MOBILE ROBOT LOCALIZATION BY CONSTRAINT PROPAGATION ON INTERVALS

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Abstract: This paper proposes to use constraint propagation on intervals to solve the mobile robot localization problem. The mobile robot is equipped with an exteroceptive sensor and dead-reckoning. These two sensors give imprecise data that are modelled by intervals. Our localization strategy is based on multi target tracking. To this aim, the data given by our two sensors are fused by constraint propagation. So, at the end of the localization process, we get a 3-D subpaving which is supposed to contain the robot's position in a guaranteed way. The localization imprecision is naturally managed by our method.

1 INTRODUCTION

Localization is a preponderant problem in mobile robotics. Mobile robots have to be able to locate themselves in their environment in order to accomplish their mission. But the knowledge of the robot's position is not sufficient. An estimation of the uncertainty and the imprecision of this position should be determined and taken into account in order to act in a robust way. In other words, the decisions about the robot's behaviour should be made considering an uncertainty and an imprecision about the robot localization. The aim is to increase the reliability in operation, that is to say to assure the success of the mobile robot mission.

The two notions of uncertainty and imprecision are distinct ones and they must be clearly define. The imprecision results from unavoidable imperfections of the sensors and of the environment map, i.e. the imprecision represents the error associated to the measurement of a value. For example, "the weight of the object is between 1 and 1.5 kg" is an imprecise proposition. On the other hand, the uncertainty represents the belief or the doubt we have on the existence or on the validity of a data. This uncertainty comes from the reliability of the observation made by the system: this observation can be uncertain or erroneous. In other words, the uncertainty denotes the truth of a proposition. For example, "John is perhaps in the kitchen" is an uncertain proposition.

The management of the uncertainty has been already done in previous work (Clérentin, 2001)(Clérentin, 2002). The key tool used in this purpose is the Transferable Belief Model (Smets, 1998), a non probabilistic variant of the Dempster-Shafer theory. Indeed, this theory enables to easily treat uncertainty since it permits to attribute mass not only on single hypothesis, but also on union of hypothesis. We can thus express ignorance. So it has enabled us to manage and propagate an uncertainty from low level data (sensor data) in order to get a global uncertainty about the robot localization. We have also shown that this uncertainty is not correlated to the robot localization imprecision (Clérentin, 2003). That's why we treat the imprecision independently from the uncertainty.

To compute imprecision, many localization methods use statistical state estimation techniques, for example the Extended Kalman Filter (Leonard, 1991)(Chung, 2001). This method provides a point estimate associated with a confidence region which quantifies the imprecision estimation. This method is simple to use, but we must assume small variations (an important odometric error brings problems with the observation equation linearization) and noise statistical modelling (*a priori* hypothesis on the noises of the state vector and the measure vector, which must be Gaussian, white and independent from the initial state of the robot).

An attractive alternative to these methods is set-membership estimation. The first set-membership methods introduced in robotics used ellipsoidal domains to enclose the robot's position (Preciado,

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1991)(Hanebeck, 1996). This choice was motivated by the availability and convenience of ellipsoidal algorithms.

The interval formalism was then used in set-membership estimation (Meizel, 2002). This formalism allows a natural representation of sensors imprecision by the way of intervals. These are supposed to contain the true measurement in a guaranteed way. In (Meizel, 2002), the localization method is based on a set-inversion algorithm and only uses external sensors (ultrasonic telemeters). The work presented in this paper proposes a localization method also based on the interval analysis, but uses dead-reckoning information in addition to external sensors. These two types of data are fused by constraint propagation on intervals.

This paper is organized as follows. In a first part, we will recall the main principles of interval analysis and constraint propagation. Then we will deal with our robot configuration determination method based on interval analysis and multi target tracking. The paper will end with the presentation of the experimental results.

2 CONSTRAINT PROPAGATION

This method can be seen as a fusion method which can be applied on imprecise data represented by intervals.

In a first time, we will briefly recall the basic notions about interval analysis. Then we will detail the constraint propagation algorithm.

2.1 Basic notions of interval analysis

An interval $[x]$ is a closed, bounded and connected set of real numbers.

$$[x]=[x^-,x^+]=\left\{x\in IR \,\middle|\, x^- \le x \le x^+\right\}$$

The set of all intervals of IR is denoted by II IR.

