

# Mapping based on a noisy Range-Only sensor

F. Herranz, M. Ocaña, L. M. Bergasa,  
N. Hernández, A. Llamazares and C. Fernández

Department of Electronics, University of Alcalá, Madrid (Spain)  
{fherranz,mocana,bergasa,nhernandez,allamazares,cfernandez}@depeca.uah.es

**Abstract.** Mapping techniques based on Wireless Range-Only Sensors (WROS) consist of locating the beacons using distance measurements only. In this work we use WROS working at 2.4GHz band (same as WiFi), which has the disadvantage of being affected by a high noise. The goal of this paper is to study a noisy range-only sensor and its application in the development of mapping systems. A particle filter is used in order to map the environment, this technique has been applied successfully with other technologies, like ultra-wide band (UWB), but we demonstrate that even using a much more noisy sensor this technique can be applied correctly.

## 1 Introduction

This paper addresses the problem of mapping using a noisy range-only sensor. These sensors have two important differences compared to other sensors. Firstly, using these sensors it is possible to avoid the data association problem because this kind of technology uses an unique identifier per sensor. Secondly, the measures do not provide too much information since information about the angles is not obtained. So, after measuring only one sample, the beacon could be everywhere within a ring with radius equal to the range measurement.

We have used WROS working at 2.4Ghz band, this band is affected by everything that contains water. Moreover, signal propagation is affected by reflection, refraction and diffraction. This effect, known as multipath effect, turns the received signal level (SL) into a complex function of the distance. In order to solve this problem, several techniques have been tested [1] [2]. In a previous work [3], authors have throughly studied the main variations that affect to this band. They identified five main variations that can appear when working with robots. Finally, they conclude that working at 2.4 GHz band the multipath effect can introduce an error of 10dBm to the SL

In this work we employ a probabilistic technique to estimate the position of the beacons. We have chosen a Monte Carlo algorithm like particle filter because it can represent multimodal distributions for position estimation [4]. Particle filters approximate distribution using a finite number of weighted samples. The estimated distribution is updated using importance sampling: new samples are drawn from the old distribution at random, propagated in accordance with robot odometry, and then weighted according to available sensor information.

The rest of the paper is organized as follows: section 2 shows the mapping process; section 3 describes the results obtained; and finally, section 4 shows some conclusions and future works.

## 2 Mapping with range-only sensors

Mapping is the process that makes possible to estimate the position of the beacons using the distance between them and the robot. First of all, in order to map these positions, it is needed to know the trajectory of the mobile, and then to estimate them using this knowledge. This problem is similar to the localization one but with a different point of view, we suppose that the robot position is known and static at different steps, and then it seems like the beacons are moving around it.

A particle filter [5] is used to achieve this aim, which is a sequential Monte Carlo algorithm, i.e., a sampling method to approximate a distribution that uses its temporal structure. A "particle representation" of distributions is used, in particular, we will be concerned with the distribution  $P(X_{bt}|z_{0:t})$  where  $X_{bt} = (x_{bt}, y_{bt}, \theta_{bt})$  is the observed beacon state at time  $t$ , and  $z_{0:t} = (r_1, r_2, \dots, r_n)$  is the sequence of observations from time 0 to time  $t$ . The transition and sensor models,  $P(X_{bt}|z_{0:t})$  are represented using a collection of  $N$  weighted samples or particles,  $\{X_{bt}^{(i)}, \pi_t^{(i)}\}_{i=1}^N$  where  $\pi_t^{(i)}$  is the weight of particle  $X_{bt}^{(i)}$  (Equation (1)).

$$P(X_{bt}|z_{0:t}) \approx \sum_i \pi_{t-1} \delta(X_{bt} - X_{bt-1}^{(i)}) \quad (1)$$

Firstly, the particles are uniformly distributed around a "ring" with radius equal to the first range measurement, we make this "ring" wide enough in order to absorb the signal noise. Then, we can obtain better results using a lower particle number.

Secondly, the particles are not propagated using any motion model since we know that the beacons are statics, instead of we apply a small random noise to the position of the particles in order to avoid that all the particles stay at the same position.

Finally, the particles are updated by the previous actions  $a_{t-1}$  and the actual observation  $z_t$ . This step is the main contribution of this work. Since we do not have information about the angle of the measurements, we build a "ring" of observations and we use this "ring" in order to weight the particles using a gaussian function. This process is described as follow:

- Measurement vectors  $Z$  are the distances between the beacons and the robot.
- The verisimilitude  $P(z_t|X_{rt})$  uses a vectorial space to represent the observations. Thus, we use a circumference equation, which is written in parametric form using trigonometric function shown in equation (2). Then, 360 observations (one per angle  $\phi$ ) are generated creating a circumference with radius equal to the distance between the beacon and the robot.

$$Obs = X_{r0} + r(\cos \phi, \sin \phi) \quad (2)$$

Where  $X_{r0}$  is the robot position,  $r$  is the radius,  $\phi$  is the angle.

Finally, it is important to highlight that this algorithm does not need to collect a high number of samples to estimate the beacon position.

### 3 Implementation and Results

We have set up a test environment outside of the Polytechnic School at the University of Alcalá (UAH), using a Seekur Jr platform (Figure 1). The robot has been equipped with a Waspote built by Libelium which is a range-only sensor, and a laptop using Linux Kubuntu 8.04 in order to collect the data along the path shown in Figure 1.



**Fig. 1.** Testbed

We have performed several tests varying the number of particles ranging from 100 to 1500 particles. Figure 2 shows the results of two beacons, which can be extrapolated to the rest of beacons. Figure 2 shows the percent of error in meters less than an abscissa and the 70 and 90 percentile per experiment. Using more than 500 particles the error is less than 3 meters, moreover we have to take into account that the signal noise sometimes is more than 10 meters. Also, it is possible to notice that increasing the number of particles our solution becomes more accurate and the error decreases.

### 4 Conclusions and future works

In this work a Wireless range-only sensor and its application to mapping system has been presented. We have proposed a solution based on a particle filter due

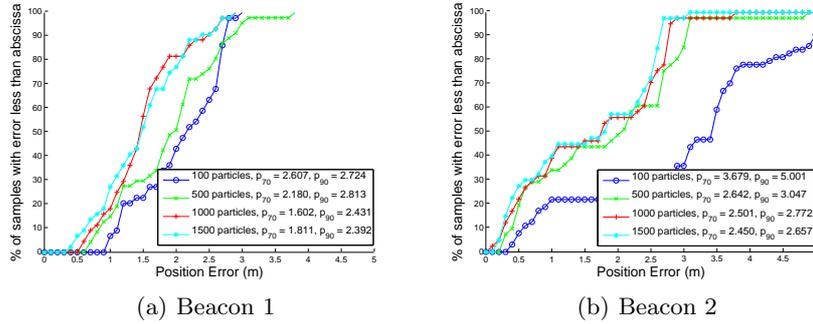


Fig. 2. Mapping error

to its ability for estimated the position of the beacon without dealy and its robustness. In near future, we have the intention of applying an SLAM algorithm and using an Inertial Measurement Unit (IMU) to improve the movement model and then the accuracy of the system.

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