Symbolic trajectory description in mobile robotics

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Abstract. Autonomous mobile robot navigation systems are based on three principal kinds of techniques: map-based navigation, map-building-based navigation and mapless navigation. We propose a method for symbolic trajectory description in unknown indoor environments. The chosen form uses a panoramic description called fresco. The method uses distance measurements from a 2D laser range finder, digitises the robot's visibility area, eliminates superfluous data and reorients their presentation. The landmarks are then extracted and organised into the fresco which is validated by means of neighbourhood rules. As the robot moves in the environment, the frescoes are created and both the amount of new information a fresco carries out and its position in relation to the preceding ones are evaluated by means of two criteria. Only frescoes selected as enough informative are stored to describe the robot's route.

Keywords: Autonomous mobile robot, environment symbolic description, symbolic navigation

1. Introduction

One main issue for mobile robots is their capacity to go from one point to another autonomously. It is based on three concepts: i) planning which computes a trajectory between the two points, ii) navigation which gives motion orders to the robot to follow the computed trajectory and iii) environment representation which permits the robot to know if it goes in the right direction. Works presented here are interested in point iii). We want to define an open method to solve the human-like problem of the high level description of a travel in a structured environment by a mobile robot. Many works are conducted in the neurosciences domain to better understand the mental moving process of human beings. Without considering the motivation of the move, a mental scheme is built before and during the move mainly based on visual landmarks and on acoustic stimuli. An anticipation phenomenon, guided by his(her) own perspectives, is also made by a human being.

The application field of our work is a middle-cost mobile robot that is sent in an apartment to do works for, for example, a physically handicapped person. Hence, the environment is of a structured indoor type. The robot is intended to supply services while other people are not in time to do them: the disabled person is alone in its appartment, nurse or relatives are absent... The environment is therefore considered as static and unknown because objects can have been moved. At this point, the problem is two-fold. Firstly, through the Human-Machine Interface (HMI), the mission must be entered and its development must be explained to the user. Secondly, the robot has to be programmed to execute the mission. Building a description of the travel as close as a human could do it has at least two advantages. This description, on one hand, is requested by the HMI between the robot and the handicapped person and, on the other hand, at the execution level, it can be a way to take into account the stumbling blocks highlighted by the conventional navigation systems. Wheel slippage, localisation error introduced by integration of data from wheel encoders, drift of inertial systems are three examples among others. Finally, beacons could be deployed in the environment with known locations but the works described in this paper consider not engineered environments.

As the environment in which the robot will travel is known, it seems not necessary to use simultaneous localisation and mapping (SLAM) methods introduced by Leonard and Durrant-Whyte (Leonard and Durrant-Whyte, 1991) and (Smith and Leonard, 1997). Nevertheless, we believe that it is possible to associate the topological and geometric structure of an environment and its symbolic description. Kuipers (Kuipers and Byan, 1991) defined symbols as distinct places situated at equal distances from the nearby obstacles. Connections between these places link symbols and represent free path (Choset and Nagatani, 2001). Figure 1 shows the Voronoii graph of an environment. In this figure, the labelled vertices represent the symbols while edges connecting the symbols are the path the robot can use.

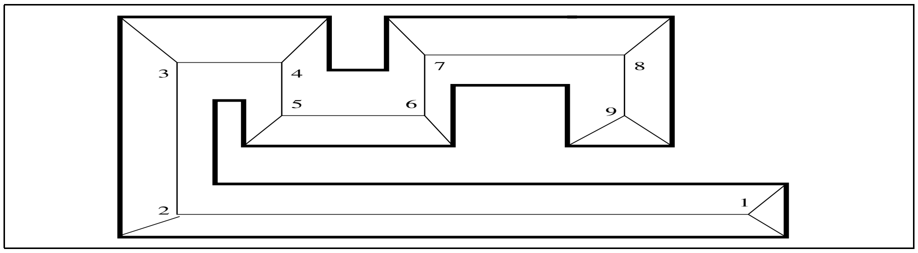


Figure 1.: Voronoii diagram whith numbers label symbols

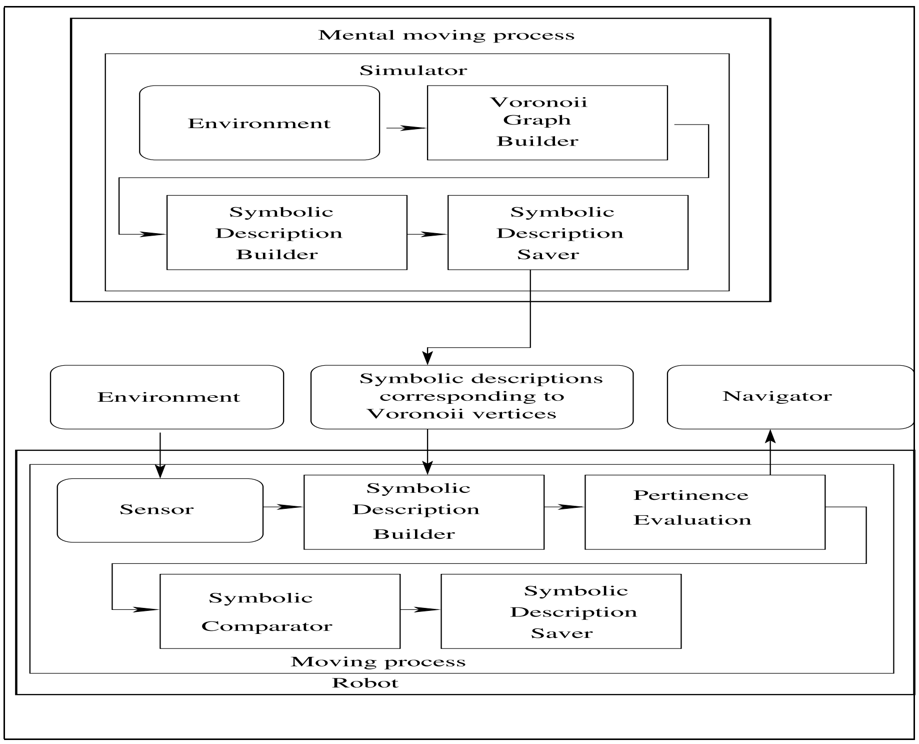


Figure 2.: System architecture overview

Our works aim at building a symbolic description of the trajectory based on the Voronoii's graph vertices. The system architecture overview is given in figure 2. It includes the moving process block that simulates the mental process by which a human being foresees a move in an environment. Assuming that the real environment is known, the Voronoii diagram is built by the Voronoii Graph Builder and for all the vertices situated on the robot's route, a symbolic description of the environment is made by the Symbolic Description Builder and saved. The set of these descriptions constitutes a high level description of the robot's route that will be used by the robot to symbolically localise in the environment. When the real robot is launched in the environment on a trajectory, a symbolic description is built from the sensor raw data every time a measurement is made. Their pertinence is evaluated and compared with the mental process output to drive the navigator.

