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Indoor Robot Localization System Using WiFi Signal Measure and Minimizing Calibration Effort

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Abstract— **This paper presents a robot localization system for indoor environments using WiFi signal strength measure. We analyse the main causes of the WiFi signal strength variation and we experimentally demonstrate that a localization technique based on a propagation model doesn't work properly in our test-bed. We have carried out a localization system based on a priori radio-map obtained automatically from a robot navigation in the environment in a semi-autonomous way. We analyse the effect of reducing calibration effort in order to diminish practical barriers to wider adoption of this type of location measurement technique. Experimental results using a real robot moving are shown. Finally, the conclusions and future works are presented.**

I. INTRODUCTION

The boom in wireless networks over the last few years has given rise to a large number of available mobile tools and their emerging applications are becoming more and more sophisticated by year. Wireless networks have become a critical component of the networking infrastructure and are available in most corporate environments (universities, airports, train stations, tribunals, hospitals, etc) and in many commercial buildings (cafes, restaurants, cinemas, shopping centres, etc). Then, new homes are slowly starting to add WiFi services in order to enable mobility to perform many routine tasks, in the known as intelligent houses. There are even emerging some projects about WiFi enabled cities as Paris, Barcelona, etc.

The recent interest in location sensing for network applications and the growing demand for the deployment of such systems has brought network researchers up against a fundamental and well-known problem in the field of the robotics as is the localization. Determining the pose (position and orientation) of a robot from physical sensors is not a trivial problem and is often referred to as "the most important problem to providing a mobile robot with autonomous capabilities" [1]. Several systems for localization have been proposed and successfully deployed for an indoor environment. Examples include infrared-based systems [2], various computer vision systems [3], ultrasonic sensors and actuator systems [4], physical contact based actuator systems [5] and radio frequency (RF) based systems [6].

Many mobile robot platforms use wireless networking to communicate with off-line computing recourses, human-machine interfaces or others robots. Since the advent of inexpensive wireless networking, many mobile robots have been equipped with 802.11b wireless Ethernet. In many applications, a sensor from which position can be inferred directly without the computational overhead of image processing or the material expense of a laser is of great use. Many robotics applications would benefit from being able to use wireless Ethernet for both sensing position and communication without to add new sensors in the environment.

WiFi location determination systems use the popular 802.11b network infrastructure to determine the user location without using any extra hardware. This makes these systems attractive in indoor environments where traditional techniques, such as Global Positioning System (GPS) [7] fail. In order to estimate the user location, wireless Ethernet devices measure signal strength of received packets. This signal strength is a function of the distance and obstacles between wireless nodes and the robot. Moreover, the system needs one or more reference points (Access Points) to measure the distance from. Triangulation on signal strength from multiple access points could be the most natural technique to be applied but unfortunately, in indoor environments, the wireless channel is very noisy and the radio frequency (RF) signal can suffer from reflection, diffraction and multipath effect, which makes the signal strength a complex function of distance. To overcome this problem, WiFi location determination systems uses a priori radio map (wireless-map), which captures the signature of each access point at certain points in the area of interest. These systems work in two phases: training phase and estimation phase. During the training phase, the system constructs the wireless-map. In the estimation phase, the vector of samples received from each access point is compared to the wireless-map and the "nearest" match is returned as the estimated user location. However, the accuracy of this technique usually depends on a meticulous calibration procedure that consists of physically moving a wireless client to many different known localizations, and sometimes orientations, inside a building. This procedure is a practical barrier to wider adoption of this type of localization technique.

WiFi location estimation techniques are divided into deterministic and probabilistic techniques. In the first one the physical area making up the environment is first divided into cells. Location is performed in the estimation phase selecting the most likely cell in order to determine which cell the new measurement fits best [8]. On the other hand, probabilistic techniques construct a probability distribution over the targets location for the physical area making up the environment. This last technique provides more precision with computational overhead. Some recent and representative works have appeared in this line. In [9] the authors utilize a Bayesian belief network to derive a posterior probability distribution over the target's location. In [10] a probabilistic approach using recursive Bayesian filters based on sequential Monte Carlo sampling is proposed. In both cases a laptop has been used for the localization tests and the best accuracy obtained is about 1.5 meters.

In this paper, we present a probabilistic localization system for a robotic platform in indoor environments based on WiFi signal strength measure. Firstly, we analyse the indoor WiFi signal propagation in our test-bed and the possibility of using this in a location application. We experimentally demonstrate that the systems based in a propagation model are not proper to use in our test-bed and we have achieved a system based on a radio map generated by a robot navigating in a semi-autonomous way. Finally we present a strategy in order to minimize the calibration effort and we extract conclusions about it.

