WiFi localization methods for autonomous robots

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Abstract

This paper compares two methods to estimate the position of a mobile robot in an indoor environment using only odometric calculus and the WiFi energy received from the wireless communication infrastructure. In both cases we use a well-known probabilistic method based on the Bayes rule to accumulate localization probability as the robot moves on with an experimental WiFi map, and with a theoretically built WiFi map. We will show several experiments made in our university building to compare both methods using a Pioneer robot. The two major contributions of the presented work are that the self-localization error achieved with WiFi energy is bounded, and that no significant degradation is observed when the expected WiFi energy at each point is taken from radio propagation model instead of an a priori experimental intensity map of the environment.

1 Introduction

Localization information is essential for a broad range of mobile robot applications, in particular those where robot behavior may depend on its position. Localization in mobile robotics can be defined as the problem of determining the position of a robotic platform in its environment, given a map of the environment and local sensorial data. This problem was early recognized as one of the most fundamental ones in mobile robotics [1], and it still is one of the primary research issues in the field.

There has been different approaches to solve this problem. Calculus based on odometric measurements in wheeled robots was the first historic approach. These systems calculate the new position of the robot given the initial position and the information about the movement of the robot provided by the odometric sensors. Unfortunately, these sensors are very noisy, and accumulate errors over time[2], so they can be used only for local movements, but are not reliable for long term or global localization.

Several techniques have been proposed to cope with odometer limitations. Most of them are based on finding landmarks of known position in the environment and integrate this information over time to get a more reliable position estimate. So, the current localization methods could be classified attending to the type of landmarks, and to the integration method used.

Concerning the landmarks, the challenge is to get the robot localized without "engineerizing" the environment. This means that solutions that imply deploying active beacons or passive landmarks are nowadays considered not suitable in research literature (but they are very common in industrial domains). Initially, the measurements of the robot range sensors (usually ultrasonic or laser) were used directly. For instance, Crowley [3] extracted lines segments from sonar data. Nowadays focus has been put in the use of "natural" landmarks, that is, marks already present in the environment. These landmarks are supposed to ease the use of mobile robots in human environments. An classical example was the use of the ceiling lights in Minerva tour-guide robot [4], more usual marks can be visually detected, as the doors and corridors' depth used in [5], etc.

In our approach the landmark used is the signal power received from the wireless Access Points (AP) "visible" (that is accessible) by the robot computer. The main interests in the use of this information in indoor robotics research are the fact that they are a cheap, and non intrusive method; and that the infrastructure has already been deployed (for instance most universities, as our, are endowed with wireless Access Points). It may also cover big areas and does not require any additional hardware or environmental engineering to work. In this way, they can be considered "natural" landmarks, because they are already deployed.

Concerning the integration methods, there have been many different approaches. For instance, segments extracted by Crowley in [3] are matched to the map using a Kalman filter. The main limitations of using the Kalman filter to update localization information is that it requires linear Gaussian likelihood and state evolution models. However, observation models are usually non-linear, non-Gaussian, multi-modal or any combination of these, which makes the system analytically intractable.

Another way of integration is the probabilistic approach, which has shown good localization results in mobile robotics using range and odometric sensors. One of the first robots using these techniques was Xavier [6]. One of the successful uses of these method was the famous tour-guide robot Minerva [4].

Probabilistic systems can deal with non-linear models. The grid based probability systems maintain a distribution of probability for every possible locations of the robot. Its main drawback is the high computational requirements needed to update the distribution. More recently, sampling methods (particle filters, Monte Carlo, etc) have been introduced in the probabilistic approach to speed up the estimation, giving also good results [7, 8] even with real-time performance.

The probabilistic approach will be used in the work presented in this paper. We show our results when it is applied to the localization problem using as main input data the power received from the wireless network access points deployed by the communications facilities service of our university, and information from the odometric sensors of the robot. This use of the wireless infrastructure does not interfere with its use as communication network itself. In other words, this sensor is a passive sensor from the point of view of the robot.

The use of wireless power has been used in other works that can be found in the literature. Some of these experiments have trusted the WiFi signal so much, that they simply triangulate the position, translating directly power received into distance to the AP. However, experiments have shown that using this method only poor resolution can be achieved, see [9] or [10].

