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Mobile Robot Set Localization for Assisting People at Home

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Abstract

The robot, as technology of daily assistance to the person, may be considered only if its availability is compatible with the expected service. The useful operating time should be around eight hours per 24 hours. One of the major issues is the reliability of the autonomy of the robot. This objective can be achieved by relying on the principle of ambient robotics, defined as cooperation between the robot and ambient environment. The article focuses on the location of the robot and the person weakened at home or in institution such as EHPAD. The robot autonomous localization remains a function difficult to make reliable over a long period, in a badly modeled environment. The localization method is based on interval analysis applied to measures modeled by a bounded error. Evaluations with a simulated and real robot show the interest of this approach.

Keywords

Robot mobile localization, Interval analysis, Inversion set, Heterogeneous measurements fusion.

1. Introduction

With the lengthening of life expectancy [1], rising health and pension spending, lower consumption of the elderly, aging is often described as a threat to the finances of developed countries like the France. However one can note that with aging, time spent in the home increases causing rising sectors related to the development of the home: equipment, comfort. Maintenance at home of handicapped or elderly people would be one of the ways to develop for, both reduce health costs, but also adapt to the ageing of the population which becomes progressively less mobile and more sedentary.

. The Silver Economy creates growth opportunities for companies in the areas of health, homecare, maintenance at home, home rehabilitation, products with a high technological content. The Silver Economy creates growth opportunities for companies in the areas of health, Homecare, habitat of the equipment of the House, products with a high technological content. The Serenitis experience, conducted in 2007 by the SAMU92 of the APHP, focused on the use of a remote service. The system consists of a box, connected to a phone, on which are located two buttons: a panic button and a button of messaging to deliver a message. The Subscriber wears either a bracelet or a medallion, which are an alert button, and a speaker that allow the communication with the remote centre. When occurring an emergency call, the call centre adapts the answer depending on the severity of the problem [2].

The results of this experiment on 23760 calls showed that 13% of calls are involved displacement of firemen or SAMU. On this percentage, 74% had a medical cause of which 69% corresponded to a fall. 26% of displacements have therefore proved useless causing mobilization of resources and unjustified additional costs. To reduce the number of unnecessary displacements we have proposed, in the ANR QuoVADis project [3], among other technologies, the use of a mobile robot equipped with audio-visual means. This robot is remotely operated by the operator from the remote centre in the domicile of the person, only when occuring alarm. The experiment at the Centre SAMU92 de Garches demonstrated the usefulness of the mobile robot to collect information allowing the adaptation of the answer. However the remote control of the robot is not usable in operational conditions. Indeed, a remote centre manages thousands of subscribers. An operator can have multiple subscribers to handle both, while it can simultaneously control only one robot. Make robot usable in this context, involves to give him the capacity to automatically perform certain tasks such as search of the person when occurring alarm. When the person is found, the remote operator takes in hand the robot control. We have recently introduced the concept of ambient Robotics which sees the robot as a component of a communicating environment. This idea fits into the broader context of ambient intelligence, i.e. devices, called communicating objects, interconnected and integrated into daily living environments, in order to participate in certain tasks. The range of uses is infinite, prevention of risks (smoke, leakage), remote (remote control), comfort... This is achieved by crossing three technology areas: artificial intelligence in the objects of everyday life, (including personal data), secure communication between heterogeneous objects and intuitive interaction with the user which implies taking account of the context of use. The point of view of ambient Robotics is that the robot has benefit for cooperating with communicating objects to improve and complete its autonomy capabilities. Wee can thus make the services rendered by the robot more reliable. Our team follows two complementary ways of research. The first focuses on the design of a computer architecture for ambient Robotics able to adapt to the context (heterogeneity, ubiquity) [4]. The second develops methods capable to perform functions necessary for the autonomy of the robot by cooperation between some communicating objects of the environment and the robot. This article focuses on the location of the robot using interval analysis in a context of bounded errors. To return to the framework described above, the search for the person by the robot asks to set the path to move the robot to the person and therefore the knowledge of their respective location in the home.