II. Test-bed

First of all we describe the environment in which we have tested our navigation system and the WiFi infrastructure needed for that. The test-bed was established on the 3rd floor of the Polytechnic School building, in the Electronic Department, at the University of Alcalá. The layout of this zone is shown in Figure 1. It has dimensions of 60 m by 60 m with about 50 different rooms, including offices, labs, bathrooms, storerooms and meeting rooms.

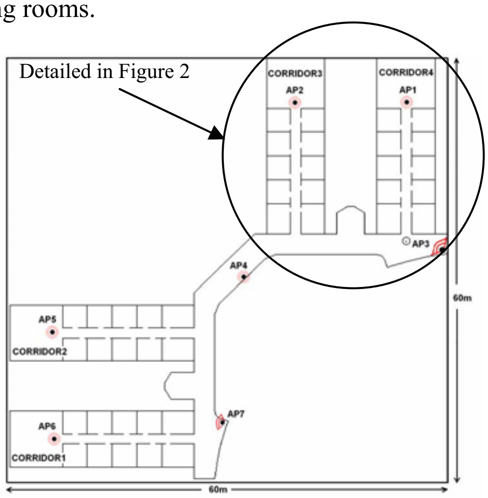

Fig. 1 Test bed environment. 3rd Floor of the Electronic Department

In Figure 2 we show a detail of the two corridors where the localization tests have been carried out. We divide the environment in 67 cells placed 80cm apart in order to build the radio-map.

Seven Buffalo Access Points (APs) (WBRE-54G) were installed at the locations indicated in figure 1, five APs were connected to omnidirectional antennas and 2 APs (AP3 and AP7) were connected to antennas of 120 degrees of horizontal beam-width. The APs acts as the wireless signal transmitters or base stations.

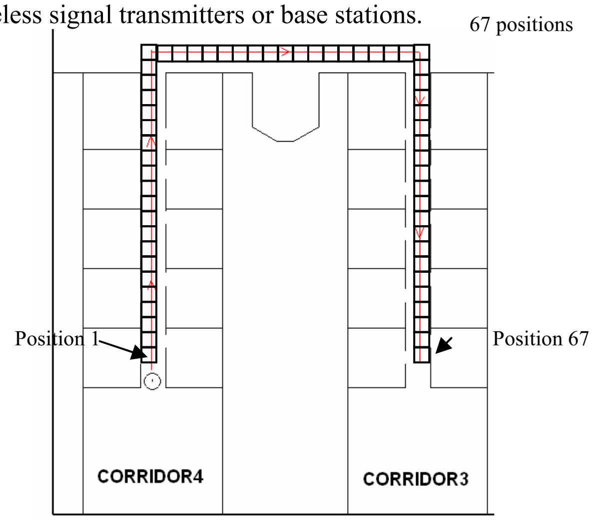

Fig. 2 Environment detailed with the corridors under test

For reducing the manual calibration we have used a robot which is able to stop in each cell automatically in order to measure the WiFi signal from the different APs. As mobile robot we have used a Pioneer 2AT of Activmedia robotics with the following configuration: one Orinoco PCMCIA Gold wireless card, Linux Red Hat 9.0 as operating system, wireless tools of Jean Tourrilhes [11] and the patch of Moustafa A. Youssef for the Orinoco driver. Figure 3 depicts a picture of the robotic prototype used in the experiments.

Fig. 3 Detail of the experimental setup

III. Indoor WiFi propagation

In this section we present the main causes of WiFi variation signal strength in indoor environments. We have carried out some real experiments with our WiFi infrastructure in order to test the feasibility and reliability of wireless positioning. The main results were presented by the authors in [12]. Here, we are going to extract the main ideas to understand the following points.

In [10] authors identify three main causes for the variation of the signal strength in an indoor environment:

1) Temporal variations: variations standing at a fixed position at a long time.

2) Large-scale variations: the signal strength varies over a long distance due to attenuation.

3) Small-scale variations: these variations happen when the user moves over a small distance and it is due to the wavelength of the signal (at 2,4GHz the wavelength is 12.5cm, then, this effect will appear for distances less than 12.5 cm).

