

# Taking inspiration from the Hippocampus can help solving robotics problems

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**Abstract.** In this paper, we present a generic robotic control architecture inspired from the hippocampus (a brain structure involved in memory). Moreover, we show how the implantation on a real robot has helped us to gradually refine the neurobiological model.

## 1. Introduction

The main goal of our research team is to design neural architectures for the control of autonomous mobile robots. Although we use a robot born in the engineer field, we have chosen to take inspiration from neurobiology to design its control system for 2 main reasons:

- first, it could give us interesting, robust, and ready-made solutions to design control architecture.
- second, biologists are unfortunately often constrained to study only sub-parts of the brain due to its complexity. Implementations on robotic systems can help understanding how a specific neurobiological model behaves once embedded (understanding the interactions between local models of the brain).

What is particularly interesting in biological systems is that they are more opportunistic than classical artificial intelligence systems. Another point is that a brain inspired machine could help us understanding how “intelligent” behaviors could result from both artificial and natural control systems.

In this article, we intend to gradually present how the study of a mammal brain structure called the hippocampus has helped us to conceive efficient control architectures which can explain how animals could acquire given behaviors (navigation, planning, imitation...). Besides, we want to show how the implementation of those models on a real robot has allowed to come back to biology to propose more accurate neurobiological models.

## 2. The Hippocampus structure

The hippocampus has been rather well studied by neurobiologists since it seems to be involved in many phenomenon linked with memory (human) as well as navigation (rats, human...). The hippocampus is a brain sub-cortical structure which takes input from the whole associative areas (see fig. 1) via the enthorinal cortex (EC) and, conversely, projects efferences into associative, pre-frontal, pre-motor cortical areas... The neuronal hippocampal circuit is as follows [1]: projections from the EC reach both CA3 and Dentate Gyrus (DG – which itself is linked with CA3). Then CA3 has efferences towards CA1. Finally, CA1 is linked with the subiculum which throw back links to the EC [1]. Moreover, it

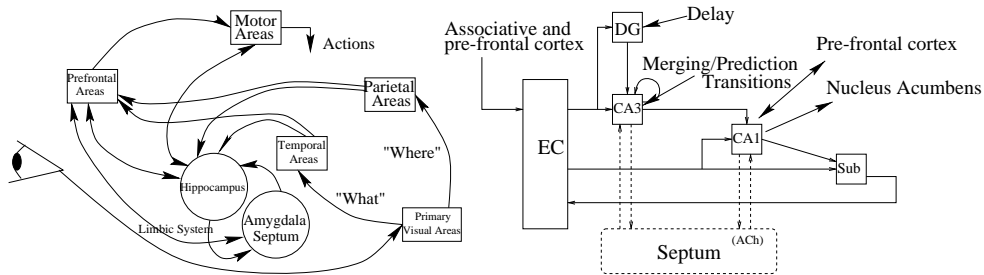


Figure 1: a) Schematic figure of the brain structures we are interested in. b) Detail of the sub-structures of the Hippocampus.

must be noticed that CA3 has recurrent connections. A schematic overview of the structure we are interested in is given in fig. 1.

On a behavioral point of view, it has been shown that hippocampus is involved in human memory processes since its ablation forbid further declarative learning [12]. Yet, it is still possible to learn conditioning even if the lack of hippocampus make it harder [4]. Besides, it has been shown that the hippocampus was used in navigational abilities. One of the first evidences has been O’Keefe’s discover of “place cells” in rats’ hippocampus [10]. The particularity of CA1 pyramidal cells is that they fire mainly when the animal is at a particular place in its environment (whatever its orientation is). Interestingly enough, “place cells” continue to fire when the rat is in the dark [14], and that they have a phasic response as the rat run through a place field [13]. Surprisingly, “place cells” have only been found recently in primates hippocampus. Mainly, there are cells in monkeys’ hippocampus which reacts when the animal recognizes a given “view”: “view cells” whose response depends on the animal orientation [16].

### 3. A model of “place cell”

The existence of “place cells” can explain many navigation behaviors: if a system is capable of locating itself precisely, it could learn “relevant” sensory-motor association in order to navigate from one place to another. Computational models taking into account these characteristics of “place cells” have been proposed. In particular, O’Keefe has suggested that the “place cells” in the hippocampus are dense enough to consider the hippocampus as a Cartesian “a cognitive map” [10].

