Comparison of WiFi Map Construction Methods for WiFi POMDP Navigation Systems

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Abstract. The framework of this paper is the robotics navigation inside buildings using WiFi signal strength measure. In most cases this navigation is achieved using a Partially Observable Markov Decission Process (POMDP). In the localization phase of this process the WiFi signal strength is used as observation. The localization system works in two stages: map construction and localization stage. In this paper we compare three different methods for obtaining the WiFi map in the construction stage. The methods have been tested in a real environment using two commercial robotic platforms. Some experimental results and the conclusions are presented.

Keywords: Navigation, WiFi, Localization, POMDP.

1 Introduction

For surveillance robots navigation over huge indoor environments design, in which the objective is to guidance the robot to a goal room using some low level behaviours to perform local navigation, a topological discretization is appropriate to facilitate the planning and learning tasks. A POMDP model provides solutions to localization, planning and learning in this robotic context. These models use probabilistic reasoning process to deal with uncertainties in the actions execution and the observations taken by a robot, very important in the case of WiFi localization sensors.

To find the pose (position and orientation) of a robot from physical sensors is not a trivial problem and is often referred to "the most important problem to provide a mobile robot with autonomous capabilities" [1]. Several systems for localization have been proposed and successfully deployed for an indoor environment. These systems are based on: infrared sensors [2], computer vision [3], ultrasonic sensors [4], laser [5] or radio frequency (RF) [6]. Within the last group we can find localization systems that use WiFi signal strength measure.

WiFi localization systems take advantage of the boom in wireless networks over the last few years. The WiFi networks have become a critical component of the networking infrastructure and are available in most corporate environments (universities, airports, train stations, tribunals, hospitals, etc). Therefore the localization stage can determine the device location without any extra hardware

R. Moreno-Díaz et al. (Eds.): EUROCAST 2007, LNCS 4739, pp. 1216–1222, 2007.

in the environment. It makes these systems attractive for indoor environments where traditional techniques, such as Global Positioning System (GPS) [7] , fail.

In order to estimate the robot location, we propose to measure the WiFi signal strength of received packets in wireless Ethernet interface. This measure depends on the distance and obstacles between wireless Access Points (APs) and the robot. Moreover, the system needs more than one base stations or AP to measure the distance from them to the device. Using these measures they can apply a triangulation algorithm to infer the estimated position [8].

Unfortunately, in indoor environments, the WiFi channel is very noisy and the RF signal can suffer from reflection, diffraction and multipath effect, which makes the signal strength a complex function of distance [6]. To solve this problem, it can be used a priori WiFi map, which represents the signal strength of each AP at certain points in the area of interest [9] [10] [11]. These systems work in two phases: map construction and estimation of the position. During the first phase, the WiFi map is built in a previous setup by mean of different ways. In the estimation phase, the vector of samples received from each access point is compared with the WiFi map and the "nearest" match is returned as the estimated robot location. The problem is that this method involves an enormous calibration effort because the WiFi observations are manually obtained.

In this paper we compare three methods to obtain this WiFi signal strength map. This map will be used in the WiFi POMDP Navigation System. We demonstrate that the automatic training method represents an improvement of the manual and calculated methods and also it manages the adaptability of the map, very important in a WiFi system.

The rest of the paper is organized in the following sections: Section 2 provides a description of the POMDP navigation system. Section 3 explains the WiFi map construction methods comparison and some experimental results, as well as a description of the used test bed. Finally, the conclusions and future work are described in Section 4.

2 WiFi POMDP Navigation System

In this section we provide a resume of our WiFi POMDP Navigation System which was explained by the authors in [12].

When a robot moves across an environment executing several actions (a_t), in execution step t, and it has free of uncertainty in the environment observation, we can modelize this system as a Markov Decision Process (MDP). The MDP is a mathematic model that permit characterize robotics systems without noise in the environment observation. The MDP considers that only the effect of the actions has uncertainty.

