Biologically-inspired robotic mapping as an alternative to metric and topological approaches

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Abstract – **This paper presents the state of the art of robotic mapping and compares current approaches: metric, topological and biological. Navigation models inspired on the neurophysiology of rat's hippocampus are described as a promising alternative to solve the problems found in metric and topological approaches.**

Index terms – **Biologically-inspired mapping, localization, metric mapping, multi-robot mapping, navigation, rat's hippocampus, topological mapping.**

I. Introduction

A critical ability of autonomous mobile robots is navigation. The functions of navigation can be expressed by four questions: where am I going, which is the better way to get there, where have I been, and where am I? In order to solve these questions, the robot needs to know its environment. As the robot explores new environments, it may be part of its mission to map them. The acquisition of spatial models of unknown environments is known as **robotic mapping**.

In the 1980s and early 1990s, the field of robotic mapping was divided into metric and topological approaches. A **metric map** captures the geometric properties of the environment, while a **topological map** describes connectivity between different places. Besides those approaches, there exists a promising alternative inspired on the neurophysiological workings of the rat brain.

This paper presents a general overview of the state of the art of robotic mapping, including metric, topological and biological approaches. The paper also compares them and describes the work that our research group is beginning to do for contributing to the field of robotic navigation.

II. Metric Mapping

Most of the algorithms for building metric maps have a common feature: they are probabilistic. This is because robotic mapping is characterized by uncertainty and sensor noise. Probabilistic techniques offer a mechanism to fuse sensor data, decreasing noise.

The dominant schema to integrate sensor data and robot's movements at different times is Bayes' filter, which estimates the map of the environment and the robot's position at time t based on the sensor measurements and the robot's movements registered until time t.

Some of the metric mapping algorithms commonly used are Kalman filters [15], the Expectation-Maximization algorithm (EM) [9], and occupancy grids [11].

In the Kalman filter approach, maps are represented by the cartesian coordinates of a group of features present in the environment, like landmarks, distinctive objects or shapes.

An advantage of this approach is that the map is estimated on-line, i.e., while the robot explores the environment. Besides, it converges with probability one to the real map and robot's position and it is able to map cyclic environments and dynamic ones. However, it cannot cope with the correspondence problem, i.e., the problem of determining if similar sensor measurements taken at different points in time correspond to the same physical object in the world or not.

An alternative to Kalman filters that solves the correspondence problem is the EM algorithm. EM generates consistent maps dealing with large scale cyclic environments even if all features look alike and cannot be distinguished perceptually. However, EM does not involve the notion of uncertainty; instead, it constructs several maps in order to find one that best corresponds to the environment. To do that, EM has to process data many times, so it cannot generate maps incrementally as Kalman filters do.

EM exploits the fact that building a map when the robot's path is known is relatively simple, as is the determination of a probabilistic estimate of the robot's location when the map is known. To do this, EM iterates between two steps: an expectation step, where the robot's position is calculated for a given map, and a maximization step, in which EM calculates the most likely map given the robot's position expectation. The result is a series of maps, where the initial map is empty. The main disadvantage of the EM algorithm is that it executes off-line.

The Kalman filter approach and the EM algorithm address the mapping problem with an unknown robot's position. This is known as the **simultaneous localization and mapping problem** or **SLAM**. There exist also algorithms in which robot's position is known. One of the most popular is occupancy grid maps, where the central problem is to generate a consistent map from noisy and incomplete sensor data. As the algorithm's name suggests, maps are two-dimensional grids that represent a fixed area in the absolute coordinate system. The grids have high resolution, in the order of 5-10 cm per cell. Bayes filters are used to predict the occupancy of each cell. The individual values of cells are refreshed incrementally as new sensor data arrive. The initial value of all cells is 0.5, indicating that it is unknown if they are occupied or free.

III. Topological Mapping

Topological mapping represents an environment as a graph, where nodes correspond to distinct situations, places or landmarks, and the arcs indicate the existence of direct paths between nodes. The robot's localization can be carried out in two ways. If mapping and localization are simultaneous, the robot perceives a place, situation or landmark and tries to find it in the next sensor data. If the robot has already built the topological map, it can localize itself in relation with places or landmarks included in the map; i.e., the robot can know by the map the next place it will reach if it moves in a certain direction from the current place.

The topological approach has been addressed by many authors; e.g., [18], [17], [16], [22], [12], [21], [24], [10], [29]. In general, they apply their own algorithms to build the topological map, in some of which they include metric information of the environment, or they combine the construction of a topological map with a metric map.

Kuipers and Byun [17], for example, proposed a hierarchical model of the environment, where the central element is a topological map. A place that corresponds to a node in the graph must be distinctive within its immediate neighborhood by some criterion definable in terms of sensory input. The authors introduce distinctiveness measures defined on a subset of the sensory features, by which some property can be maximized at a distinctive place. Travel paths that correspond to arcs in the graph are defined by control strategies, which describe how the robot can follow the link connecting two distinctive places.

