Local Positioning System Based on Artificial Neural Networks

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Abstract. This work describes a complete indoor location system, from its creation, development and deployment. This location system is a capable way of retrieving the position of wireless devices using a simple software solution, no additional hardware is necessary. The positioning engine uses artificial neural networks (ANN) to describe the behaviour of a specific indoor propagation channel. The training of the ANN is assured using a slight variation of the radio frequency fingerprinting technique. Results show that the location system has high accuracy with an average error below two meters.

Keywords: Location, positioning, wifi, wireless, artificial neural networks, backpropagation.

1 Introduction

The location paradigm began years ago when systems like Decca, OMEGA, Alpha and Loran C were developed. Loran C was developed by the United States Navy during World War II. This system main objective was to help US and UK military ships navigation. Several radio beacon towers were deployed along sea coast. Using these radio beacons and their known location, the ships were capable of locating themselves. This was an important tactical advantage and it is still used today, although some modifications were made. Current location systems are more technical advanced, but almost all of them use the same principle of Loran – radio triangulation. This is the case of the well known Global Positioning System (GPS). GPS uses geo-stationary satellites as radio beacons, and provides almost a global coverage real time location system.

1.1 Current State of the Art

Satellite navigation systems, like North American GPS or the future European Galileo, are mainly focused on providing position for outdoor environments. These systems provide a global coverage with a three to five meters average error available for public usage. Although satellite navigation systems have good accuracy they are not suitable to indoor environments where a good clear view to the sky is not available [1]. Other systems are mainly focused on indoor location environments. Systems like Active-Bat [2] developed by AT&T and Cricket [3] use ultrasound time of flight measurements, others like Active-Badge [4] use small infrared tags that

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provide symbolic information, like a name of a room. Infrared has limited range hence it has not become very popular. PinPoint 3D [5] uses radio frequency lateration to provide an accuracy of three meters and requires a special developed infrastructure. SpotON [6] project developed a 3D location system using RFID tags. SmartFloor [7] uses a sensor grid installed on a floor and the accuracy depends of the sensor spacing distance. These systems require a special infrastructure that needs to be deployed.

Implementing a location system using WLAN communication infrastructure has been for some time target of intensive research. Various approaches have been proposed, mostly based on the received signal strength. One of the first systems to be introduced was RADAR [8], developed by Microsoft Research Group. RADAR uses received radio strength to map the user current location and it uses an empirical model (K-Nearest Neighbor) as well as a simple signal propagation model. The accuracy of this system is about four meters for 75% of the time and it uses special developed access points.

R. Battiti et al. [9] describe a system capable of deriving the location using neural networks. In this work it is described the training phase, always present in a RF fingerprinting based system, and the neural network architecture used. Despite the accuracy (about 2.3 meters), the results are only compared to test data and information about software developed, radio strength reading method and system architecture is inexistent. M. D. Rodriguez et al. [10] also describe a location system for hospital services based on a neural network. In this work the SNR is used to calculate the user position and all the processing is done in the wireless client. Their results show an error below 4 meters 90% of the time. Bayesian models are also used to calculate a wireless device position, D. Madigan et al. [11] propose a system with an accuracy of four meters. A. Haeberlen et al. [12] describe a probabilistic approach and their location system provides symbolic information, like the office number inside a building.

1.2 Indoor Location System

Indoor location can be important when one thinks of services that can be applied in huge buildings, like shopping centers, office buildings, museums, warehouses, universities, etc. Imagine a warehouse equipped with a location system, one can know exactly the position of a package allowing an increase in the company's efficiency. Think of a museum where tourists can receive in their cell phones important information depending on the place they are or the art work they are seeing. Imagine receiving on your cell phone great price discounts when you walk along a store in your favorite shopping center. This one might not be so great, but the applications and advantages of an accurate and reliable indoor location system are tremendous. This is the aim of this work, to develop a low cost, reliable and accurate location system using today's technology.

2 Technical Description

The indoor location system was developed taking in account two different scenarios. The first, named macro-location, is a large scale implementation and provides symbolic information, like the name of room. This information is retrieved from the access point where the client is associated. The second scenario, named micro-location, gives the position of the wireless client by using spatial coordinates with high accuracy. The macro-location system is a simple solution to retrieve a client location in a symbolic way. Since micro-location solution provides the exact location, with spatial coordinates it was the target of a much more intense research and development. The two systems complement each other.

2.1 Macro-location

In a typical office wireless LAN there are several access points distributed in a defined way in order to offer good signal reception and sufficient bandwidth. Knowing which client is associated with which access point plays a critical role in the macro-location scenario. In fact, the main objective of the macro-location is to retrieve the location of the mobile client using the access point coverage. Despite the existence of several ways of knowing in which access point the client is associated some disadvantages can be found in each one of them. There is the need for a general solution that can be easily deployed to the existing variety of vendors and manufacturers.