In order to test temporal variation effect in our system a stationary measurement experiment was achieved. We collected samples along a complete day (Friday to Saturday) from two access points (AP1 and AP2) and for a fix position of the robot near the AP1. The sampling rate was 1 s. The signal strength obtained from the AP1 (mean=-56.8dBm, σ=4.5dBm) was larger than from AP2 (mean=-70dBm, σ=3.7dBm). The reason was because the AP1 was closer than the AP2 from the robot and then because the AP2 signal had to cross two walls with the corresponding attenuation. Other conclusion was that the standard deviation of AP1 signal was bigger than the AP2 one. The reason was because the effect of the secondary paths from the AP2 was lesser that the AP1 one. Then, almost all the signal received from AP2 was due to the direct path, while that the received signal from AP1 had high multi-path fading influence.

On the other hand, the signal strength was quite stable and consistent without people working, but it was highly affected by some environment elements such as the movement of people, the computer noise and the influence of other radio signals (Bluetooth mouse and keyboard links, etc). This influence provoked changes in the measures between 5 to 15 dBm. We must remark that the conditions of this experiment was very extreme because at working time a lot of people was moving around the robot and almost all the offices have PCs with Bluetooth links.

For testing large-scale variations, signal strength from AP1 and AP2 were collected several samples with the robot moving across the three corridors. We took the radio map locations on the corridors on a grid placed 80 cm apart and taking 300 samples for each position. The variation of the average signal strength over a distance of 18 meters was about 20 dBm. Moreover, there wasn't a linear variation of the signal with the distance due to the multi path effect. This is the reason because it was very difficult to built a propagation model for indoors environments.

For demonstrating small-scale variations we achieved several measures from the AP1 in different points separated a short distance (<12,5cm) and we generated a histogram for each case. Variations up to 3 dBm were measured in a distance small than 10 cm with different profiles for the histograms.

We also analysed the effect of the robot orientation in our environment. We took several signal strength measures and we obtained its histograms in orthogonal orientations to observe that it is possible to obtain the orientation and not only the position of the robot. The histogram profile was different for the test orientations and there was a maximum difference in the average signal for the test cases of 8dBm. The reason of this variation is because the antenna is not in the centre of the robot, as can be seen in Figure 3.

IV. Indoor WiFi Localization

In this section we present the localization system designed based on a radio map. For building and testing it we have used a mobile robot Pioneer 2AT.

In order to probe that a system based on a propagation model doesn't work properly in our environment we have developed a localization system applying the propagation model based on the log-distance path loss model [13] shown in equation (1).

$$PL(dB) = PL(d_0) + 10\,n \log \frac{d}{d_0} + X_\sigma \qquad (1)$$

PL indicates the path loss level, the value of n depends on the surroundings and building type, d_0 is the close-in reference distance which is determined from measurements close to the transmitter, d is the distance between the transmitter and the receiver, and X_σ represents a normal random variable in dB having a standard deviation of σ dB.

Figure 4 shows the result of this propagation model for the AP1 signal applied to our environment.

The asterisks show the log path loss level and the circles the real measures obtained for the 67 positions of the environment. Each position was obtained each 80 cm.

As can be seen in this figure, the measures obtained from the propagation model can differ of the real values up to 15 dBm and the mean squared error for this trajectory is 7 dBm. This means that the localization error obtained in our environment can be up to 12 meters. This value is not useful in the practice for our localization system, this is the reason because we have rejected this technique and we have chosen a localization technique based in a priori radio map.

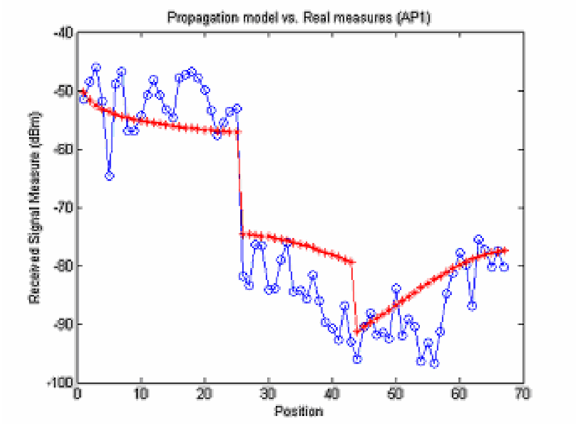

Fig. 4 Propagation model vs. Real measures

Once that we have decided to work with a radio map, there are two possibilities of using it:

1) *Discrete map*. In this case we divide the environment in cells, we obtain several measures for each cell and we assign them to the centre of the cell position. Once that the training phase has concluded, in the localization phase we obtain the position of the robot comparing the signal received from each access point

with the discrete ones of the wireless-map and the "nearest" match is returned as the estimated robot location. As can be seen, positions of the robot obtained with this technique are discrete.