The combination of odometric data and the WiFi energy received has also been explored by Jason Small [11], Andrew M. Ladd [12] or Sajid M. Siddiqi [13]. They have developed different statistical methods to calculate the location probability. These methods are based on models of the actions that the robot can perform (turn, going forward, etc.) and the predicted observation after these actions had been performed. This prediction is based on an a-priori map of the WiFi energy. Building this a-prori map is really a hard task, that usually has to be performed manually which is a time consuming and tedious task.

The major contribution of our work is that we introduce the use of theoretical model of indoor propagation of the signal from the APs. This avoids the need of manually building a "wireless energy map" of the environment. Using this theoretical model we get localization error similar to that obtained with the energy map, as we will show in section 3, and it results on an easier implementation.

The remainder of this paper is organized as follows. Next section explains the theory underneath our experiments. Third section is devote to analyze the results obtained, and last section summarizes the conclusions we have reached, and the future lines.

2 Probabilistic localization

The goal of this paper is to show that a robot can localize itself with a bounded error in a typical indoor environment using as main sensor input the power received from the several access points. Localization evidence is stored as the probability of being in each possible location, which generates a “probability grid”. Such probabilities are continuously updated with the information coming from sensor observations and movement commands, in the same way as it is used in [14]. The Bayes rule is used to fuse new information with that already stored. We will take the best position estimation as that which the highest accumulated probability.

As stated in equation (1), the probability of the robot being at location x is defined as the conditioned probability of such location given all the past observations from robot sensors, which adds some indirect position information. Considering only independent observations, or at least Markovian independence equation (2), and following the analysis of [14], the probability can be expressed and computed in an incremental fashion equation (3).

$$\begin{aligned}
p(x(t)) &\models p(x(t)/obs(t), obs(t-1), ...) && (1)\\
p(x(t)) &= p(x(t)/obs(t)) * p(x(t)/obs(t-1), obs(t-2), ...) && (2)\\
p(x(t)) &= p(x(t)/obs(t)) * p(x(t-1)) && (3)\\
p(x(t)) &= p(x(t)/mov(t-1), x(t-1)) * p(x(t-1)) && (4)
\end{aligned}$$

2.1 Action model

Information about the robot movements are integrated in the probability estimation following a given *action model*, as shown in equation (4). That model stores the probability of being at position x if the robot was previously at position $x(t-1)$ and it makes the movement $mov(t-1)$ at time $t-1$.

In practice, the effect of such action model is an evidence displacement over the probability grid. Such displacement follows the robot movement, and in our work is computed from the encoders readings, so it does not require to know the movement orders commanded, it just "read" them from the encoders measurements. Some Gaussian noise in translations and rotations in added to take into account slippages and encoder deviations from real movement. The noise blurs the evidence displacements.

2.2 Wi-Fi sensor model

The sensor observations also modify the probability grid. In (equation 3) $p(x(t)/obs(t))$ represents the posterior sensor model, which contains all the position information carried by the observation, in a probabilistic way. Sometimes this sensor model can be expressed as a priori sensor model, $p(obs(t)/x(t))$, which contains the probability to obtain the given sensor measurement $obs(t)$ in time t if the robot were at position x at time t.

We use the WiFi energy measurements as the main sensor observations. In a typical indoor scenario there are several access points which provide wireless connectivity to the computers inside, mainly mobile ones. The access points are bridges with two interfaces, wireless and ethernet networks, bridging both worlds.

The wireless hardware in mobile computers, on-board the robot in our case, can provide the current WiFi energy of the radio signal received. Inside the personal computers this information is used in the link level to choose the best access point to actually perform the data transmission. In right picture of the figure 4 the wireless card of our robot is remarked.

We take advantage of such hardware capability to use the wireless card as a *WiFi sensor*. Using this sensor we define the *WiFi measurement* as a vector with several components: number of visible access points, the signal and error energy levels for each visible access point.

We have developed an ad-hoc posterior sensor model to integrate the indirect position information they provide. In order to a WiFi energy measurement to provide some location information it has to be compared with the expected value at each location. In this way, we have defined a normalized distance function that reflects the similarity between the expected reading and that actually obtained by the WiFi sensor, that returns 0 to two identical values, and 1 to two completely different readings. Using that distance function we define the likelihood probability $p(x/obs)$.