Thus, the problem is building the symbolic description of the route followed by the robot. In fact, the question is three-fold: how to build the qualitative descriptions in accordance with the robot's sensors, how to describe the route by a sequence of the most pertinent descriptions and how to use these descriptions with the control-command level of the robot. The symbolic builder architecture is fully developped in (Pradel and al., 2000). This paper is focussed on the evaluation of what new information is brought up by a new symbolic description. Since the approach is mainly qualitative, we do not need precise scalar quantities to denote the position of a landmark insofar the robot does not hit it. We choose to describe the surrounding environment by means of landmarks such as "Opening, Closure, End_of_Closure, Angle_of_Closures,..." organised into ordered series called frescoes according to the data delivered by the sensors. These landmarks are the most perceivable (consistent) and the most easily distinguishable (distinctive) whatever the sensor used. One immediately thinks to the memorisation of the frescoes describing the parts of the environments that the robot chronologically covers during a journey leading to the symbolic description of the trajectory.

2. Related works

Related works can be found in the fields of Image Based Navigation systems, shape understanding using sensor data, vision based homing. Vision for mobile robot navigation did have specific development during the last twenty years. (DeSouza and Kak, 2002) gives a complete survey of the different approaches. For indoor navigation, systems are classified in three groups: map-based navigation using predefined geometric and/or topological models, map-building-based navigation constructing by themeselves geometric and/or topological models, and mapless navigation using only object recognition and actions associated to these objects (Gaussier and al., 1997).

In Image Based Navigation systems, several great classes of systems can be identified from the literature. The first one uses conventional telemeters and vision to find and identify objects in the environment (Wichert, 1996). The second one is the class of the systems coupling more or less directly sensor data to motor control thanks to a supervised learning process. Among them neural networks systems used as classifiers are noticeable. These systems begin to classify the environment into global classes such as "corridor, corner, room, crossing ..." (Al Allan, 1996) (Pomerleau, 1993) are often followed by a second processing unit that outputs a navigation command. In addition to restrictions related to the supervised learning, these classes give only a global description and are of least interest in cluttered and complex environments. The third class includes the systems which compare current sensor data and predefined models both at a low level (edges, planes ...) (Kim and Neviata, 1994) and at a high level (door, room, object ...). These systems use mainly vision sensors (cameras) that provide a huge amount of data that must be reduced to be processed in real time. The elements extracted from the data are compared to reference models known a priori. The fourth class evoked here includes the systems trying to geometrically build environment models before deciding an optimised path plan (Crosnier, 1999).

In the field of shape understanding using sensor data, environment interpretation stresses the use of natural landmarks to ease the navigation and the pose estimation of a mobile robot. Among other works, one can pinpoint (Simhon and Dudek, 1998) which is interested in defining islands of reliability for exploration. He proposes strategies to couple navigation and sensing algorithms through hybrid topological metric maps. (Oore and al., 1997) considers the problem of locating a robot in an initially unfamiliar environment from visual input. In the same way, (MacKenzie and Dudek, 1994) involves a methodology to bind raw noisy sensor data to a map of object models and an abstract map made of discrete places of interest.

Several implementations of vision based homing systems are presented in (Franz and al., 1997). A method aiming at highlighting salient features, as for example landmarks, between these two views and deriving a decision is used in (Hong, 1991). In these works, a homing system extracts landmarks from the view and allows a robot to move to home location using sequence target locations situated en route between its current location and home. Other works are biologically inspired. (Judd and Collett, 1998) showed that ants store series of snapshots at different distances from their goal to use them for navigating during subsequent journeys. Judd and Collett experimented their theory with a mobile robot navigating through a corridor, homing successive target locations. (Weber and al, 1999) proposes an approach using the bearings of the features extracted of the panoramic view leading to a robust homing algorithm. This algorithm pairs two landmarks situated into two snapshots to derive the homing direction. The bearings pairing process uses a list of preferences similar to neighbourhood rules.

Symbolic processing methods are described in Tedder's works (Tedder and Hall, 2001). This formal approach is often called structural or syntactic description and recognition. The general method for perception and interpretation proposes to symbolically represent and manipulate data in a mapping process. (Tedder and Hall, 2001) solve the problem in modelling the 3D environment as symbolic data and in processing all data input on this symbolic level. The results of obstacle detection and avoidance experiments demonstrate that the robot can successfully navigate the obstacle course using symbolic processing control. These works use a laser range finder. A way for defining suitable landmarks from an enviuronment as the robot travels is a research problem pointed out by Fleisher and al. in (Fleisher and al., 2003). An automatic landmark selection algorithm chooses as landmarks any places where a trained sensory anticipation model makes poor predictions. The landmark detection system consists of a sensory anticipation network and a method of detecting when the difference between the prediction of the next sensor values and the current measured values can reveal the presence of a landmark. This model has been applied to the navigation of a mobile robot. An evaluation has been made according to how well landmarks align between different runs on the same route. These works show that the robot is able to navigate reliably using only odometric and landmark category information.

In (Lamon and al., 2001), a method is proposed for creating unique identifiers called fingerprint sequences for visually distinct significant features in panoramic images. This localisation system proves that the actual position of a robot in an environment can be recovered by constructing a fingerprint sequence and comparing it wit a database of known fingerprints.

The proposed work goes on the way proposed by (Tedder and Hall, 2001) and (Lamon and al., 2001). According to these works, our contribution applies mainly on a method to extract clues of interest among raw distance data delivered by a 2D panoramic laser range finder installed on the robot. These clues of interest, i.e. the landmarks, are gathered in a sequence that we call a fresco. We consider that the trajectory of the robot can be described by the set of the frescoes. To do that, we have to select the frescoes that bring new information. The originality of this work stays in the simple but efficient criteria used for the construction and the validation of the fresco baut mainly to select the most pertinent frescoes along the route of the robot. In addition to this qualitative approach, one must consider that the system will have to be embarked on a vehicle, which vibrates, runs at variable speeds on a non-uniform ground. This leads to constraints of speed, size, robustness, compactness and cost, implying various choices both at the design and at the development levels of the system. The methods used have been chosen as simple as possible to reduce the cost and the complexity of the processing. Nevertheless the method must be robust compared with the robot movements, the sensor accuracy and the variations of the complexity of the environment.

The paper firstly presents the landmarks used (section 3 and the criteria used to select the relevant frescoes (sections 3.1 and 3.2). Section 4 briefly explains the fresco construction (section 4.1). Section 4.2 shows and discusses the experimental results in simple environment and section 4.3 examplifies the behaviour of the system in a complex environment. We conclude with ways to improve the method.

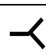
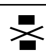
3. Criteria used to detect relevant changes in the environment evaluation

As told in the introduction, environments are described using a fresco made of ordered series of landmarks. An example of fresco is given in figure 4f. The robot is situated in the middle of the environment. The environment is divided in four quadrants. In each quadrant appears a variable number of landmarks. The set of landmarks is shown in table 3.