2) C*ontinuous map.* In the training phase we take the measures obtained for the discrete map and we interpolate them in order to obtain a continuous map for our environment. In the localization phase the robot position is estimates as the position in the wireless-map for which the signal received match. In this case these positions are continuous.

A. *Discrete mode localization system.*

In this case a discrete map is necessary and the system works in two phases: training phase and location determination phase. In the training phase, a wireless-map is built taking the radio map locations on the corridors on a grid with cells placed 80 cm apart (the corridor width is 160 cm). For each location, 100 samples from the seven APs were taken and the histogram of each AP was loaded in a database. This wireless-map forms a statistical representation of the environment based on the APs. This phase has to be executed only once for a given environment. It is necessary that the environment remain consistent from this phase to the localization phase for localization to work. In the location determination phase the histogram of the samples received from each AP are correlated with the histograms of the wireless-map and the position associated to the highest correlation is estimated as robot location.

In order to test that the environment remains consistent between the training phase and the localization phase we have obtained the mean value of the received measures for the different 67 positions in the training phase and on a different excursion through the same space a few hours later. Figure 5 shows the signal consistency for the AP4. The mean values for the training phase are shown with asterisks and the mean values for the posterior phase are shown with circles.

Location of the robot is defined as a point with two degrees of freedom. A specific point in the environment is chosen as the origin and the location of the robot is specified in terms of Cartesian coordinates with respect to this origin.

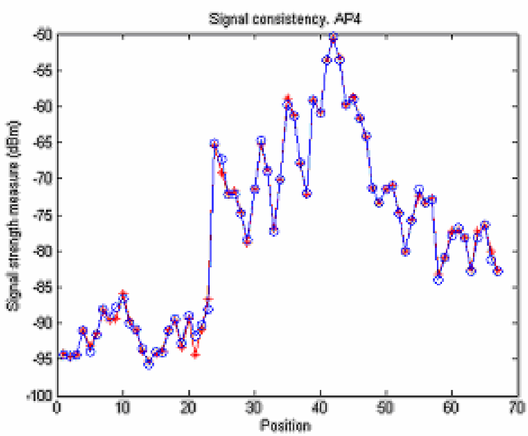

Fig. 5 Signal consistency from AP4

We represent the wireless-map tuple by one set of readings from each Access Point per cell, as can be seen in equation (2):

$$(x, y, \{AP_1, AP_2, ..., AP_k\}) \quad (2)$$

where (x,y) represent Cartesian coordinates of a physical point centre of each cell on the map and $\{AP_1, AP_2, ..., AP_k\}$ represent vectors containing the set of readings collected from Access Point 1,2, …k.

B. *Continuous mode localization.*

The explained discrete mode is useful for localization purposes but doesn't work very well when the goal is to fusion WiFi information with the information obtained from other sensors (odometry, laser, etc.) in order to develop a robust metric navigation system for a robot. In this case is more interesting to obtain a continuous measure. To solve this problem we propose to interpolate the mean values of the received signal from each access points using a Radial Basis Function (RBF) network. Using this technique we obtain interpolated radio maps for the environment where the robot can moves and for each AP as the shown in Figure 6 for the Access Point number 2. The input points for the RBF network are remarked with crosses and the solid surface shows the interpolated map.

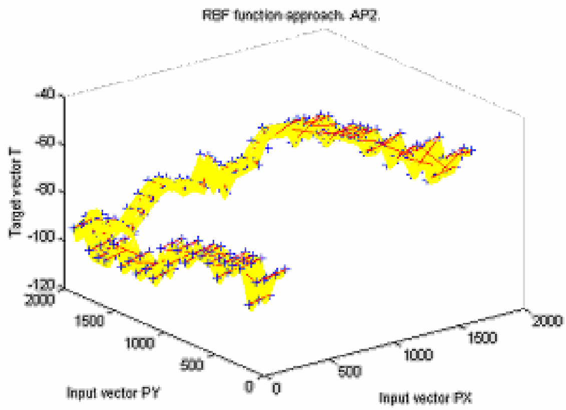

Fig. 6. Interpolation for received signal from AP2 with RBF Input network 2

The inputs of the RBF are the real location of the robot and the outputs represent the mean value of the histogram in this location {APx}.