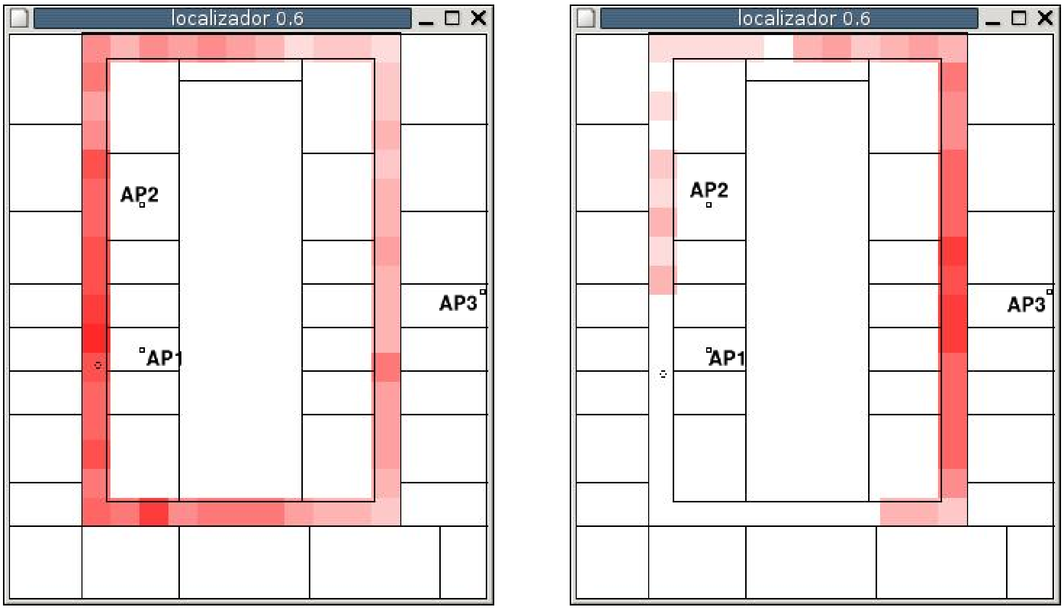

Figure 1: WiFi energy maps for Access Points 1 and 3

The intuition of this probability is that the closer the values, the more likely the location is. If expected and observed readings differ significantly, it is not likely the robot be currently in that location. Otherwise the values would be similar. Nevertheless, if expected and observed readings are similar then the likelihood of the robot being at that position is high. Putting it in another way, the current WiFi energy provided by the wireless network card will raise the probability of the locations with a similar expected energy and will decrease the probability that of the locations with a very different energy value.

We have tested two probabilistic models to manage WiFi data. The first one obtains the expected energy value from an experimental energy map of the environment. Such map was built taking various measurements in all possible locations and collecting the energy received at each one. The second sensor model gets the expected energy value from a theoretical WiFi propagation model. These two models are described in detail in the next two sections.

2.2.1 A priori WiFi energy map

The a priori energy map that the robot uses is in fact a set of maps, one for each access point, so we have three maps in our test scenario. Figure 1 shows those for access point 1 and 3. The energy becomes lower as locations are further from the access points, as it can be expected, however this attenuation was much lower than expected.

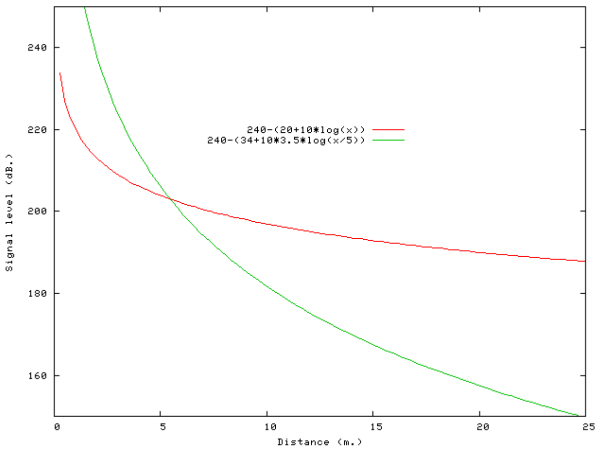

Figure 2: Breakpoint model function with exponent 3.5 after breakpoint

The sensorial model used was $p(x/obs(t)) = 1 - d(t)\sigma$, where σ is an amplification factor and $d(t)$ is computed as the percentage of energies from the sensor reading vector that fall close to its corresponding element in the expected vector. A given threshold is set to consider two energies as close enough.

The maps were built moving the robot through all possible positions and storing the measured WiFi energy values for each access point. In practice the robot position is bounded to the corridors of our Computer Science Department, so no reading was stored inside the different rooms. We discretized the world into 2x2 meter square cells. This distance was chosen because we couldn't find significant differences in the signal level for smaller distances.

