# COOPERATIVE MAP BUILDING USING QUALITATIVE REASONING FOR SEVERAL AIBO ROBOTS

David Graullera, Salvador Moreno
*Instituto de Robótica,Universidad de Valencia, Paterna, Valencia, Spain.*

M. Teresa Escrig
*Departamento de Ingeniería y Ciencia de los Computadores, Universitat Jaume I, Castellón, Spain.*

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Abstract: The problem that a robot navigates autonomously through its environment, builds its own map and localizes itself in the map, is still an open problem. It is known as the SLAM (Simultaneous Localization and Map Building) problem. This problem is made even more difficult when we have several robots cooperating to build a common map of an unknown environment, due to the problem of map integration of several submaps built independently by each robot, and with a high degree of error, making the map matching specially difficult. Most of the approaches to solve map building problems are quantitative, resulting in a great computational cost and a low level of abstraction. In order to fulfil these drawbacks qualitative models have been recently used. However, qualitative models are non deterministic. Therefore, the solution recently adopted has been to mix both qualitative and quantitative models to represent the environment and build maps. However, no reasoning process has been used to deal with the information stored in maps up to now, therefore maps are only static storage of landmarks. In this paper we propose a novel method for cooperative map building based on hybrid (qualitative+quantitative) representation which includes also a reasoning process. Distinctive landmarks acquisition for map representation is provided by the cognitive vision and infrared modules which compute differences from the expected data according to the current map and the actual information perceived. We will store in the map the relative orientation information of the landmarks which appear in the environment, after a qualitative reasoning process, therefore the map will be independent of the point of view of the robot. Map integration will then be achieved by localizing each robot in the maps made by the other robots, through a process of pattern matching of the hybrid maps elaborated by each robot, resulting in an integrated map which all robots share, and which is the main objective of this work. This map building method is currently being tested on a team of Sony AIBO four legged robots.

## 1 INTRODUCTION

An autonomous mobile robot, able to explore an unknown but structured environment, must first be able to perform several related tasks, which can be illustrated by the answers to the following questions (Levitt, 1990):

- What should I remember? (mapping)
- Where am I? (localization)
- Where should I go? (path planning)
- How can I go? (motion control or navigation)

Acquiring and maintaining internal maps of the world is a necessary task to carry out a successful navigation in complex environments.

We are going to solve in this paper the problem of map building for several cooperating autonomous mobile robots on an unknown labyrinth made of rectangular walls. The walls are distributed randomly forming a labyrinth and the robots are left inside with no knowledge of the environment. The robots have to explore the environment and to cooperate to build a map of the environment.

There are in the literature a lot of approaches for building maps in static, structured and relatively



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small environments. They can be divided into three main strategies: qualitative, quantitative and hybrid approaches.

Qualitative models focus on the boundaries of the objects, making divisions of the space more or less detailed. These approaches deal with imprecise information in a manner inspired by the cognitive processes used by humans. The qualitative concept of a topological map, which represents the world using nodes (places) and arcs (relations), has been used in several approaches, such as the one introduced by (Kuipers, 1978). Another model is defined by (Freksa, 2000), where schematic maps are used to reason about relative positions and orientations. Other qualitative models have been carried out by several authors. Most of these qualitative models have been implemented mainly in simulations.

Quantitative methods represent the environment by metrical information obtained by the sensors. The major exponent of this strategy is the grid-based model, introduced by (Moravec and Elfes, 1985). Quantitative models are affected by odometric and sensory errors. In recent years, many quantitative approaches have been developed using probabilistic techniques to cope with partial and inaccurate information. All of these approaches are based in implementations of the Bayes filter, as the Kalman filter, hidden Markov models, partially observable Markov decision processes or Monte Carlo localization. A survey on this techniques can be found in (Thrun, 2001) and (Thrun, 2002).

Hybrid approaches handle with qualitative and quantitative information, combining the best of the each model. One of the first models for map building was proposed by (Thrun, 1998), which combines the occupancy grids with topological maps. Other hybrid models can be found in numerous papers, as (Escrig, 2005). More hybrid models use probabilistic techniques to cope with partial information.

The work presented in this paper represents hybrid information into a map: quantitative data provided by robot sensors (most of the times this data contain imprecision); and qualitative data. Moreover, our approach is going to use a qualitative reasoning process which will allow us to solve the four problems above mentioned: mapping, localization, planning and navigation.