Once we have obtained a continuous radio map in the training phase, we implement a new RBF network to obtain the robot position estimation. In this case, the RBF inputs are the received signal of the different Access Points {AP1,AP2,…,AP7}, and the outputs are the estimated position $(\hat{x}, \hat{y})$. Figure 7 shows the process of the localization in continuous mode.

For testing this method we have obtained 1000 random locations in the environment and we have calculated the error between the RBF estimated position and the real value. The mean square error obtained is 2.47 m. This value can be acceptable considering that no training points have been using in the testing.

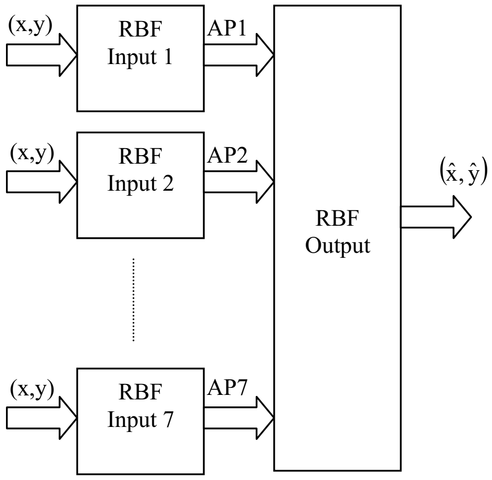

Fig. 7 Continuous mode localization architecture

V. REDUCING CALIBRATION EFFORT

The main problem that present the localization systems based in WiFi with radio map is the manual generation of the map. The accuracy of such systems usually depends on meticulous calibration procedure that consists of physically moving a wireless client to many different known locations, and sometimes orientations, inside a building. It may be unrealistic to expect anyone to spend the recourses on such work. Conscious of this problem we have used a robot which is able to take automatically the WiFi signal in the different locations and we have achieved an experiment to minimize the effort of the calibration.

As is explained in [14] the calibration effort is reduced by way of reduce:

1) The *time at each location*: the time that they spend in a static position to obtain the received signal measures.

2) The *number of locations*: represent the necessary locations to obtain a reference radio map.

They reduced the time at 17% of total and they obtain only a growth of 12% in the mean square error.

In this work, the number of calibration locations from the original full set is progressively reduced. The authors choose k locations from the original calibration set running a k-means clustering algorithm on the original locations to make k clusters. Then, they picked the k original locations nearest the k cluster centroids as those for calibration.

In our case, we have used the reducing of the locations number with the k-means algorithm but instead of selecting the k locations nearest the k cluster centroids we have used the k cluster centroids. An example for a reducing of 90% of the calibration positions is shown in Figure 8.

Respecting the reduction of time at each calibration, we have reduced the number of measures taken in each position from 100 to 10. This measures reduction supposes a time reduction from 35 s to 3,5 s. The results of these experiments are shown in the next section.

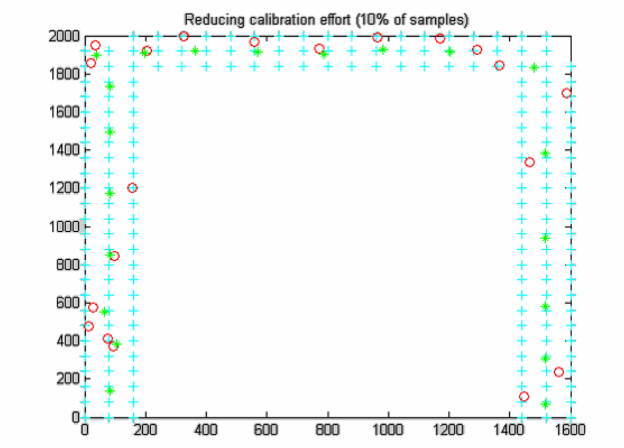

Fig. 8. The k cluster centroids for 10% of reducing

VI. EXPERIMENTAL RESULTS

In this section, we present the experimental results of our robot localization system in a simulated mode using data collected in real mode.

In this mode, the robot moves in the environment and the WiFi readings are collected to a file during the moving.

The simulation environment is shown in Figure 9. This figure shows three corridors (corridor 3 and 4 and main corridor of the environment). Also the trajectory followed by the robot to collect the information is shown. Then, this collected information will be used to obtain the results in simulate mode.