2.2.2 WiFi propagation model

In the second WiFi sensor model the expected value was obtained from a theoretical propagation model for the WiFi energy. In particular it follows the equation 6, where distance function decreases exponentially with the differences in energy. In this equation r_x^i is the expected signal level (using the propagation model) in position x for AP i, and r_{obs}^i is that measured by the WiFi sensor.

$$d = (\sum_{i=0}^{AP}(\frac{|r_{obs}^i - r_x^i|}{100})\sigma)^2 \quad (5)$$

$$p(x/obs(t)) = e^{-d} \quad (6)$$

There have been a lot of research about propagation of radio signals in indoor environments, we have chosen the breakpoint model [15]. Our model will compute the signal level for each point as the equation (7). This is a free space loss model that takes only into account the distance from the emitter, and ignores any walls in between. Two different regions are used, before and after a given breakpoint, which was set at 5 meters for our experiments. The energy falls down faster after the breakpoint, as it can be seen in figure 2.

$$signal\_level = \begin{cases} 240 - (20 + 10 * \log(l)) & \text{if l<=5 meters} \\ 240 - (34 + 10 * 3.5 * \log(l/5)) & \text{if l>5 meters} \end{cases} \quad (7)$$

The use of the theoretical propagation model allowed us to obtain the expected WiFi energies at every location of the grid without actually acquiring the data in a previous phase, neither moving the robot. This is very convenient as the map building phase is very tedious, and takes time. Figure 3 shows the appearance of expected energy readings for access points 1 and 3 according to the propagation model.

In this case, we can easily calculate the energy map for the whole building, not just for the corridors as in the previous approach. We do not need explicit permission to enter private rooms, etc. In this way the experiments made using this approach use the whole map, which are harder conditions (larger grid and

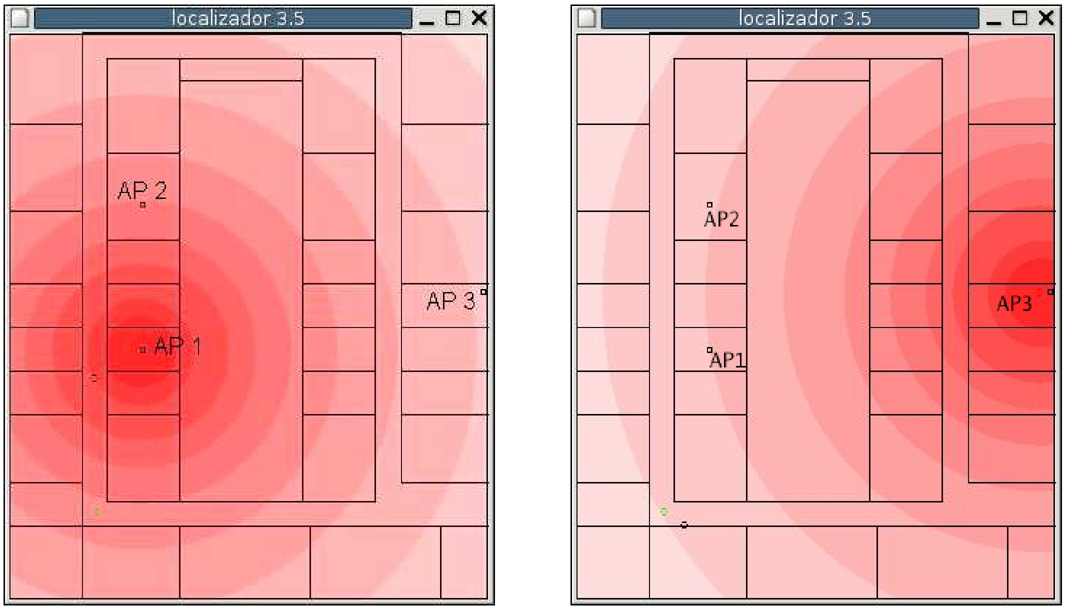

Figure 3: Propagation models for AP1 and AP3

more possible errors) than in the previous approach. However, as we will point out in the next section, results are quite similar.

3 Experiments

Our experiments have been made in the environment shown in left part of figure 4. This area corresponds to the wing where the robotics lab of the URJC is located. In this area three access points (AP1, AP2, and AP3) have been placed, and their locations are known. Robot used is a Pioneer carrying a standard WiFi card, as shown in right part of figure 4.

