Extensive Ultrasonic Local Positioning System for navigating with mobile robots

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***Abstract*—This paper presents an extensive local ultrasonic positioning system for mobile robots (MRs) based on the fusion of the information from the MR internal odometer sensor and the measurements of position obtained with a set of external ultrasonic beacons that form an Ultrasonic Local Positioning System (ULPS). The extensive ULPS is formed using several single ULPS, each one of them covering a particular area of the total working area. In each single ULPS, five ultrasonic beacons are used that emit simultaneously and are detected by an ultrasonic receiver on board the MR. Direct Sequence Code Division Multiple Access (DS-CDMA) techniques have been used to avoid interferences between them. When the MR navigates on the working area, it continuously obtains its relative position thanks to the internal odometer. The cumulative errors of the odometer are corrected when the robot is on a place where the positioning data obtained with any of the single ULPS are available. The fusion of information (from odometer and ULPS) is made using an H-Infinite filter. The extensive ULPS has been built and tested experimentally.**

Keywords— Ultrasound; LPS; Mobile robots; H-Infinite filter; Odometer.

I. Introduction

Due to the problems of using GPS inside buildings, in the last decade several indoor Local Position Systems (LPS) has been proposed [1-3]. Within these kinds of systems, 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 [4-6].

In Ultrasonic systems normally the absolute distance between the robot and the ULPS is measured [7] (spherical trilateration) but in this case it is necessary a synchronization between the ULPS and the robot. One way to avoid that synchronization is the use of hyperbolic trilateration [8] using, in this case, the increment of distance between the reception of a reference signal and the reception of the signals of the rest of the emitters.

In many cases these systems are used with mobile robots (MR) [9, 10], that use the internal odometer of the robot to estimate the MR position and orientation by integrating the number of rotations of the axes. These measurements are very accuracy but suffer from cumulative errors, that is, at the beginning of the robot movement the position is very accurate but it increases with time.

By fusing the odometer information with the ULPS location data the errors due to wheel slippage, small obstructions on the floor or related with the encoder pulse counting can be significantly reduced [11]. Thus, it is possible to obtain a better estimation of the position avoiding the odometer cumulative errors.

Bayesian methods are normally used to merge the information from the ULPS and the odometer [12]. These methods use statistical distributions to estimate the MR position from a set of numerous measurements, dealing with the uncertainty associated to real measurements and with the possibility of adding the a priori knowledge of the system.

The most common algorithm is the Extended Kalman Filter (EKF) [13]. This filter is optimal for Gaussian noise as it minimizes the quadratic mean error between the different data. Some improvements of the EKF have been proposed: the Ensemble Kalman Filter (EnKF) uses a Monte-Carlo method to predict the statistical errors [14] and the Unscented Kalman Filter (UKF) [15] is an estimator for non-Gaussian errors.

In addition to the EKF there are other Bayesian techniques to merge the information, such as particle filters [16] that use a Monte-Carlo method to describe the probability density function or the H-Infinite filter that minimizes the worst case estimation error [17]. This last filter can be used in systems where the statistics errors are unknown or are not well characterized.

This work presents an Ultrasonic Local Position System, which allows a robot mobile to navigate in an extensive area using an H-infinite filter to merge the odometer and the ULPS information. When the robot is in a place where the ULPS is not available, the filter only use the odometer information, but when it reaches to a place covered by the ULPS it uses the Ultrasonic information to improve the MR position.

The paper is organized as follows: Section II describes the Extensive ULPS implementation; Section III introduces the RM Navigation algorithm with the H-Infinite filter to merge the data; realization and analysis of real experiments are shown in Section IV and, finally, some conclusions are discussed in Section V.

II. Extensive LPS Implementation

A. Single LPS implementation

In order to build the LPS, the Prowave 328ST160 ultrasonic transducer was selected as beacon. According to its

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datasheet this transducer has a resonance peak at the frequency of 32.8 KHz with a bandwidth of 2.5 KHz and it has a wide angle beam. The information available in the datasheet only provides information up to 38 KHz. Testing the transducer for higher frequencies we discovered that it has a second resonance peak at 46 KHz, so if it is used a central frequency of 40KHz the transducer has a bandwidth of 18 KHz (Fig. 1).

