Particle filter for merging internal and external positioning information in mobile robot navigation

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***Abstract*—This paper reports a local positioning systems for mobile robots based on merging the information from the internal odometer sensor of the mobile robot and the measurements from a set of external ultrasonic beacons. The cumulative errors of the odometer localization are corrected by using the positioning data obtained with an ultrasonic local positioning system (ULPS). It consists of four beacons placed at known positions of the ceiling, all of them emitting periodically and simultaneously. To avoid interferences among the simultaneous emissions, Direct Sequence Code Division Multiple Access (DS-CDMA) techniques have been used. The arrival instant from each beacon emission is detected by a mobile robot, which obtains its position by hyperbolic trilateration. Then, a Bayesian localization technique (implemented by a particle filter) is used to merge these measurements with those obtained with the odometer and produce a better estimation of the robot's position.**

I. INTRODUCTION

Indoor local positioning of objects and people is required on in-building context-aware applications [1]. From the different possibilities, Ultrasonic Local Positioning Systems (ULPS) provide high accuracy (with errors below the centimeter in some cases) at close ranges and allow the use of low cost sensors [1-4]. Nevertheless there are still many factors that influence the performance of those ULPS: frequency response and bandwidth of the transducers, characteristics of the multiple access method employed to emit the ultrasonic signals, multipath propagation, near-far effect, non-line of sight paths, etc. [5]. To mitigate these effects, this work proposes the fusion by means of Bayesian techniques of the positioning data coming from the ULPS and the inner odometer sensor of the robot.

The internal odometer of the robot allows estimating the position and orientation of the robot by integrating the number of left and right driving wheel rotations. These low cost sensors suffer from cumulative errors, so they are usually used together with an absolute positioning technique, such as an ULPS. By fusing the odometry with the ULPS location data the uncertainties and errors due to wheel slippage, the encoder pulse counting or due to small obstructions on the floor can be significantly reduced [6]. Thus, it is possible to obtain a better estimation of the position, without increasing the system cost.

Bayesian methods can be used to merge the information from the ULPS with that coming from the odometer [7]. These methods use statistical distributions to estimate the position from the mobile robot from a set of numerous measurements, dealing with the uncertainty associated to real measurements and allowing to incorporate the a priori knowledge of the system. From the different implementation options (Kalman filters, multiypothesis tracking, the grid-based approach, etc. [8]), the particle filter is an efficient technique which reduces the computation requirements by focusing in the area with higher position probability.

This work uses a particle filter for fusing the odometry and the measurements of a Code Division Multiple Access (CDMA) based ULPS. The rest of the paper is organized as follows: Section II describes the ULPS. Section III introduces some details about the measurements performed by the ULPS and the odometer sensor. Section IV presents a basic framework of Bayesian localization methods and particle filters. Section V deals with the particle filter implementation. Simulated and real experiments are shown in Section VI. Finally, conclusions are discussed in Section VII.

II. ARQUITECTURE OF THE ULPS

Fig. 1 is a photograph of the ULPS used for the real tests. It has four beacons (B1 to B4- note that the one in the middle is not used) oriented downward and placed at known positions in the ceiling of a rectangular room, with a height of 3.45 m and into a 0.67 m x 0.75 m surface. The beacons are hardware synchronized and together cover an area of 20m^2 over the floor. CDMA techniques based on complementary sets of sequences (CSS) [9] have been used to achieve multiuser access and increase the robustness to noise and precision in the distance measurements. Thus, each beacon is assigned a different complementary set, uncorrelated with those assigned to the others beacons. All the beacons emit simultaneously and periodically their corresponding sets.

Inside the operating area, a mobile robot correlates the received signal with the complementary codes that identify the beacons to obtain the arrival instant of each one of the emissions. Then, computes the difference in times of arrival