When a MDP achieves some execution steps and it goes along a different states $(s_0, s_1 \dots s_n)$ executing some actions $(a_0, a_1 \dots a_n)$, the probability of being in a s_{t+1} state in the $t+1$ execution step is obtained using equation 1.

$$p(s_{t+1}|s_0, a_0, s_1, a_1, \dots, s_t, a_t) = p(s_{t+1}|s_t, a_t) \quad (1)$$

The actions uncertainty model represents the real errors or failures in the execution of the actions. The transition function T incorporates this information to the MDP. In the discrete case, T is a matrix that represents the probability of reaching the state s_{t+1} when the robot is in the state s_t and it has executed the action a_t.

There is a recompense function R for each state s and action a. The robot reaches the maximun value of the recompense function when it reaches the target state travelling through the ideal trajectory and executing the ideal actions.

Although MDP considers that the environment observation is free of uncertainty, in the real robotic systems, there are some uncertainties associated to their sensors observations. These are more significant when the observations are provided by the noisy WiFi sensor [13].

The POMDPs are mathematic models that permit to characterize these noisy systems. A POMDP is defined by the same elements than in a MDP: S (states set), A (actions set), T (transition function), R (recompense function); and then it adds the following elements: O (observations set ($o \in O$)) and ν (observation function).

A POMDP doesn't know its real state because the uncertainty of the observation. A POMDP maintains a belief distribution called $Bel(S)$ or Belief Distribution (Bel) over the states to solve it. This distribution assigns to each state a probability that indicates the possibility of being in the real state. This is the main reason to divide the control stage of a POMDP in two stages, as can be seen in Figure 1:

1. State estimator: the inputs of this block are the current observations and its output is the Bel. This block calculates the probability over all possible states.
2. Politics: the input of this block is the current Bel and its output is the action to perform. This block obtains the optimal action to perform in the next execution step to maximize the recompense (R).

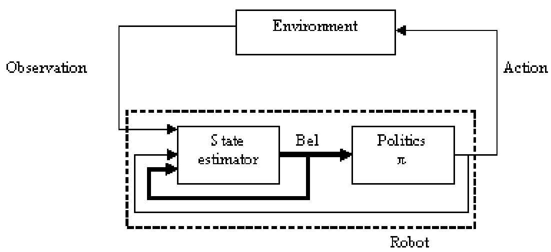

Fig. 1. Partially Observable Markov Decission Process (POMDP)

The state estimator block is known as localization system. This updates the Belief Distribution when a new action or observation is carried out. In the robotics context, these conditions usually are simultaneous. When an action a is executed and a new observation o is taken, the new probabilities became as it is shown in equation 2.

$$Bel_t(s') = \eta \cdot p(o|s') \cdot \sum_{s \in S} p(s'|s,a) \cdot Bel_{t-1}(s), \forall s' \in S \tag{2}$$

In the context of robot navigation, the states of the Markov model are the localizations (or nodes) of the topological representation of the environment. Actions are local navigations behaviours that the robot executes to move from a state to another, such as move forward (a_F), turn around (a_T), turn to the left (a_L) and turn to the right (a_R). The observations are perceptions of the environment that the robot can extract from its sensors that in our case are obtained from the WiFi ($obs_{WIFI_{APx}}$) and Ultrasound (obs_{US}) sensors. In this case, the Markov model is partially observable because the robot never may exactly know the state where the robot is. To solve the POMDP model we have used the WiFi Simultaneous Localization And Mapping (WSLAM) in order to obtain the WiFi observation function and, an extension of the EM algorithm to obtain the Ultrasound observation function.

Observations from the WiFi and the Ultrasound sensors are complementary. The first one obtains an estimation of the global localization and the second one obtains a good estimation of the local environment. The fusion of these observations will produce a good observability of states. POMDP provides a natural way for using multisensorial fusion in their observations models ($p(\vec{o}\,|s)$) by mean of Bayes rule. Assuming that the observations are independent, the observation model can be simplified as in the following way:

$$\begin{aligned} p(\vec{o}\,|s) &= p(obs_{WiFi1}, \ldots, obs_{WiFix}, obs_{US}|s) = \\ &= p(obs_{WiFi1}|s) \cdot \ldots \cdot (obs_{WiFix}|s) \cdot p(obs_{US}|s) \end{aligned} \tag{3}$$

In the next section we show the results of the three methods to obtain a WiFi signal strenght map.