The paper addresses the global localization of mobile robots operating in an indoor cooperative environment. The set of home sensors and robot onboard sensors builds a cooperative network robot space. Global localization refers to the problem of estimating the position of a robot (xmr, ymr , θmr) in a 2D reference frame, given the real-time data from the robot onboard sensors and the real-time data coming from sensors located in the environment. The paper describes a localization method based on interval analysis In the context of bounded-error. The method takes account: i) heterogeneous measurements, ii)a flexible number of measurements, iii) no statistical knowledge about the inaccuracy of measurements, only an admissible interval specified by lower and upper values; he interval is deduced from the sensor tolerance given by manufacturers and iv) measurements both coming from the robot onboard sensors and from the home sensors. The precise characterization of the measurements errors is conceivable in a laboratory but not at a large scale in the framework of cooperative network space. The number and the diversity of sensors are obviously a difficulty for such specific characterization. The errors are usually expressed in terms of stochastic uncertainty models. Due to incomplete information about measurement process, a stochastic error approach is questionable. [5] proposes that the measurement error is no longer considered as a random variable with known probability density function but assumed as bounded between lower and upper values. The set representation is thus poorer but it requires less statistical knowledge on the variables. When the error of measurement on experimental data is known only in the form of a tolerance, which is often the case for the sensors or the network of sensors used in house automation and more generally in the context of ambient intelligence, the set approach is a well-suited approach. On the contrary and moreover if the problem is a linear and Gaussian problem, this approach is not justified because well solved by probabilistic approaches. The set approach gives a guaranteed result i.e. the solution contains surely the value. The set approach remains little used in the field of mobile robotics. [6] was interested in the localization of a robot starting from measurements of ultrasonic sensors by using the interval analysis and by proposing a treatment of the outliers under certain conditions. [7] uses the interval analysis for modelling inaccurate measurements of two omnidirectional sensors. This work only uses the measurements provided by onboard sensors for robot localization. This idea has been applied by [8] for locating a vehicle with inaccurate telemetric data. More recently, in the field of urban vehicles, works uses various sources of outside or onboard measurement [11]. [9] was interested in multisensor fusion by propagation of constraints on the intervals of measurement provided by the hybridization of a GPS, a gyrometer and an odometer. [10] focused on the robustness of set methods in presence of outliers for multi-sensory localization. Our solution is based on works of [6], more precisely on the algorithm RSIVIA which allows the calculation of solutions by tolerating a number q of outliers. Although the advantages of the probabilistic methods, by far the most used and the best known ones, we have chosen a bounded-error approach based on the interval analysis for the following reasons.

The only assumption to verify is that all the errors are bounded. The respect of this assumption is difficult to prove but there are techniques to reject outliers [12]. If this assumption is verified, then the result is guaranteed. Moreover, as the dimension of the state vector, in our case the x and y position and the orientation of the robot, is equal to three, the data processing is relatively simple and fast. [13] presents a bounded-error state estimation (BESE) to the localization problem of an outdoor vehicle. Authors claim that the biggest advantage of the BESE approach is the ability to solve the localization problem with better consistency than Bayesian approach such as particle filters. Experiments point out that the particle filter can locally converge towards a wrong solution due to bias measurements which lead to a huge local inconsistency. Similar experiments with an Extend Kalman Filter (EKF) show the same phenomenon. EKF strongly underestimates its covariance matrix in presence of repeated biased measurements. The efficiency and accuracy of the particle filter depend mostly on the number of particles. If the imprecision, i.e. bias and noise, in the available data is high, the number of particles needs to be very large in order to obtain good performances. This may give rise to complexity problems for a real-time implementation [14].

The paper is organized as follows. Section 2 describes the principles of the method of localization by multiangulation based on analysis by bounded errors interval. Section 3 shows how the principle can be extended easily to merge heterogeneous measures from various sensors: goniometer, rangefinders, odometers, gyroscope, touch... A solution is proposed to synchronize the measures, recurring problem in embedded systems. Results of simulation and actual evaluations, described in sections 4 and 5, show some contributions of the approach. Average computing time respects the real time constraint, criterion essential in robotics.

