Mobile Robot Navigation in Indoor Environnements by using the Odometer and Ultrasonic data

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Abstract

In this work we examine the strategy and the control architecture to allow an autonomous mobile robot to navigate in indoor environment. One fundamental property a really useful autonomous mobile robot equipped with is the capability to effectively avoid collisions in realtime. The robot's control s system includes several processes which run in parallel by using a specialized hardware. The navigation subsystem of the mobile robot integrates the position estimation obtained by ultrasonic system with the position the estimated by odometry, using the extended Kalman filter. Obstacle detection is performed by means of set of ultrasonic sensors. The results presented whether experimented or simulation, show that our method is well adapted to this type of problem.

1 Introduction

Although the robots we see in science fiction movies appear to navigate with effortless precision, in reality mobile robot navigation is a difficult research. Stated most simply, the problem of navigation can summarized by the following three questions : 'where am I ?', 'where am I going ?', and 'how should I get there ?'[12]. The task of a navigation system is to plan a path to a specified goal and to execute this plan, modifying it as necessary to avoid unexpeced obstacles.
An autonomous mobile robot is a mobile system capable of interpreting, planning and executing a given task without any external support. Therefore , an autonomous robot must be able to explore an a priori unknown environment systematically in order to perform some useful, goal-oriented operation after the exploration phase is finished. During this exploration phase the robot's perception system has to incrementally build up internal models of the environment which most accurately represent topological and geometrical properties. Consequently, these world models are the basis for goal oriented behaviour. The major difficulty in robot perception is to find out what the sensor signals tell about the real world-in other words ; the problem is to interpret the sensor signals in such a way that each world model represents an optimal estimate of the real world's state with respect to the model's specific purpose We feel that the design of a system for sensor signal interpretation basically is an optimization process, since on the one hand the requirements of the problem to be solved have to be considered and on the other the information which can be provided by the individual sensors. A crucial problem in sensing is that of coping with uncertainty. The sensory integration is the process of combining measurements obtained by multiple sensors in a statistically significant way. This is important task in the navigation of autonomous mobile robots, because the use of several sensors may reduce uncertainties associated to each sensor and provide sufficient and reliable information about the system status, relating to the environment. One of the main problems in the development of robot systems, which are able to navigate in unknown environments, is the monitoring of the vehicle position. Determination of the actual position and orientation is a fundamental task in goal-oriented navigation , where a mobile vehicle starts from an initial point and reaches a destination in accordance with a pre-planned path.
Our work concerns the problem of monitoring position and orientation of an autonomous mobile robot in a goal oriented indoor navigation using the measurements obtained by the odometer and the ultrasonic sensors. The static objects of the environment are modeled by means of a geometric modeler, so that all the objects detected on the path during robot navigation must be considered obstacles
A set of elementary motion actions (translations and rotations of the robot) constitute the initial programmed path, as computed by the path planner for the target position indicated by the master process. The path must be re-computed only when unknown obstacles are detected along it or sensible deviations are estimated. Once the path to be followed has been defined, the master process activates the following independent processes.
This paper is organized as follows : section two presents our experimental autonomous mobile robot, the VAHM. Thereafter, section three gives a brief survey of related work in sonar world modeling while section four describes

our approach, Environmental Modeling Approach for the VAHM in detail. Sections five and six are about the collision avoidance and the odometer resetting methods. Finally experimental results and conclusions are summarized in sections seven and eight.

2. Context

Our experimental autonomous mobile robot is a V.A.H.M. project (Vehicule Autonome pour Handicapé Moteur, Autonomous vehicle for the disabled) which is centred on the development of a powered wheelchair for the disabled (see figure 1). This vehicle is intended to help the disabled with motor deficiencies in theirs displacements. Due to its specific application, the system is designed to navigate in rather structured indoor environnement. The goal of the V.A.H.M. project is to provide the wheelchair with such functionalities as automatic path and motion planning, fast obstacle avoidance, wall and person following, by means of adapted man-machine interfaces. The low-cost nature and the real time use the final wheelchair require simple and easy to handle sensors. Our experimental wheelchair is equipped with a pair of front castors and a pair of rear drive wheels, and his localisation and perception are assured by a belt of 14 ultrasonic sensors and an odometer.