3 Implementation and Results

The Test-Bed environment was established on the 3rd floor of the Polytechnic School building, concretely in the corridor number 4 of the Electronic Department. The layout of this zone is shown in Figure 2. It has a surface of 60m x 60m, with about 50 different rooms, including offices, labs, bathrooms, storerooms and meeting rooms.

Seven Buffalo Access Points (APs) (WBRE-54G) were installed at the all environment. Five APs were connected to omnidirectional antennas and two APs (AP3 and AP7) were connected to antennas of 120 degrees of horizontal beam-width. The APs act as wireless signal transmitters or base stations.

For simplicity, the tests were achieved in the corridor 4. This was discretized into 11 nodes placed at the positions indicated in Figure 2. For each node some radio measures from all the APs in the two main orientations of the corridor

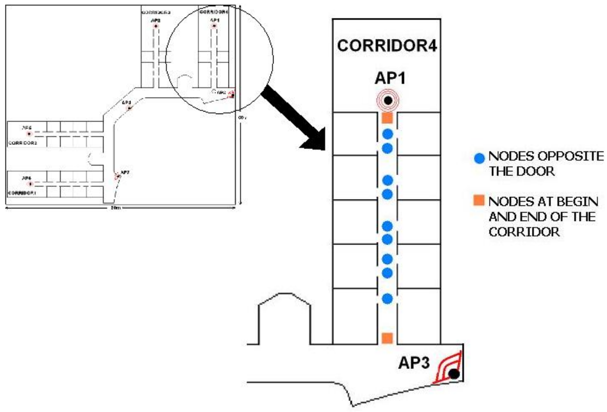

Fig. 2. Test-bed. Department of Electronics (Corridor 4).

were taken to obtain the WiFi radio map, and to extract the results of the WiFi POMDP navigation system.

In order to obtain experimental results of the three methods we used two robots based on the 2AT platform of Activmedia Robotics, as shown in Figure 3. They have the same configuration (Orinoco PCMCIA Gold wireless card, Linux Red Hat 9.0 operating system, wireless tools, a 16 ultrasound sensor ring and a SONY pan-tilt-zoom camera), but in one of them, a metallic structure was added in order to carry out a laptop and to increase the height of the camera.

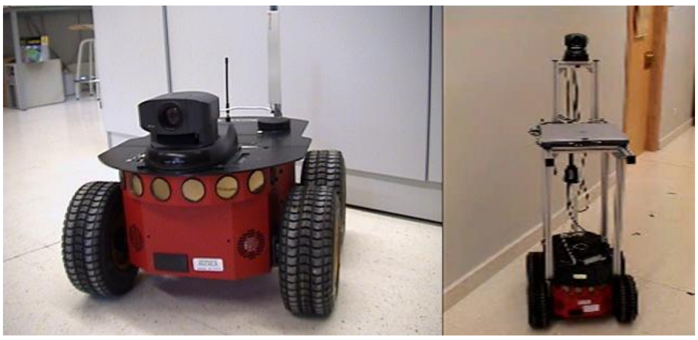

Fig. 3. Real prototypes used in the results extraction

First, the WiFi map was calculated using a propagation model. The WiFi radio signal propagates through the air following a radio propagation model. This model is very difficult to obtain for indoor environments, due to the multipath suffering and the temporal variation of the WiFi signal. Although an exact and general model doesn't exist, an approximated model can be used. We calculated the WiFi map with a generic log distance model as shown in equation 4.

$$R_{SL} = T_{SL} + G_{TX} + G_{RX} + 20log(4\pi) - 10n_W logd - X_a \tag{4}$$

Where the R_{SL} is the received signal level, T_{SL} is the transmitted signal level, G_{TX} and G_{RX} are the transmitter and receiver antennas gain respectively, λ is the wavelength (12.5cm for the 2.4GHz of the WiFi signal), n_W is a factor that depends on the walls effect, X_a is a random variable and d is the distance between the emitter and the receiver.

The main advantage of this method is that only required a few seconds of execution and a very slightly work-man effort.

Then, we used the manual training method by mean of positioning the robot along the several states in a manual mode. The robot took 60 WiFi signal samples to calculate the mean value at each state. This needed 9 hours and a half of an intensive man-work.