To each landmark are associated three qualitative attributes representing three properties of landmarks. The off-sight attribute is set when the landmark stands close to or beyond the end of the sensor range. The position attribute can take the following values: crosswise, diagonal or lengthwise according its position related to the lenghtwise and crosswise robot axis. The certainty attribute is introduced to take into account landmarks whose evolution can be forecast. It is false for every landmark (for instance, diagonal "End_of_Closure", "45^o_angles") that could come from a possible noise introduced in the digitisation process and whose evolution cannot be known.

Every time the laser range finder scans the environment, a fresco is built. In our case, the fresco built-in period is 300ms. Hence, if all frescoes are stored, one, their number grows quickly and, second, some of them are not useful. Storing all the frescoes when the robot runs in a corridor is a trivial example. All frescoes are very similar excepted

Table I. Landmark language used in the fresco construction

Symbol	Landmark	Position	Off-sight	Certainty
	Angle_of_Closure			true
	End_of_Closure	lengthwise		true
	End_of_Closure	lengthwise	off_sight	false
	End_of_Closure	crosswise		true
	End_of_Closure	crosswise	off_sight	false
	End_of_Closure	diagonal1		false
	End_of_Closure	diagonal1	off_sight	false
	End_of_Closure	diagonal2		false
	End_of_Closure	diagonal2	off_sight	false
	45^oAngle	lengthwise		false
	45^oAngle	crosswise		false
	Opening	lengthwise		true
	Breakthrough	lengthwise		true
15 	Opening	crosswise		true
	Breakthrough	crosswise		true

at both ends. If only few frescoes are useful, how then is it possible to select them? Is a specific sequence of frescoes able to describe a part of the environment? Answering, at least partially, to these questions is the aim of this paper. Two criteria, called barycentre and resemblance, are proposed to evaluate a kind of distance between frescoes. A new fresco is kept only if its distance to the previous stored one regarding one of the criteria is greater than a threshold. The two next sections describe these criteria. A systematic study gives an evaluation of the thresholds to use to make the criteria effective.

3.1. Resemblance evaluation between two frescoes

This criterion uses a nearby principle of that presented in (Hong, 1991). A correlation function allows to calculate the resemblance between two frescoes. This criterion has been tested in the same environment as that used for the construction and the validation of the frescoes. The use of this criterion shows that the landmarks that are not certain make very difficult the evaluation of the resemblance so only the certain elements were kept. The resemblance between two consecutive frescoes is calculated by taking into account the difference between the number of certain landmarks in the respective quadrants of two consecutive frescoes. The comparison of this difference with a reference threshold indicates if the current fresco should be kept or rejected because not bringing enough information. The algorithm used to compute the resemblance is (Algorithm 1):

Function Resemblance(F_i,F_j : **fresco**) : **pertinent : boolean**

  Compute $N_i[0]$, $N_i[1]$, $N_i[2]$, $N_i[3]$
  the number of certain landmarks in quadrants
  0, 1, 2, 3 respectively in fresco F_i;
  Compute $N_j[0]$, $N_j[1]$,$N_j[2]$,$N_j[3]$
  the number of certain landmarks in quadrants
  0, 1, 2, 3 respectively in fresco F_j;
  Compute the resemblance between frescoes F_i and F_j :
  $$r_{ij} = |N0_i - N0_j| + |N1_i - N1_j| + |N2_i - N2_j| + |N3_i - N3_j|;$$

End

Algorithm 1: Resemblance algorithm

3.2. Barycentre evaluation between two frescoes

This criterion is inspired by the distance of Hausdorff which measures the distance between two sets (Ahuactzin and al., 1995) and (Huttenlocher, Klanderman and al., 1993). In our case, this notion was very simplified to respect real-time constraints. It takes into account only the number of certain landmarks in every quadrant. This number of landmarks was positioned as indicated on the figure 3 and the barycenter was positioned. Any variation of the number of elements in a quadran implies a movement of the barycenter. If this displacement is superior to an experimentally fixed value, the fresco is considered as bringing up new relevant information. The algorithm used to compute the barycenter is (Algorithm 2):

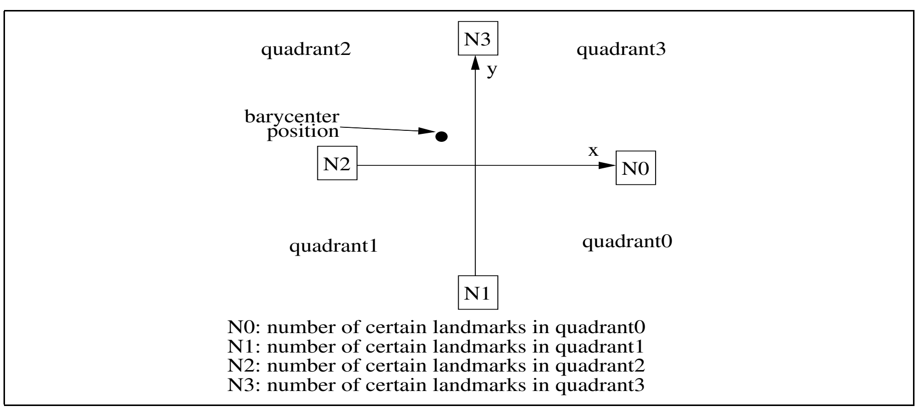


***Figure 3.*:** Certain landmarks barycenter calculation

Function Barycentre(F_i, F_j : **fresco**) : **pertinent : boolean**

Compute $N_i[0]$, $N_i[1]$, $N_i[2]$, $N_i[3]$
the number of certain landmarks in quadrants
0, 1, 2, 3 respectively in fresco F_i;
Compute $N_j[0], N_j[1], N_j[2], N_j[3]$
the number of certain landmarks in quadrants
0, 1, 2, 3 respectively in fresco F_j;
Compute the number of certain landmarks
in every quadrants and the total number of certain
landmarks in frescoes F_i and F_j;
Compute the barycenter between frescoF_i
and fresco F_j :
$x_{ref} = \frac{N_i[0]-N_i[2]}{N_{toti}}; \quad y_{ref} = \frac{N_i[1]-N_i[3]}{N_{toti}};$
$x = \frac{N_j[0]-N_j[2]}{N_{totj}}; \quad y = \frac{N_j[1]-N_j[3]}{N_{totj}};$
$bary_{ij} = \sqrt{(x_{ref} - x)^2 - (y_{ref} - y)^2};$
If $(bary_{ij} \geq threshold)$ **then**
  return pertinent=True;
else
  return pertinent=False;
end If

End

Algorithm 2: Barycenter algorithm

3.3. Route symbolic description

The symbolic trajectory description is made by the storage of the pertinent frescoes detected by either resemblance or barycentre criteria. These frescoes can be stored in a FIFO or in a LIFO depending the future use. A LIFO arrangement could be more useful if the robot has to return to its starting point. In that case, the last fresco pushed onto the top of the LIFO is the first fresco the robot will encounter at the beginning of the return part of the trajectory. Generation of the symbolic trajectory uses the following algorithm 3:

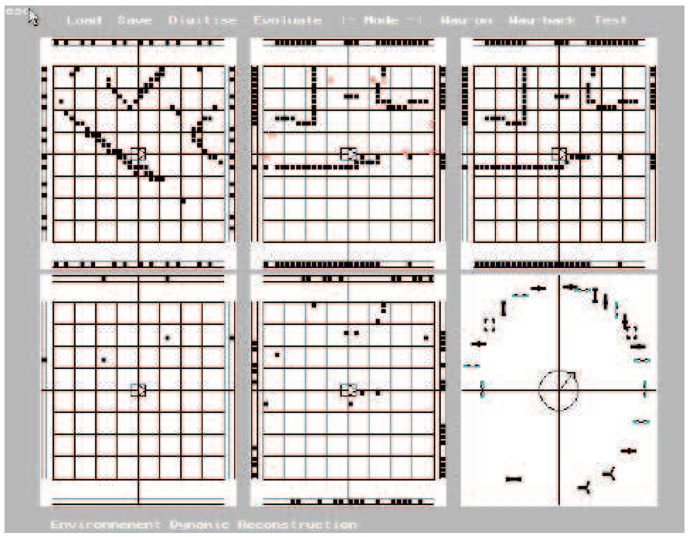
```
Function SymbolicTrajectory() :
    Fi, Fj : fresco
    i : integer
    Create a fresco from sensory data
    Fi=Create_fresco(sensory_data);
    Store the 1st fresco in the LIFO
    Push_Fresco(Fi);
    While (!End_trajectory) do
        The robot moves and another fresco can be built
        Create a fresco from sensory data
    done
    Fj=Create_fresco(sensory_data);
    If (criteria(Fi,Fj) == True) then
        Push_Fresco(FJ);
    end If
    Fi=Fj;

End
```

Algorithm 3: Symbolic trajectory algorithm

4. Experimental results

4.1. Symbolic description

To build the fresco, the "Opening, Closure, End_of_Closure, Angle_of__Closures" landmarks have to be extracted from the raw distance data given by the panoramic laser range finder. Three steps are necessary. The first one consists of environment perception. It is realised with a laser range finder. The second step builds the digital representation of the environment. The third one extracts the landmarks. More details can be found in (Pradel and al., 2000). The size of the non holonomous robot is (width x length) 0.50m x 0.75m. Its linear and angular speeds are up to 1m/s and 2.45rad/s. The robot is placed at the geometrical centre of the environment captured bt the panoramic telemeter. Sizes of the environment are 6m x 6m. Experiments in the following have been made with measurements coming from both a simulated laser range finder and the real telemeter. Figure 4 examplifies the symbolic description process. Figure 4a shows the environment detected by the sensor. When the laser beam hits an obstacle the corresponding cell will appear in black in the cellular space. Elimination of the noise introduced by the oblique walls needs a reorientation and a filtering process (figures 4b and 4c) (Bras and al., 1995). Extraction of the landmarks ("End_of_Closure", "Closure" and "Angle_of_Closures") from the grid is made by a set of laws similar to those used in cellular automata (Pradel and al., 2000). Figures 4d and 4e examplify the landmark extraction process for the "Angle_of_Closures" and "End_of_Closure" landmarks. Finally, figure 4f shows the corresponding fresco.



a(upper left): real world from raw measurements,
b(upper centre): reoriented cellular space,
c(upper right): refined space after superfluous data elimination,
d(lower left): Angles_of_Closure extraction,
e(lower centre): End_of_Closure extraction,
f(lower right): Constructed fresco.

***Figure 4.*:** Example of the digitised constructions:

Building the fresco uses the language presented in table 3 which gathers landmarks identity and attributes. This operation aims mainly at eliminating the notion of distance to the profit of a spatial series and highlights the qualitative representation of the environment. Every time a fresco is built, a validation checking is made thanks to strict laws of neighbourhood (for example, the neighbours of an Angle_of_Closure can only be Angle_of_Closures or End_of_Closures) and either the fresco is saved or lost with only slight effects on the mission of the robot.

Moreover, the disturbance introduced by this loss is very attenuated because the process of transitions detection and environment memorisation eliminates a great part of the frescoes. When it is validated, the fresco appears as shown in figure 4f. A fresco will contain at most 64 landmarks symbols. At this point, a certainty attribute is introduced to reflect the evolution of the landmarks when the robot is moving. This evolution is well defined for the certain landmarks while it is not for the other ones (e.g.: an End_of_closure off-sight can transform in itself or End_of_closure or Angle).

4.2. Application of the criteria in simple environment

The two criteria apply only on the certain landmarks and have been tested in two types of environments. In a first step, experiments in simple environments led us to point out the thresholds relevant ranges. In a second step, a complex environment has been used to validate these thresholds.

The problem is to find the right threshold for each criterion. A representative panel of situations is first established and systematic tests are made on each situation in which the frescoes are listed for different thresholds of the two criteria. Then a reference threshold for each criterion is fixed taking into account firstly the ratio of kept frescoes and secondly the position of these frescoes with respect to their situation along the robot's route in the considered environment. Finally, thresholds that have been defined are tested in a complex environment.

4.2.1. *Choice of different types of environment*

Indoor environments can be described using a limited number of situations (Al Allan, 1996): openings, walls, angles, room, corridor, dead-end and crossings. So far, tested situations are listed in table 4.2.1.

Figure 5 shows the example of the "opening on the left situation". Numbers on the left of the figure show the different positions where frescoes have been constructed. In this example, frescoes are built from position 1 to position 31 (only one of five is drawn to make the figure readable).