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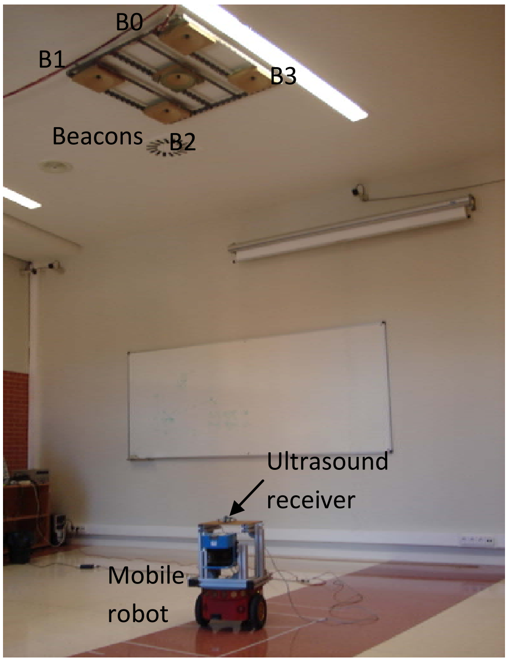

Figure1. Experimental set-up.

among a reference beacon and the others to obtain its position by hyperbolic trilateration. That avoids the use of additional hardware, such as radiofrequency or infrared signals to synchronize emitters and receivers.

At the emission stage, the transducers employed are piezoelectric polymer by MSI, and have a resonant frequency of 40 kHz with a 8 kHz bandwidth [10]. On the other hand, the receiver on board the mobile robot is a WM-61 Panasonic omnidirectional electret microphone [11], which has a flat frequency response between 20 Hz and 45 kHz.

III. SENSORY INFORMATION FROM THE LPS

A. Ultrasonic measurements

As mentioned in the previous section, the position of the mobile robot is calculated by hyperbolic trilateration. Specifically, a Caley-Menger bideterminant-based algorithm [12] has been used, since it offers a good Dilution of Precision (PDOP) with a low computational cost.

The beacons distribution, all at the same height in the ceiling, entails a high positioning error in the Z axis. Since the height of the mobile robot is known, the aforementioned error can be overcomed restraining the 3D-positioning to 2D-positioning (X and Y).

B. Odometer measurements

The mobile robot employed in this paper is the Pioneer3DX [14], which moves using two wheels with differential traction. The robot also has a caster wheel to ensure the stability of the structure. The linear (v_l) and angular (w_i) motion are generated from the differences in the rotation speeds between the left and right wheels. The subscript $i=\{r,l\}$ indicates the right or left wheel, respectively. Assuming that the radius of both wheels is r and the separation between them is L, the equations that link the linear and angular motion with the rotation speed of the wheels are:

$$v_l = \frac{r}{2}\left(w_r + w_l\right) \quad \Omega_a = \frac{r}{L}\left(w_r - w_l\right) \tag{1}$$

Thus, the motion equations of a robot at time k can be computed from the position at time k-1 as is indicated in (2), where Ts is the sampling period:

$$\begin{bmatrix} x_k \\ y_k \\ \theta_k \end{bmatrix} = \begin{bmatrix} x_{k-1} + v_l \cdot T_s \cdot \cos(\theta_k) \\ y_k - v_l \cdot T_s \cdot \sin(\theta_k) \\ \theta_k - \Omega_a \cdot T_s \end{bmatrix} \tag{2}$$

IV. BAYESIAN LOCALIZATION METHODS

A. Overview

The high levels of uncertainty in the ultrasonic and odometric measurements suggest the use of Bayesian probabilistic models to perform the location and tracking of the mobile robot. These techniques estimate the position of the mobile robot taking into account that uncertainty. As a result, these methods are able to recover from failures and are more robust to noise and measurement errors. The Bayesian probabilistic navigation methods are based on two fundamental statistical concepts: the Bayes theorem and Markov chains [15].

When a system that can be in a finite number of states, X_i, (where the probability distribution of all states in the instant k-1, X^{k-1}, is known), is applied a control signal, U^{k-1}; it is possible, by using the law of the total probability, to obtain the a priori probability that the new system state is X_i^k following (3) (this stage is known as prediction stage):

$$P\left(X_i^k / X^{k-1}, U^{k-1}\right) = \sum_j P\left(X_i^k / X_j^{k-1}, U^{k-1}\right) P(X_j^{k-1}) \tag{3}$$

If, at the same time, the measurement Z^k is obtained, this probability can be updated by using the Bayes theorem following (4) (this stage is known as update stage):

$$P\left(X_i^k / Z^k, X^{k-1}, U^{k-1}\right) = \frac{P\left(Z^k / X_i^k, X^{k-1}, U^{k-1}\right) P\left(X_i^k / X^{k-1}, U^{k-1}\right)}{P\left(Z^k / X^{k-1}, U^{k-1}\right)} \tag{4}$$

