

MODEL STRUCTURING AND CONCEPT RECOGNITION :  
TWO ASPECTS OF LEARNING FOR A MOBILE ROBOT

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ABSTRACT

We present here a method for providing a mobile robot with learning capabilities. The method is based on a model of the environment with several hierarchical levels organized by degree of abstraction. The mathematical structuring tool used is the decomposition of a graph into its k-connected components (k=2 and k=3). This structure allows the robot to improve navigation procedures and to recognize some concepts, such as a door, a room, or a corridor.

1- INTRODUCTION

This paper presents two aspects of learning : concept Learning and procedure learning by generalization. It deals specifically with navigation and locomotion problems for a mobile robot. Actual practical applications for such a robot are for example: night-watchman (patrolling and anomaly detecting in a known environment) robot- cleaner, robot-conveyor, waiter\_\_

The experimental support for our system is HILARE\*, a mobile robot. A navigation procedure based on an initial level of modelling of the universe has been defined by R. Chatila / 1 / . Our approach uses his work which is summarized in part 1. The initial model is a graph. We shall see the motives (part 3) which have led us to the structuring of this model by a decomposition of the graph into connectivity components (part 4). The tools, some of them original, come from graph theory. We shall define a new itinerary procedure as being a generalization of the navigation procedure (part 5). Sub-graph labelling of the decomposition leads to concept learning (part 6) ; its implications in the improvement of man-robot communication will be dealt with. Finally, in part 7, in a more prospective way, we shall tackle the problem of area recognition by subgraph isomorphism.

2. HILARE, UNIVERSE MODELLING, NAVIGATION

As far as learning is concerned, we shall limit our presentation of HILARE to decision-making, universe modelling and navigation.

2.1. Hilare's decision-making consists of :

- multiple independant modules (vision, locomotion, navigation, object identification,..) which are used to build a plan, and

"Heuristiques Integrees au Logiciel et aux Automatismes dans un Robot Evolutif". HILARE is also used as an experimental support for the learning of decision rules in plan generation.

- a coordinator supervising the development and execution of the plan 12 - 3/.

As yet, this system is not entirely defined and is a current research topic. It may be progressively enriched by adding new modules. The integration of learning capabilities for each module can thus be taken into account. It is the case for the itinerary.

2.2. Universe modelling : HILARE moves in a closed space of rooms cluttered with objects a priori considered as obstacles and whose geometrical projection on the locomotion plane is modelled by polygons. This set of polygons, together with the "floor plan" of the rooms leads to a initial geometrical model.

The navigation space is then partitionned into convex cells free of obstacles in which any two points can be linked by a straight line (Fig.1). This leads to a planar graph \* representation : nodes correspond to cells and edges to common frontier-segments for adjacent cells (Fig.2). This model is topological ; every single face\*\* characterizes an obstacle. Notice that the graph representation is easily extended as new rooms are explored.

2.3. The navigation procedure allows the research for a trajectory between two points S1 and S2 to be transformed into a path search in a graph by the following procedure :

1. Find the cells C1 and C2 which contain S1 and S2 (1 and 5 in Fig.1).
2. Search a path T between C1 and C2 in the cell graph (1-2-3-10-9-5 in Fig.2).
3. Find the corresponding geometrical path G formed with the middle of the frontier-segment between the cells in T (dotted line in Fig.1).
4. The trajectory is obtained by smoothing G.

The most important part of the procedure (the determination of the trajectory draft) is made in stage 2, by an admissible heuristic search which includes cell metrics. Learning improves this search.

3. MOTIVATIONS

If in order to go from a point S1 (contained in a cell CD to a point S2 (contained in a cell C2) of the navigation space (of the cell graph), the robot must go through a door (cell A), the problem of finding a trajectory (path search) may be decomposed into : find a path from S1 (CD to the door (A) and a path from the door (A) to S2 (C2). In the \* ; \_\_\_\_\_

A planar graph has a representation in the plan such that two edges intersect in a node.

\*\*A face is a cycle in which a defined area of the plan contains no nodes.

graph representation A is an articulation node whose removal will disconnect the graph. Hence the graph decomposition into connectivity components will enable us to decompose and simplify the navigation procedure.