Yet, we have proposed a model which shows that even with a few place cells, it is possible to construct an architecture explaining some navigation strategies (homing, goal reaching, dangerous area avoidance – see [5, 21, 19]). This is possible thanks to two mechanisms: the first one is a generalization mechanism on the recognition map, which allows to recognize the most similar learned situation; the second is a competition process on the motor group between the different possible sensory-motor associations [7] (in fact, it is not really important to “recognize” the situation, but to perform the appropriate in a

given situation). This “place cell” model uses the neurobiological evidence showing that there are 2 paths to compute information extracted by the visual system [20]. The first path integrates the information linked to the position of a given object in the visual field (“where” pathway – parietal area), while the second path “recognizes” the object whatever its position is (“what” pathway – temporal area). We have proposed to use a neuron group (inspired by the hippocampus connectivity) to merge the information coming from both the “what” and “where” pathways in order to build a composite representation. This representation can be learned in another group of hippocampal neurons as a signature of the place [9]. A simple conditioning learning can then allow to link the recognition of the place to a given movement. We have shown that learning only a few places around a goal location and associating the movement pointing towards this place allows to reach this place from any position in an open environment.

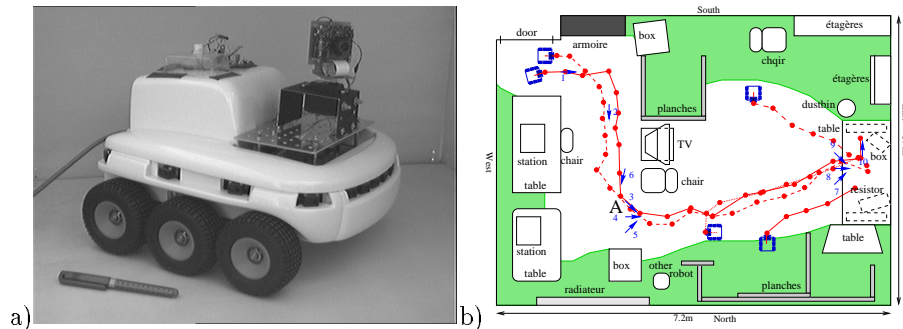


Figure 2: a) The KOALA<sup>TM</sup> robot. b) Example of trajectories of the Koala robot in an experiment consisting in coming back to a goal position.

Moreover, reducing the vision field in this model, the robot’s hippocampal cells exhibit “views cells” activity (the neurons were activated more preferentially in a given direction [6]). We suggest that this specific abilities for monkeys to recognize a view and rats to recognize a place could come from the position and the field of vision of their eyes. Yet, the internal mechanism could be exactly the same ! We can wonder why there are so many “place cells” in the hippocampus since very few cells could allow navigation in an open environment ? More “place cells” may in fact be needed when only odometry is used or navigating in more complex environment (a maze for instance).

#### 4. Transition cells

In case of a complex environment, the navigation problem becomes a planning problem: the best route must be found among several possible ones. Experiments performed by Tolman have suggested that rats were able to learn internal representation of their environment although no reward was given (latent learning – [18]). Several algorithms inspired both by hippocampus and the “cognitive map” concept have thus been proposed. Schamujk proposes a model in which the cognitive map learns the relationships between “places” and

“views”, and a motor module selects the appropriate movement according to the prediction performed by the cognitive map [17]. During planning, the robot needs to perform the different possible movements (Vicarious Trial and Error – [18]), comes back to the place, and then chooses the most appropriate among them. This is difficult to imagine in a real robot experiment. Scholkopf has proposed a model inspired by Schmajuk but using only views to build a “view graph” [11]. The problem is then to learn and exploit at the same time (they consider the learning is performed by a first neural network and that a classical planning system is then used to plan!). An interesting attempt of Waxman has been to develop an architecture implemented on a real robot [2]. In this model, an internal representation, which merges the “what” and “where” pathways is built, and the idea is then to learn a representation of topological relationships between places in order to build a map which can predict “when” an event may happen. This model was just used to predict but was not yet coupled with a motivational system which would allow to react on the motor system, and thus, to plan the actions.

