. To train each MLP, sub-datasets were created from the Radiomap collecting the samples that belong to each cluster. To get a minimal generalization error we have used the early stopping technique, which uses validation samples (usually a 30% of the total set) to control the overfitting effect. For this reason, each sub-dataset was divided in two sub-sets: training set (80%) and validation set (30%). The training algorithm selects the weights that minimize the risk function, which is defined as the MSE of the output (X‘,Y‘) with respect to the real position (X,Y). The backpropagation training algorithm used has been Levenberg Marquardt which provides very good results [10]. Finally, the samples have been normalized and denormalized in a range [-1,1] with a pre-processing and post-processing since it has been shown that it improves the generalization ability of the network after the training.

4.6 Testing and getting results

In our study, we employ our simulation tool for creating a test set of 125 samples. From this test set, statistical parameters such us Mean Absolute error and Precision are calculated, offering performance information from the global system. Test samples are located at relevant points of the scenario where it is assumed that the positioning system should achieve a bounded an reduced error.

VII. RESULTS AND ANALYSIS

In this section we evaluate the error and precision trend when using clusters of Reader. We start with an only cluster of 9 Readers as depicted in figure 1; a single MLP processed the nine RSS measures from the Readers to estimate a tag location. It is achieved a Mean Absolute Error of 0,74 meters and a precision of 1,49 meters with a probability of the 90%. So as to enhance the system, we modified the location engine by introducing the cluster of Readers concept.

A three Reader clusters scenario is evaluated where the cluster 1 is formed by Access Points AP1, AP3, AP4, AP5, and AP8. Cluster 2 is formed by Access Points AP2, AP4, AP6, AP7, and AP9. Finally cluster 3 is set up by Access Points AP1, AP2, AP3, AP4, and AP9. At this scenario, each cluster has 5 Access Points, therefore the related multilayer perceptron has 5 inputs of the corresponding Access Points RSS measurements. It has to be remarked that the same AP is able to belong to a few clusters; the key is that the conjuntion of several Access Points measures a particular RSS pattern. When it is increased the number of clusters to three, the mean error is reduced to 0,7 meters with a precision minor to a meter with a probability of the 90%.

Also a scenario of seven Reader Clusters is evaluated. Each cluster is made of three Readers.

As it is summarized in Table 1 the trend is to decrease the mean error and the precision estimation when increasing the amount of clusters but using the same amount of deployed Readers and its gathered RSS measurements.

In figure 2 is depicted the cumulative density function of the error for 1 cluster, 3 clusters, and 7 clusterss scenarios. It is shown that the 3 and 7 cluster of Readers scenarios convergers faster than the 1 cluster scenario; due to each MLP is specialized in a smaller area and it easier to recognize its RSS pattern.

VII. CONCLUSION

In this paper, an indoor location system based on Active RFID using neural networks is modified to improve the estimated users' location. We analyzed the clustering technique in order to enhance the system precision. The results show that, keeping the number of Readers deployed, and the size of the Radiomap generated for an initial non-clustering system, the precision (for 90% test samples) of the system was doubled, being 1.49m for the non-clustering system and 0.78m for the clustering system.

Our future research work will be focused on evaluating other cluster configuration such us different number of Readers per cluster, and the minimum amount of RSS samples needed to train.

TABLE 1 – PERFORMANCE EVALUATION OF DIFFERENT CLUSTER OS READERS SCENARIOS

CONFIGURATION	MAE (m)	PRECISION (90%) (m)
1 CLUSTER / 9AP C1(AP: 1-9)	0.74	1.49
3 CLUSTER (C1, C2, C3) /5AP C1(AP: 1,3,4,5,8) C2(AP: 2,4,6,7,9) C3(AP: 1,2,3,4,9)	0.47	0.96
7 CLUSTER (C1-C7) / 3AP C1 (AP: 1,5,8), C2 (AP: 3,4,9) C3 (AP: 2,6,7), C4 (AP: 1,4,5) C5(AP: 1,3,8), C6(AP: 2,4,6) C7 (AP: 2,7,9)	0.38	0.78

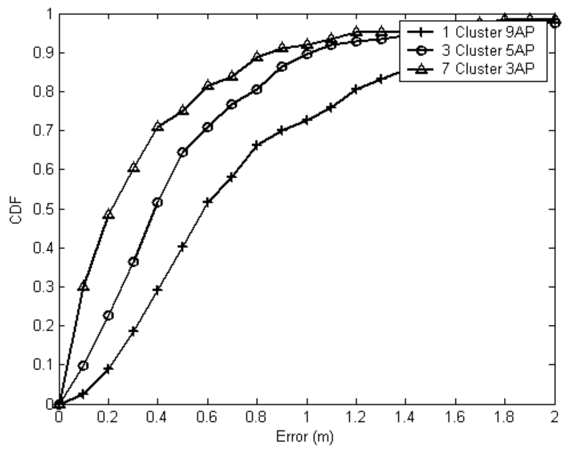

FIGURE 2 – ERROR (EUCLIDEAN DISTANCE) VS SEVERAL CLUSTER CONFIGURATIONS

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