All classical arithmetic operations can be performed on intervals (Moore, 1979)(Jaulin, 2001).

A box $[S]$ is the Cartesian product of n intervals of II IR.

2.2 Constraint propagation on intervals

A constraint is a mathematical relation between several variables. For instance, let consider this constraints set:

$x_1 \in [1,4]$
$x_2 \in [1,2]$
$x_3 \in [5,7]$
$x_3 = x_1 + x_2$ (1)

This example can represent three sensors. Each sensor gives an imprecise measurement x_i ($i \in [1..3]$) represented by an interval way $[x_i]$. These three values are linked by the equation (1). Given this equation, some values are not consistent, i.e. they do not satisfy all the constraints. For example, x_1 can not be equal to 1, else the constraint $x_3 = x_1 + x_2 \in [5,7]$ is not satisfied. This shows that it is possible to reduce the interval which contains x_1 in order to eliminate inconsistent values.

So, a constraint satisfaction problem (CSP) is composed of:

– A set of real-valued variables ($\{x_1, x_2, x_3\}$ in our example)
– A set of interval domains ($\{[x_1], [x_2], [x_3]\}$ in our example)
– A set of numerical equations over the given set of variables (equation (1) in our example)

The problem is to find in the initial box $[x_1]\times[x_2]\times[x_3]$ all the consistent values with respect to all the constraints.

A CSP is solved in two steps (Jaulin, 2001):

– Decomposition of all the constraints in primitive constraints, i.e. one operator of function should be involved at each one
– Contraction of the intervals by forward-backward propagation

The forward-backward propagation algorithm is divided into two parts. In the forward propagation step, we calculate the equations of the system. In the backward propagation step, we calculate the inverse equations of the system. At each iteration of the forward and backward propagation, the computed interval domain has to be intersected with its previous value. These two steps are applied while the intervals are significantly contracted. The complexity of this propagation algorithm is polynomial (Jaulin, 1991). More precisions about this algorithm can be found in (Jaulin, 1991).

Applied on our example, this algorithm gives the following results:

In the forward propagation step, the interval x_3 is reduced:

$x_3 = x_1 + x_2 = [5,7] \cap ([1,4]+[1,2]) = [5,7] \cap [2,6] = [5,6]$

Then, in the backward propagation step, we reduce x_1 and x_2 by inversing the constraint $x_3 = x_1 + x_2$:

$x_1 = x_3 - x_2 = [1,4] \cap ([5,6] - [1,2]) = [1,4] \cap [3,5] = [3,4]$

$x_2 = x_3 - x_1 = [1,2] \cap ([5,6] - [3,4]) = [1,2] \cap [1,3] = [1,2]$

Since the intervals have been significantly reduced, we repeat the algorithm:

$x_3 = x_1 + x_2 = [5,6] \cap ([3,4]+[1,2]) = [5,6] \cap [4,6] = [5,6]$

Backward propagation step :

$x_1 = x_3 - x_2 = [3,4] \cap ([5,6] - [1,2]) = [3,4] \cap [3,5] = [3,4]$

$x_2 = x_3 - x_1 = [1,2] \cap ([5,6] - [3,4]) = [1,2] \cap [1,3] = [1,2]$

The intervals have not been reduced in comparison with the previous iteration, so the algorithm stops. The final intervals are: $x_1 \in [3,4]$, $x_2 \in [1,2]$, $x_3 \in [5,6]$.

3 LOCALIZATION BY CONSTRAINT PROPAGATION

3.1 Overview of the problem

We consider here the localization problem of a mobile robot in a 2D-mapped environment. Its configuration vector $q=(x, y, \theta)$ is defined by the coordinates of the robot together with its orientation in a world reference frame (Xe, Ye).

The robot is equipped with an exteroceptive sensor composed of a range finder system and the conical mirror SYCLOP (Conical System for Localization and Perception), an omnidirectional vision sensor used for several year in our laboratory (Clérentin, 2001).