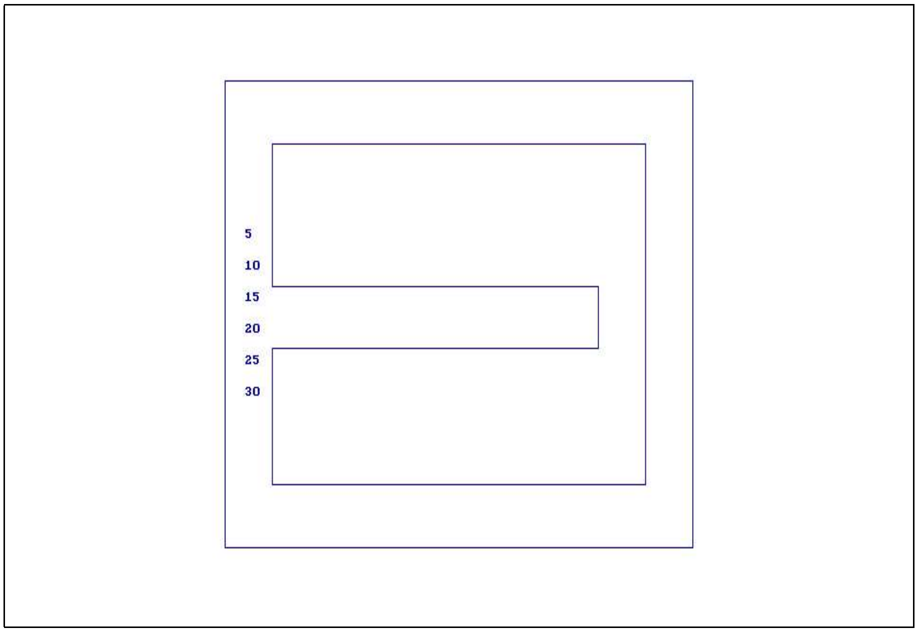


Figure 5.: Example of situation: Opening on the left

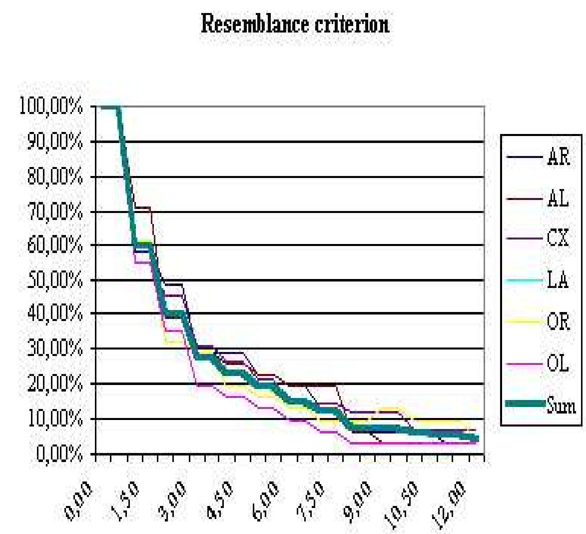
In the different situations, the initial numbers of frescoes are different (Table 4.2.1).

Table II. Initial number of built frescoes

Situation	Abbrev.	Number of frescoes
Angle to the left	AL	31
Angle to the right	AR	31
Opening on the left	OL	31
Opening on the right	OR	31
X-crossing	CX	42

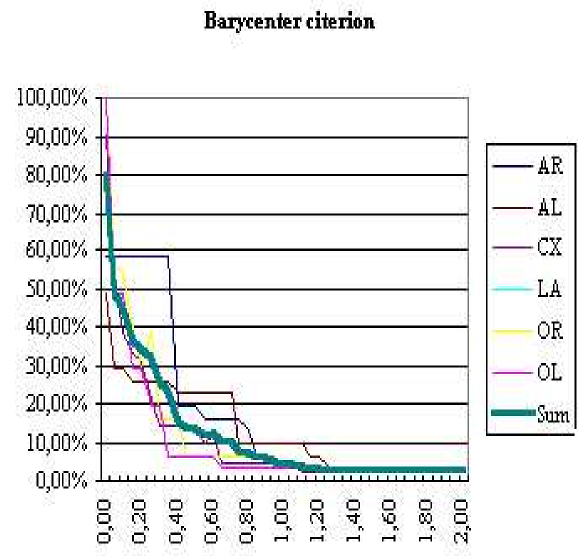
4.2.2. *Number of pertinent frescoes vs. criterion*

It is firstly interesting to observe the number of frescoes kept for different values of thresholds. For barycenter criterion, values between 0 and 2 with a step of 0.05 are tested. For resemblance criterion, values between 0 and 12 with a step of 0.5 are tested. Beyond these limits, only fresco number one is kept. As the initial number of frescoes is different in all situations, the ratio between the number of frescoes kept and the initial number of frescoes is analysed. Figure 6 shows the results for resemblance criterion. Figure 7 shows the results for barycenter criterion. It can be seen that curves in each figure are similar, meaning that criteria have the same response in all the environment situations. It seems then possible to find a common threshold.



AR/AL: angle on the right/left,
CX: X-crossing,
LA: lab,
OR/OL opening on the right/left,
Sum: add up.

Figure 6.: Percentage of frescoes selected by resemblance criterion vs. threshold value



AR/AL: angle on the right/left,
CX: X-crossing,
LA: lab,
OR/OL opening on the right/left,
Sum: add up.

***Figure 7.*:** Percentage of frescoes selected by barycenter criterion vs. threshold value

It also can be noted that curves fall quickly for low thresholds values. In figure 5, frescoes between 1 and 10 represent the same part of the environment with very slight differences. The objective is to keep a reasonable part of frescoes between 10% and 20% in the first approximation. For resemblance criterion, that means thresholds values between 5 and 7 and between 0.4 to 0.6 for barycenter criterion.

4.2.3. *Positions of pertinent frescoes*

For both criteria, it is interesting to visualise which frescoes are considered as pertinent. For the barycenter criterion applied to the "angle on the left" situation, figures 8, 9, 10, 11 and 12 show the positions of the pertinent frescoes vs. the threshold value.