# 2 COOPERATIVE MAP BUILDING

We are going to solve the problem of cooperative map building for several autonomous mobile robots on an unknown labyrinth made of rectangular walls. We suppose each robot is able to explore an area in front of it, in order to detect if this area is free or if it is occupied by one or more walls, or by other robot. Taking into account that the walls are straight, each robot must detect the distance and orientation of each wall which enters in its exploring area, and the position of a circle enclosing each other robot it detects in the area. In the case of AIBO robots, we have implemented a multisensory approach to explore this area, by using the TV camera of the robot, and the infrared range sensor.

The cooperative map building procedure is composed of the following steps:

- Individual Map Building
- Map Sharing and Self-Localization
- Integrated Map Building

# 3 INDIVIDUAL MAP BUILDING

For each robot, we build a individual map taking as input the distance and orientation of each wall which enters in its exploring area, and the position of a circle enclosing each other robot it detects in the area, and have as output the generated map, and the orders to the robot for exploring the environment, in the terms of “walk XX centimetres”, and “turn YY degrees”.

## 3.1 Initialization

At the beginning, the robot map is empty, and the robot detects nothing in the area in front of it, therefore it assumes the initial hypothesis that the scenario is composed of an infinite floor surface, without walls, with only an explored point: the current position of the robot. The robot starts walking ahead until the explored area in front of the robot is occupied by a wall. This situation can be seen at the snapshot 1 of figure 1. Each step the robot gives is memorized in the database (only to make an approximate evaluation of the distance the robot walks in free walking). When the robot detects a wall, it enters into the wall following mode.

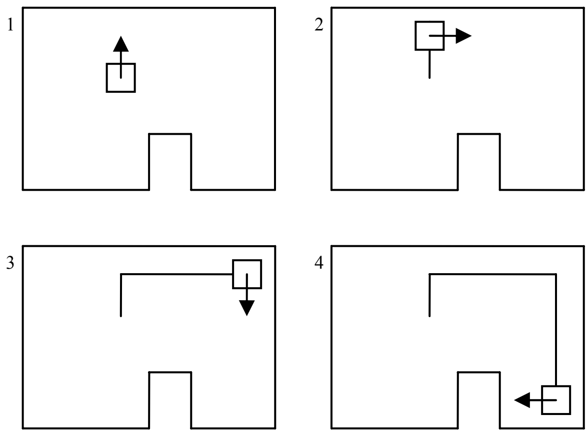



Figure 1: An example of scenario.

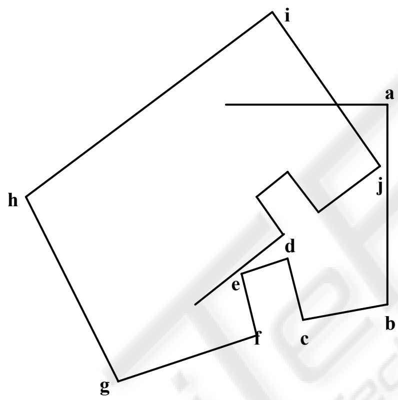



Figure 2: The scenario map as build by the wall following process alone.

## 3.2 Wall Following

When the robot detects an unknown wall, it starts following the wall by turning right and following the wall. While it is walking along a straight wall, it stores the distance it walks as an approximate measure of the length of the wall. When it reaches a corner, it labels the corner and it stores the approximate turning angle of the corner before start following a new wall. This process can be seen at snapshots 2, 3 and 4 of figure 1.

Nevertheless, the process is not as simple as this. The imprecise information about robot position and orientation given by odometry, makes impossible to generate a map of the scenario as the one shown in figure 1. In fact, the real map is more or less as the one shown in figure 2.

The map information stored in the database when the robot discovers point d is the following:

```
point(nonreal,p01).
point(real,a,95).
line(p01,a,3).
point(real,b,100).
line(a,b,3).
point(real,c,105).
line(b,c,1).
point(real,d,-85).
line(c,d,1).
```

Taking into account the uncertainty in direction and length, we can easily see that it will be impossible to recognize directly the corner i as the corner a, therefore it will be seen as a different one and the robot will give infinite loops around the room. This process will end when the following module, the hybrid shape pattern matching, proposes that corner a is corner i, so the shape is totally explored.