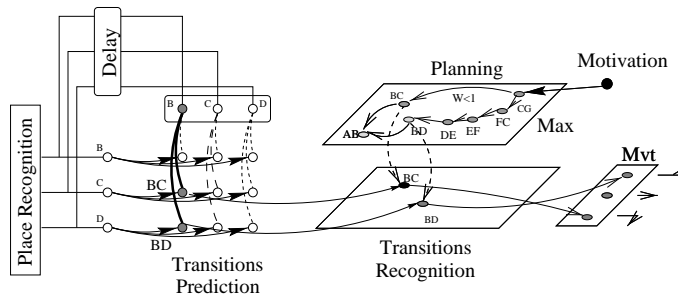


Figure 3: Fusion mechanism: direct input is merged with the delayed input in order to build a representation of the transition.

In our model, a “cognitive map” is superimposed on the recognition and runs in 2 different ways: during exploration of the environment, the system learns different places and the movement allowing to go from one place to another. It also learns the topological relationship between those places (at the “cognitive map” level) and the places which can be associated with the satisfaction of a motivation. During planning, information learned during exploration at the “cognitive map” level can be used to bias the competitive recognition mechanism in order to propose the movement allowing to reach the goal. Yet, we have shown that an internal representation which is based on the recognition of a single place cannot allow to plan because of the ambivalence of this representation: during exploration, what is only possible is to learn what movement is possible to reach or to leave this place while during planning what is interesting is to know which movements are allowed from a given place, and, among them, choosing which is the best one to reach the goal (see [15] for details). We thus need to learn something linking at the same time the departure position, the arrival position and the movement to be performed to go from one to the other. A solution consists in building a representation of the transition between

two situations. Let  $AB$ , the internal representation of the transition between  $A$  and  $B$ . The associated action (the movement allowing to go from  $A$  to  $B$ ) can be learned using, for instance, a probabilistic conditioning rule (see [8] for details). During planning, a motivation backpropagation mechanism (use of the “cognitive map” to plan – [15]) activates the neuron indicating the movement that it is necessary to perform in order to reach the goal. The systems learns to predict the possible transition(s) from the current scene. The idea of learning to predict transitions comes from a collaboration with a neurobiologist on modelling the way the hippocampus can learn sequences and timing of events. A detailed model of the DG and CA3 region of the hippocampus has been conceived [3]. This model proposes that clusters of granular cells of DG could act as a delay lines and that links with CA3 could be learned to build a temporal signature of an event. For the planning system, the DG/CA3 model has been simplified and works in 2 steps: During learning, when the situation  $B$  and then  $C$  (resp.  $B$  and  $D$ ) are encountered, the memory of  $B$  is still in DG and can thus be combined with  $C$  (resp.  $D$ ) to build a representation of transition  $BC$  (resp.  $BD$ ) which can be learned thanks to the known plasticity of links between DG and CA3 (see fig. 3-a). During planning, the recognized situation, after the propagation delay within DG, activates the possible transitions. Then, the planning system allows to select among those possibilities the one which allows to reach the goal by biasing the recognition of the “good transition” (see fig. 3).

## 5. Conclusion

In this paper, we have tempted to present our research framework, emphasizing the interest of a mutual help between robotics and biology. We have shown how computational models have been elaborated thanks to neurobiological inspiration. Conversely, we have shown that the difficulty in implementing some models on a real robot could help understanding the intrinsic mechanism of brain structures. We have principally focused our attention on the hippocampus since it seems to play an important role in “merging” and “learning” (generally speaking). Yet, we must pay attention not to jump to quickly to conclusions on the “real” role of a given structure. Many data on the brain are still fuzzy or incomplete and we have only paid attention to some of the functionalities of the hippocampus. In particular, we are not sure of which hippocampal region is dedicated to the computation of a given part of our architecture. For instance, the cognitive map model we have proposed could be learned within the CA3 region (thanks to its recurrent connections). Thus, our model would suggest that “place cells”, “transition cells” and the cognitive map would be all computed in the hippocampus. The problem is then to know *how* those different functional cells could cohabit (if they really do !). The next step of our work is thus to come back again to neurobiology in order to verify the hypotheses we have proposed in the robotic design phase.

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