Finally, we used an automatic training method based on a robust local navigation task to carry out the robot centred along the corridor and using a modified Expectation-Maximization algorithm proposed in a previous work [14]. The user only needed to launch the local navigation application with a slightly supervision during about 2 hours to ensure that the task was carried out correctly by the robot.

The three maps was used in the localization stage of the POMDP for testing the error percentage in this phase. The comparison of these methods is shown in Table 1.

Table 1. Comparison of WiFi Map Construction Methods

Method	Training Time	Man-Work (%)	Error Percentage(%)
Propagation model	$<$ 30 sec	5	98
Manual	9 h 30 min	100	24
Automatic	2 h	10	8

4 Conclusions and Future Works

In this work we have compared three WiFi Map Construction Methods. We have demonstrated that the automatic method reduce the training time of the manual mode. Although the method based on propagation model achieves the best training time, it also achieves the worst error percentage. We conclude that the automatic method is the best compromise between training time, man-work needed and error percentage. In the near future, we have the intention to improve our automatic algorithm to be faster than the current.

Acknowledgment. This work has been funded by grant S-0505/DPI/000176 (Robocity2030 Project) from the Science Department of Community of Madrid, TRA2005-08529-C02-01 (MOVICOM Project) from the Spanish Ministry of Science and Technology (MCyT) and SIMCA (CM-UAH: 2005/018) from the University of Alcala.

References

1. Cox, I.: Blanche-an experiment in guidance and navigation of an autonomous robot vehicle. IEEE Trans. Robot. Automat 7(2), 193–204 (1991)
2. Want, R., Hopper, A., Falco, V., Gibbons, J.: The active badge location system. ACM Transactions on Information Systems 10, 91–102 (1992)
3. Krumm, J., Harris, S., Meyers, B., Brumitt, B., Hale, M., Shafer, S.: Multi-camera multi-person tracking for easy living. In: Proc. of 3rd IEEE International Workshop on Visual Surveillance, pp. 3–10 (2002)
4. Priyantha, N., Chakraborthy, A., Balakrishnan, H.: The cricket location support system. In: Proc. of the 6th ACM MobiCom, pp. 155–164 (2002)
5. Barber, R., Mata, M., Boada, M., Armingol, J., Salichs, M.: A perception system based on laser information for mobile robot topologic navigation. In: Proc. of 28th Annual Conference of the IEEE Industrial Electronics Society, pp. 2779–2784 (2002)
6. Bahl, P., Padmanabhan, V.: Radar: A, in-building rf-based user location and tracking system. In: Proc. of the IEEE Infocom, pp. 775–784 (2000)
7. Enge, P., Misra, P.: Special issue on gps: The global positioning system. Proc. of the IEEE 87(1), 3–172 (1999)
8. Serrano, O.: Robot localization using wifi signal without intensity map. Proc. of the V Workshop Agentes Físicos (WAF 2004), 79–88 (2004)
9. Howard, A., Siddiqi, S., Sukhatme, G.: An experimental study of localization using wireless ethernet. In: Howard, A., Siddiqi, S., Sukhatme, G. (eds.) Proc. of the International Conference on Field and Service Robotics (July 2003)
10. Ladd, A., Bekris, K., Rudys, A., Marceu, G., Kavraki, L., Wallach, D.: Robotics-based location sensing using wireless ethernet. In: Proc. of the MOBICOM 2002 (2002)
11. Youssef, M., Agrawala, A., Shankar, A.: Wlan location determination via clustering and probability distributions. In: Proc. of the IEEE PerCom 2003, IEEE Computer Society Press, Los Alamitos (2003)
12. Ocaña, M., Bergasa, L., Sotelo, M., Flores, R.: Indoor robot navigation using a pompdp based on wifi and ultrasound observations. In: IROS2005. Proc. of the IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 503–509 (August 2005)
13. Ocaña, M., Bergasa, L., Sotelo, M.: Robust navigation indoor using wifi localization. In: MMAR 2004. Proc. of the 10th IEEE Internacional Conference on Methods and Models in Automation and Robotics, pp. 851–856 (August 2004)
14. Ocaña, M., Bergasa, L., Sotelo, M., Flores, R., López, E., Barea, R.: Training method improvements of a wifi navigation system based on POMPDP. In: IROS 2006. Proc. of the IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 5259–5264 (October 2006)