Figure 1 : The robot V.A.H.M.

3 Related work in sonar environment modeling

In this work, we use the term sonar to describe airborne ultrasonic range sensing. Crowley, L. Parisot, Leonard and Durrant-white have developed world modeling for mobile robot using ultrasonic ranging [9], [10], [17], [12]. Their approach based on the representation of the robot environment by set of the geometric primitives such as planes, lines, corners, edges,... Crowley in his approaches, introducing the concept of the composite local model. The composite local model is built by extracting straight line segments from sonar data, and is matched to a previously stored global line segment map to provide localisation. Beckerman and Oblow have developed a rule-based approach which deals with the treatment of systematic errors [2]. Each cell of their grid is either labeled as empty, occupied, unknown, or conflict. Conflicts may occur whenever an object is being observed at different times from different locations. The approach has disadvantages concerning dynamic obstacles, and moreover is time-consuming since they use a two dimensional sensor model. The probabilistic approach of Elfes and Moravec generates an occupancy grid which explicitly represents free and occupied regions in space [10]. Their sensor model is two-dimensional, as well. Since they take into account the ultrasound beam as a whole a large number of grid cells corresponding to the projection of the beam has to be updated. This approach requires quite a lot of computing time, as well. Borenstein and Koren call their method for grid-based mapping the vector field histogram [3]. They use one dimensional sensor model which reduces the real sound wave to the beam’s acoustic axis. This trivial sensor model causes a drastic transfer of the sensing-computation ratio to the credit of sensors and leads to surprisingly good results.

4 Environmental Modeling Approach for the V.A.H.M.

In this section we present a modelization method of the robot environment using sonar. In our work, we have used the geometric representation of the environment. The model is built by extracting straight line segment.

4.1 General description of the method

The idea used for ultrasonic calibration has been applied to realise a perception system to locate the ultrasonic sensors in the environment. Our approach of modelization permits to extract the straight line segments of the vehicle environment. The theory behind our approach to sonar interpretation follows directly from the published works of Crowley [8], [9],. The contribution that we feel we have provided many modifications (alternations) in the modelization approach. A main difference with Crowley is that in our approach, the segments are created from alone impact point. These segments are characterized by their nil length (the start point equal the arrival point), and their orientation is perpendicular to the ultrasonic sensor axis. We have provided a little modification when the segment is processed, a new point is added. Figure 2 shows the model of the segment used in our approach.

The segment equation is :

$$x*sinq - y*cosq + r=0 \qquad (1)$$

where *q* is the segment orientation and *r* the minimal distance of the segment in comparison to the set reference origin.

The parameters of the created segments are estimated by a method of the Recursive Least Square (RLS) with weighting from the data which are validated by the detection tests. These tests are based on the trigonometric criterion such width of the robot. The advantage of the provided modification to this method is that , the ultrasonic data are not kept in the memory. These data are directly used and processed to create the segments.

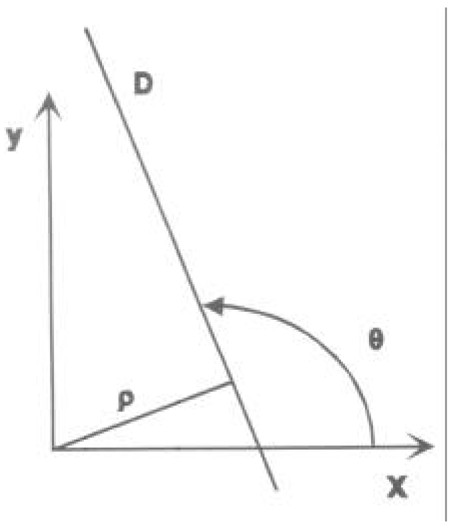

Figure 2 : The model of the segment

4.2 Model Building

This sub-section attempts to develop a method of the model building for the robot mobile navigation. Unfortunately, combining the capabilities of localization and map building described earlier is not as straightforward as one might hope. Wile these issues are important regardless of the sensing modality employed, for our purpose here we shall maintain our exclusive focus sonar.