$P\left(Z^k / X_i^k, X^{k-1}, U^{k-1}\right)$ is unknown, but assuming that the system follows a Markov process, that is, that the current state only depends on the previous state, then $P\left(Z^k / X_i^k, X^{k-1}, U^{k-1}\right) = P\left(Z^k / X_i^k\right)$, so the probability of being in the state X_i at time k is:

$$P\left(X_i^k / Z^k, X^{k-1}, U^{k-1}\right) = \frac{P\left(Z^k / X_i^k\right) P\left(X_i^k / X^{k-1}, U^{k-1}\right)}{P\left(Z^k\right)} \tag{5}$$

This process is repeated for all possible values of the state X_i; thus, the probability of being in each of the possible states

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at the current time can be calculated from the probability distribution at time k. The denominator in (5) is the same in all the possible states X_i, and acts as a normalization factor. Thus, $P\left(Z^k / X_i^k\right)P\left(X_i^k / X^{k-1}, U^{k-1}\right)$ is usually computed for all the possible values of X_i to obtain a normalization factor η that makes the sum of all of them being one. Hence eq. (5) can be rewrited as:

$$P\left(X_i^k / Z^k, X^{k-1}, U^{k-1}\right) = \eta P\left(Z^k / X_i^k, X^{k-1}, U^{k-1}\right)P\left(X_i^k / X^{k-1}, U^{k-1}\right) \quad (6)$$

According to this criterion, at each time k there is no absolute certainty of being in a specific state X_i, instead there is a probability of being in each possible state. That is, there is a distribution of probabilities, denoted as system state belief distribution.

The main problem of the Bayesian filters for continuous variables is that the computation of the integrals and multiplications of the belief probability density function requires a high computational load, what makes these models very difficult to use in real time systems. In order to reduce the computational complexity, a method based on particle filters has been employed [8].

B. *Particle Filter*

A particle filter is an estimation of the system state belief probability density using a Monte-Carlo simulation [16]. To implement this filter a set of initial particles is defined. Each particle has associated a possible value of the system state, x_l, and a weight, w_l, that represents the probability of being in this state. Thus, the set of particles $\{x_l, w_l\}_{l=1..N}^k$, represents the belief probability density at time k. The number of particles must be high enough to adequately represent the belief probability density function.

In the prediction stage, a new set of particles is created from the previous set of particles $\{x_l, w_l\}_{l=1..N}^{k-1}$. For this purpose, the set of particles at time *k-1* is randomly sampled according to the weights of each particle, w_l. Once a particle is selected $\{x_l, w_l\}^{k-1}$, its state, x_l^{k-1}, is modified by using the statistical action model, $P\left(x_l^k / x_l^{k-1}, u^{k-1}\right)$, to obtain the new particle state x_l^k. The sampling process is performed N times to obtain the new set of states, $\{x_l\}_{l=1..N}^k$.

The new weights of the particles are obtained in the update stage by using the perception model $P\left(Z^k / x_l^k\right)$. Each state x_l^k is assigned a weight proportional to the probability of getting the observation Z^k, being in the state x_l^k:

$$w_l^k = \eta P(Z^k / x_l^k) \quad (9)$$

Where η is a normalization factor. A new set of particles that represents the belief of the probability density function at time k is obtained. Fig. 2 shows the block diagram of a particle filter.

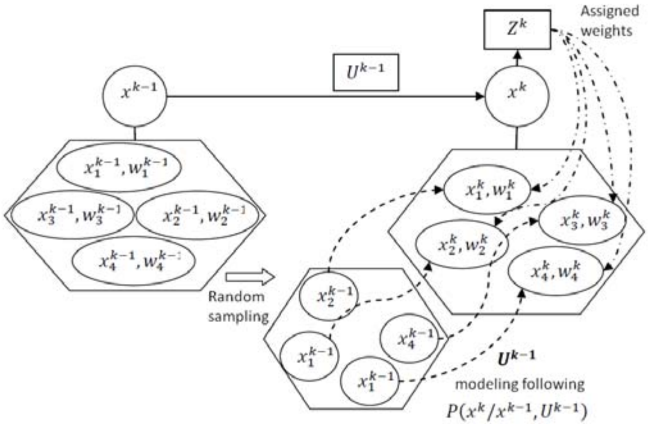

Figure 2. Block diagram of a particle filter.