The final solution is based on the remote syslog [13] capability of most access points in the market. Remote syslog allows a device to send important messages to a central server that gathers all the data.

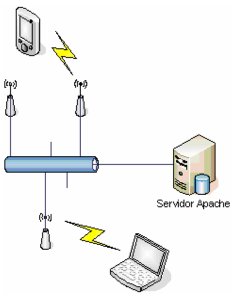

Fig. 1. Macro - location system architecture

With this method when a client associates/disassociates, the access point informs the server of this event by sending a syslog packet. The server has specific developed software in order to treat these messages and collect them into a database. Then it is possible to search for the location of a client or to see which clients are in an area.

2.2 Micro-location

The micro-location system allows the location of a WiFi device in an indoor scenario with an average error below two meters. The system uses a location method, called radio frequency fingerprinting. This technique requires profiling the entire location scenario before the location itself takes place. At each location or point, several measurements are taken and stored. This phase is often denominated calibration. Due to propagation effects, like fading, several measurements are taken to minimize this effect. After profiling the entire area, typically one building with multiple floors, the location system is ready to answer location requests. After the calibration phase is finished there are several RSSI vectors associated to each spatial coordinate. In a typical office floor, the adequate number of RSSI vectors was found to be between 10 and 20. Considering that *n* base stations exist, then the signal strength vector (*R*) is defined as:

$$R_i = (a_{i1}, a_{i2}, ..a_{in}). \tag{1}$$

Where a_{ij} corresponds to the measurement collected from point *i* from base station *j*. The complete RF fingerprinting matrix (*M*) is given by combining spatial information with the RSSI vector:

$$M = \{(x_i, y_i, R_i)\}, i = 1..m. \tag{2}$$

The RSSI vectors become the input of an artificial neural network (ANN)[14]. The number of neurons and of hidden layers of the ANN depends of the application and the size of the input data. The ANN inputs are the RSSI values measured by the wireless client and the output are the spatial coordinates X and Y. In scenarios where a third coordinate is necessary, like multiple floor buildings, the ANN output number increases to three. The multilayer perceptron architecture combined with the nonlinearity of the input and hidden layer activation functions, which are based on the hyperbolic tangent sigmoid function provided the generalization and adaptability needed for a proper and accurate location system.

The ANN training uses the backpropagation algorithm [4] based on a batch approach. The algorithm modifies the weights of each of the neurons to minimize the median square error between the output and the real values. The output layer activation function is linear, since the outputs are spatial coordinates. The number of outputs is typically two, since a two-dimensional plane was used to describe the possible locations of a device in an office floor.

The training process of a neural network must be adequate so that problems like over-fitting should not arise. Over-fitting occurs when too much training is applied to the ANN. This means that the ANN will be fitted exactly to the training data, therefore losing all the generalization capabilities. On the other hand, a poor training makes the ANN not to learn adequately

Another significant parameter in artificial neural networks is the learning rate. It affects the learning capability of the ANN, and a suitable value is required to perform an adequate training. The correct setting of the learning rate is often dependent on the size and type of input data and is typically chosen through experimental testing. Its value can also be adapted during the training phase, therefore becoming time dependent. The value for the learning rate chosen was 0.01. This low value is related to the nature of the input values that were between -1 and 1.

After the training process the ANN is ready to receive data and calculate the wireless client position. The location process follows a client-server architecture. Each time a request is sent by the server, the wireless client that is being located gathers RSSI values and sends them back to the server. The request handling, RSSI measurement and measurement report is assured by special developed software that must be installed on the client. This software does not affect the client processing power and does not require a huge amount of memory usage. After receiving the RSSI measurements, the server normalizes them and uses the trained ANN to calculate the client's position. This position is showed on a web interface special developed for this system. This interface provides a real-time location visualization of the wireless client.

Fig. 2. Wireless client position using a floor plan

Typically, a floor plan is used to help identify the location of the client. Displayed expressions should be numbered for reference. The numbers should be consecutive within each section or within the contribution, with numbers enclosed in parentheses and set on the right margin.

3 Results

3.1 Macro-location

The macro-location system was tested in the *Instituto de Telecomunicações* building using three Cisco access points. These APs were configured to send all the logs to the central server. Various location scenarios were tested, including fast moving clients, turning off one or more APs and also turning off the client. In all cases the location system provided the location information correctly. Increasing the number of access points has little effect in the system. The network performance is unaffected since the log packets are small and not in sufficient number to cause a major impact on typical office LAN.

3.2 Micro-location

Since the location system performance depends on the RSSI values from the various access points, it is important to study the behavior of these signals over time. The standard deviation from the several RSSI values at the same location can not take large values, since it will degrade the location system performance. Normally, the transmitted power in access points in a typical WLAN is constant. The results presented here were collected in a typical deployment scenario – a shopping center.

