Fingerprints of Places: A Model of Hippocampal Place Cells

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Abstract - **The undeniable trend of research in robotics is to endow robots with the capability of understanding the world we are in, thus permitting them to help us and to be a part of our lives. In this paper we address the problem of autonomous navigation seen from the neuroscience and the robotics point of view. A new cognitive navigation system is presented. It combines local features (i.e. visual and distance cues) in a unique structure – the "*fingerprint of a place*" – that permits encoding of a huge amount of place-related information and results in a consistent, compact and distinctive representation. Overall, the results suggest that a process of fingerprint matching can efficiently determine the orientation, the location within the environment, and the construction of the map, and may play a role in the emerging of spatial representations in the hippocampus.**

Index Terms – fingerprints of places, topological navigation, cognitive mapping

I. INTRODUCTION

The undeniable trend of research in robotics is to endow robots with the capability of understanding the world we are in, thus permitting them to help us and to be a part of our lives. An ideal companion-robot should be designed to feature sufficiently complex cognitive capabilities permitting it to understand and to interact with the environment, to exhibit social behaviour, and to focus its attention and communicate with people.

In all our daily behaviours, the space we are living and moving in plays a crucial role. Many neurophysiologists dedicate their work to understand how our brain can create internal representations of the physical space. Both neurobiologists and robotics specialists are interested in understanding the animal behaviour and their capacity to learn and to use their knowledge of the spatial representation in order to navigate. The state of the robot can be represented in a qualitative manner, similar to the way humans do it. The information can be stored as cognitive maps – term introduced for the first time in [12] – which permit an encoding of the spatial relations between relevant locations in the environment. This has led to the concept of topological representation. The topological map can be viewed as a graph of places, where at each node the information concerning the visible landmarks and the way to reach other places, connected to it, is stored. The topological representation is compact and allows high-level symbolic reasoning for planning.

Several methods, each with its advantages and drawbacks, have been proposed to construct maps in the framework of autonomous robot navigation, from precise geometric maps based on raw data or lines to purely topological maps using symbolic descriptions.

II. FINGERPRINTS OF PLACES: SPATIAL COGNITION

Representing and interpreting a scene from the environment is a hard task. Humans use various sensory cues to extract crucial information from the environment. This is processed in the cortex of the brain in order to obtain a high-level representation of what has been perceived. Intuitively, it appears that humans represent knowledge in a hierarchical fashion. With a view of having robots as companion of humans, we are motivated towards developing a knowledge representation system along the lines of what we know about us. While recent research has shown interesting results, we are still far from having concepts and algorithms that represent and interpret space, coping with the complexity of the environment.

The seminal discovery of place cells, by O'Keefe and Dostrovsky [6], in the rat hippocampus – cells whose firing pattern is dependent on the location of the animal in the environment – led to the idea that the hippocampus works as a cognitive map of space [7]. It was shown in [1] (for a review see e.g. [8]) that the lesion of the hippocampus impairs the performance of rodents in a wide variety of spatial tasks indicating a role of the hippocampus in map-based navigation.
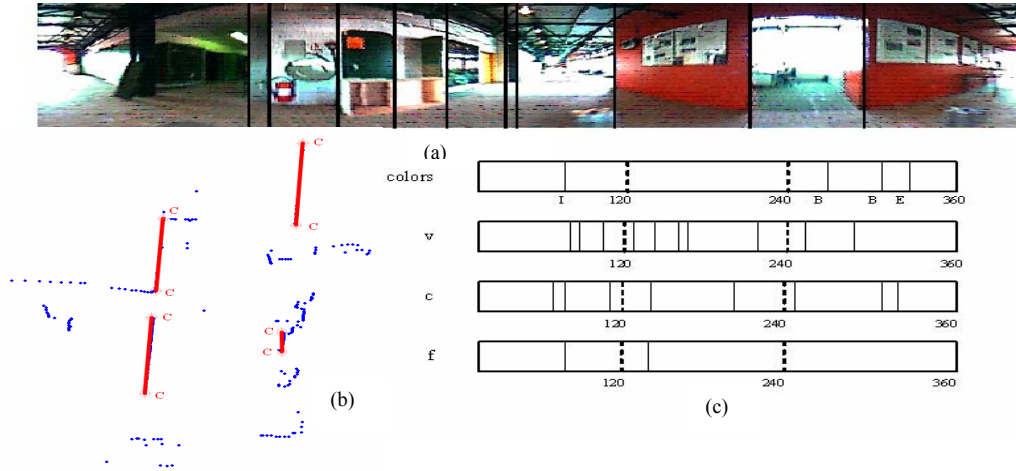
Figure 1: Fingerprint generation. (a) panoramic image with the vertical edges and color patches detected, denoted by ′v′ and ′A′…′P′, respectively ; (b) laser scan with extracted corners ′c′; (c) the first three images depict the position (0 to 360°) of the colors (I-light blue, B- orange and E-light green), vertical edges and corners, respectively. The forth image describes the correspondence between the vertical edge features and the corner features. By regrouping all these results together and by adding the empty space features, the final fingerprint is: cIfvnvcvfnvvncvnncvBnvBccE