Moreover, when we consider Fig.1, in order to go from any point in the room R2 to any point in the room R4, we must go through room R3 ; it would be much better to memorize definitively the path within room R3.

Finally, area concept learning is necessary in order to build a man-robot communication language close to natural language (see /4/). The graph decomposition can be analysed with a view to this aim.

#### 4. DECOMPOSITION OF THE GRAPH

By definition, a graph with at least  $k+2$  nodes is k-connected iff it is still connected after the withdrawal of  $k-1$  nodes (or equivalently iff there exist at least  $k$  distinct paths between any pair of nodes). An articulation set is a node set whose withdrawal leads to an unconnected graph. The decomposition is the search of  $k$ -connected subgraphs. We shall deal only with the cases  $k=2$  and  $k=3$ . The chosen method is specific to planar graphs. The input data of the algorithm are the faces of the graph ; easily obtained from the geometrical model by following around the sides of obstacles. These data lead to simpler algorithms than the classical ones /5/. Decomposition up to the triconnectivity level is based on the characterisation of articulation nodes and pairs, established in /6 - 7/ :

- A node is an articulation node iff it appears twice in a face.
- A node pair is an articulation pair iff it appears in two faces (or three faces if this pair is an edge).

The decomposition algorithm into biconnected components\* goes over every face in the graph. When an articulation node appears, it partitions the face. The partition elements are the bases of the biconnected components. In the example of Fig.2, the external face gives the partition 1-2-3-4, 3-10-9-11-14-20-19-17-16-15, 9-5, 5-6-8-7, 19-24, 24-25, and 25-23-22-26 with the nodes 3,9,5,19,24,25 as articulation nodes (see /6/ for details).

For the decomposition into triconnected components\*\*, we propose in /6/ a quadratic algorithm which finds all articulation pairs. It compares favorably to the linear algorithm developed by Hopcroft and Tarjan /5/ for planar graphs with up to 300 nodes and 800 edges.

The set of articulation nodes, articulation pairs, biconnected and triconnected components can be structured into a tree /8/. Two nodes representing triconnected components are adjacent if they contain the same articulation pair ; two subtrees representing biconnected components are adjacent if they contain the same articulation node.

Fig.3 represents the decomposition tree of the graph in Fig.2 (up to biconnected components).

#### 5. ITINERARY PROCEDURE

This procedure generalizes the navigation procedure ; it decomposes the path search problem into

The biconnected components are biconnected subgraphs or edges.

\* The triconnected components are triconnected subgraphs or elementary cycles.

subproblems which are almost all solved by an initial processing.

5.1. Preprocessing : it memorizes the path between the nodes of separation sets belonging to the same component. These paths are found by the navigation procedure. Fig.3 shows an example of a memorized path.

5.2. Itinerary : the decomposition structure and the prememorization having been defined, the search of a path between two points S1 and S2 by the itinerary procedure is done as follows :

1. Find the cells C1 and C2 containing S1 and S2.
2. Find the components K1 and K2 of decomposition tree containing C1 and C2.
3. 1-If  $K1=K2$ , return the path given by the navigation procedure used only in K1  
2-Else 1-Find the path between K1 and K2 in the tree (K1-K4-K2 in Fig.3)  
2. Fetch the corresponding prememorized path P.  
3. Find the path P1 between C1 and the first node of P, using the navigation procedure in K1, and the path P2 between the last node of P and C2, using the navigation procedure in K2.
4. Return the path  $P1 \cup P \cup P2$ .

The complete set of algorithms mentioned here (navigation, planar graph decomposition, preprocessing, itinerary) have been implemented in APL.

5.3. Complexity : the use of the navigation procedure in the steps 3-1 or 3-2-3 gives its complexity to the itinerary procedure. The step 3-2-1 is linear. Therein lies the originality of the itinerary module : it transforms the path search in a GRAPH into a path search in a TREE. The preprocessing complexity is also determined by the navigation procedure for the path prememorization. Graph decomposition is linear. According to our experiments, the cost of the preprocessing is paid off by a few robot moves. In a more complex example than the one presented here (57 cells), 12 calls to the itinerary procedure were sufficient in the average.