For each sensor measurement acquisition, the fourteen ultrasonic data are processed one by one in the trigonometric direction (anticlockwise). As soon as the first sensor data is processed, a segment in the model building is initialized. This segment whose length is nil (start point equal and arrival point are equal), has its orientation perpendicular to the acoustic axis of the sensor (more details in 4.2.2). For next acquisition, each new data is treated as shown in the Figure 3.

Once the fourteen ultrasonic data are treated, the segmentation algorithm stops. The integration of the new point to the segment is validated by the following tests [Crowley] :

the orientation test : this test is to verify if the measurement impact angle on the segment of two points, permits an acoustic reception to the corresponding ultrasonic sensor. The condition is that :

$q \le q_{segment} + p/2 + var(d)$

where *var(d)* is the variance of the sensor range angle (acoustic axis)

the proximity test : this text is to determine if the minimal distance of the new point to the segment is inferior to the uncertainty in point position :

$d_{min} \le s_d^2 + var(r)$

where σ_d is the sensor measurement uncertainty which is given by the constructor. s_d=1% of the measured distance. *Var(r)* is the variance of the segment coefficient *r*.

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the distance test : this test is to verify if the new point is moving away from the segment less than the robot width. *d* ≤ the robot width.

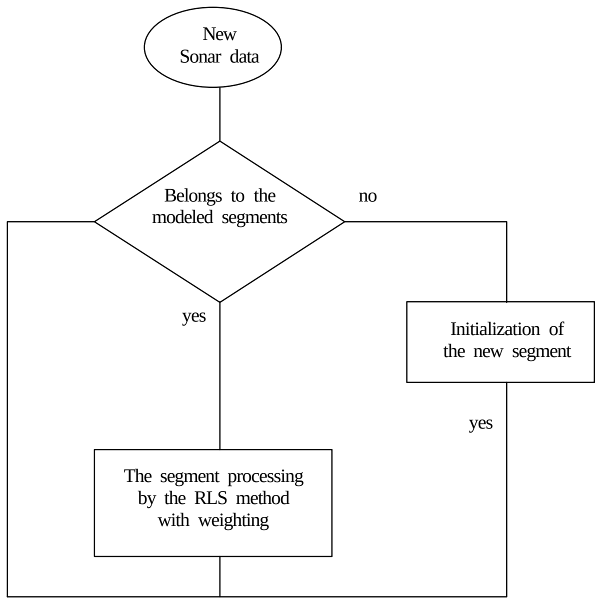

Figure 3 : The model algorithm .

4.2.1 The segments parameters estimate

In this point, we use the method of the Recursive Least Square (RLS) with weighting. The line segment equation is always : *x*sinq - y*cosq + r=0.* The algorithm of RLS with the weighting has the form :

$$D_{k+1} = D_k - \frac{a_k * B_k * Z_k}{1 + a_k * Z_k^T * B_K * Z_k} \left(Z_k^T * D_k \right)$$

(2)

$$B_{k+1} = B_k - \frac{a_k * B_k * Z_k}{1 + a_k * Z_k^T * B_k * Z_k} \left(Z_k^T * D_k \right)$$

(3)

where D_k, Z_k, B_k, and a_k are respectively the segment estimate in the step *k*, the variance of D_k, the new measurement to integrate into the segment estimate, and the weighting on Z_k.

$$a_k = \frac{1}{\mathrm{var}(d_k)}, \qquad (4)$$

var(d_k) is the variance of the distance d_k which is the distance between the echo sonar sensor and the line segment D_k.