Using this method, the weights of the states that less match with the observations, have lower values, making their particles less likely of being choosed for the next stage. Thus, the particles tend to have values closer to the actual system state, in agreeing with the observation performed.

The initialization of the particle filter to obtain the first set of particles should be carried out considering the available information of the initial position of the mobile robot. Therefore, if the initial position of the robot is unknown, the initial value of the particles should be completely random, following a uniform distribution among all the possible values of the state x_l^0. Its associated weight should be the same for all the particles $w_l^0 = 1/N, \quad \forall l = 1...N$ where N is the number of particles.

If there is available some information about the initial position of the robot, a large number of particles should be placed close to this value. Finally, if the initial position of the robot is known, all particles should be placed in this position.

One of the drawbacks of the particle filter is that to ensure the convergence and to reliably represents the belief probability density function of the robot, a large number of particles are required, what implies a high computational load. However, when the system evolves and a large number of measurements are available, the particles are concentrated around the actual value of the system state, therefore the filter converges and the number of particles can be reduced. On the other hand, when the observed measurements start to disagree with the state where the particles are concentrated, it would be necessary to increase the number of particles, and to distribute uniformly some of them among all the possible values of the system state in order make the filter converge again. In [16] it is proposed how to modify the particle filter in order to solve the convergence problems.

V. Implementation of the Particle Filter

In order to implement the particle filter, the location information provided by the ULPS is considered as the environment measurement. As well as this, its statistical model is considered as the observation model. The odometry and its statistical distribution are used as the action model.

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The vector state of the system is the robot position and orientation:

$$P = [x \quad y \quad \theta]^T \tag{10}$$

The robot linear and angular speed read from the odometer are the measures for the action model, U^{k-1}. Therefore the robot motion model (section III.B) is applied to each of the particles computed during the sampling stage.

On the other hand, the positions obtained by the ULPS are the observation data, Z^k. The statistical distribution between the measured position and the actual one is considered a two-dimensional Gaussian in the X and Y axes. In this Gaussian the standard deviation is the product between the HDOP (Horizontal Dilution Of Precision) in the point and the standard deviation in the measured distance. Hence, the weight, w_l, for the particle whose state is $P_l=[x_l \ y_l \ \theta_l]$ can be computed as indicated in (11), assuming that the data $P_z=[x_z, y_z]$ have been measured:

$$w_l = \frac{\eta}{HDOP(x_l, y_l)\cdot\sigma_d} e^{-\frac{(x_l-x_z)^2+(y_l-y_z)^2}{2(HDOP(x_l,y_l)\cdot\sigma_d)^2}} \tag{11}$$

Where η is a normalization factor, $HDOP(x_l,y_l)$ is the HDOP in the position (x_l,y_l), and σ_d is the standard deviation in the measured distance.

Since in the initialization of the particle filter the robot position is unknown, it is assumed a random distribution of the particles in all the coverage area. After each filter iteration, the robot position is the mean of all particles positions adjusted according to their weights.

In order to weight the angles of the particles to obtain the robot orientation, and since the ULPS does not provide angle information, the following steps are proposed:

- The estimated value of the angle is taken from the previous iteration, θ_{k-1}.
- The current angle is predicted assuming an ideal behavior of the odometer:

$$\theta_{k,pred} = \theta_{k-1} + \Omega_a \cdot T_s \tag{12}$$

- The standard deviation of the angular speed of each particle is obtained as a function of the linear speed of the robot, as indicated in (13):

$$\sigma_a = \begin{cases} K_a / v_l & si \ v_l > 0.015 m/s \\ K_a / 0.015 & si \ v_l < 0.015 m/s \end{cases} \tag{13}$$

  Where v_l is the robot linear speed, and K_a is a constant. For linear speed values below 0.015 m/s it is assumed that the robot is not in motion and the standard deviation is set to a maximum value.