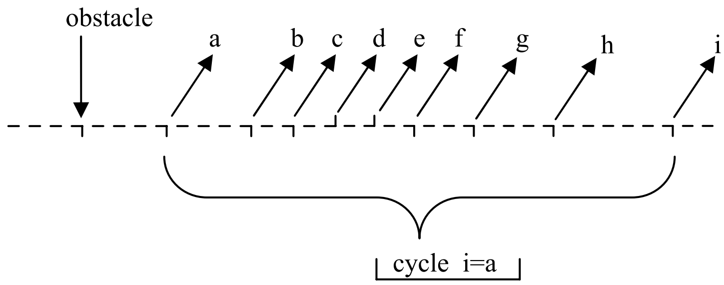



Figure 3: The hybrid pattern matching process.

## 3.3 Hybrid Shape Pattern Matching

The hybrid shape pattern matching is continuously monitoring the output of the previous module, which can be seen in figure 3. In this figure, we can see from left to right the movements of the robot, as a straight line for each straight step, an angle down for inner corners, and an angle up for external corners. The pattern matching process tries to detect cycles in the trace shown in figure 3. The first hypothesis which we can make is to suppose that corner a is the same as corner i, but the pattern matching process is only sure when corner d is revisited, as is one of the two only external corners of the scenario, and it is very difficult to misrecognize this.

Note that this hypothesis can be wrong, therefore it will be stated and maintained only if subsequent measures are compatible with this hypothesis. If not, the hypothesis must be revised through a truth maintenance process which we implement thanks to the backtracking mechanism of prolog, the language we have implemented this algorithm.

Once the hypothesis has been stated, the scenario map is corrected under the assumption that corner a is corner i, and the position and orientation error between i and a, is cancelled by splitting it in several minor corrections to angles and distances in order to achieve that point a and point i will be the same, resulting in a map as the one seen in figure 4.

## 3.4 Inner/Outer Area Exploration

Once the shape of the scenario has been resolved, it is necessary to see if it is a shape enclosing the robot, or if it is a shape surrounded by the robot. This can be seen by simply seeing if the total angle is +360 degrees, in which case the robot is inside the shape, or -360 degrees, if the robot has surrounded a shape from the outside. Now it is necessary to split all the unexplored area by using the two-dimensional qualitative orientation model of (Zimmerman and Freksa, 1993). The model defines a Reference System (RS) formed by two points, a and b, which establishes the left/right dichotomy. The fine RS includes two perpendicular lines by the points a and b. This RS divides the space into 15 qualitative regions (Figure5a). An iconical representation of the fine RS and the names of the regions are shown in Figure 5b).

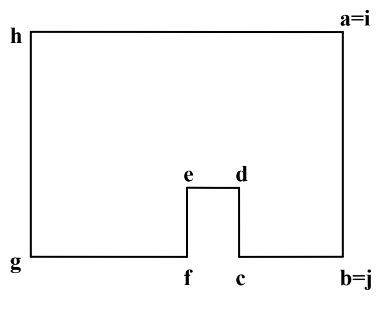
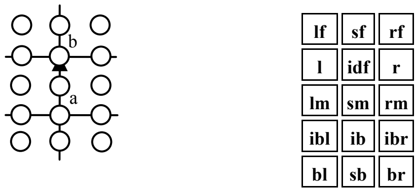



Figure 4: The scenario map corrected by the hypothesis a=i.




a) b)

Figure 5: a) The fine RS and b) its iconical representation.

The information which can be represented by this RS is the qualitative orientation of a point object, c, with respect to (wrt) the RS formed by the point objects a and b, that is, c wrt ab. The relationship c wrt ab can also be expressed in other five different ways: c wrt ba, a wrt bc, a wrt cb, b wrt ac and b wrt ca, which are the result of applying the inverse (INV), homing (HM), homing-inverse (HMI), shortcut (SC), and shortcut-inverse (SCI) operations, respectively.

The composition of relationships for this model, what we call Basic Step of the Inference Process (BSIP), on qualitative spatial orientation is defined such that “given the relationships c wrt ab and d wrt bc, we want to obtain the relationship d wrt ab”.

The idea is to split the unexplored area in several subareas where the position of the robot does not vary with respect to any pair of corners of the scenario shape. As there are many subdivisions, secondly, we select not all, but only a few, which makes all the subareas convex, and which maximizes the probability of recognizing the corner (for instance, corners d and e will be preferent). In our case, the whole area is splitted in three convex regions: abcd, dahe, and fehg. Then the robot starts walking along the borders of these regions (lines a-d and e-h).