After computing the new segment estimate, it is necessary to determine the new segment ends. In order that the previous ends and the new measurement are projected into the new line segment, then we choose among these points the two very distanced points.

4.2.2 Creation of the new segment

When one measurement is not belongs to any model segment, a new segment of nil length is created. Its initial point and final point are equal to impact point, and its orientation is orthogonal to sonar sensor axis. Its uncertainty is calculated from the uncertainty of the sensor measurement.

When a new segment is initialized, the initial conditions of the support straight line are defined. Given Z_0 the coordinates of the measurement point in order to construct the segment.

$$Z_0 = \begin{bmatrix} x_0 \\ y_0 \\ 1 \end{bmatrix}$$

(5)

The segment has the form :

$$D_0 = \begin{bmatrix} \sin\left(q_{sensor} + p/2\right) \\ -\cos\left(q_{senor} + p/2\right) \\ r \end{bmatrix}$$

(6)

The variance-covariance matrix of the segment parameters is :

$$B_0 = J_D * r\left(x, y, q_m\right) * J_D^T$$

(7)

where $r\left(x, y, q_m\right)$ the variance-covariance matrix of the impact point coordinates and J_D the jacobian matrix of the segment coefficients.

$$J_D = \begin{bmatrix} 0 & 0 & \cos\left(q_{segment}\right) \\ 0 & 0 & \sin\left(q_{segment}\right) \\ -\sin\left(q_{segment}\right) & \cos\left(q_{segment}\right) & -x*\cos\left(q_{segment}\right) - y*\sin\left(q_{segment}\right) \end{bmatrix} \qquad (8)$$

If the created segment really corresponds to an object in the environment, the other measurements can be rapidly put to correspondence with this segment, and the say object will be modelized. If the case of the new segment measures are bad, the say segment is destroyed. We have given the point threshold. The segment which contains less than ten points is destroyed.

4.2.3 The reduction of the emission cone

The ultrasonic sensors have a bad lateral resolution proportional to the width of their emission cone : in fact we do not know the reception axis for the possible received echo. In the fault, the measure is placed in the acoustic axis, which can be a very important error if the measured distance is considerable. Because of that, the created line segments from these measurements have the bad orientation and distance from the reference origin. It is a

navigation. It's very import to correct this error (Figure 4).
All that to calculate the angle a between the normal to the acoustic axis and the estimated segment

$$a = \left(q_{sensor} + p/2\right) - q_{segment} \qquad (9)$$

After to have calculated the angle a, the impact points coordinates are again treated on taking into account this angle, in order to replace the veritable obstacle orientation in the emission cone of the correspondent sonar sensor.
From the certain points number(ten) belongs to the segment, it is supposed that this segment has a good orientation estimate. Then it can be again processed on

using the RLS algorithm.

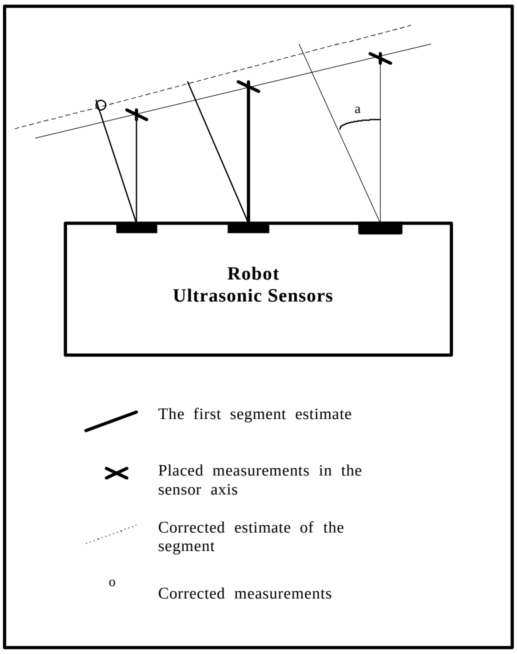

Figure 4 : The error reduction of the sonar emission cone.