2. Set method using goniometric measurements

The objective of our work is the localization of a mobile robot by using measurements available at a given moment and the a priori known coordinates of the markers or the sensors. The goal is not the building of an environment map but the localization of an assumed-lost robot. The environment is modelled by the coordinates of the home markers seen by the robot onboard sensors and by the coordinates of the home sensors able to detect the robot. The markers and the sensors are known by their identifier which makes it possible to establish their location in the building.

The localization process is divided into two steps. The first step consists in finding the room of the building in which the robot is located by using the specific identifier associated to each measure. As said before all sensors and markers are labelled by a specific identifier and associated to one room of the building. The second step localizes the robot inside the room by the set approach described below. The paper focuses on this second step.

2.1 Set Inversion for Estimating Parameters

Interval analysis [13] is based on the idea of enclosing real numbers in intervals and real vectors in boxes. The analysis by intervals consists in representing the real or integer numbers by intervals which contain them. This idea allowed algorithms whose results are guaranteed, for example for solving a set of non-linear equations [14], [12], [15].

An interval [x] is a set of IR which denotes the set of real interval

$$[x] = \{x \in IR \mid x^- \leq x \leq x^+, x^- \in IR, x^+ \in IR\} \quad (1)$$

x^- and x^+ are respectively the lower and upper bounds of [x].

The classical real arithmetic operations can be extended to intervals. Elementary functions also can be extended to intervals.

Given f: IR → IR, such as f ∈ {cos, sin, arctan, sqr, sqrt, log, exp, …}, its interval inclusion [f]([x]) is defined on the interval [x] as follow :

$$[x] \rightarrow [f]([x]) = [\{f(x) \mid x \in [x]\}] \quad (2)$$

In addition, if *f* is only composed of continuous operators and functions and if each variable appears at most once in the expression of *f*, then the natural inclusion function of *f* is minimal. The periodical functions such as trigonometric function require specific treatment. The inclusion function is evaluated by dividing *f* into a continuous set of monotonic subfunctions.

A *subpaving* of a box [**x**] is the union of non-empty and non-overlapping subboxes of [**x**]. A guaranteed approximation of a compact set can be bracketed between an inner subpaving X^- and an outer subpaving X^+ such as $X^- \subset X \subset X^+$.

Set inversion is the characterisation of

$$X = \{\mathbf{x} \in IR^n \mid \mathbf{f}(\mathbf{x}) \in Y\} = \mathbf{f}^{-1}(Y) \quad (3)$$

For any $Y \subset IR^n$ and for any function **f** admitting a convergent inclusion function [**f**], two subpavings X^- and X^+ can be obtained with the algorithm SIVIA (Set Inverter Via Interval Analysis). To check if a box [**x**] is inside or outside X,the inclusion test is composed of two tests :

If [f] ([**x**]) ⊂ Y then [**x**] is feasible

If [f] ([**x**]) ∩ Y = ∅ then [**x**] is unfeasible

Else [**x**] is ambiguous that is feasible, infeasible

Boxes for which these tests failed are bisected except if they are smaller than a required accuracy ε. In this case, boxes remain ambiguous and are added to the ΔX subpaving of ambiguous boxes. The outer subpaving is $X^+ = X^- \cup \Delta X$. The box is assumed to enclose the solution set X.

The inversion set algorithm can be divided into three steps:

– Select the prior feasible box [$\mathbf{x}_0$] assumed to enclose the solution set X;

– Determines the state of a box, feasible, unfeasible or ambiguous;

– Bisect box for reducing ΔX.

Algorithm #1 **SIVIA** ([$\mathbf{x}_0$])

```
if ( [f] ([x0]) ⊂ Y), [x0] is feasible ;
else if  [f] ([x0]) ∩ Y = ∅, [x0] is unfeasible ;
      else if (ω ( [x0] < ε),  [x0] is ambiguous ;
            else
                  bisect [x0], [x1], [x2]) ;
                  SIVIA ([x1]);
                  SIVIA ([x2]) ;
             endif
      endif
endif
```

This recursive algorithm ends when $\omega\,[\mathbf{x}] < \varepsilon$. The number N of bisection is less than

$$N = \left(\frac{\omega(|x_0|)}{\varepsilon} + 1 \right)^n \quad (4)$$

with [$\mathbf{x}_0$] the prior feasible box and n the dimension of the vector [$\mathbf{x}$]. Since in the case of the mobile robot localization the dimension of [$\mathbf{x}$] is three, the solution can be computed with respect to real time.