- Each particle, $\{P=(x_l, y_l, \theta_l), w_l\}$, of the new set of particles modifies its weight according to a Gaussian distribution with mean $\theta_{k,pred}$ and standard deviation σ_a:

$$w_l = \frac{\eta}{HDOP(x_l, y_l)\cdot\sigma_d\sigma_a} e^{-\frac{(x_l-x_z)^2+(y_l-y_z)^2}{2(HDOP(x_l,y_l)\cdot\sigma_d)^2}} e^{-\frac{(\theta_l-\theta_{k,pred})^2}{2\sigma_a^2}} \tag{14}$$

One of the main drawbacks of this kind of filters is its computational load. In the initial moments there is a big uncertainty about the mobile robot position, so a large number of particles are required to ensure the filter convergence. However, when the particles are concentrated into a small area, their amount can be reduced since the tracking of the mobile robot does not have a high level of uncertainty. Therefore, an adaptive particle filter has been implemented. In this filter the resampling process can be interrupted when the sum of the particles weights are higher than a predetermined threshold Ver_{max}, so the number of particles in the system can be reduced. It has also been established a maximum threshold for the number of particles.

VI. Results

This section presents some location and tracking results. The tests have been carried out using the following values for the different parameters: sample period, Ts=200ms; maximum number of particles, N_{max}=8000; maximum likelihood, Ver_{max}=750; angular standard deviation, K_a=0.03*π rad s/m.

A. Simulation Results

In order to test the proposed particle filter a circular path has been simulated: *v_lin*=0.1 and *v_ang*=π/100 rd/sg. The trajectory starts in the test position [0 0]. No errors in the odometry has been considered for this test, and therefore the measurement errors correspond to the location algorithm σ_d=1cm.

Fig. 3 shows the path that the robot is asked to do (red line), the trajectory estimated by the particle filter (green line), and the points where the ULPS location algorithm estimates the position of the robot (blue circles). It can be observed that, at the beginning, the particle filter has trouble following the right trajectory of the robot, but after a few iterations is able to follow the robot path.

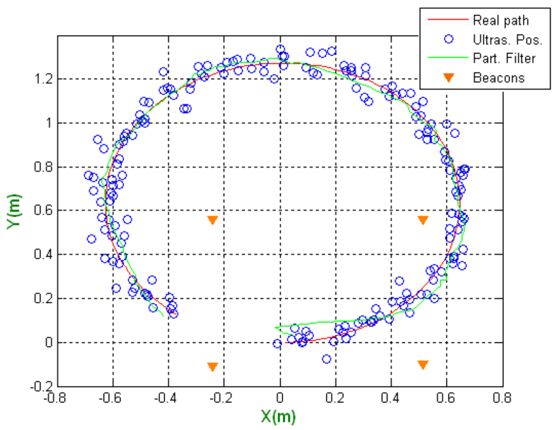

Figure 3. Trajectory obtained by the Particle Filter considering that the odometry measurements do not have errors.

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Fig. 4 shows the same path considering a standard deviation in the linear speed of 25% from the robot magnitude, and an angular standard deviation of 200 rad/s. Furthermore, during the trajectory it has been included an impulsive noise in the robot linear speed during 2 seconds. It can be observed that, despite the errors in the odometer and the impulsive noise, the particle filter is able to follow the correct robot path.

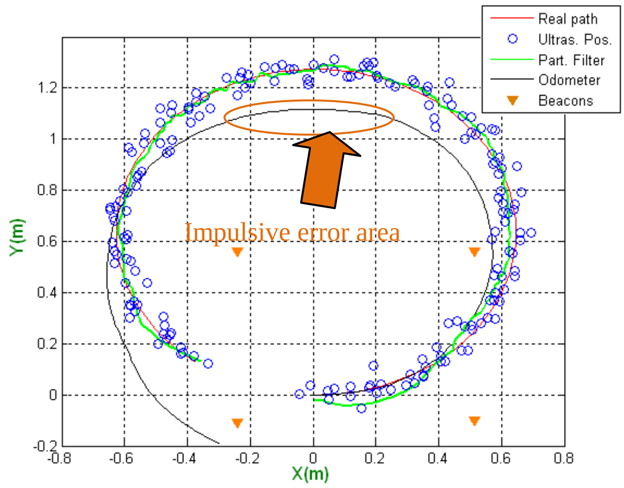

Figure 4. Trajectory obtained by the particle filter considering that the odometer has errors.

B. Real results

To test the proposed particle filter in a real scenario, the mobile robot has been tracking during 45 seconds in the ultrasonic ULPS described in the section II. The particle filter algorithm has been computed offline by using the data provided by the ULPS and by the odometer.