The *fingerprint of a place* concept [4] is used here to represent the environment in a qualitative manner. We propose to organize spatial maps in cognitive graphs, in which the *fingerprints of places* represent the nodes. This may be seen as a possible mechanism for the emergence of place cells. The computational model describes how a mobile agent can efficiently navigate in the environment, by using an internal spatial representation (similar to some extent to hippocampal place cells). The fingerprints of places are used for spatial cognition. By combining the information from all sensors available to the robot, they reduce perceptual aliasing and improve the distinctiveness of places. A fingerprint of a place is a circular list of features, where the ordering of the set matches the relative ordering of the features around the robot. We denote the fingerprint sequence using a list of characters, where each character represents an instance of a specific feature type. Omnidirectional sensors are preferred because the orientation as well as the position of the robot may not be known a priori. In this work, we choose to extract color patches and vertical edges from visual information and corners (i.e. extremity of line-segments) from laser scanner. The letter ′v′ is used to characterize an edge, the letters ′A′,′B′,′C′,...,′P′ to represent hue bins and the letter ′c′ to characterize a corner feature. A gap between features is also denoted by the character ′n′ in the sequence, providing the angular distance between the features, which is some kind of very rough metric information. More details about the fingerprint concept can be found in [4].

A fingerprint is associated to each distinctive place within the environment and so the result given by the fingerprint matching algorithm (Global Alignment[5] with Uncertainty[11]) is strongly linked to the location of the mobile agent in the environment, giving high or the highest

probability to the correct place associated to the fingerprint. The firing of place cells units can be seen as the manifestation of fingerprint matching. The closer to the center of the place field the animal is, the higher the rate of neural firing. Similarly, the nearer the new observation of the robot (i.e. the new observed fingerprint) will be with respect to the registered (learned) place (i.e. a known fingerprint), the higher the probability of the mobile agent of being in an already explored place.

One of the main issues in topological map building is to detect when a new node should be added in the map. Our approach is based directly on the differences in the perceived features. Instead of adding a new node in the map by following some fixed rules (e.g. distance, topology) that limit the approach to indoor or outdoor environments, our method introduces a new node into the map whenever an important change in the environment occurs. This is possible using the fingerprints of places. A heuristic is applied to compare whether a new location is similar to the last one that has been mapped. A node is composed of several similar fingerprints that will be regrouped at the end in a mean fingerprint. The value of the threshold is determined experimentally. The incremental nature of the approach permits incremental additions to the map and yields the most up-to-date map at any time. By choosing a suitable threshold the mean fingerprint enables clustering of places in nodes. In this way, the mean fingerprints are analogous with the hippocampal place fields [10].

In order to validate our model experimentally, we have tested it with a real autonomous mobile robot. The mobile agent continuously interacted with the environment and thereby accumulated information about its space. Thus, an

incremental and dynamic navigation framework was built, allowing the mobile agent to cope with unknown situations.

III. Discussions

The method we presented in the previous section can efficiently create representations of places in an environment and locate the robot/animat in the environment. It was possible to see all along this paper that a fingerprint of a place is associated to each distinctive place within the environment.

Thus, the result given by the fingerprint matching algorithm is strongly linked to the location of the mobile agent in the environment, giving high or the highest probability to the correct place associated to the fingerprint. The firing of place cell units can be seen as the manifestation of fingerprint matching. The closer to the center of the place field the animal is, the higher the rate of neural firing. Similarly, the nearer the new observation of the robot (i.e. the new observed fingerprint) will be with respect to the registered (learned) place (i.e. a known fingerprint), the higher the probability of the mobile agent of being in an already explored place. The methodology presented here can efficiently create representations of places in an environment and locate the robot/animat in the environment. The place cells in the hippocampus accomplish the same task: the activation of a place cell, or perhaps better, of an assembly of place cells connected to each other, indicating that the hippocampus is locating the animal in a certain place.

It can be suggested here that the hippocampus may indeed extract place from its sensory input by constructing fingerprints of places, similar to that described in this work. Indeed, in environments rich in landmarks, or features, the hippocampal cognitive map is dominated by the sensory inputs. Many theoreticians have proposed models of place cells based on visual inputs, where the visual stream is encoded in metric terms, that is, in terms of the distances between the landmarks, and between each landmarks and the agent ([2] and [3]).

Fingerprint representations are based on the relative angular position of the landmarks from a given point of view, a much simpler and robust measure, and may be able to explain many of the experimental evidences on place cells, at least those in which multiple landmarks were available to the animal. This vision of hippocampal space representations highlights the role of the hippocampus as a processor of combinatorial information, whose importance transcends the purely spatial domain. In the case of space computation the hippocampus would process combinations of landmark identity and relative position information, and produce an index, which can be attached to a physical location.

In our view, the computation of places from sensory input (through a fingerprint-like procedure), is integrated by the idiothetic information, which plays an important role especially in conditions in which only poor sensory input is available (for example, in the dark), and to disambiguate situations of perceptual aliasing (see e.g. [9]).

The topological navigation framework based on fingerprints of places presented in this work, underlies the interest of mutual inspiration between robotics, biology and neurophysiology. Our computational model finds a counterpart in neurobiology, being similar with the *hippocampus*, which plays a crucial role in spatial representation. The proposed spatial representation is an incrementally learned representation, based on fingerprints of places; the fingerprint place modeling being comparable with the place coding model in the animals (rats) hippocampus.

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