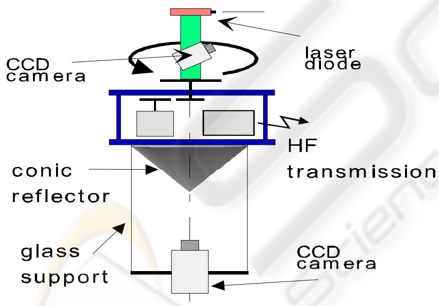

Figure 1: The perception system

The range finder system is an active vision sensor (Clérentin, 2001). It allows to obtain a robust omnidirectional range finding sensorial model. The interest of this system is on the one hand its low cost and on the other hand its robustness facing a high incidence angle. The SYCLOP system (Clérentin, 2001) is composed of a conic mirror and a CCD camera. It enables us to get radial straight lines which characterize angles of every vertical object such as, for example, doors, corners, edges (Figure 2). These association of two sensors can be assimilated of a depth sensor which can give a 2-D panoramic view of the environment. See figure 2 for an example of an experimental map.

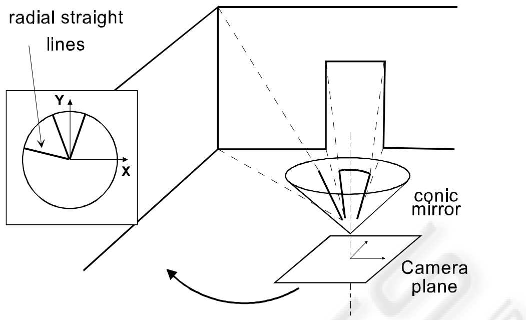

Figure 2: Principle of the omnidirectional sensor SYCLOP

Due to the imprecision of the sensor, the polar coordinates of the sensed primitives are expressed as two intervals [d] and [ϕ], cf. Figure 3.

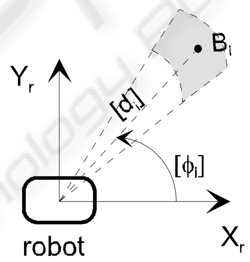

Figure 3: The polar coordinates of a sensed landmark Bi.

Besides, the robot is equipped with two odometers that can give an estimate about its position.

To localize itself, the robot has in its possession four world maps that describe the evolution environment: a map of segments and three maps of high level primitives (a map of “corners”, of “edges” and of “other primitives”). The interest of this kind of high level primitives is explained in (Clérentin, 2001).

The problem is to find the robot configuration q using the exteroceptive and dead-reckoning information. The imprecision on the sensors measurements is modelled by intervals.

3.2 Localization principle

Our localization strategy is based on multi-target tracking (Clérentin, 2001). The tracked primitives are the high level primitives described before (“corner”, “edge”, etc.). When a track is initiated, the robot try to pursue it by matching a sensed primitive with it. In our case, this multi-target tracking can be seen as a propagation of a matching between a theoretical primitive with sensorial primitives during the robot displacement. Its advantage is a lower computation time than classical matching methods: we match a sensed primitive only with the managed tracks at time *t*, not with all the theoretical primitives.

The algorithm is then the following and will be detailed in the next paragraphs. At each acquisition, the robot scans its environment with the exteroceptive sensor. It gets a map composed of segments. Then it classifies these segments into four classes of high level primitives: “corner”, “edge”, “wall” and “other” (Clérentin, 2001). With the help of the odometry information, we try to match these primitives with one of the managed tracks. In other words, we try to pursue the tracks. When all the sensed primitives have been analysed, we now consider the primitives that have not been matched with a track and we try to associate them with a theoretical primitive of the map in order to initiate a new track.

3.3 Odometer modelization

Odometry is the most widely used navigation method for mobile robot positioning. Odometry provides good short-term accuracy, is inexpensive, and allows very high sampling rates. The fundamental idea of odometry is the integration of incremental motion information over time. Unfortunately, this leads inevitably to an accumulation of errors. Despite this limitation, most researchers agree that odometry is an important part of a robot navigation system and that navigation tasks are simplified if odometric information is available.

The elementary displacement Δd and elementary rotation $\Delta\theta$ of the robot are given by the following equations:

$$\Delta d = \frac{Rl\,\omega l + Rr\,\omega r}{2} \qquad \Delta\theta = \frac{Rl\,\omega l - Rr\,\omega r}{L}$$

where *Rl* and *Rr* are the radius of the left and right wheel, and ωl, ωr are the elementary rotations of the left and right wheel.