Each component in the model, places and paths, has also local geometric information, which constitutes the metric level of the model. This information can include the distance and directions towards nearby objects, their shape, and the length and width of the path.

The robot's current position is described at the topological and metric level. At the topological level, is described by a distinctive place or by a travel path and a direction. At the metric level, when the robot is at a distinctive place, its position is described by the current sensory information and its current orientation, and when the robot is on a path, its position is described by the place it is coming from, the distance it has traveled and its current orientation.

Thrun et al. [24] addressed robotic mapping by integrating a representation based on an occupancy grid and a topological representation. In order to build the occupancy grid map, the authors trained an artificial neural network to map sonar measurements to occupancy values. They included a second source of occupancy information: a stereo camera system, which provides pairs of images recorded simultaneously from different spatial viewpoints. Stereo images were used to compute depth information, estimating the proximity of obstacles and projecting it onto the occupancy grid.

Sensor interpretations were integrated over time to build a consistent map using a Bayes' filter.

On top of the grid-based maps, the authors built topological maps by the following algorithm. A Voronoi diagram is constructed over the occupancy grid map. This diagram is the union of the points in the free space that form an equidistant path to the closest occupied points called base points. Then, the critical points are found in the Voronoi diagram, which minimize locally the distance between the point (x, y) and the two base points. Critical lines are obtained by connecting each critical point with its base points. These lines partition the free space of the grid into regions which correspond to the nodes of a topological graph, where arcs correspond to the critical lines.

Franz et al. [12] proposed a vision-based system to build a topological map of an open environment. They used only topological knowledge, not metric, so the graph stored relevant views of the environment and the adjacency between views, not the movement that conducts from one view to another. The only sensorial input to the robot was snapshots of the environment taken by the robot's camera. The authors used the following algorithm to build the topological map. If the current view is sufficiently different from the views already stored in the graph, the robot takes a new snapshot and adds it to the graph as a new node connected with the last node stored; then, the system determines the next direction of exploration. If the current view is similar to some other view already stored in the graph, the robot localizes the corresponding node and connects it with the last stored node; then, exploration continues from there.

The algorithm proposed by Duckett et al. [10] builds a geometrically consistent topological map, using metric information.

The topological map is built during the incremental exploration of the environment. The map includes two types of places: predicted and confirmed. An artificial neural network is used to predict new places, classifying sonar measurements taken at all directions. A predicted place becomes confirmed when the traveled distance from the last confirmed place is one meter; otherwise, the predicted place is deleted from the map. When a confirmed node is added to the graph, the neural network is reused to predict more places, and connections are established between the new confirmed node and all confirmed places lying less than two meters from the added node. The construction of the map ends when all predicted places have been confirmed or deleted.

Each node in the graph is associated with a local occupancy grid which represents the signature of the place and is used to recognize it. Each link between nodes is labeled with metric information estimated by the robot: the distance and the absolute angle between the places connected. As this information is not precise, the authors assign to different places of the topological map globally consistent cartesian coordinates. This is done by using an algorithm that minimizes an energy function. Each link minimizes its energy when the relative displacement from node *i* to *j* equals the vector (distance, angle) estimated by the robot. Equilibrium is reached in the whole map when all links minimize their energy.

IV. BIOLOGICALLY-INSPIRED MAPPING

A promising alternative to classical robotic mapping is based on the workings of the rat's brain.

Experimentation has shown that rats are able to solve spatial problems, to navigate by near or far visual landmarks, and to use spatial information creatively, finding shortcuts to reach a goal.

To explain the ability to process the spatial information, Tolman [26] argued in 1948 that animals should have a **cognitive map** in some part of the brain, and in 1978, O'Keefe y Nadel [20] argued that the map was in the hippocampus.

According to Hölscher [14], experimental work has shown that there exist at least two distinct populations of neurons in the rat hippocampus known as **place cells** and **head-direction cells**. Place cells codify information about physical locations of the animal. The areas of the environment where place cells respond are known as place fields. Head-direction cells, on the other hand, codify orientations of the animal's head.

There exist many navigation models inspired on the hippocampus' neurophysiology. Some of them are proposed by Burgess and O'Keefe [4, 5, 6, 7, 8], Touretzky and Redish [27], Balakrishnan, Bhatt and Hanovar [2], Trullier and Meyer [28], Arleo and Gerstner [1], Gaussier, Revel, Banquet and Babeau [13], and recently Milford and Wyeth [19].

The model proposed by Burgess et al [6] consists of a neural network composed by four layers of cells: sensory cells, *entorhinal* cells, place cells and goal cells. Sensor data activate sensory cells; the activation propagates to build a spatial representation in the layer of place cells. Connections to the goal cells are learned when the robot is at the goal place. These cells codify the direction and proximity of the goal during subsequent movement.