The localization performance of the probabilistic approach using the two WiFi sensor models previously described was tested over a simulator. The quality of the algorithm will be measured as the localization error, given that the simulator provides the ground truth and our algorithm continuously delivers a position estimate. For the sake of comparison we also include the deadreckoning estimate, that is, the position computed from encoders, without any correction.

The module architecture of the software is shown in figure 5. We used the standard simulator of our Pioneer robot, SRIsim, which gives the *real* location of the robot, the position computed from the encoders and simulates the effect of movement commands. It also provides the simulated sonar and laser readings, but

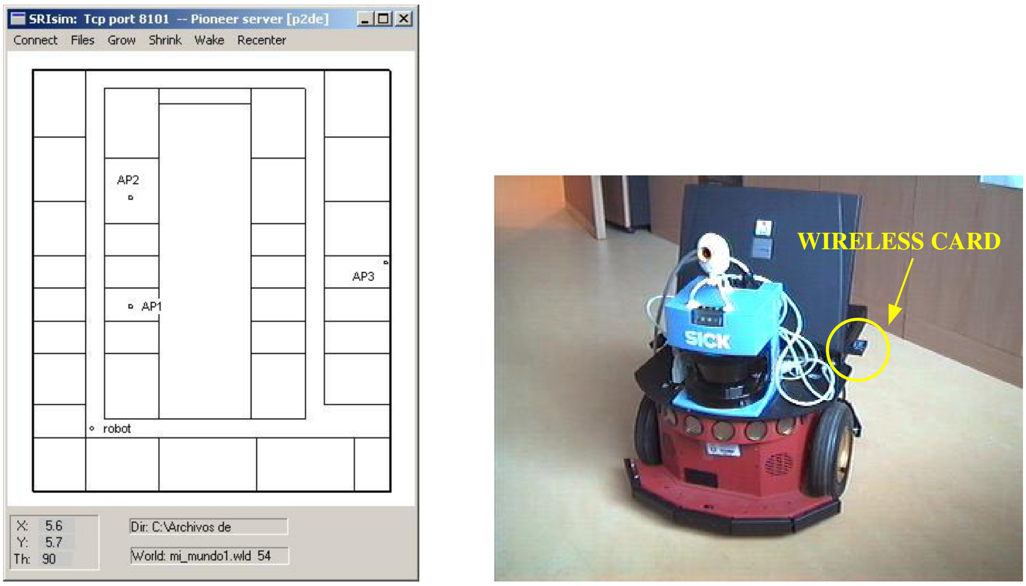

Figure 4: Indoor scenario with 3 access points (left) and our robot with wireless card (right)

they were ignored in our experiments. We have also coded a wireless module to simulate the WiFi readings using the measures taken by the robot to make the energy map described in section 2.2.1.

Given the real position (Position in figure 5), the WiFi readings are always taken from the experimental energy map, and some noise is added to provide the *observed* energies. Obviously, the localization algorithm does not use it except for the error measurement, it only uses the signal level from the WiFi sensor and the odometers readings. It continuously delivers a position estimate for the robot, following one of the approaches described in last section.

In the experiments, we let the robot move freely through the Computer Science Department of our university, using a wander behavior. As shown in figure 5 that area is made up by two 34 meter long hallways in the east and west and two 22 meter hallways in the north and south forming a rectangle surrounded by several rooms of different shapes and sizes. In the same figure three access points can be seen, which were deployed time ago before our experiments.

3.1 Localization using a WiFi energy map

In this experiment the average localization error in 4 random runs of 400 cycles each is 1.08 meters with a standard deviation of 0.70 meters, the error is smaller