From these equations, we can deduce from the robot position at time n $q_n=(x_n, y_n, \theta_n)$ the configuration at time n+1 $q_{n+1}=(x_{n+1}, y_{n+1}, \theta_{n+1})$:

$$x_{n+1} = x_n + \Delta d \cos\left(\theta_n + \frac{\Delta\theta}{2}\right) \quad (2)$$

$$y_{n+1} = y_n + \Delta d \sin\left(\theta_n + \frac{\Delta\theta}{2}\right) \quad (3)$$

$$\theta_{n+1} = \theta_n + \Delta\theta \quad (4)$$

Some values involved in equations (2), (3) and (4) are imprecise: *Rl*, *Rr*, *L*, ωl, ωr are not precisely known. They are thus expressed by the way of intervals: $[Rl]$, $[Rr]$, $[L]$, $[\omega l]$, $[\omega r]$. So the robot configuration estimation at time n+1 given by the odometers is now represented by a 3-D subpaving $[q_{n+1}]=([x_{n+1}], [y_{n+1}], [\theta_{n+1}])$, where:

$$[x_{n+1}] = [x_n] + [\Delta d]\cos\left([\theta_n] + \frac{[\Delta\theta]}{2}\right) \quad (5)$$

$$[y_{n+1}] = [y_n] + [\Delta d]\sin\left([\theta_n] + \frac{[\Delta\theta]}{2}\right) \quad (6)$$

$$[\theta_{n+1}] = [\theta_n] + [\Delta\theta] \quad (7)$$

3.4 Initialisation of a new track

The problem is here to initiate a new track, that is to say to match for the first time with a theoretical primitive a sensed primitive that has not been matched with a track. We will first argue in the case of a primitive of type “corner”, “edge” and “other”. We will then explain the case of a wall primitive.

Let $([d], [\phi])$ be the imprecise coordinates (expressed by intervals) of the junction point of a “corner”, “edge” or “other” primitive (see Figure 4 for the case of a corner). Let $[q_{n+1}]=([x_{n+1}], [y_{n+1}], [\theta_{n+1}])$ be the robot configuration estimation given by the odometry. With this estimation, we can compute the Cartesian coordinates $([x], [y])$ of the sensed landmark in the world reference frame (Xe, Ye):

$$[x] = [d] \times \cos([\phi] + [\theta_{n+1}]) + [x_{n+1}] \quad (8)$$

$$[y] = [d] \times \sin([\phi] + [\theta_{n+1}]) + [y_{n+1}] \quad (9)$$

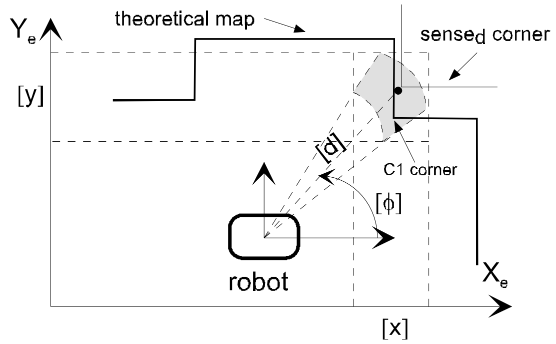

Figure 4: A corner primitive case: the theoretical corner C1 is candidate for a matching.

With this result, the association method is quite simple: a new track is initialised if a theoretical landmark of the same type is included in the subpaving ([x], [y]). For example, on figure 4, the theoretical corner C1 is candidate for a matching since its Cartesian coordinates are included in ([x], [y]).

