Dynamics of cortical maps coding objects for robot vision

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This article features a neural network model for object recognition using cortical maps. We apply it to the recognition of a set of mailboxes using two prototype images. They are coded in the same cortical map.

I. INTRODUCTION

Our group works on unsupervised neural networks models for controlling an autonomous robot. The goal is to simulate an insect-like behaviour. A robot has to find "food" in its environment. This search is triggered by a hunger signal increasing in time. At first, the robot doesn't know anything about the world around it. It has an image of the scene through a CCD camera, and bumpers indicate whenever it runs into something. Its first task is to extract objects from the scene and to associate them with particular movements. These objects are called landmarks. For the moment, we have defined three types of landmarks: left arrows, right arrows and food location. When the robot sees an arrow, it has to learn to perform the movement shown by the direction of the arrow. Since it doesn't know which one he has to do when it sees an arrow for the first time, it chooses an interpretation at random. If after a while it doesn't reach the food location, it can reevaluate his first interpretation in order to go to the right place. All algorithms are based on a simple neural networks model [1]. In particular arrows are coded on a topological map [2]. We describe here a particular application of this general frame. Our robot has to find a place where there is a set of mailboxes. The internal representation of this set is performed at two different ranges. First close to the mailboxes: this gives a clear image of all details. And then far from the boxes: now the image only displays the external border of the boxes. These two images are encoded in the same topological map.

II. MODEL AND EXPERIMENT

The model is based on the PerAc architecture [3]. This architecture has two levels: the first one enables to learn a pattern on a topological map. The second level performs the association between a learned pattern and a particular movement. In order to recognize an object, the visual system focalizes on a succession of characteristic points (typically edges). The succession of these edges constitutes an object (or pattern) [4].
Then each object is linked to a particular movement through binary weights. Each weight is linked to a probability giving the certainty of the movement they enable. If after some time, food is not found, these probabilities allow to change the weights so that another movement can be considered when the same object is seen [5].
We will work on the recognition of a set of mailboxes. At low resolution (far away from the mailboxes), the robot only sees a big rectangle which is the external border of all boxes. As it gets closer, the individual boxes begin to appear. Hence the low resolution representation is not seen anymore so that we have to store this new image.
The robot tries to match the picture it gets with one of the two representations coding the boxes. When it sees something matching with one representation, it goes towards it. If after some time the new image it gets is not corresponding to a representation encoded on the map, it goes away from it, as it may not be a mailbox that is standing in front of it.
When the image seen matches the representation coded on the map, this triggers a movement towards the object seen.

III. DISCUSSION

This PerAc model gives very good results on simulations as well as on a real robot. It is inspired by neurobiological features. It even allows to test hypothesis about brain structures. For instance, a project is under way with neurobiologists in order to model the hippocampus.
It is also worth to emphasize again that the robot has no a priori information about the external world. He builds

alone an association between landmarks and movements. Hence as long as the landmarks have the same meaning, the robot is able to navigate in totally different environments: he does not construct a real map of the external world. This gives to our system a very high flexibility.

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