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Adaptive Behavior 2005; 13; 87

DOI: 10.1177/105971230501300202

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More is known of the navigation skills of mice and rats than of any other vertebrate. The discovery of place cells (cells whose firing rate correlates with the spatial position of the animal) in the rat's hippocampus has inspired various attempts to model these cells. This work presents one such model which has been optimized on simulated autonomous agents and implemented on a mobile robot which learns to navigate within its environment through exploration using vision as its main sensory modality. The artificial mouse robot *aMouse*, a mobile robot with active whiskers and omnidirectional vision, is presented as an ideal robotic platform to study rodent navigation. The visual field of the robot is similar to the large visual field of rats and mice, and its whisker system uses real rat whiskers for texture recognition. The paper suggests how tactile information from the active whisker array on the robot can be used as an additional sensory modality for the place cell model described earlier.

Keywords cognitive maps mobile robots · navigation · place cells · rat whiskers · artificial mouse

1 Introduction

Rodents are amazing navigators which can rely on a range of different sensory cues. Rats and mice, for example, rely on visual and olfactory cues for navigation, but also possess whiskers which enable them to discriminate textures of different roughness by actively whisking the surfaces (Carvell & Simons, 1990; Guic-Robles, Valdivesco, & Guajardo, 1989). Many intelligent mobile robots are inspired by biological findings, both in their morphology and their behavior. One example of such a robot is the artificial mouse robot *aMouse* that has been developed at the University of Zurich (Artificial Intelligence Laboratory, 2004). This mobile robot is equipped with omnidirectional vision and an active array of whiskers. The whisker sensors of *aMouse* are unique in the sense that they consist of real rat whiskers attached to microphone membranes in order to produce high-resolution sensor data.

In this paper, we consider biologically inspired cognitive map models, which provide an artificial navigating agent with a topological map of places that can be enhanced with additional metric information after an exploration and learning phase in a previously unknown environment. Similar models and implementations can also be found in Schölkopf and Mallot (1995), Arleo and Gerstner (2000), Hafner (2000a), Gaussier, Revel, Banquet, and Babeau (2002), and Filliat and Meyer (2002). A cognitive map model which mainly relies on visual information is presented and tested in a simulated environment, which allows for parameter optimization using evolutionary strategies (ES) (Rechenberg, 1973). The model has been applied to a mobile robot platform using an omnidirectional camera as the main sensory modality. Finally, we will

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(2005), Vol 13(2): 87–96.
[1059–7123(200506) 13:2; 87–96; 054247]

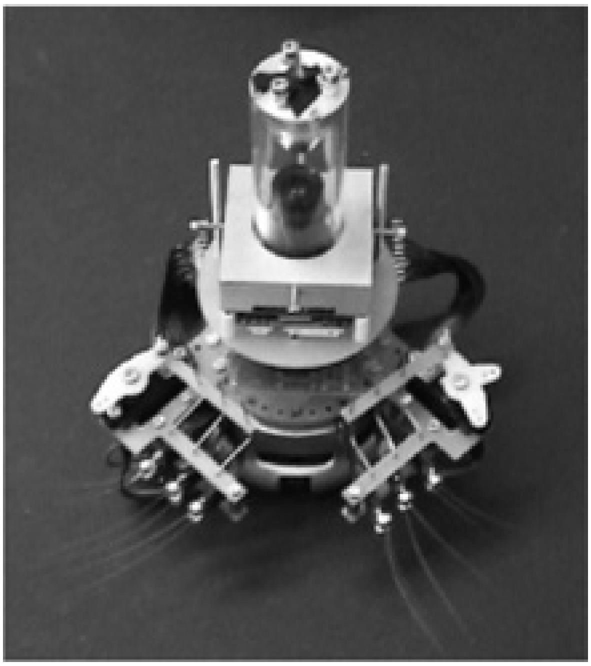

Figure 1 Picture of the *aMouse* robot with whiskers and omnidirectional camera.

discuss how the cognitive map model could be implemented on the *aMouse* robot using both vision and tactile information from its whiskers.

2 *aMouse*: An Artificial Mouse Robot

aMouse is based on a Khepera platform with two active artificial whisker arrays and an omnidirectional camera (see Figure 1). This robot has been designed in close cooperation with biologists and neuroscientists to serve as a tool for studying biological models of rodent behavior. We designed and built an artificial whisker system to record tactile data signals similar to those rats are exposed to with their whiskers.