When a theoretical candidate whose coordinates are (x_{theo}, y_{theo}) is found, the resulting matching links the polar coordinates of the sensed landmark ([d], [ϕ]) with the robot position estimation $[q_{n+1}]=([x_{n+1}], [y_{n+1}], [\theta_{n+1}])$ through these two equations :

$$[d]=\sqrt{\left([x_{n+1}]-x_{theo}\right)^2+\left([y_{n+1}]-y_{theo}\right)^2} \tag{10}$$

$$[\phi]= \arctan \frac{\left(y_{theo}-[y_{n+1}]\right)}{\left(x_{theo}-[x_{n+1}]\right)} - [\theta_{n+1}] \tag{11}$$

These two equations (10) and (11) implies two new constraints on the robot position estimation $[q_{n+1}]=([x_{n+1}], [y_{n+1}], [\theta_{n+1}])$ given by constraints (5), (6) and (7). So we have to solve a CSP by using the forward backward propagation algorithm explained on paragraph 2.2. Naturally, the constraints (10) and (11) reduce the size of the subpaving of the robot configuration $[q_{n+1}]$. In other words, they decrease the localization imprecision.

This propagation can give a non-valid solution, that is to say there is no solution for the CSP because all the values are inconsistent. This means that the theoretical landmark that has been selected for the matching is not valid, so it is rejected. In this case, the algorithm is eventually restarted with an other theoretical landmark which is included on the subpaving ([x], [y]). If there is no other theoretical candidate, the sensed landmark is considered as an outlier.

The initialisation of "wall" track is performed as the same way, except that we have to consider two coordinates : the two wall endpoints.

This algorithm is performed on each sensed primitive which is not associated to any track. At each new initialisation, the localization imprecision, i.e. the robot configuration subpaving, is reduced thanks to the CSP solving.

So, at the end of this stage, we have several new tracks that are characterized by the subpaving ([x], [y]) which permitted to initialise them. Let call this subpaving the "track subpaving".

3.5 Propagation of a track

In this part, we try to propagate the matchings initialised in the previous paragraph with the observations made during the robot's displacement. In other words, we try to associate tracks with sensed landmarks.

Suppose we manage q tracks at time n. Each track is characterized by its "track subpaving" (expressed in the world reference frame). Let call this track suppaving ([x_t], [y_t]). Suppose the robot gets p observations at time n+1. As we have explained in paragraph 3.4, we are able to compute each observation localization subpaving ([x], [y]) in the world reference frame thanks to the equations (8) and (9). So, for each track, we have to search among the p sensed primitives the one that corresponds to the track. In other word, we have to match a track subpaving ([x_t], [y_t]) with an observation subpaving ([x], [y]), cf. figure 5. The matching criterion we choose is based on the percentage of overlapping between these two kinds of subpaving ([x_t], [y_t]) and ([x], [y]) in comparison with the size of the track subpaving.

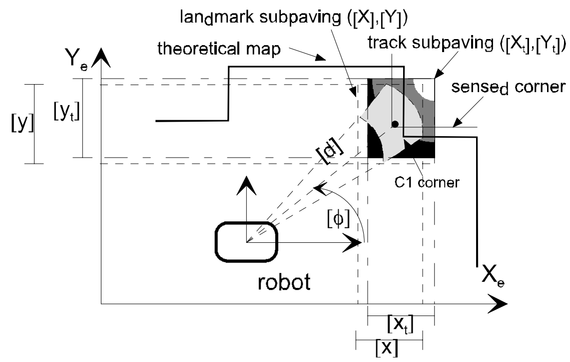

Figure 5: The track propagation principle in a corner primitive case.

So at this level, the problem is to match for each type of primitive the p observations obtained at the acquisition n+1 with the q tracks. To reach this aim, we use the Transferable Belief Model (Smets, 1998) in the framework of extended open word (Royère, 2002) because of the introduction in the frame of discernment of an element noted * which represents all the hypothesis which are not modelled.

For each track Qj ($j \in [1..q]$), we apply the following algorithm:

- The frame of discernment Θ is composed of:
- the p observations represented by the hypothesis Pi ($i \in [1..p]$). Pi means "the track Qj is matched with the observation Pi")
- and the element * which means "the track Qj cannot be matched with one of the p observations".
  So: $\Theta=\{P_1, P_2, \ldots, *\}$
- The matching criterion is the overlapping percentage between the subpaving of observation Pi and the track subpaving of Qj (Figure 6)
- Considering the basic probability assignment (BPA) shown figure 6, we compute for each observation Pi:
- $m_i(Pi)$ the mass associated with the proposition "Pi is matched with Qj".
- $m_i(\neg Pi)$ the mass associated with the proposition "Pi is not matched with Qj".
- $m_i(\Theta)$ the mass represented the ignorance concerning the observation Pi.
  The BPA is shown on Figure 6.