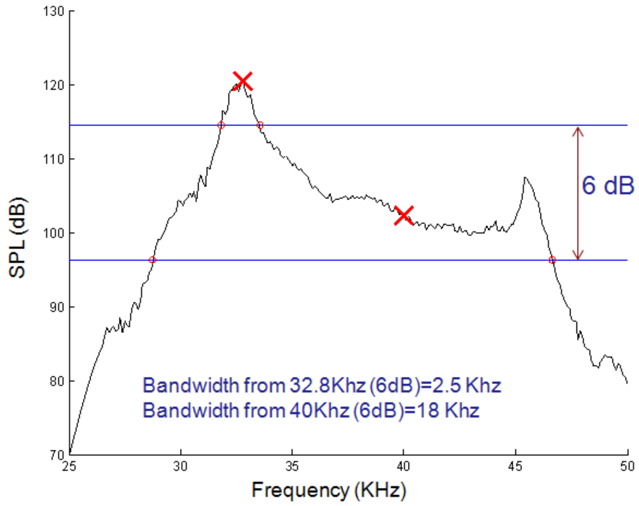

Fig. 1. Prowave 328ST160 frequency response.

In order to increase the performance of the LPS, 1023 bits Kasami codes are assigned to each transducer. These codes are modulated with a BPSK modulation with a carrier frequency of 40 KHz. These orthogonal codes are selected due to its good autocorrelation and crosscorrelation properties (Fig. 2). Using this code it is possible to have errors in the distance measurements below one centimeter [18].

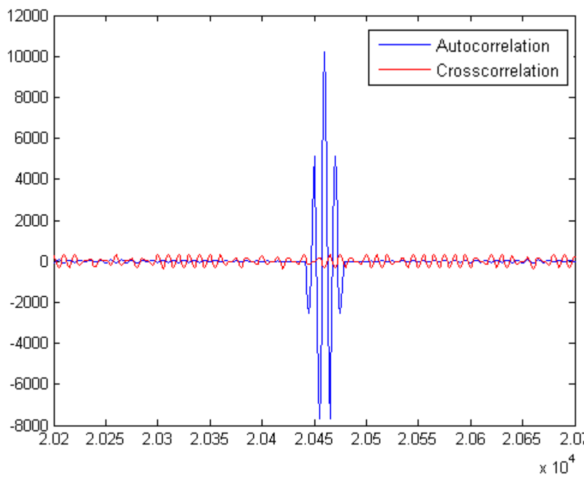

Fig. 2. Ideal autocorrelation (blue) and ideal crosscorrelation (red) for a Kasami code of 1023 bits modulated with a BPSK with a carrier frequency of 40KHz.

To control the LPS the microcontroller LPC1768 was selected. This ARM processor is very cheap and easy to program. The main disadvantage is that it only has one DAC so it is necessary to use TDMA techniques in order to use the 5 transducers that form the single ULPS, and in addition it is necessary to include additional hardware (multiplexors and control signals) to select the right transducer during the different intervals of time.

Furthermore the LPS has a FM RF-Module that emits a small pulse every time a transducer starts the emission of a code. These modules were included not for use in the robot navigation but in the calibration stage (see Section II.B). The Fig. 3 shows an image of a single LPS, it is possible to see the five transducers: one in the center and four at the end of the arms. And also the dimensions of the structure.

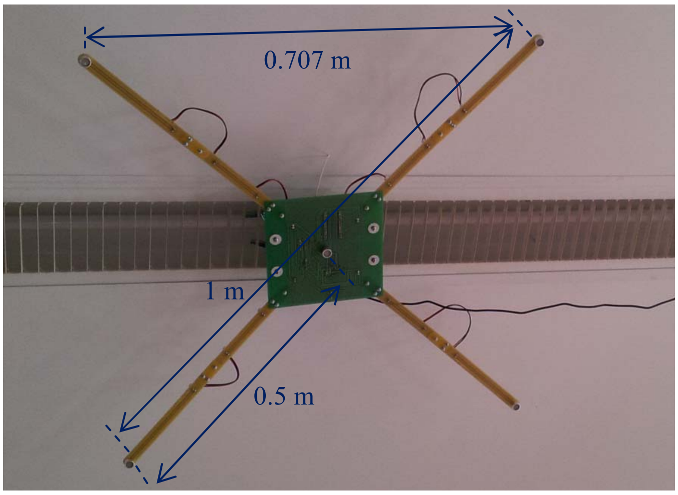

Fig. 3. Single LPS structure and dimensions.

B. LPS Calibration

Once a single ULPS is installed the next step is to calibrate it, in order to get the position of the transducers (beacons) in the global map. To perform this task the algorithm proposed in [19] is used. These method obtain the position of the transducers measuring the distance to each transducer from three known points, that is, their positions are known in the global map, and some distance measurements (in our case eight) from unknown points, that is, their positions are unknown.