Fig. 5 shows the robot positions obtained with the ULPS (blue circles), and the trajectory obtained with the particle filter (green line). The conclusions are similar to those of the simulation case.

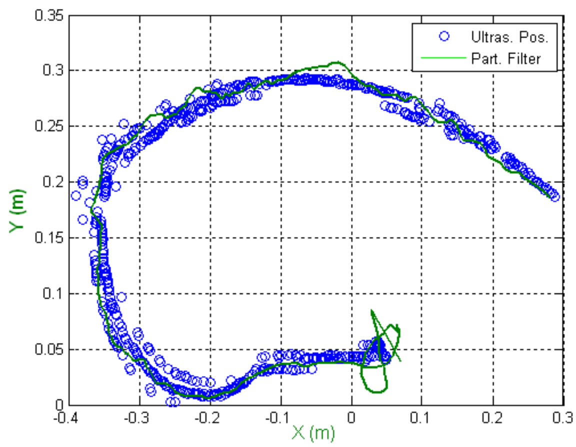

Figure 5. Particle filter and ultrasound trajectories obtained in the real tests.

The particle filter does not need to weight the orientation of the particles to obtain a good estimation of the orientation. The particles that have a bad orientation are not going to match the observation when the filter evolves because of the motion model. However, when the robot is in motion, the trajectory obtained when the orientation is weighted is softer than that obtained without considering the robot orientation. The differences among weight or not the orientation estimation in the particle filter can be seen in the real test depicted in Fig. 6, where the robot has follow a longer trajectory than that of Fig. 5 and where the wheels have been forced to slip in a specific zone.

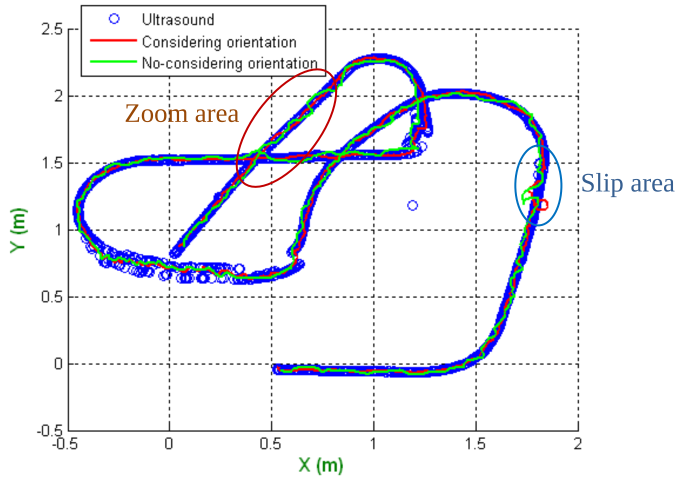

Figure 6. Comparison of the particle filter results with and without the orientation estimation.

For a better illustration, Fig. 7 depicts a zoom of the trajectory in Fig. 6. If the orientation is used in the particle filter, the final estimated trajectory is more similar to that obtained with the ultrasounds.

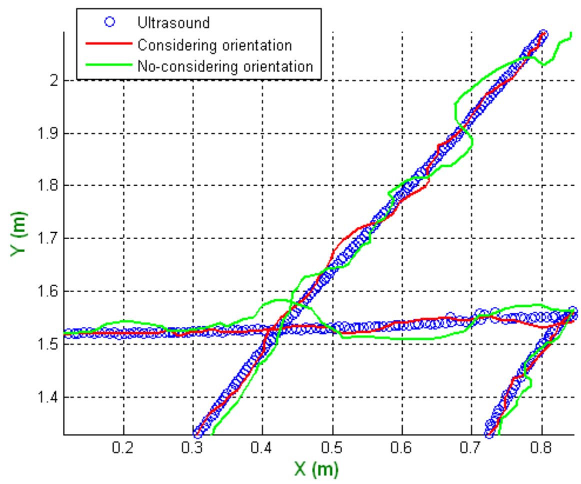

Figure 7. Zoom of the trajectories obtained in Fig. 6.

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VII. Conclusion

In this paper, the position estimation coming from an ultrasonic local positioning system has been merged with that coming from the inner sensors of a mobile robot. The fusion has been done by means of Bayesian techniques (an adaptative particle filter). First results with the systems show a better position estimation, even in those positions which are more affected by the multipath or where is not possible to receive the ultrasonic signals.

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