This test bench had four day duration and consisted of placing a WiFi device collecting 20 measurements at each time in intervals of five minutes. The access points used on this test were the ones that existed on the shopping centre that are from several ISPs. Since the shopping centre entrances are equipped with counting sensors, the RSSI results were crossed with the number of people that were inside the building. This way it might be possible to conclude something about the effect of the constant movement of people and its effect on the radio propagation.

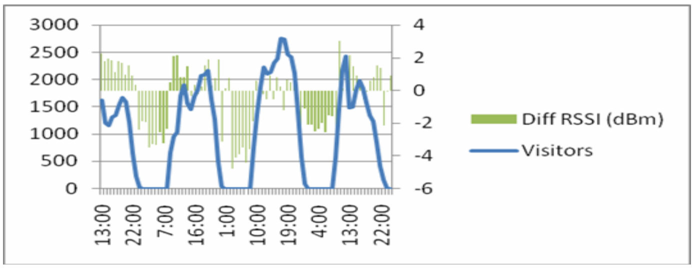

Fig. 3. Shopping center scenario - RSSI difference from its average and visitor number over time -channel 1

Analyzing figure 4, it is clear that the number of people roaming in the shopping centre has an effect of the RSSI value measured, since the difference from the average RSSI has its maximum values (about -4 dB) at night. Most of the time, the RSSI variation is not large enough to have a profound impact on the location system. A signal variation between 0 and 4 dB is a typical small scale fading value, which is observed on the measurements taken at the same point with 300 milliseconds intervals.

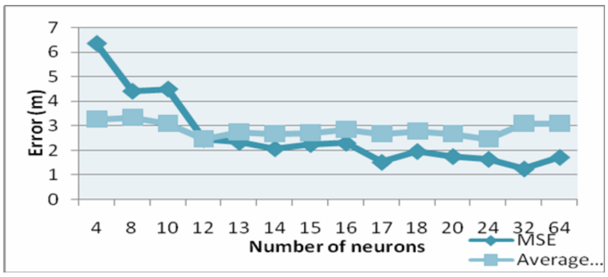

Fig. 4. Average location and training error versus number of neurons

The behavior of the artificial neural network, as mentioned before, has a dependency on the parameters values. The mean square error (MSE) value provides an understanding of the number of neurons that should be used. Crossing the MSE values with the average error gives the optimal number of neurons that, in this case, is near twelve (Figure 5).

In this situation the ideal number of neurons of the hidden layer was found to be twelve. This number makes a good commitment between the training MSE and the average error. Nevertheless, the number of neurons used in the hidden layer must be adapted to each situation and to the size of the training data set. During the location phase the wireless client is asked to perform RSSI measurements. The number of measurements has influence in the accuracy and duration of the location process. Increasing the number of measurements improves accuracy but increases the location duration. A good compromise between location response time and accuracy is a number that goes from five and eight readings, that corresponds to a 2 seconds time interval.

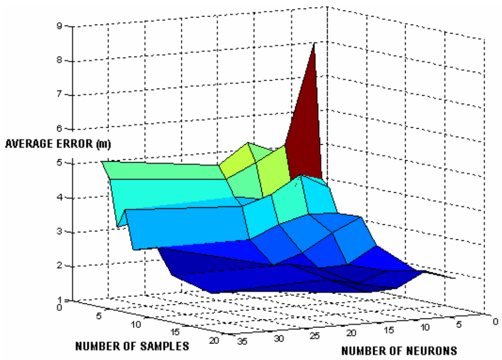

Fig. 5. Average error variation versus number of neurons and sampling size

Analyzing the behavior of the average error when there is a variation in the number of neurons in the ANN hidden layer and the number of samples (readings) used, it is possible to understand that there is an optimal neural network size. According to figure 6, the average error is minimized when the number of neurons of the neural network hidden layer is between 10 and 16. The sampling size also matters, as it is shown on the graphic, a low number of samples, has a negative impact on the location system performance. A low number of samples degrades the final average error values, compromising the system accuracy. This phenomena is explained when one thinks of radio propagation characteristics. Indoor propagation is always affected by effects like small scale fading, multipath, scattering and diffraction. Retrieving just one sample is just too low, since the location algorithm is based on the average RSSI values.

The mean square error is the output value of the neural network training. It is a figure of merit of the NN training and according to its value it is possible to conclude how well the NN has adapted to the input values. As figure 7 shows, MSE has large values when a low number of neurons is used. This is a natural behavior of the neural network, since there is a large set of data, and it is almost impossible to converge to a good final solution with a low number of neurons no matter the number of readings. A low number of readings also degrades the neural network capability of converging. The adequate number of readings should be higher than five. A higher number of readings does not significantly improve the neural network learning performance. The number of neurons used has a high impact on the mean square error of the learning phase.