To carry out the calibration we used a spherical positioning algorithm because it introduces much less error than the hyperbolic one. Then, in the calibration stage, it is necessary a synchronization between the emitters and the receiver to obtain the absolute distance between them, so to get this synchronization we use the FM RF-module.

After this calibration we obtain the positions of the transducers with a maximum structure error (error in the distance between the transducers) below 7 mm and an error mean of 4 mm.

C. Extensive ULPS deployment

Fig. 4 shows the space to cover with the extensive ULPS. This space is around 442 m^2 and we have installed six LPS. Each LPS has a short cover area (the space where at least the signal of three transducers is received) of 36 m^2. We need to obtain these three measurements to carry out the two dimension position of the mobile robot (x, y); and a long cover area (the space where at least the signals of two transducers are received) of 49m^2; in order to navigate using an H-infinite filter only the signal of two beacons is needed.

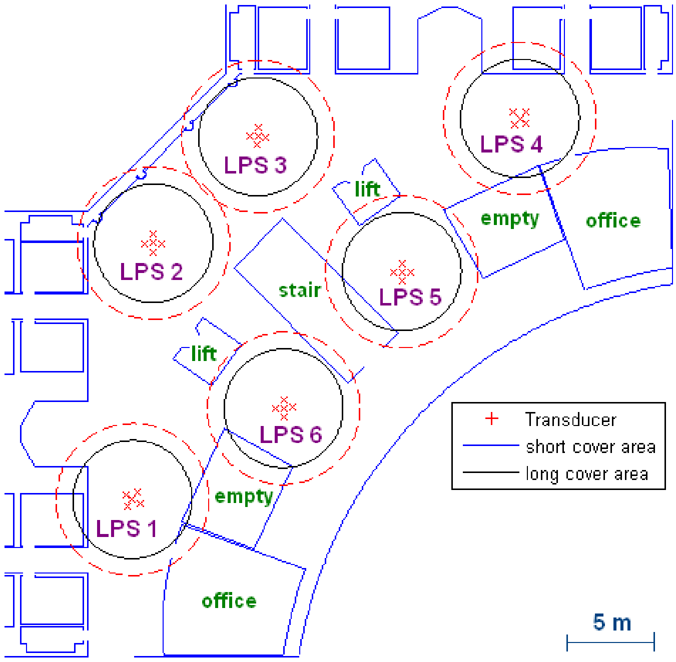

Fig. 4. Ultrasonic-LPS installation in the work area.

III. Robot Navigation

In order to navigate with the robot we use an H-infinite filter to merge the internal robot odometer data and the ULPS information. This filter is similar to the Extended Kalman Filter but instead of minimizing the quadratic mean error between the different data, it minimizes the maximum error, so this filter is also known as minimax filter [17].

In our case we want to obtain the position and the orientation of the mobile robot, so for the filter the estate vector at time k is:

$$\boldsymbol{q_k} = [x_k, y_k, \theta_k]^T \tag{1}$$

The equations of the H-infinite filter adapted to the robot navigation are:

Prediction stage:

$$\widehat{\boldsymbol{q}}_{k,odo} = f(\widehat{\boldsymbol{q}}_{k-1}, in) \tag{2}$$

Update stage:

$$\begin{aligned} \boldsymbol{L}_k &= (\boldsymbol{I} - \gamma \cdot \boldsymbol{P}_{k-1} + \boldsymbol{C}_k^T \cdot \boldsymbol{V}^{-1} \cdot \boldsymbol{C}_k \cdot \boldsymbol{P}_{k-1})^{-1} \\ \boldsymbol{K}_k &= \boldsymbol{A}_k \cdot \boldsymbol{P}_{k-1} \cdot \boldsymbol{L}_k \cdot \boldsymbol{C}_k^T \cdot \boldsymbol{V}^{-1} \\ \widehat{\boldsymbol{q}}_k &= \widehat{\boldsymbol{q}}_{k,odo} + \boldsymbol{K}_k(\boldsymbol{d}_k - \widehat{\boldsymbol{d}}_k) \\ \boldsymbol{P}_k &= A_k \cdot \boldsymbol{P}_{k-1} \cdot \boldsymbol{L}_k \cdot \boldsymbol{A}_k \cdot \boldsymbol{W} \end{aligned} \tag{3}$$

Where:

- $f(\widehat{\boldsymbol{q}}_{k-1}, in)$ is the function that relate the robot estimate position at time k-1, $\widehat{\boldsymbol{q}}_{k-1}$, with the position of the robot at time k, $\widehat{\boldsymbol{q}}_k$, using the data from the robot odometer (See section III.A).
- $\widehat{\boldsymbol{q}}_{k,odo}$ is the state estimated vector with the robot position and orientation using the robot odometer data.
- $\boldsymbol{A}_k$ and $\boldsymbol{C}_k$ are the Jacobian matrix of the robot and LPS dynamics respectively, these matrixes are defined in sections III.A and III.B.
- $\boldsymbol{K}_k$ is the filter gain.
- $\boldsymbol{d}_k$ is the vector with the measurements from the Ultrasonic-LPS.
- $\widehat{\boldsymbol{d}}_k$ contains the estimated measurements to the LPS there are obtained from the estimated position of the robot.
- $\boldsymbol{V}$ and $\boldsymbol{W}$ are the odometer and distance measurement noise matrices respectively. See section III.C.
- $\boldsymbol{I}$ is the identity matrix.
- $\boldsymbol{P}_k$ is the filter covariance matrix.
- γ is a filter parameter. In our case it is set to 1e-3.

A. Robot dynamics

In our system we use a pioneer DX5000 robot, so the position of this robot using the odometer information can be obtained as:

$$\boldsymbol{q}_{k,odo} = \begin{bmatrix} x_k \\ y_k \\ \theta_k \end{bmatrix} = f(\widehat{\boldsymbol{q}}_{k-1}, in) = \begin{bmatrix} x_{k-1} + \Delta D_k \cdot \cos(\theta_k) \\ y_{k-1} + \Delta D_k \cdot sin(\theta_k) \\ \theta_{k-1} + \theta_k \end{bmatrix} \tag{4}$$

Where ΔD_k is the distance travelled by the robot between the instant k-1 and the instant k. $\Delta\theta_k$ is the angle increment in the robot orientation between the two instant of time (See Fig. 5). Also it has been suppose that the height of the robot (z) is known so we perform a 2D location.

From the movement model of the robot it is possible to calculate its dynamic model ($\boldsymbol{A}_k$) differentiating $\boldsymbol{q}_{k,odo}$ in regards to the vector state.

$$\boldsymbol{A}_k = \frac{\partial q_{k,odo}}{\partial q_k}\bigg|_{q_k=\widehat{q}_k} = \begin{bmatrix} 1 & 0 & -\Delta D_k \cdot sin(\theta_k) \\ 0 & 1 & \Delta D_k \cdot \cos(\theta_k) \\ 0 & 0 & 1 \end{bmatrix} \tag{5}$$

B. LPS dynamics

In our system the mobile robots are not synchronized with the LPSs, so instead of knowing the absolute distance, it is measured the increments of distance between the receptions of the signals taking one of the signal as reference (Hyperbolic trilateration [8]).

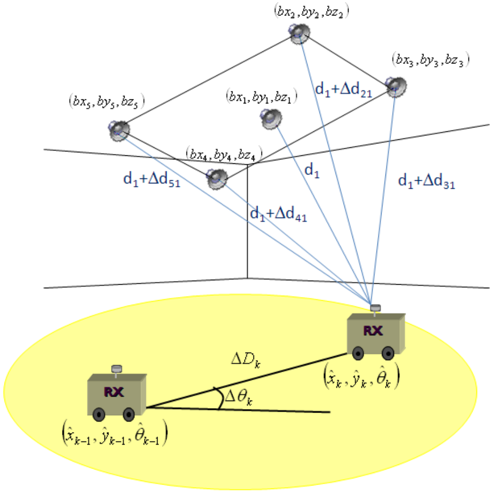

Fig. 5. Variation of the robot position between two instants of time, and measurements from the beacons.

Supposing the first transducer of each LPS as the reference one, the distance increment between the transducer i placed on (bx_i, by_i, bz_i) and the mobile robot in the position (x_k, y_k, z_k) can be expressed at time k as:

$$\Delta d_{i1,k} = \sqrt{(x_k - bx_i)^2 + (y_k - by_i)^2 + (z_k - bz_i)^2} - \sqrt{(x_k - bx_1)^2 + (y_k - by_1)^2 + (z_k - bz_1)^2} \quad (6)$$

So the measurement vector at time k can be expressed as:

$$\boldsymbol{d}_k = \left[\Delta d_{21,k}\ \Delta d_{31,k}\ \Delta d_{41,k}\ \Delta d_{51,k}\right]^T \quad (7)$$