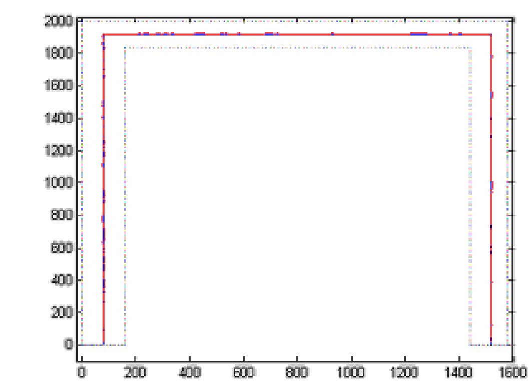

Fig. 9. Environment of simulation and the trajectory followed by the robot to collect information.

In a first experiment we have tested the reduction of the locations number. To do that, we have used a reduction about all training locations progressively from 100% to 10%. We have run a k-mean algorithm to progressively reduce k cluster centroids, and then we have selected those as the training locations. We have tested this reducing method with the *Continuous Mode* localization system, and we have achieved the next results shown in Figure 10. In this, the mean square error versus the calibration effort is shown. The x axis represents the locations fraction used for the system training respect of the overall. The y axis represents the obtained mean square error.

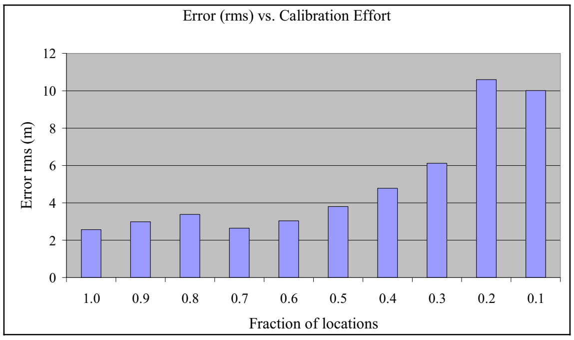

Fig. 10. Reducing the number of calibration locations for training.

Is important to note that our system is working in worse conditions than in the [14] because our test positions are random and in [14] are training positions. Nevertheless, we have obtained a mean square error of 2.57m for all locations in training phase, which is lower than the obtained in [14]. Taking a 40% of the overall training locations, the mean square error increases up to 4.78m.

The second experiment that we have carried out is to reduce the samples per location as in the training phase as in the localization phase.

To test this experiment we have used the *Discrete Mode* localization system to obtain the decrease of the correct localizations. As can be seen in Figure 11, we can generate a radio map using the 10% of the overall samples obtaining a percentage of correct localizations of 92,53% with only 18 samples collected in the localization phase.

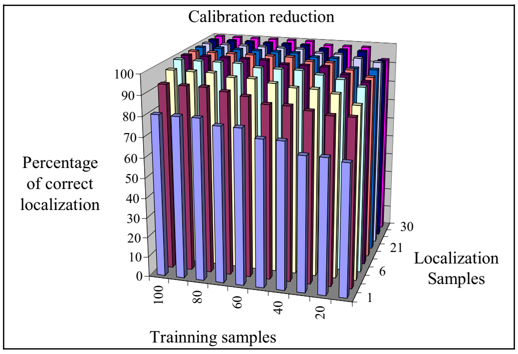

Fig. 11. Reducing the number of calibration locations for training.

VI. Conclusions and Future Works

In this paper, we have presented a robot localization system based on a priori wireless-map for indoor environment using different methods of localization such as continuous mode localization and discrete mode localization. The radio map has been obtained automatically using a robot able to navigate in semi-autonomous way.

We have analysed the main causes for the variation of the WiFi signal strength and we have demonstrated that this variations are easily reduced by way of obtaining a histogram instead of a simple measure.

With our system we have obtained a global localization error of 0% for discrete mode localization in a real mode with real data obtained from the WiFi robot interface for 50 samples in training phase and 18 samples in localization phase.

Also we have obtained a global localization system with a mean square error of 2.57m in a continuous mode in a simulated mode with real data recollected from the WiFi robot interface. Although this error can seem high for a navigation application we must think that this has been obtained using single locations. In the practice this value can be reduced using tracking techniques over time and applying data fusion with other sensors of the robot.

We have obtained some preliminary results of WiFi and odometry fusion using a Particle Filter [12] and we have obtained a location error below to 40 cm.

In the near future we have the intention of testing this system in the all environment with the four corridors instead of the corridors 3 and 4.

Also we want to apply the system to a different mobile platform such a PDA carried by a man.

Acknowledgment

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