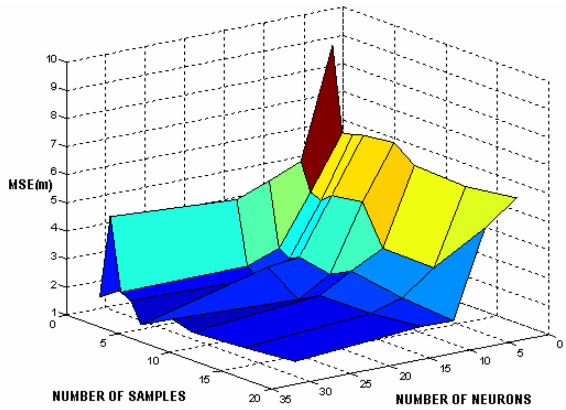

Fig. 6. MSE variation according to number of neurons and samples

It is important to study the behavior of the error in the location system. A low average error is not always a sign of optimal performance. The error histogram provides a clear insight of the location system accuracy.

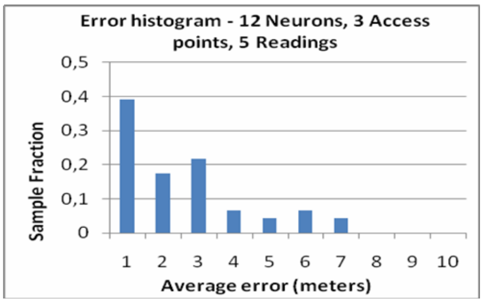

Fig. 7. Error histogram using 12 neurons, 3 access points and 5 readings

Using different settings, like the number of hidden neurons, access points and readings, it is possible to acquire the optimal settings for different scenarios and user requirements. Using a sufficient number of readings for an adequate accuracy (5 readings), the average error value is 2.4 meters (Figure 8). The maximum error value is 7 meters, and for about 80% of the samples, the error is below 3 meters. This result is improved increasing the number of readings to 20 (Figure 9), where the average error drops down to 1.9 meters.

Using additional measurements decreases the maximum error to five meters. According to figure 43 the location system offers an error less than one meter for 50% of the samples. Also for 90% of the samples the error is below three meters.

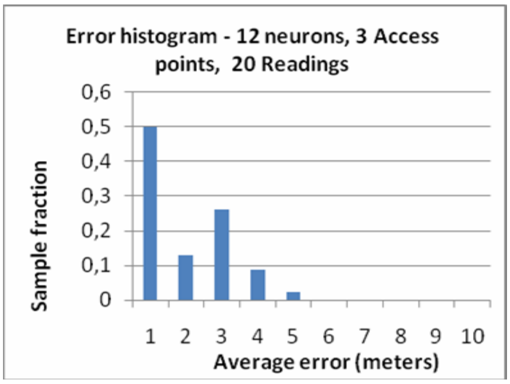

Fig. 8. Error histogram using 12 neurons, 3 access points and 20 readings

4 Conclusion and Future Work

This work provides a description of a wireless location system. Using a simple software solution, with no additional hardware, the location system has a good accuracy that can be improved by increasing the number of readings at the cost of lowering the location response time.

The use of RF fingerprinting is a valid solution to provide accurate positioning techniques. Nevertheless, it can be time consuming gathering measurements and profiling a large indoor scenario. This time was minimized using a simple and fast RSSI measurement and calibration tool, which can be used in an easy way. The usage of radio frequency fingerprinting requires employing mathematical approaches to solve the location problem. Methods like using propagation models and nearest neighbor were evaluated and it was concluded that their performance was inadequate. Artificial neural networks applied to the location paradigm offer sufficient adaptability between different scenarios, contrary to other algorithms used in other location applications. ANN based location algorithm provides enough flexibility and its final accuracy competes directly with the best known location applications.

The idea behind an indoor location system is its capability of providing accuracy while being simple to use. The location system developed can be easily deployed in existing WLAN with minimal cost and difficulty. Additionally it does not require any changes in the existing WLAN infrastructure, only a small software program must be installed in the client's device. This software does not interfere with the client's normal usage of its device. The system robustness is not compromised by minimal environmental changes in the indoor scenario, and it is immune to the multi-path and small scale fading effects, typical encountered on indoor radio propagation.

This location system is divided into two parts, the macro and the micro-location. Although some testing was made to ensure the interaction between those two systems, a final and efficient solution was not achieved. The main goal is to choose the adequate neural network according to the output of the macro-location system. Possible future work includes a seamless integration between the two systems.

Presently, the local system has been deployed in two different scenarios with an average location error below two meters. In the future, one can expect to improve its accuracy and lower the time required to perform the initial calibration.

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