2.2 Application to Localisation by Multiangulation

The robot localization is computed from several goniometric measurements by multiangulation. Measurements are provided either by robot onboard sensors or/and by home sensors. Onboard robot sensors detect markers located in the environment. Markers can be either RFID tags or visual tags such as Datamatrix, or reference images. On the contrary, what we call home sensors are able to detect the robot and are fixed on a wall, a ceiling or a corner of the rooms. Whatever sensors, the measurement model can be represented by a cone inside which the presence of the robot is guaranteed. This model is simple enough for including a large variety of bearing sensors such presence detector, laser and US telemeters, camera, RFID …

In the context of bounded-error method, a measurement λ_i is defined by an interval bounded by the lower and upper limits:

$$[\lambda_i] = [\lambda_i - \Delta\lambda_i, \lambda_i + \Delta\lambda_i] \qquad (5)$$

The variables to be estimated are the components of the state vector

$$\mathbf{x} = (x_R, y_R, \theta_R)^T \qquad (6)$$

which defines the position and orientation of the robot relatively to the reference frame R_e of the environment.

The coordinates of the environment markers $M_j = (x_j,y_j)$ and the coordinates and orientation of the environment sensors $C_j = (x_j,y_j, \theta_j)$ are supposed to be known , to be precise coordinate interval is restricted to a scalar value, for sake of readability. However the method we propose can easily take into account inaccuracies on the marker and sensor coordinates.

In our case the problem can be described by two types of equation. In one hand, if a robot sensor detects an environment mark M_i, the measurement depends on the marker coordinates M_i $(x_i,y_i,)$ and the state vector.

$$\lambda_i = tg^{-1}\left(\frac{y_R - y_i}{x_R - x_i}\right) - \theta_R \qquad (7)$$

In the other hand (Fig.1b), if the robot is detected by an environment sensor C_i , the measurement depends on the sensor coordinates and orientation C_j (x_j,y_j,θ_j) and the state vector.

$$\lambda_j = tg^{-1}\left(\frac{y_R - y_j}{x_R - x_j}\right) - \theta_j \qquad (8)$$

The state vector $\mathbf{x} = (x_R, y_R, \theta_R)^T$ is then to be estimated from the M observations $\boldsymbol{\lambda} = (\lambda_1, \ldots, \lambda_M)$ with the associated bounded errors $[\boldsymbol{\lambda}] = ([\lambda_1], \ldots, [\lambda_M])$ and the known data $\mathbf{x_i} = (x_i,y_i)$ and $\mathbf{x_j} = (x_j,y_j,\theta_j)$.

Estimating state vector $\mathbf{x}$ consists in looking for the set S of all admissible values of $\mathbf{x}$ that are consistent with the equations (7) and/or (8) and (5). Multiangulation algorithm based on the algorithm SIVIA uses $f(\mathbf{x}) = tg^{-1}(\mathbf{x})$ which is a discontinuous function on the interval $[0,2\pi]$. The estimation of the arctangent inclusion function takes into account both the discontinuities and the border effects due to the fact we manipulate intervals and not values. If we want to consider most of cases, the range of angular measurement can be $\lambda_i \in [0,2\pi]$ and $\Delta\lambda_{imax} = \pi/2$. Indeed, a presence detector can cover an angular sector up to π radians. For each available measure λ_i, the inclusion test is done using data associated to λ_i. The test fusion is based on the following rule:

Algorithm # 2 Fusion rule of n inclusion tests
if (T_1 = = T_2 = = … = = T_n), Fusion_test = T_1 ;
else if ((T_1 = = unfeasible) or … or (T_n = = unfeasible), Fusion test = unfeasible
else Fusion_test = ambiguous ;
endif
endif

This rule leads to reject the result of the algorithm when existing outliers. For processing outliers the fusion rule must to be modified [17].