5 Collision avoidance

This module is activated when the obstacle detection module discovers some obstacles along the vehicle path. The task of this module is to provide a steering command letting a mobile robot reach a goal while avoiding collision with obstacles by use the of fuzzy logic technique.
More details about this module technique can be found in [15].

Navigation

Previous work in navigation has to treat the problems of localization, obstacle avoidance, and map building in isolation. Approaches to obstacle avoidance, such as the method of potential fields[18], are typically of no use for localization. Algorithms for globally referenced position estimation, such as the work of Cox[7], rely on a priori map, but do not incorporate the construction of such a map. Many algorithms for map building do not address the issue of localisation while the is being constructed, relying instead on odometry or hand measuring of sensing locations. The challenge posed by a complete implementation of autonomous navigation is the simultaneous realisation of these different capabilities.

Sensory fusion can be performed employing an extented Kalman filter (EKF) model to obtain an optimal estimate of vehicle position and orientation. The EKF is the basic tool of our approach to navigation[ ]. Kalman filters are well-known

tools in theory of stochastic dynamic systems which can be used to improve the quality of estimates of unknown quantities .Kalman filtering techniques have been applied to the problems of map-making and position estimation.
In the framework we have defined for navigation, it is necessary, step by step, to integrate the two measures of vehicle position and orientation : the odometer and the ultrasonic sensor. As we have the segments positions from the robot, we can use them like <<geometric beacon>> in order to reset the odometry. The position and orientation of the vehicle at time step k by the state vector $\boldsymbol{X}(k) = [x(k),y(k),q\ (k)]^T$ comprising a Catersien location and a heading defined with respect to a global coordinate frame. At initialisation, the robot starts at a known location, and the robot has an a priori map of n_T geometric beacons, whose locations are specified by set of the known vectors $\{\square_t \,|\, 1 \leq t$ ³ $n_T\}$. A localization is a cyclic procedure that is repeated as frequently possible. The robot evolution equations are given by the odometry :

$$\boldsymbol{X}(k+1)=\boldsymbol{F}(\boldsymbol{X}(k),dd,dq)+\boldsymbol{v}(k) \qquad (10)$$

where $\boldsymbol{F}(\boldsymbol{X}(k),dd,dq)$ is the (non-linear) state transition function, $\boldsymbol{X}(k)$: the vehicle's position and orientation, dd and dq : the robot elementary moving ;and $\boldsymbol{v}(k)$ a noise disturbance.

The observations equations are provided by the ultrasonic data :

$$Z(k+1)=h_t(p_t,X(k+1))+w(k+1) \quad (11)$$

where the measurement function $h(p_t,X(k+1))$ expresses an observation $Z(k+1)$ from ultrasonic data to target t as function of the vehicle location $X(k+1)$ and the geometric beacons ; and $w(k+1)$ is the gaussian noise disturbance. The state transition function $F(X(k),dd,dq)$ has the form :

$$\begin{cases} x(k+1) = x(k) + dd(k)\cos\left(q(k) + dq(k)/2\right) \\ y(k+1) = y(k) + dd(k)\sin\left(q(k) + dq(k)/2\right) \\ q(k+1) = q(k) + dq(k) \end{cases} \quad (12)$$

The measurement prediction is :

$$\breve{z}(k+1)=h(V(k+1),X(k+1|k)) \quad (13)$$

where $\mathbf{V}(k+1)$ is the segment estimation and $X(k+1 \mid k)$ the state prediction provided by odometry.