As in the previous case, differentiating (7) in regards to the vector state it is obtained the dynamic model of the measurements ($\boldsymbol{C}_k$):

$$C_k = \frac{\partial \boldsymbol{d}_k}{\partial \boldsymbol{q}_k}\bigg|_{\boldsymbol{q}_k = \hat{\boldsymbol{q}}_k} = \begin{bmatrix} \frac{\partial d_{21,k}}{\partial x_k} & \frac{\partial d_{21,k}}{\partial y_k} & \frac{\partial d_{21,k}}{\partial \theta_k} \\ \vdots & \vdots & \vdots \\ \frac{\partial d_{51,k}}{\partial x_k} & \frac{\partial d_{51,k}}{\partial y_k} & \frac{\partial d_{51,k}}{\partial \theta_k} \end{bmatrix} \quad (8)$$

Where:

$$\begin{aligned} \frac{\partial d_{i1,k}}{\partial x_k} &= \frac{(x_k - bx_i)}{\sqrt{(x_k-bx_i)^2+(y_k-by_i)^2+(z_k-bz_i)^2}} - \frac{(x_k - bx_1)}{\sqrt{(x_k-bx_1)^2+(y_k-by_1)^2+(z_k-bz_1)^2}} \\ \frac{\partial d_{i1,k}}{\partial y_k} &= \frac{(y_k - by_i)}{\sqrt{(x_k-bx_i)^2+(y_k-by_i)^2+(z_k-bz_i)^2}} - \frac{(y_k - by_1)}{\sqrt{(x_k-bx_1)^2+(y_k-by_1)^2+(z_k-bz_1)^2}} \\ \frac{\partial d_{i1,k}}{\partial \theta_k} &= 0 \end{aligned} \quad (9)$$

C. System Noise

In the proposed system it is supposed that the main errors are in the odometer information and in the measured distances from the LPS.

In the odometer case the Chenavier and Crowley model is used [20]. This model assumes that the errors are uncorrelated and follow this expression:

$$\boldsymbol{W}_k = \begin{bmatrix} K_{ss}|\Delta D_k cos(\theta)| & 0 & 0 \\ 0 & K_{ss}|\Delta D_k sin(\theta)| & 0 \\ 0 & 0 & K_{s\theta}|\Delta D_k| + K_{\theta\theta}|\Delta\theta_k| \end{bmatrix} \quad (10)$$

Where K_{ss} is the odometer drift coefficient when the robot follow a path, $K_{s\theta}$ is the angle drift coefficient when the robot follow a path and $K_{\theta\theta}$ is the angle drift coefficient when the robot only turns.

In the case of the distance measurements it is assumed that the noise is Gaussian and is uncorrelated, so **V** is a diagonal matrix whose elements are the standard deviation in the distance measurements:

$$\boldsymbol{V}_k = \begin{bmatrix} \sigma_2 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \sigma_N \end{bmatrix} \quad (11)$$

IV. RESULTS

The Fig. 6 shows the space where the tests are carried out and the location of the LPS.

Fig. 6. Location of the extensive ULPS .

In order to test the accuracy of the single ULPS, a grid of 3x2 m whit a step of 0.5 m was created under the ULPS 1. In 21 position of the grid, 100 measurements are taken, (the positions are obtained using the algorithms described in [21]. Some of these points are close to the beacons to test the near-far effect (P_1-P_{11}), some are far away of the beacons (P_{18}-P_{21}) and some of them are located in multipath areas (P_{12}-P_{17}).

Fig. 7 shows the locations of the 21 test points and Fig. 8 shows the mean error and the standard deviation in 'X and Y' for each one of the 21 test points in mm. It can be observed that the mean error in most of the points is below 2 cm and in the worst case, P_{18}, is below 4 cm. The standard deviation of the 100 measurements in each point in most of the cases is below 2.5 mm and in the worst case P_{13} is below 6 mm.

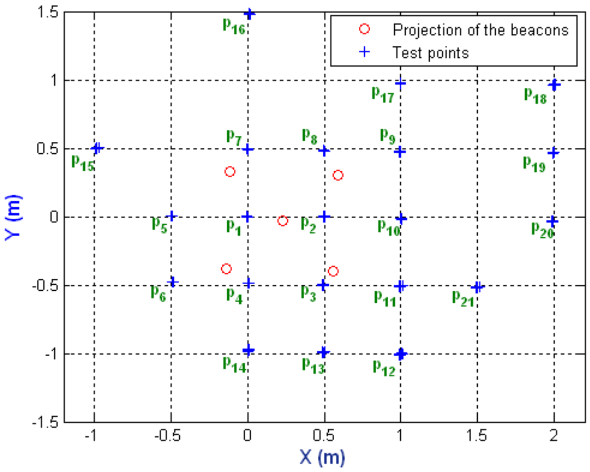

Fig. 7. Location of the 21 test points. In each point one hundred measurements are taken.