3. Localization using heterogeneous measurements

The approach is able to take into account heterogeneous set of measurements. The inclusion test is the same as in the algorithm #1. It only requires another inclusion function well suited to the measurement type. The right inclusion function is selected thanks to the identifier associated to the sensor. The identifier defines the type of measurement. Combining several measurements is performed by the algorithm # 2. The following examples are taken from home automation sensors. Figure 1 shows the features of the three types of measurement with the additional inaccuracy. A ring for goniometric measurement (Fig.1a), a ring and a cone for goniometric and range measurement (Fig.1b) and a square band for tactile tile (Fig.1c).

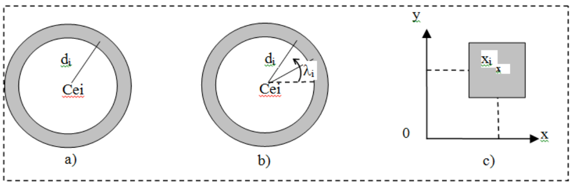

Fig. 1. Measurement type: a) Range, b) Goniometric and range, c) Tactile tile

Goniometric Measurement

As said in previous section, the measurement is an angle λ_i or λ_j, the measurement model is given either by equation (7) or by equation (8) and the inclusion test is either **[*f*]** ([**x**], [$\mathbf{x_i}$]) ⊂ [λ_i] or **[*f*]** ([**x**], [$\mathbf{x_j}$]) ⊂ [λ_j] with $\mathbf{x_i}$ the environment sensor coordinates and $\mathbf{x_j}$ the marker coordinates.

Range Measurement

The measurement is a range d_i (Fig.1a), the measurement model is given by

$g(x) = \sqrt{(x_R - x_j)^2 + (y_R - y_j)^2}$ and the inclusion test is [***g***] ([**x**], [$\mathbf{x_i}$]) ⊂ [d_i].

Goniometric and Range Measurements

The sensor is supposed able to measure both the angle λi or λj and the range di (Fig.1b) , the measurement model is given either by (***f***$_i$(**x**) or ***f***$_j$(**x**)) and ***g***(**x**) and the inclusion test is either [***f***] ([**x**], [$\mathbf{x_i}$]) ⊂ [λ_i] or [***f***] ([**x**], [$\mathbf{x_j}$]) ⊂ [λ_j] and [***g***] ([**x**], [$\mathbf{x_i}$]) ⊂ [d_i].

Tactile Tile, Door Crossing Detector and Complex Shape

The measurement are the coordinates of the center of the tile (Fig.1c), the measurement model is $x_i = x_R$, $y_i = y_R$ and the inclusion test is [**x**] ⊂ [$\mathbf{x_i}$]. The door crossing detector is a variation on the tile model. It is considered as a narrow tile in which the interval associated to each coordinate [x_i] and [y_i] is different. A complex shape can be considered as a set of tactile tiles. The measurements are { C_{ei} (x_i, y_i)} for i= 1 to n, the measurement model is for i= 1 to n, $x_i = x_R$, $y_i = y_R$ and the inclusion test is for i= 1 to n, [**x**] ⊂ [$\mathbf{x_i}$]. The literature offers other examples of measure processing by the set approach for localisation, [18] with GPS data or [15] with dead reckoning data. We propose both ways to process the latter kind of measurement.

Dead Reckoning

The first way is the same as in cases presented previously. The measurements are Δx_i, Δy_i, $\Delta\theta_I$, the measurement model is $x_{Rn}=x_{Rn-1}+\Delta x_n$, $y_{Rn}=y_{Rn-1}+\Delta y_n$, $\theta_{Rn}=\theta_{Rn-1}+\Delta\theta_n$ at time n and n-1 and the inclusion test is [$\mathbf{x_n}$] ⊂ [$\mathbf{x_{n-1}}$]+ [$\Delta\mathbf{x_n}$].

4. Simulation results

The simulation aims at showing: i) the feasibility and the interest of the localization method whatever the position of the sensors and the markers, ii) the ability to integrate a variable number of measurements iii) the ability to mix heterogeneous measurements, iv) the influence of the parameter ε on the computing time of localization. The algorithm is implemented on Matlab software.

The robot coordinates are specified in the reference frame. The true measures from the sensors are computed given the known coordinates of the sensors and the markers. Then a specified inaccuracy is added to the measurements in the form of upper and lower bounds.