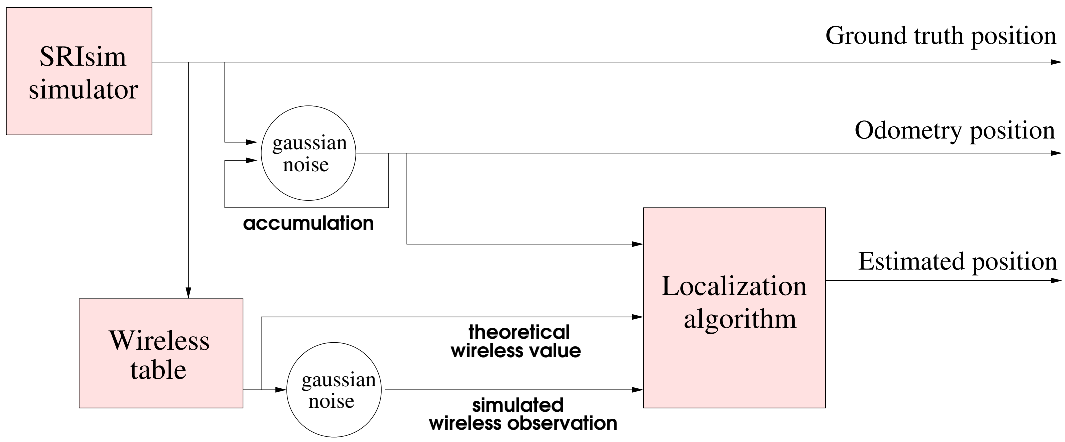

Figure 5: Software architecture for the experiments

than 1.5 meters in 82.27% of the times and is smaller than 3 meters in 97.9%. We are going to bound the problem to the localization of a P2DXE robot in the corridors of the Computer Science department.

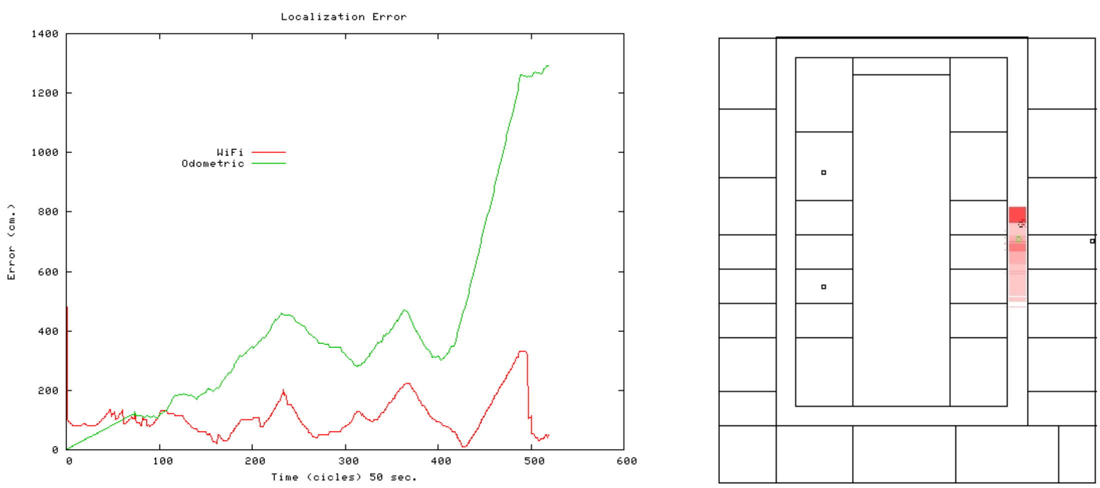

Figure 6: Localization error evolution and evidence after 250 seconds using a WiFi energy map

The left graph of figure 6 shows the distribution of the localization error of this algorithm compared to the accumulated odometric error. The X-axis is the time in seconds and the Y-axis is the distance in centimeters. The accumulated odometric error starts at 0 and is not bounded, however using the WiFi information (lower graph) the error is bounded around a maximum of 3 meters.

The shape of the error using the wireless network is similar to the shape of the odometric error graph because the motion model also relies on the data provided by odometric sensors. There can also be observed some discontinuities in the error graph of our localizator. This is due to the fact that the information provided by the wireless card is strong enough to change the belief based on the measurements of the odometric sensors.

In the right picture of figure 6 can be observed a snapshot of the interface of the localizator algorithm working. The probability cloud is represented in a scale of colors being the darker ones the positions with higher beliefs. The real position of the robot is also shown as a small circle.

3.2 Localization using a WiFi propagation model

Using the theoretical propagation method we have obtained an average error of 2.00 meters with a standard deviation of 1.38 meters, 42% of the times the error is smaller than 1.5 meters and 83% is bellow 3 meters. These data were obtained making the same experiments that in the previous case.

Figure 7, which is the equivalent to figure 6 but using the theoretical propagation model, shows the distribution of the error of the localizator versus the odometric error. After the initial steps in which the robot it still updating its beliefs, the error is bounded around 2 meters, which compare with the cell size means that maximum error is one cell.