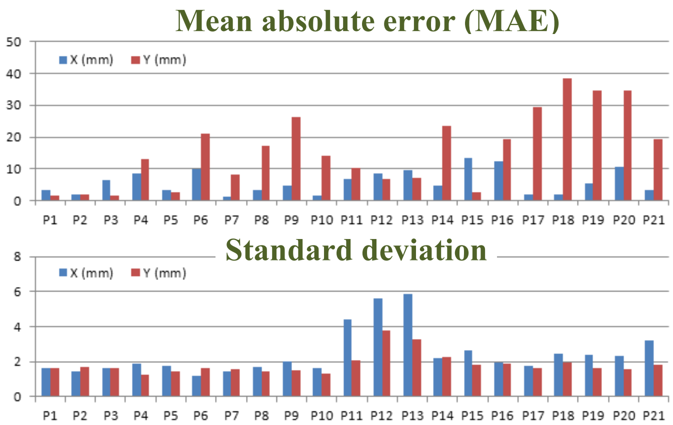

Fig. 8. Absolute mean error and standard deviation in mm of the 100 measurements for the 21 test points.

Fig. 9 shows a long path performed with the robot on the floor, inside the extensive coverage area, in order to test the extensive LPS. The red line is the robot positions obtained using only the odometer; the green points are the positions obtained using the different ULPS (the positions are obtained using the algorithms described in [21]); the black line is the robot positions using the H-infinite filter (merging the odometer and ULPS information) and the blue points are the position of the beacons.

It can be observed how at the beginning the position obtained with the odometer is very accurate but when the robot starts to move the error is increasing and at the end the final robot position obtained with the odometer is completely erroneous.

Using only the LPS information (green points) we do not have information during the entire path and in some points there are some outliers due to errors in the distance measurements.

Finally it can be seen how the path obtained using the H-infinite filter allows to recover the positions of the robot filtering the odometer errors using the different ULPS information. In the coverage area of each single ULPS the outliers obtained using only the ULPS are also filtered.

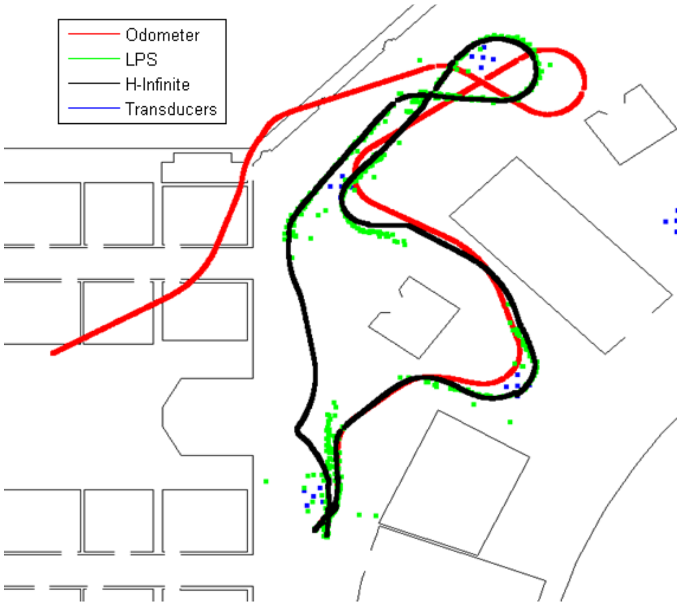

Fig. 9. Robot mobile path obtained using the odometer (red) the LPS (green) and the H-infinite filter (black) the blue points are the projections of the transducers.

V. Conclusions

In this paper, an extensive ULPS has been presented. It has been shown its structure and introduced the codification techniques that have been used in order to increase its accuracy. A single ULPS has been tested and in most of the cases, inside its coverage area, the absolute position mean error is below 3 cm with a standard deviation below than 4 mm.

Several single ULPS have been used to cover a large area in a building. Furthermore in order to merge the odometer and the ULPS information, when it is available, an H-Infinite filter has been implemented, this filter allows a MR to navigate combining the odometer and LPS information achieving a better performance.

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