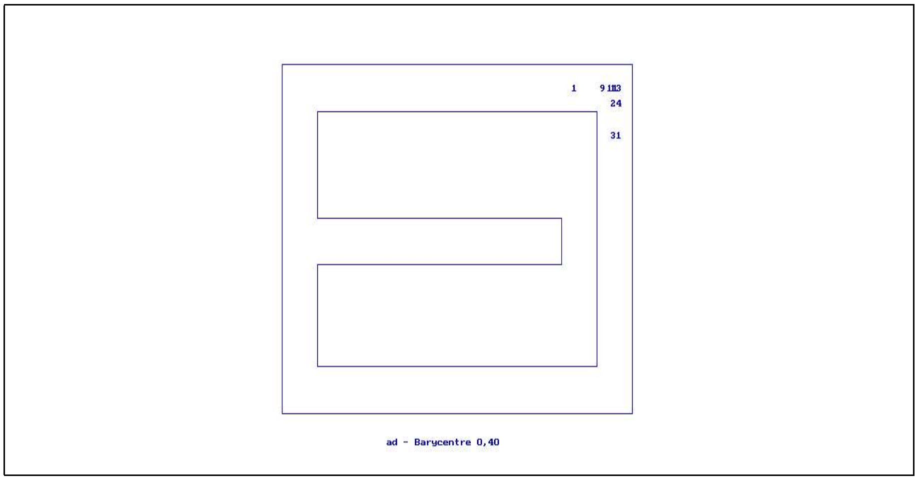


***Figure 8.*:** Pertinent frescoes vs barycenter criterion; threshold=0.40

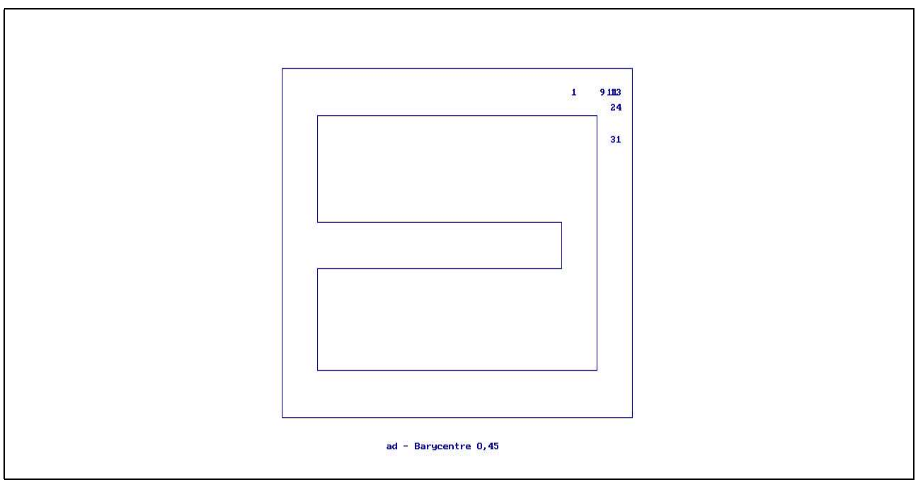


***Figure 9.*:** Pertinent frescoes vs barycenter criterion; threshold=0.45.

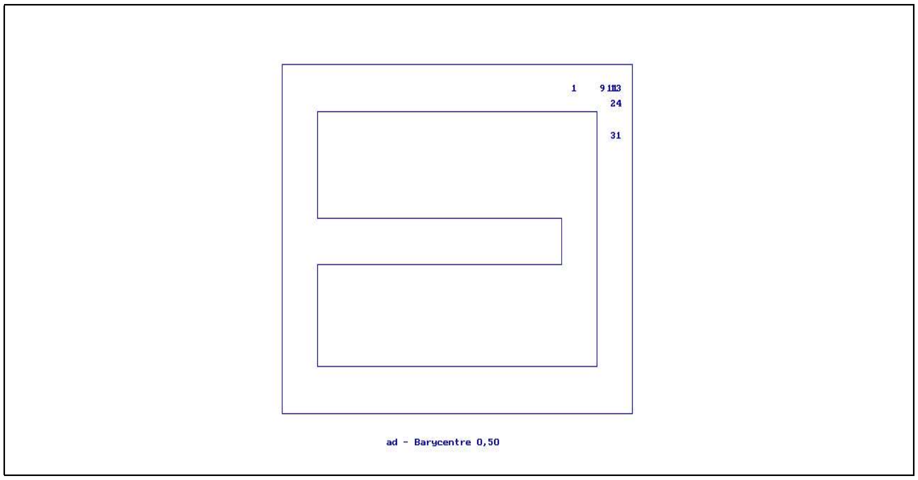


***Figure 10.*:** Pertinent frescoes vs barycenter criterion; threshold=0.50 (AL situation).

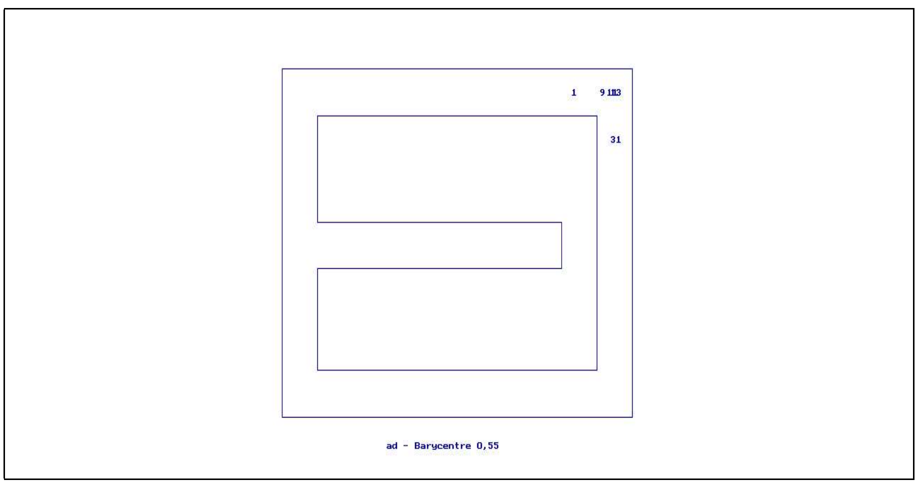


***Figure 11.*:** Pertinent frescoes vs barycenter criterion; threshold=0.55 (AL situation).

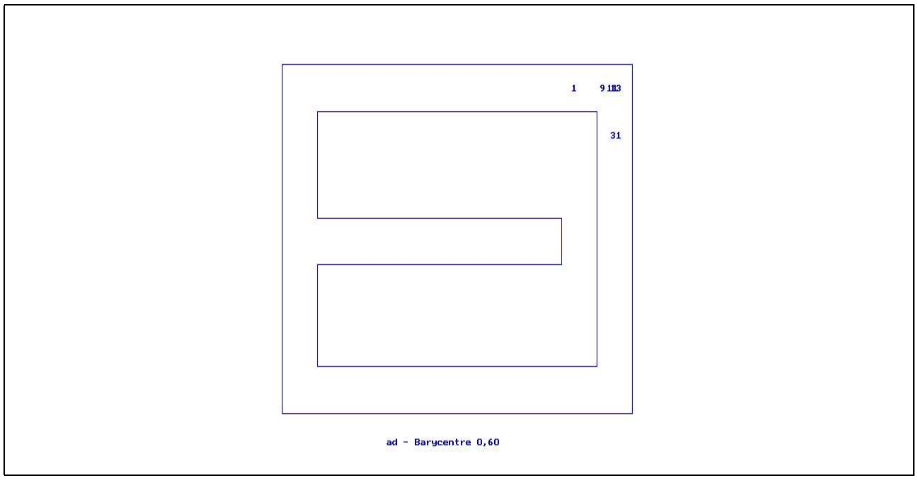


Figure 12.: Pertinent frescoes vs barycenter criterion; threshold=0.60 (AL situation).

Frescos number 1 and 31 represent the beginning and the end of the trajectory: they appear for all the thresholds. Frescoes 9, 11, 13 and 24 represent the heart of the turning. They are very close considering Euclidean distance but they differ in term of orientation. Fresco number 24 disappears for thresholds equal to 0.55 or 0.60. The value 0.50 is the central threshold value for barycenter criterion. A similar analysis has been conducted for all other situations. In the same way, the resemblance criterion leads to the same conclusion with 6.0 as central threshold.

4.2.4. *Discussion*

If only the number of the frescoes considered as pertinent to describe the travel of the robot is taken into account, we firstly see that the response for each criterion is similar for every situations and, secondly, that for every criterion the thresholds values giving the best results are very close. It is then possible to evaluate an acceptable threshold whatever the situation. This number is not significant of the efficiency of the criteria. The position of selected frescoes plays an important role. The pertinent frescoes must be positionned as close as possible of the labels of the Voronoii vertices. The visualisation of the selected frescoes for all the combinations of situations and criteria shows that retained frescoes are well situated in the environment to have a satisfying representation. Figures 13 and 14 show the positions of pertinent frescoes vs. the criterion used. Resemblance criterion keeps 3 frescoes situated before the opening, in the middle of the opening and after the opening. It is the best representation of the changes in the environment in terms of concision and precision. In other situations, the barycenter criterion gives the best result.