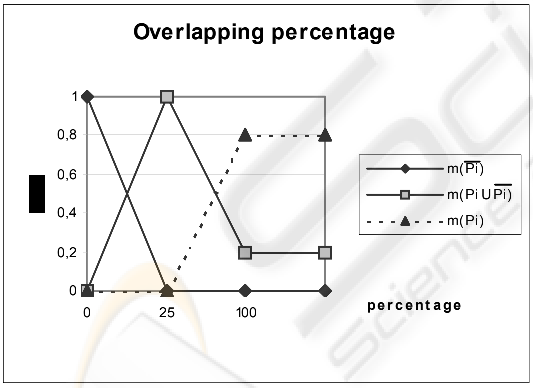

Figure 6: BPA of the matching criterion.

- After the treatment of all the Pi observations, we have p triplets :

$m_1(P_1)$ $m_1(\neg P_1)$ $m_1(\Theta)$
$m_2(P_2)$ $m_2(\neg P_2)$ $m_2(\Theta)$
…
$m_p(P_p)$ $m_p(\neg P_p)$ $m_p(\Theta)$

We fuse these triplets using the disjunctive conjunctive operator built by Royère (Royère, 2002). Indeed, this operator allows a natural conflict management, ideally adapted for our problem. In our case, the conflict comes from the existence of several potential candidates for the matching, that is to say some near sensed landmarks can correspond to a track. With this operator, the conflict is distributed on the union of the hypothesis which generate this conflict.

For example, on figure 7, the subpavings P_1 and P_2 are candidate for a matching with the track subpaving ($[x_t]$, $[y_t]$). So $m_1(P_1)$ is high (the expert concerning P_1 says that P_1 can be match with ($[x_t]$, $[y_t]$)) and $m_2(P_2)$ is high too. If the fusion is performed with the classical Dempster operator, these two high values produce a high conflict. But, with the Royère operator, the conflict generated by $m_1(P_1)$ and $m_2(P_2)$ is rejected on $m_{12}(P_1 \cup P_2)$. This means that both P_1 and P_2 are candidate for the matching.

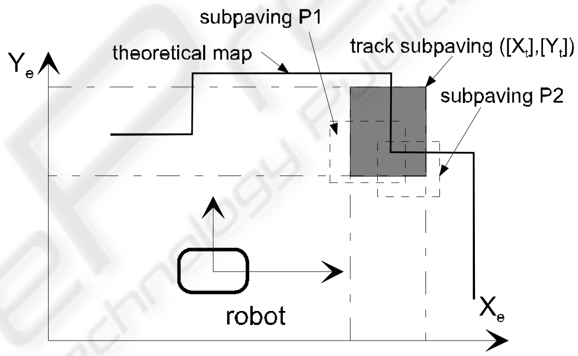

Figure 7: An example of two landmark subpavings that generate some conflict.

- So, after the fusion of the p triplets with the Royere operator, we get a mass on all single hypothesis $m_{match}(Pi)$, on all the unions of hypothesis $m_{match}(Pi \cup Pj \ldots \cup Pk)$, on the star hypothesis $m_{match}(*)$ and on the ignorance $m_{match}(\Theta)$.
- The final decision is the hypothesis which has the maximal pignistic probability (Smets, 1998). If it is the * hypothesis, no matching is achieved. This case corresponds to temporary or definitive disappearance of the track, due to a temporary or complete occultation of the primitive.

Once a matching is achieved, the method is like the initialisation step (paragraph 3.4): the robot position and the track, that is to say a theoretical landmark, are linked by the polar coordinates ($[d]$, $[\phi]$) of the sensed landmark. Therefore, these considerations imply the same two constraints given by the equations (10) and (11) on the robot localization estimation given by equations (5), (6) and (7). These equations form a CSP we solve by using the forward backward propagation algorithm explained on paragraph 2.2.

When this propagation has no solution, the matching is cancelled and the relative observation could be used to an other matching, for pursuit or for initialisation.