The robot position is represented by two subpavings which include the set of the solution boxes, the feasible subpaving in red (or dark grey) and the ambiguous subpaving in blue/yellow (or light grey). It is necessary to consider both subpavings to guarantee a set containing all possible robot location given the measurements and the noise bounds. The simulation parameters are $[\lambda_i] = [\lambda_i - \Delta\lambda_i, \lambda_i + \Delta\lambda_i]$ with $\Delta\lambda_i = \pi/36$, $\varepsilon = 0.02$ m. Robot Localisation uses heterogeneous measurements (Fig. 2). Label C stands for home goniometric measurement, M for robot goniometric measurement, Di for range measurement, CGR for home range and goniometric measurement, MGR for robot range and goniometric measurement, Da for tile measurement. The true robot configuration is (5; 3)m

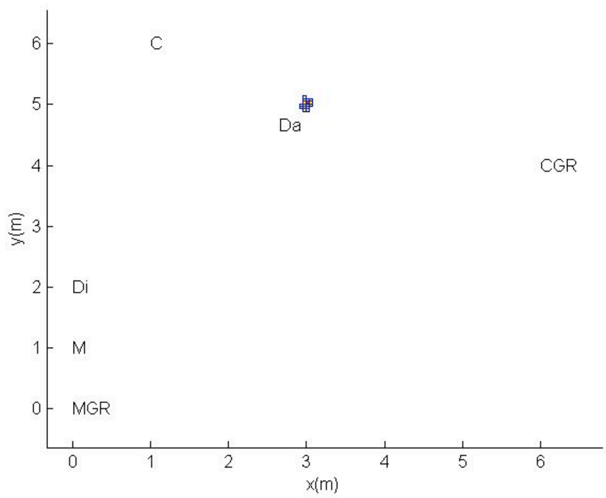

Fig. 2: 2-DOF robot localization with 6 heterogeneous measurements.

4.3 Computing Time of Robot Localisation

In order to verify if the computing time of localization is compatible with the real time constraint of robotic application we have realized two evaluations. The algorithm is implemented on Matlab software. The first test evaluates the influence of the localization accuracy and of the parameter number on the computing time (Table 1).The simulation parameters are $[\lambda_i] = [\lambda_i - \Delta\lambda_i, \lambda_i + \Delta\lambda_i]$ with

$\Delta\lambda_i = \pi/144$, the robot position accuracy ε_{xy} varies from 0.5 m to 0.001 m, the robot orientation accuracy ε_θ does not change. The room size is 6x6 m^2. The values of table are the mean time for 100 different positions of the robot. The robot orientation does not change, $\theta_R = Pi/4$. In the first row the 2-dof robot localization is computed from the measurements provided by three goniometric sensors located at (3 ; 0), (0 ; 6), (6 ; 6) m. The second row gives the mean time needed for the 3-dof robot localisation. In the latter case the experimental conditions are the same as for the first row. The only difference is that one of the three measurements is necessarily acquired from the robot in order to calculate the robot orientation. A 2-dof robot localization can be computed below a second up to 0.01 m accuracy. A 3-dof robot localization can be computed below a second up to 0.1 accuracy. The robot orientation is time consuming.

Accuracy (m)	Computing Time (s)	
	(x_R, y_R)	(x_R, y_R, θ_R)
0.5	0.01	0.24
0.1	0.019	0.44
0.05	0.03	0.22
0.025	0.05	0.22
0.015	0.09	1.44
0.01	0.17	5.29

Table 1. Computing time of the 2-DOF or the 3-DOF robot localization with respect to the localisation accuracy

5. Experimental results

Real experiments have been performed with a physical robot in a smart environment composed of two rooms for evaluating the localization method based on interval analysis.

The global dimensions of the test bed are 9.4m x 6.4m. The rooms are equipped with presence sensors, video cameras fixed on the top of the walls, a pan video camera embarked on the robot and visual markers. The markers located on the walls are detected by the robot video camera. The markers located on the robot are detected by the video cameras fixed on the walls. The robot is positioned at a specified coordinates (x_R, y_R, θ_R). Measurements are collected by a gateway which handles the exchanges between the localisation computer and the smart environment.