If the robot found a wall while exploring the area, the shape is explored by using the same procedure of wall following and hybrid pattern matching. If not, the subareas are finally explored until the map is complete, or until the cooperative map building process decides that the integrated map is complete and that the individual maps must not be completed, as it would result in duplication of effort.

# 4 MAP SHARING AND SELF-LOCALIZATION

Each robot builds its own map independently according to the procedure stated in the previous point. In this point, which is made concurrently with the previous one, each robot shares its individual map with the other robots, so each robot has a copy of the maps of the other ones. The objective is that each robot must self-localize itself in the maps of the other robots.

The procedure is very similar to the problem of SLAM (Simultaneous Localization and Map Building problem), which is described in (Lu, 1997). In the SLAM problem, a mobile robot must explore an unknown environment and to build a map of the environment. Once the map is built, the robot is kidnapped and located in other place of the labyrinth. The robot must then be able to localize itself in its map. A solution for this problem, making use of an hybrid approach very close to the one we describe, is described in (Escrig, 2005).

The key problem of the SLAM, which is the same of this point, is to localize the robot in a map already built. Is not important if the robot must localize itself in a map of the environment made by itself, or made by other robot.

The hybrid map of the environment, corresponding to the exploration of figure 1, will be the following (from point a to e):

```
point(real,a,95).
point(real,b,100).
line(a,b,3).
point(real,c,105).
line(b,c,1).
rel(a,b,c,[r]).
point(real,d,-85).
line(c,d,1).
rel(b,c,d,[r]).
point(real,e,-90).
line(d,e,1).
rel(c,d,e,[l]).
```

Where the predicate rel(a,b,c,[r]) means that the qualitative orientation c wrt ab is r (see figure 5).

The process of self-localization of the robot in the maps of others robots takes into account the own map of each robot, and the fact that the robot is localized in this map. Then the map of each robot is compared with the maps of other robots, first by comparing the qualitative orientation of the corners (In the above example, the rel/4 predicate, which says to us that the corner c is located at the right [r] of system ab, that corner d is located at the right [r] of system bc, and so on). The comparison of the qualitative orientations is very simple in computational cost and gives a few possibilities of matching, which are then compared quantitatively by using the line/3 and the point/3 predicates, which allow us to compare the angles and distances, and then the better matching is selected.

A simplification of this process is when a robot detects another one, because then it is possible to take advantage of the fact that two maps must match exactly starting from the localization of their robots, thus making simpler this process.

# 5 INTEGRATED MAP BUILDING

The last point is to integrate all maps in a single map. This process can be done starting from the individual maps and the matching corners that have been identified in the previous point. This allows to assert as working hypothesis (which can be wrong, so this point must take into account a possible backtracking of matching points) an integrated map and the matching of each individual map in the cooperative map. This hypothesis is maintained until a robot generates a individual map which does not match with the integrated map, resulting in a backtracking process to detect which corner matching is erroneous, according to new data. This is a constraint solving problem, in which we offer the integrated map as the map which better adjusts to each individual map, but taking into account that is not the only solution (for example, a solution where the environment is composed of all individual maps without any matching is always possible, but is not the simpler one). A good way to select the working hypothesis is to select the integrated map with fewer corners of all solutions, compatible with current matchings.

Finally, the integrated map building process must decide if the integrated map is complete. If it is, it will send a signal to all robots to make them interrupt its individual map building process and to accept the integrated map as complete, and to give the environment as completely explored. If we do not take this step, each robot will individually explore the environment, so the exploring work would be repeated as many times as robots we have, and the idea is to accelerate the environment exploration by using more robots.

# 6 CONCLUSIONS

This paper describes a procedure to the problem of exploring a unknown environment with several robots, which makes the exploration faster as the number of robots increases. This is a good procedure for starting cooperative works with several mobile robots, as for example to explore an area for finding things, or for vacuum cleaning of huge surfaces (as commercial centres), and so on. The algorithm can be programmed in a main host connected by wireless with the mobile robots, or can be implemented in each robot without a central host (useful for autonomous systems), if a common memory is shared among them by wireless. Currently we are working on its implementation on a team of Sony AIBO four legged robots, on an unknown environment composed of boxes on a room, to form a labyrinth which must be explored.

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