The model was implemented on a Khepera robot, which included a video-camera and infrared proximity sensors. The robot was tested on a rectangular environment of 50 x 50 cm with white walls and dark floor. Visual estimations of the distance from the robot to the walls were used to activate sensory cells, *entorhinal* cells and, then, place cells.

When the robot finds the goal, a reinforcement signal causes a one-shot Hebbian increment in the synaptic connections to the goal cell from the place cells that are active at that location. Thus the activation of each goal cell represents the proximity of a goal location, allowing navigation, and the neural network can be used to guide the robot's motion back to the goal location from different places in the environment [7, 8].

Arleo et al. [1] proposed a model which integrates in time visual data taken from the environment and internal data generated by the robot (proprioceptive[1] and vestibular[2] stimuli referred as *path integration*), in order to create a spatial representation at the hippocampus.

The model consists of a multi-layer neural network. Visual stimuli are interpreted by a layer of cells that are activated according to specific properties, like the distance between a landmark and the robot and the egocentric orientation of the robot relative to landmarks. There exists a second layer which codifies spatial representation, i.e., a layer of place cells. Every time the robot is at a new place, all active cells in the first layer are connected with a new place cell. Initially, the connection weight is random between 0 and 1; then, it is modified according to the Hebbian learning rule.

There exists also a layer of path integration cells which codifies proprioceptive and vestibular stimuli.

Place cells are projected to another layer of CA3-CA1 cells created progressively. Synapses between this layer and path integration cells are also learned by the Hebbian rule.

Finally, the model includes a layer of action cells whose activity represents direction of movement commands. Reinforcement learning is used to modify synapses between the layer of CA3-CA1 cells and action cells in order to map spatial locations to movement commands.

A Khepera robot was used to test the model in a 60 x 60 cm environment, where walls were covered by random sequences of white and black bars with different widths. Combinations of those bars are the input patterns for the layer of cells which represents the vision system.

The model of Gaussier [13] is also a multi-layer neural architecture. When the robot recognizes a place in the environment, that place is represented by a place cell; when a new place appears, other place cell represents it. The Hebbian rule is used to learn the time relation and the topological relation between the two situations. When this mechanism is generalized, a graph is built to represent spatial relationships between the places of the environment.

When the robot reaches the goal place, a motivational neuron is activated by the associated place cell. Synapses between these neurons are reinforced by the Hebbian learning rule; then, during path planning process, the motivational activity propagates backwards in the graph. The activity of any neuron in the map is a function of its topological distance to the goal place.

Path planning implies to determine the current location of the robot; i.e., the place cell with the highest activity. Then, the robot selects the next node to visit, which must be linked with the current node and must have the highest activity. When the robot reaches that place, the process repeats until the goal is reached.

The model was tested on a mobile robot in an open environment, but it was impossible for it to distinguish between visually similar places.

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[1] Internal stimuli that give information about body's position and orientation.
[2] Internal stimuli caused by body's motion.

Recently, Milford and Wyeth [19] proposed a model called RatSLAM that uses competitive attractor networks to carry out SLAM.

The general model consists of two competitive attractor networks, one for representing the population of head-direction cells and the other for the population of place cells. The activity of both networks represents the robot's location in the environment and its head's orientation.

Wheel encoder information is used to perform path integration by injecting activity into both networks. Vision information is converted into a local view matrix representation that feeds also both networks. When a local view is familiar to the robot, activity is injected to the head-direction and place cells associated to that view.

The robot's camera can see colored cylinders perceived as rectangles. A local view matrix codifies the cylinder's color, the distance and orientation of the robot relative to the cylinder.

Generally, in competitive attractor networks, neurons are fully connected; each unit will excite units close to itself and inhibit those further away, which leads to a clump of activity known as an *activity packet* eventually dominating. Activity injected into the network near the winning packet will tend to move that packet towards it. Activity injected far away from it will create another packet that competes with the original. If enough activity is injected, the new packet can win and the old packet disappears.

Neurons with the highest activity in both competitive networks represent the head's orientation and the physical position of the robot.

The robot's orientation is estimated by path integration, measuring the robot's rotation. Inherent errors in that measurement make necessary the use of visual information to calibrate orientation. The authors do not apply this calibration to the robot's position.

The model was simulated and tested on a Pioneer2-DXE robot in a 2 x 2 m environment. Just outside the arena, colored cylinders were placed. The system RatSLAM was able to keep the robot localized just for small periods of time. When the robot auto-localized on a familiar scene, its orientation was not updated; and when it could orient itself, its localization was not updated. That happened because of the independence of orientation and position systems. Besides, RatSLAM was unable to maintain multiple hypotheses about the orientation and position of the robot. Although the system could maintain multiple position hypotheses, all activity packets were associated with the same orientation. If ambiguous visual input suggests two possible positions and orientations, it was impossible to verify or deny one.