The innovation has the form :

$$\nu(k+1)=[Z(k+1)-h(V(k+1),X(k+1)|k))] \quad (14)$$

The innovation variance :

$$S(k+1)=\mathrm{var}(Z(k+1))+\mathrm{var}(\breve{z}(k+1))$$
(15)
$$= \mathrm{var}(w(k+1)) + J_x * P(k+1 \mid k) * J_x^T + J_V * B(k+1) * J_V^T$$

where $w(k+1)$ is the ultrasonic data variance, $P(k+1 \mid k)$ the prediction variance from the odometry ; and J_x and J_V are the jacobian of $h(p_t,X(k+1))$ in the comparison to the variables X and V.

$$J_x^T = \begin{bmatrix} \sin(q) \\ -\cos(q) \\ -\sin(q)*\left(y_{sensor} - Y(k+1/k)\right) - \cos(q)*\left(x_{sensor} - X(k+1/k)\right) \end{bmatrix} \quad (16)$$

$$J_V^T = \begin{bmatrix} x_{sensor} & y_{sensor} & 1 \end{bmatrix}$$
(17)

$$P(k+1/k) = J_X F \cdot P(k/k) \cdot J_X F^T + J_{dd,dq} F \cdot C(dd,dq) \cdot J_{dd,dq} F^T \quad (18)$$

where $J_X F$ is the jacobian matrix of the robot position, $J_{dd,dq}$ is the jacobian matrix of the robot moving, and $C(dd,dq)$ is the variance-covariance matrix of the robot moving increments.

$$C(dd,dq) = \begin{bmatrix} \dfrac{s_d^2 + s_g^2}{2} & \dfrac{s_d^2 - s_g^2}{2L} \\ \dfrac{s_d^2 - s_g^2}{2L} & \dfrac{s_d^2 + s_g^2}{L^2} \end{bmatrix}$$
(18)

s_d^2 et s_g^2 represent the moving increments variances of each wheel and L the axle way.

The Kalman gain can be written as:

$$K(k+1) = \frac{P(k+1/k) * J_x^T}{S(k+1)}$$
(19)

to compute the updated vehicle position estimate

$$X(k+1/k+1) = X(k+1/k) + K(k+1) * n(k+1)$$
(20)

with associated variance

$$P(k+1/k+1) = P(k+1/k) + K(k+1) * S(k+1) * K^T(k+1)$$
(19)

In order to improve the extraction precision of the beacons,
we realised the odometer resetting just before integrating the measurements in the segment (RLS).

7 Experimental results

Several experiments have been carried out to study the validity of the proposed integration approach. Currently we are combining the measurements provided by odometers and the measurements obtained from the set of the fourteen ultrasonic sensors to monitor continuously the robot’s position and orientation.

The modules path planner, environmental modeling, obstacles avoidance and odometer resetting are implemented on our wheelchair controlled by PENTIUM, with the MATLAB software.

The experiments have been realised in the rectangular room. Using the path planner in the Figure 5 an optimal path is computed on the basis of the starting and goal points. This path has the ellipse form. The vehicle moves along this path which has the ellipse form. For these experiments, the vehicle has made three circumferences of this route. The length of the path is 53 metres while the total distance traveled amounts to 51 metres.

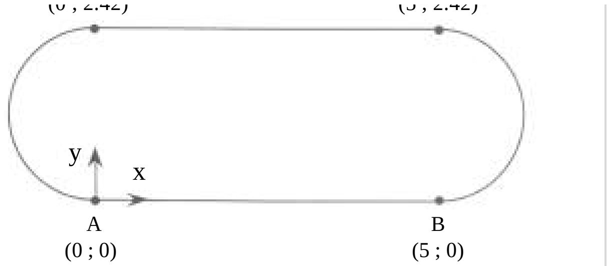

Figure5 : The optimal path in the trigonometric direction with the passage points (coordinates in metres)
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The variances of the increments moving are modeled by the Mourtalier and Chatila method :

$$s_d^2 = (0.01 \cdot d_d)^2 \,,\; s_g^2 = (0.01 \cdot d_g)^2$$

The variance of sonar measurement is proportional to the measure :

$$s_s^2 = (0.02 \cdot d)^2$$

The odometer resetting process integrates, in the sense of the EKF approach, the measurements provided from the odometer and sonar data. The EKF inverts when a Segment has more 15 points.