The Figure 3 shows the robot position estimated by the method from the measurements provided by two wall cameras (C1, C2). The feasible subpaving is in red (or dark grey) and the ambiguous subpaving in blue/yellow (or light grey).The true robot position is (3, 3.2) ± 0.2 m is depicted by an ellipse. A third measurement from the robot video camera not only improves the position accuracy but also allows the robot orientation, $\theta_R = 3*pi/2$ (Fig.12). C1 and C2 represent the two wall cameras and M3, the marker detected by the robot video camera.

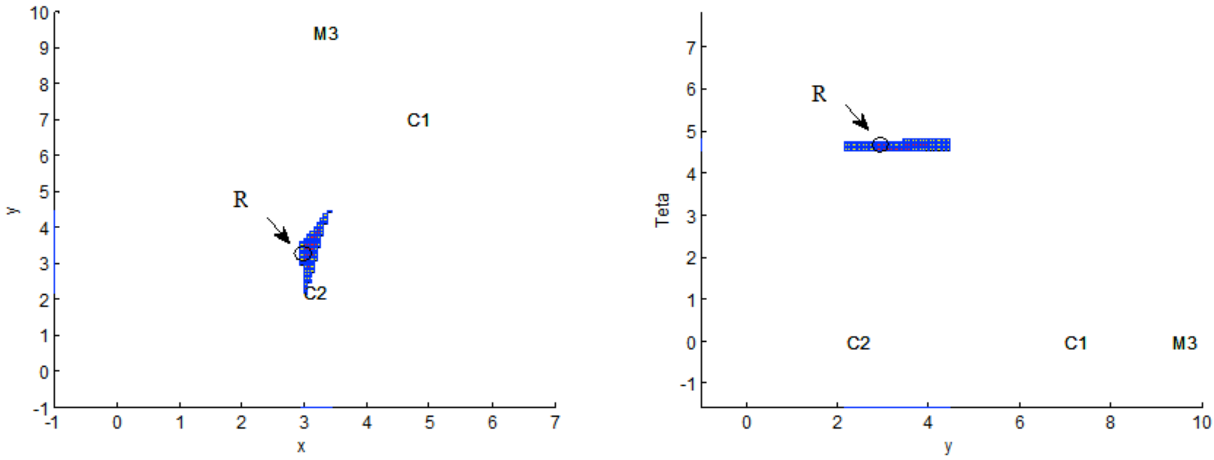

Fig.3. 3-DOF robot localization (x,y) in meters and θ in radians. a) Projection in the x-y plane, b) Projection in the y-θ plane.

The results of the real experiments are very close of those obtained in simulation. Such results are very useful in poor environment with little sensors because the robot position and orientation are modelled as areas. These areas can be more or less large but it is sure that the robot is inside.

6. Conclusion

The robot localization is based on a interval analysis method applied on data both coming from robot and home sensors. The problem of parameter estimation is solved by a set inversion applied on error bounded data. As the parameter vector dimension is two or three, the computing time is compatible with the real time constraint of mobile robotics as showed in sections 4 and 5. The interest of the solution lies on the ability to integrate a large variety of sensors, from the roughest to the most complex one. The method is able to take into account i) a heterogeneous set of measurements, ii) a flexible number of measurements, a statistical knowledge on the measurements limited to the tolerance; the sensor model only considers that the measurement is bounded between the lower and upper limits, iii) the ability to include measurements both coming from the robot onboard sensors and from the home sensors. The algorithm is able to provide a result of localization as soon as only one measure is available. The results show that the computing time depends little on the number of measurements. It is not necessary to develop a strategy for selecting among available measurements. We can take all the measurements available.The coordinates of the environment markers $M_j = (x_j,y_j)$ and the coordinates and orientation of the environment sensors $C_j = (x_j,y_j, \theta_j)$ are supposed known for paper readability. However the method we propose can easily take into account inaccuracies on the marker and sensor coordinates. We also explain how to handle environment model inaccuracies.

Works in progress address the case where the assumption of bounded error is not verified. The approaches proposed in the literature for processing outliers have to be improved in order to solve all the cases.

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