V. WHICH IS BETTER: METRIC OR TOPOLOGICAL MAPPING?

As we said before, generally, in the metric approach, robotic mapping consists in determining free and occupied places of the environment using probabilistic techniques. In the topological approach, on the other hand, the central problem is to identify distinguishable places, situations or landmarks in the environment, and the topographic relations between them. The construction of the map in the first case can be solved by proximity sensors which indicate the presence of obstacles. In the topological case, it is very convenient to have a vision of the scenes where the robot has passed in order to define distinguishable places.

Many proposed topological navigation algorithms show that the topological and metric mappings are not clearly divided. Links between places in a topological graph are usually associated with metric characteristics like distance or angle between places connected. That is the case of the models proposed by Kuipers [17] and Duckett [10].

An advantage of metric mapping is the possibility to know the absolute or allocentric localization of any place in the environment and of the robot. Therefore, during path planning or navigation, the robot could find a specific "address" through the map. Nevertheless, metric mapping has the following disadvantages:

- The techniques used are computationally expensive considering big environments; particularly those techniques which are based on a fine occupancy grid because they imply the computation and storage of many probabilistic estimations, one per each cell in the grid.
- Some of the algorithms cannot be executed in real time because they need to compare different possible maps in order to obtain one that corresponds to the real environment.
- Some of the algorithms that can be executed in real time require knowing the environment's dimensions in order to define the grid's dimensions.

Considering topological mapping, some of its advantages are:

- There is no need to map the whole environment, only the distinguishable places, views or landmarks, and the adjacency relations between them. This can lead to a lower computational cost.
- The construction of the map is carried out in real time as the robot explores the environment. Then, path planning or navigation can be done through classical graph search algorithms.

However, an evident disadvantage of the topological approach is the mentioned correspondence problem, in which two places could seem similar to the robot when they are different. The result is a map that does not include all relevant situations of the environment, so the robot could have trouble localizing itself.

In general, choosing an approach implies considering the problem to solve. If the environment's dimensions are known and the map must specify occupied spaces geometrically without the need to be built in real time, metric mapping could be used. But, if there is a large-scale environment, its precise dimension is not known a priori and the map must be built on-line, topological mapping could be used.

VI. Our Work: Biologically-Inspired Topological Navigation Model for Multiple Robots

Metric and topological robotic mapping approaches have existed since more than two decades ago with their corresponding evolution, but their main disadvantages have not been completely solved: the correspondence problem, the construction of the map off-line, and the exploration of unknown large-scale environments.

Biologically-inspired robotic mapping offers a very promising alternative to propose better navigation models. The inspiration on neurophysiology of animals that are able to solve spatial problems efficiently must lead to find a better way for mapping an environment.

As we described in this paper, many of the current models of biological mapping are based on a topological approach, which is perfectly understandable since experimental workings on the rat's hippocampus have shown that recognizing places implies activity in neurons associated with these places and with particular head orientations.

We are working on proposing a biologically-inspired topological robotic navigation model, which will offer solutions to some of the problems presented by current models like [1] and [19]. In particular, we are interested in exploring and mapping less-structured environments, solving the correspondence problem and eliminating odometry errors.

We will implement our model on individual and multiple robots. We will propose and test different strategies to explore and learn the environment in a distributed manner. We will also propose strategies for integrating partial maps obtained by individual robots in a global map of the environment. There are some current studies that have addressed multi-robot exploration and integration of partial maps [25, 3, 23], but they are based on the metric approach and ours will be a biologically-inspired model.

VII. Summary and Conclusions

The navigation of an autonomous mobile robot in an environment includes four interrelated activities: exploration, which is the strategy that guides the robot to select the next direction to go; mapping, which implies the construction of a spatial representation of the environment; localization, which is the strategy for determining the robot's position in the map; and path planning, also called navigation, which is the strategy the robot follows to find a path to the goal place, where that path could be optimal or not.

This paper has focused on mapping activity. The differences between metric and topological mapping have been explained. Biologically-inspired mapping has been described as a promising alternative to solve some of the problems presented by the other approaches.

The paper discussed also the state of the art in the algorithms and models proposed by metric, topological and biological approaches.

Finally, the paper described our work: to propose a topological navigation model inspired on the workings of the neurophysiology of the rat's hippocampus. This model will control the exploration and mapping of the environment and the localization of the robot. The model will be implemented on multiple robots in order to explore the environment in a distributed manner and build local maps which will be integrated to compose the global map of an unknown and less-structured environment.

We hope to contribute to a fundamental field in robotics which allows us to talk about really autonomous mobile robots: navigation.

VIII. References

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