3.6 Summary of the localization method

Let resume our localization paradigm. When the robot has done a sensorial acquisition, the multi target tracking algorithm explained on paragraph 3.5 is performed for each existing tracks. Then, all the sensed primitives that have not been matched with any tracks are used to initialise new tracks, as explained in paragraph 3.4.

4 EXPERIMENTAL RESULTS

In this part, we present the experimental results we obtained after several acquisitions in an indoor environment (the end of a corridor shown figure 8). The mobile robot execute two paths composed of forty-six acquisitions made every 30 cm and computed in a Pentium PC located on the robot.

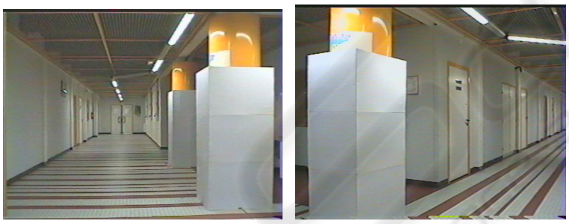

Figure 8: The experimental environment.

On figure 9, we show the 3D localisation subpavings of the robot obtained using only the odometric information. We can note the classical phenomena of cumulative error: the size of the subpavings increases unceasingly. This shows the need to add to dead reckoning the measurements given by an other sensor.

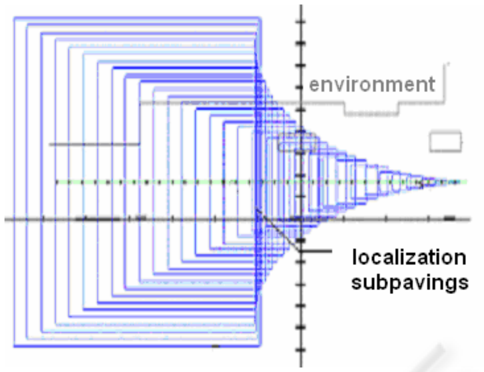

Figure 9: Localization results using only odometry.

An example of sensed map obtained with our omnidirectional sensor with associates the SYCLOP sensor and a telemeter is shown on figure 10. The crosses represent the depth points given by the telemeter. The red lines on the centre of the figure are the radial straight lines issued of the treatment of the SYCLOP image. Finally, a segmentation stage gives us a set of segments (the black ones on figure 10).

The experimental results using dead reckoning and the depth sensor are shown on figure 11. The true localizations are represented by the black points. Firstly, we note a relatively precise localization: the localization subpavings have a small size (lower than 20 cm in X and Y, and 11 degrees in orientation). The error is weak (10 cm in position and one degree in orientation).

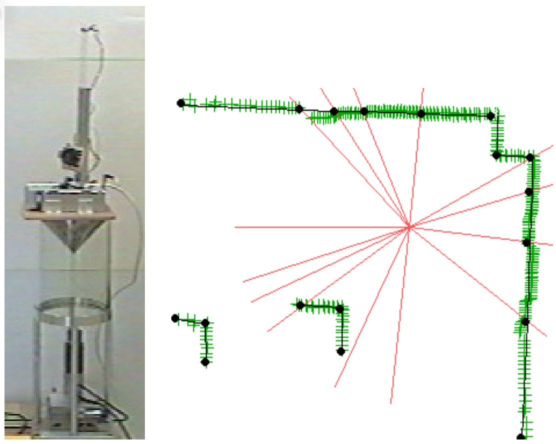

Figure 10: the perception system and an example of high level primitive map.

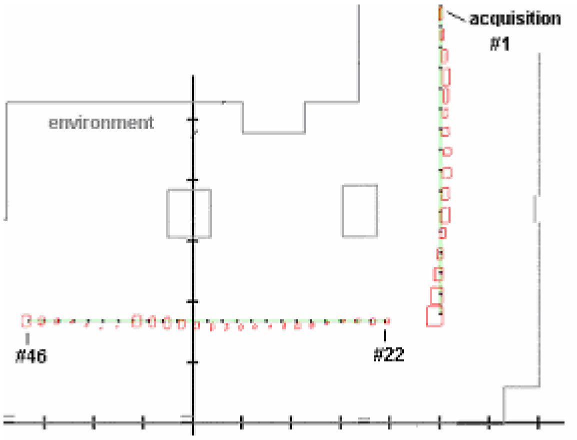

Figure 11: two dimensions localization results.