5.4. Note : as a matter of fact, the prememorization cannot take into account the advent of unexpected obstacles during room traversal. This kind of event is specifically processed by the supervising coordinator (cf. § 2.1) : it should, in this case, put into action an obstacle avoidance module.

#### 6. AREA CONCEPT LEARNING

Here we understand "learning" as the recognition of area concepts such as doors, rooms and corridors. This is done by the analysis of the decomposition tree of the graph. We first consider that a room is a biconnected or triconnected component in the decomposition tree, and a door or a corridor is an edge linking two components. Yet, this approach is limited. In the analysed example, cell 25 cannot be viewed as a door as is the case of cell 24 ; both of them are separation nodes (edges in the decomposition tree) ; metrical considerations must be introduced to improve the Labelling. Examples of rules used are :

- Two adjacent biconnected components which are not edges, are labelled as two different rooms if their common separation node is a cell with a small surface.

- Two adjacent biconnected components, one being an edge, are Labelled as one room, if their common separation node is a cell with a large surface.

Fig.4 presents two possible labellings corresponding to whether cell 3 is considered as small or large. In fact, we can improve the labelling by other criteria : for example the frequency of cell crossing. All considered, the decomposition tree is a "skeleton" which is used as a basis for area concept learning. The tree is the model of the room connectivity graph.

7. AREA RECOGNITION

This paragraph presents more prospective ideas. The model of the robot increases as it explores the univers. In a rather complex case, the robot may reach a room already known through doors and corridors unknown to it. It must recognize this area. Several means of recognition are possible :

1. The metrical identification with absolute coordinates. This may be inefficient due to uncertainties in measurement and to robot positioning errors.
2. The identification of characteristic objects in the room if these exist.
3. A third possibility is topological recognition.

The above structuring of space permits to solve this recognition as a subgraph isomorphism problem. The general problem is NP complete (even in the planar graph). We can nevertheless expect a solution through the labelling of the graph (approximate metric, number of obstacles in the rooms, number of doors,...) and through the reduction of the general problem to isomorphism of planar graph (for which efficient algorithms, based on the same graph decomposition techniques, are known (7 - 9)).

8. CONCLUSION

The learning procedures presented in this paper lead to a significant improvement in the robot navigation system. Furthermore, they enable a modelling of space at a high level of abstraction, and a

labelling of subspaces close to human concepts of area. Orders such as : "Take corridor C and enter into room R through door D" will refer for the robot to data structures with precise algorithmic meaning. While carrying out this research on learning by data structuring, we have developed original and efficient algorithms for planar-graph processing.

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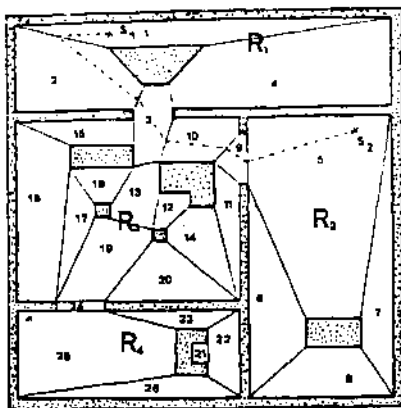


Fig.1. The geometrical model

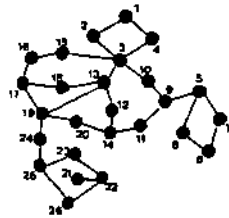


Fig.2. The cell graph

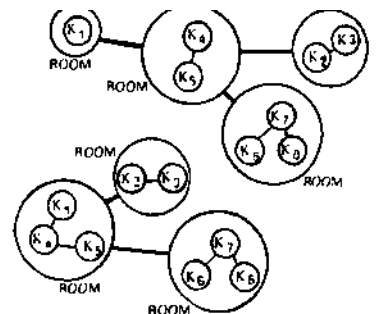


Fig.4. Two possible labellings of the decomposition tree

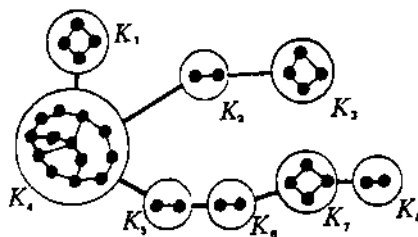


Fig.3. The decomposition tree. Example of a prememorized path between K2 and K5 : 9-11-14-20-19