Fig. 6 shows the real paths executed by the vehicle with the odometer and with the odometer-sonar integration. Fig. 7 shows the real path executed with the odometer resetting using the EKF. Fig. 8 shows the errors of the different navigation methods.

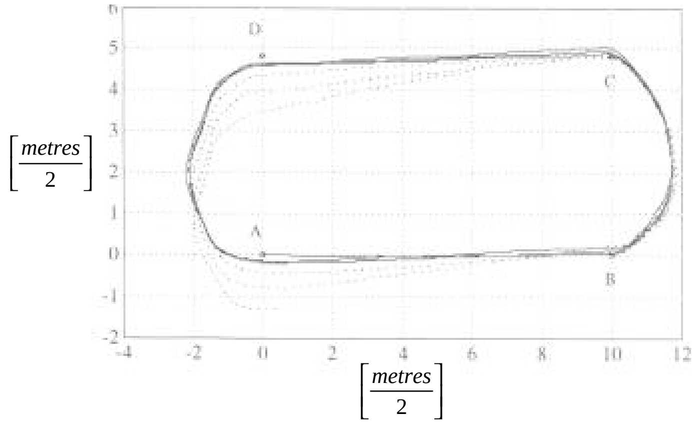

Figure 7 : The real path executed by the vehicle with the odometer resetting using the EKF ( )

	Position Error ε_{final} [mm]	Error relating the traveled distance ε_{final} / distance[%]	Orientation Error $\Delta\theta_{final}$ [°]
Odometry	**466**	**0.93**	**5.2**
odometer - sonar Integration	**399**	**0.78**	**-2**
The odometer restting with the EKF	**71**	**0.14**	**-0.5**

Figure 8 : The different localisation errors during the vehicle navigation.

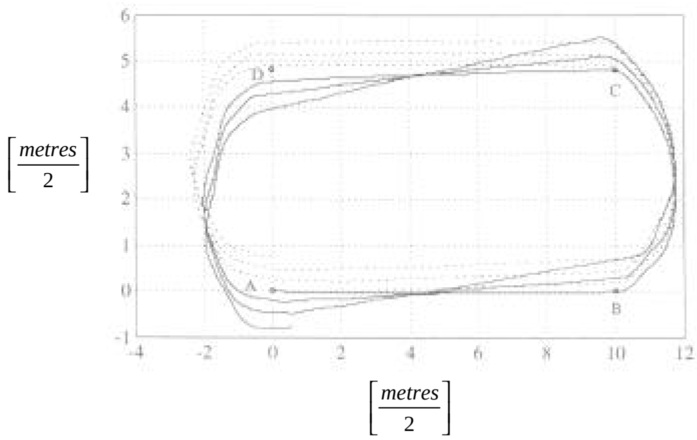

Figure 6 : The real paths traveled by the vehicle
: odometer
: odometer-sonar integration

During the motion of robot, the obstacle detector builds up a map of the environment using ultrasonic data. In our experiment we used only the four walls or the room as obstacles. With our environmental modeling approach, the walls are modeled with a great precision.

7. Conclusions and future work

In this work we have discussed a strategy and a control architecture to allow an autonomous mobile robot to navigate indoors a goal oriented context. We are developed the environmental modeling approach for the robot navigation. This approach gives a great results. The use of the Extented Kaman Filter in the odometer resetting process provides a framework to integrates the measurements of the robot's position and orientation derived from the odometer and the measurements provided by the ultrasonic sensors. Experimental results indicate orientation.

8. References

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