5 CONCLUSION

We have presented in this article a localization method based on constraint propagation on intervals. Indeed, the localization problem can be modelled as a constraint satisfaction problem (CSP). In our case, the imprecise information used to localize the robot come from two sensors: two odometers and an exteroceptive sensor. These two sensors give measurements which are linked by some constraints. These constraints induce a reduction of the subpaving which represents the robot localization.

Another advantage of this method is its ability to treat naturally and easily imprecise data: these data are represented by intervals. So, the localization imprecision quantification is intrinsically managed by our algorithm.

The localization strategy is based on multi target tracking. This strategy, which can be seen in our case as a propagation of a matching during the robot's displacement, is less complex than classical methods. Besides, our matching method, which is based on the use of the TBM, gives us an uncertainty value about each matching done. This value can allow to estimate an uncertainty about each track, and thus manage the problem of track cancel: if a track is to uncertain, it will be cancelled. This track uncertainty management is one of the main future perspectives that will concern this work.

REFERENCES

Smets, Ph, 1998. The Transferable Belief Model for Quantified Belief Representation, *Handbook of Defeasible Reasoning and Uncertainty Management Systems*, Kluwer Ed, pp 267-301.

Jaulin L, Braems I, Kieffer M, Walter E, 2001. Nonlinear state estimation using forward-backward propagation of intervals in an algorithm, In *Scientific Computing, Validated Numerics, Interval Methods*, pp191-204, Kluwer Academic Publishers.

Moore R.E, 1979. Methods and applications of interval analysis, *SIAM*, Philadelphia.

Jaulin L, Kieffer M, Didrit O, Walter E, 2001. *Applied interval analysis*, Springer-Verlag

Leonard J, Durrant-Whyte H, 1991. Mobile robot localization by tracking geometric beacons, *IEEE Trans. on Robotics and Automation*, Vol. 7, n°3, pp. 89-97.

Chung H, Ojeda L, Borenstein J, 2001. Sensor fusion for Mobile Robot Dead-reckoning With a Precision-calibrated Fiber Optic Gyroscope – proc. of the 2001 *IEEE Int. Conf. on Robotics & Automation*, pp.3588-3593.

Bouron P, Meizel D, Bonnifait P, 2001. Set-membership non-linear observers with application to vehicle localisation, *ECC'01 European Control Conference.*

Clerentin A, Delahoche L, Brassart E, 2001. Omnidirectional sensors cooperation for multi-target tracking, *IEEE Int . Conf. on Multisensor Fusion and Integration for Intelligent Systems (MFI 2001).*

Clerentin A, Delahoche L, Brassart E, Cauchois C, 2002. An Uncertainty Propagation Architecture for the Localization Problem, *Workshop on Performance Metrics for Intelligent Systems PerMIS2002*, NIST, Washington, USA, August 2002

Royere C, 2002. Contribution à la résolution du conflit dans le cadre de la théorie de l'évidence, PhD thesis, Université de Technologie de Compiègne, 2002

Clerentin A, Delahoche L, Brassart E, Drocourt C, 2003.. Uncertainty and error treatment in a dynamic localization system, *proc. of the 11th Int. Conf. on Advanced Robotics (ICAR03)*, pp.1314-1319, Coimbra, Portugal.

Preciado A, Meizel D, Segovia A, Rombaut M, 1991. Fusion of multi-sensor data: a geometric approach", in proc. *IEEE Int. Conf. On Robotics and Automation (ICRA'91)*, vol 3, pp. 2806-2811, Sacramento, USA.

Hanebeck U.D, Schmidt G, 1996. Set theoretic localization of fast mobile robots using an angle measurement technique, in proc. *IEEE Int. Conf. On Robotics and Automation (ICRA'96)*, pp. 1387-1394.

Meizel D, Leveque 0, Jaulin L, Walter E, 2002. Initial Localization by Set Inversion. *IEEE trans. on Robotics and Automation*. Vol 18, n° 6, pp 966-971.