There are more discontinuities than in previous experiment because our model is now also giving signal measures to the points outside the corridor, as can be seen in figure 7. This makes it possible for the localizator to believe that the robot is outside the corridor which forces sudden changes in the beliefs. Most of the sudden changes in our localizator are happening when odometric errors are growing too fast, which pushes the beliefs to positions far away from the right one and in most cases outside of the corridor.

In the right picture of figure 7 it can be seen how our localizator algorithm works. This time there are probabilities clouds outside the corridor. There are no clouds in the rooms because we are assigning near 0 probability to positions in walls (they are impossible) and the Bayesian propagation of evidences gives very low probabilities to locations inside the rooms, as well as produces the stripes that can be observed.

The setup in this experiment is exactly the same as in the previous one, the only change is in the sensorial model. With this new sensorial model we are getting a better localization than with the previous one. The average error in 4 random runs of 400 cycles each is just of 1.53 meters, with a standard deviation of 1.52

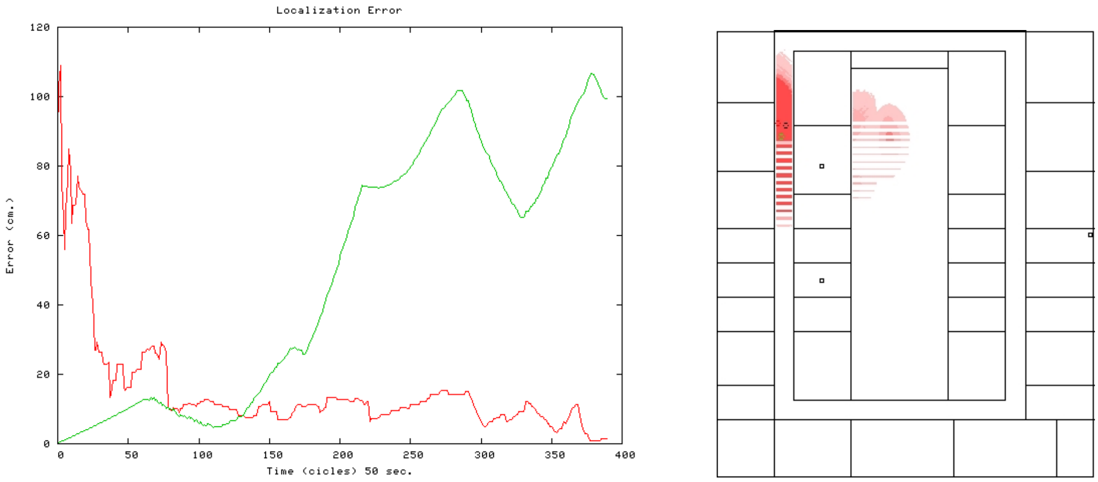

Figure 7: Localization error evolution and evidence after 50 seconds using propagation model

meters. 61% of the times the error is under 1.5 meters and 94.1% is smaller than 3 meters.

Figure 7 presents the distribution of the error of our localizator versus the accumulated odometric error. After the initial steps in which the robot it still updating the beliefs the error is delimited around 2 meters.

4 Conclusions and future work

A probabilistic localization algorithm has been presented which uses a WiFi network card as another sensor in combination with odometric encoder data. The card measures the energy received from different communication Access Points in the environment. Experiments described in previous section have shown that, even though the wireless information isn't very discriminative, it's clear it helps in the robot localization task, improving the accuracy estimation over the odometric itself.

In this paper we have also shown that the power signal received from the wireless Access Points can be exploited without any a priori experimental energy map. We have used a Breakpoint model of indoor radio propagation obtaining similar results or even better than the ones reported in the literature, and in our experiments, with an experimental energy maps. This kind of methods, without using energy maps, are the most promising ones as they are the only ones that don't require any additional information about the wireless network apart from the positions of the Access Points.

Experiments have shown that at the beginning the algorithm with the theoretical propagation model offers localization errors higher than the algorithm with the experimental energy map. But they also indicate that after the initial cycles, error is bounded around 2 meters and the position estimates are better than using the map.

We also argue that though it has been said that orientation affects signal strength [12], in our experiments the changes are slight and it's not possible to use this information to obtain a good estimation of the orientation.

In the near future we plan to test the feasibility of using a sampling method as Monte Carlo to reduce the computational cost of the localization algorithm. We are also considering the use of a topological map instead of a metric one. This will let us use the probabilistic approach described here, as well as, integrate another sensor inputs (visual detection of the doors is the more promising one).

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