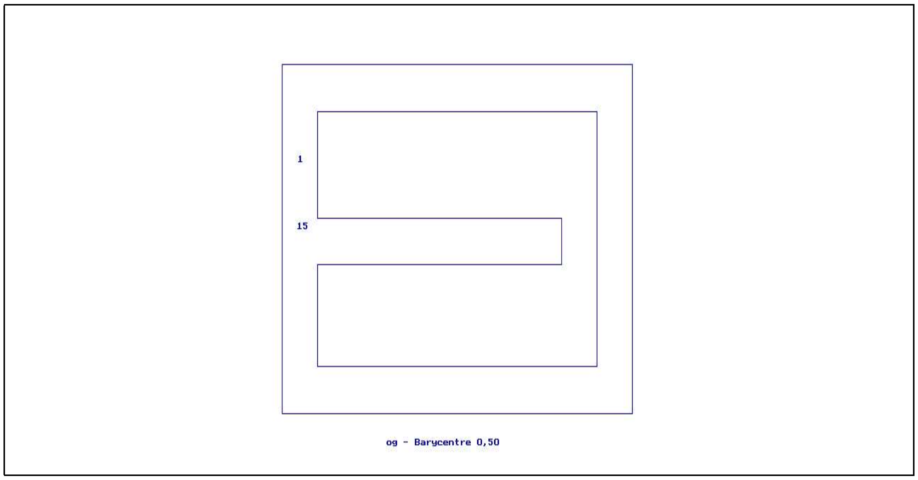


***Figure 13.*:** Position of pertinent frescoes with barycenter criteria (AL situation).

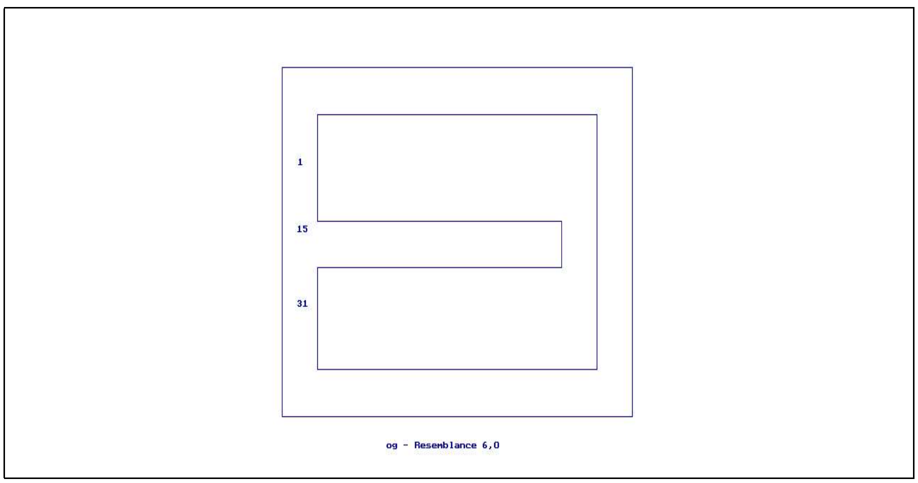


***Figure 14.*:** Position of kept frescoes with resemblance criteria (AL situation).

4.3. Complex environments

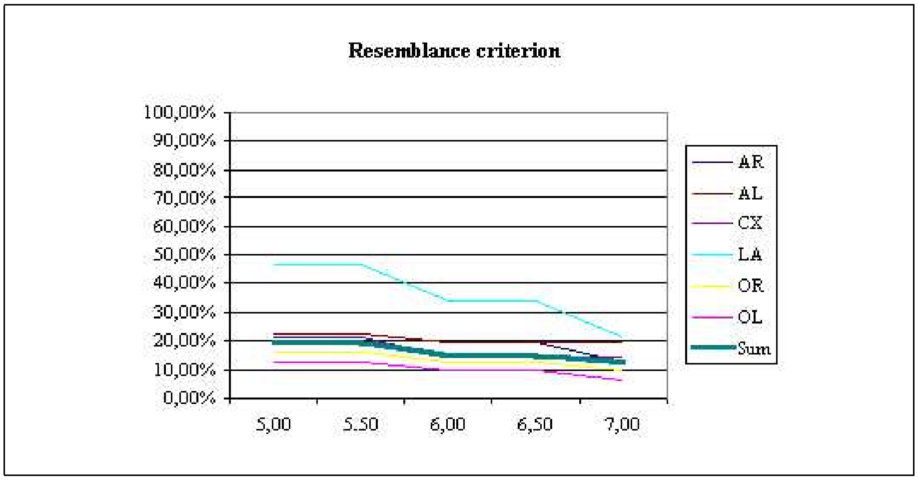


Figure 15.: Comparison of percentage of frescoes selected by resemblance criterion in complex (LA) and simple environments vs threshold.

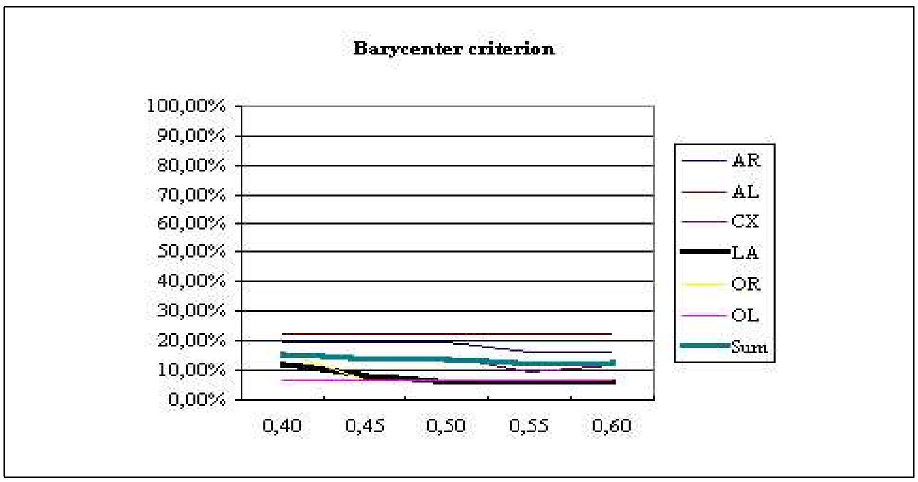


Figure 16.: Comparison of percentage of frescoes selected by barycenter criterion in complex (LA) and simple environments vs threshold.

A complete trajectory has been studied in a complex environment (figure 17). The two criteria have been applied. The variations of the thresholds have been limited to the range determined by the tests in simple environments: 5 to 7 for resemblance and 0.4 to 0.6 for barycenter. Figures 15 and 16 show the percentage of kept frescoes for

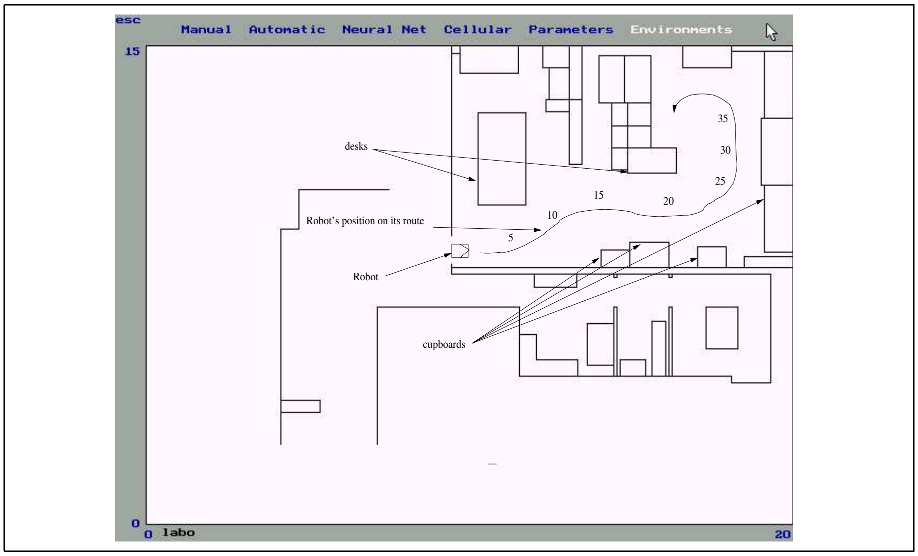


Figure 17.: Test environment: the lab

both criteria. For barycenter criterion, there is no significant difference between the complex and the simple environments. For resemblance criterion, the ratio is greater in the complex environment than in the simple ones. Nevertheless, for a threshold equal to 7.0, the ratio becomes close to the ratio obtained in simple environments. Figure 18 shows pertinent frescoes for the resemblance criterion with a threshold equal to 7.0. Figure 19 shows pertinent frescoes for the barycenter criterion with a threshold equal to 0.4.

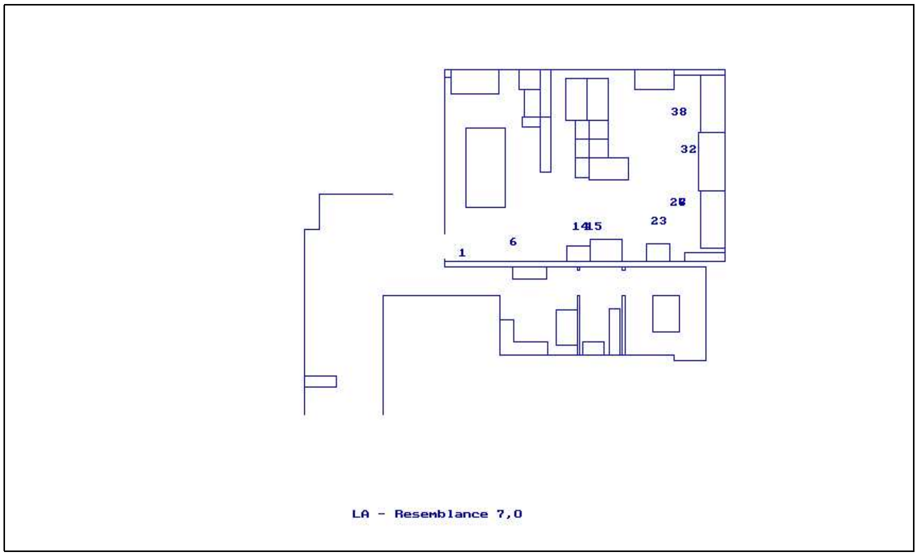


***Figure 18.*:** Position of pertinent frescoes with resemblance criterion in the complex environment.

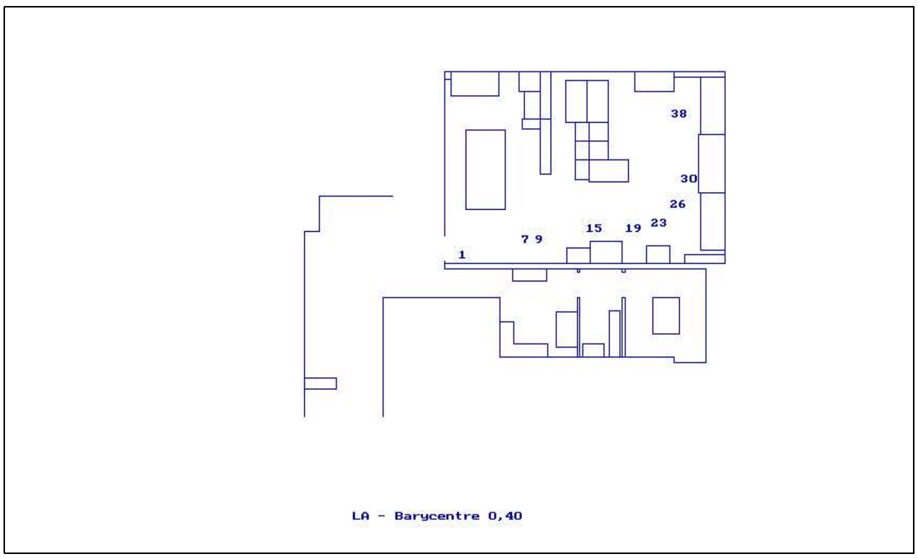


***Figure 19.*:** Position of pertinent frescoes with barycenter criterion in the complex environment.

5. Conclusion and perpectives

Human beings, as well as insects (Collett and al., 1992), use resemblance (or dissimilarity) to compare views of the environment rejecting those that do not bring up new elements without using metrics, only using the occurence of landmarks. In this paper, we present a qualitative method inspired of homing methods (Weber and al, 1999) to construct the environment surrounding an indoor mobile robot equipped with a 2D telemetry sensor. Every times distance measurements are made, landmarks are extracted and organised into series called frescoes. From this point, distance information are not more used. In order to derive the pertinent frescoes that can describe the trajectory of the robot, we plan to use a pairing-like method. The first criterion that is primarily being investigated uses a resemblance between two frescoes. The landmarks are bounded and a correlation function measures the difference between consecutives frescoes. The second criterion is based on the difference between the barycentre positions of consecutive frescoes(Huttenlocher, Klanderman and al., 1993). Those frescoes separated by a difference higher than a threshold are considered as pertinent to describe the robot's route. In both cases the differences are compared with thresholds that are experimentally set up. Despite the criteria simplicity, the results in the very changing test environment (figure 17) show that the thresholds experimentally trimmed in simple environments are well fitted to a complex environment.

Depending the environment, it has to be noticed that the behaviour of the two criteria can differ and one can be a bit more efficient than the other. An improvement of the method will introduce a global information situation in the choice of the best criterion. A neural classifier will output the class of the situation of environment. According this class, the most efficient criteria, resemblance or barycentre, will be chosen. Another direction should be the use of more sophisticated criteria such as, for example, Lievenshtein distance. A good evaluation of the criteria could be their use in a return journey. Remember that the application field of the robot is supplying services for a handicapped person. The robot has to go in the flat and move back to the user. If it is able to go back to its starting point, we do consider that the method is validated.

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