Rats can distinguish surface properties purely on the basis of cues from their whiskers (Guic-Robles et al., 1989; Carvell & Simons, 1990). They can furthermore use their whiskers to discriminate objects (Brecht, Preilowski, & Merzenich, 1997) or simply to perform obstacle detection. As the rat explores its environment, its whiskers are moved over surfaces of various shape and texture. Whiskers are often used as a replacement for vision when this sensory modality is not available, or in addition to increase accuracy.

The desired artificial whisker should be functionally comparable to a natural rat whisker and therefore be sensitive to small amplitude deflections and fast oscillations. We investigated different designs, including piezo-electric crystals and small capacitor microphones. The influence of different whisker materials (metal wire, polyvinyl, human hair, rat whiskers) has also been compared (Lungarella, Hafner, Pfeifer, & Yokoi, 2002). We found that the natural rat whiskers had the most diverse frequency spectra when moved over different textures. The whisker sensor consists of a rat whisker attached to the diaphragm of a capacitor microphone with cyanoacrylic super-glue. Vibrations and displacement of the hair results in deformations of the microphone membrane. The resulting change in voltage is pre-amplified and digitally recorded.

One preliminary experiment that used the active whisker array studied the discrimination of different textures (Fend, Yokoi, & Pfeifer, 2003). In another study (Hafner, Fend, König, & Körding, 2004), we used sparse coding techniques on a group of artificial neurons which received their input from whisker data recorded with the artificial whisker system. This method allowed us to preprocess the original signal into a much sparser signal using the independent components. In addition, we predicted some properties of receptive fields of neurons in the somatosensory system of the rat.

Some navigation experiments have already been performed using the *aMouse* robot. One is an experiment on phototaxis with a subsumption architecture for light following using infrared (IR) sensors and obstacle avoidance using the artificial whiskers (Fend, Bovet, & Hafner, 2004). Another experiment implemented visual homing using the average landmark vector (ALV) model (Lambrinos, Möller, Labhart, Pfeifer, & Wehner, 2000) on the *aMouse* robot using the omnidirectional camera. An important future experiment will be the combination of visual and tactile sensory information for cognitive map learning.

Apart from *aMouse* (Artificial Intelligence Laboratory, 2004), there are three other projects that have the goal to build an artificial mouse that has whiskers. These are *Psikharpax* (Meyer et al., 2005), *WhiskerBot* (Adaptive Behavior Research Group, 2004) and *Darwin IX* (Seth, McKinstry, Edelman, & Krichmar, 2004). *aMouse* has the advantage of having roughly the size of a rat and is therefore able to use real rat whiskers for its active whisker system.

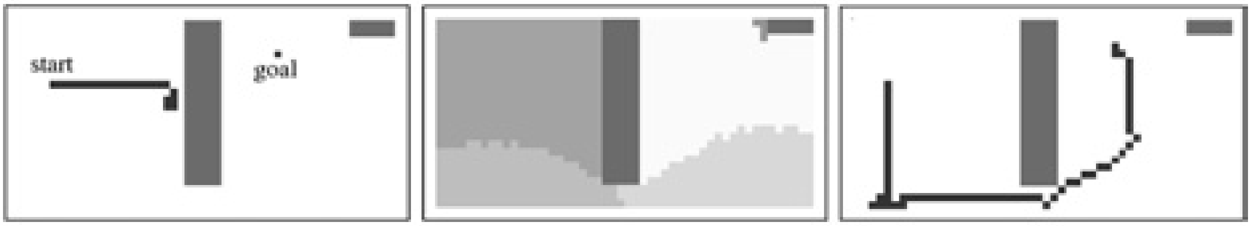

Figure 2 Example of an environment where visual homing alone does not lead to good navigation, but the combination of cognitive maps and visual homing does. The starting position of the agent is on the left side of the wall, the goal position is on the right side. Left: only visual homing fails. Center: place fields created after an exploration tour in the environment. Right: a combination of visual homing and cognitive mapping leads the agent to the goal position.

3 Navigation Strategies

The navigation strategies of animals can be categorized according to their complexity, ranging from systematic search at the simplest end of the spectrum to complex wayfinding, with intermediate strategies such as local visual homing (Trullier, Wiener, Berthoz, & Meyer, 1997; Franz & Mallot, 2000). The same categories can be applied to the behavior of mobile robots or simulated agents navigating in their environments, where the choice of the navigation strategy is usually both task dependent and dependent on the sensory information available to the agent.

More complex navigation strategies require an internal (neural) representation of the environment and are often referred to as “cognitive maps” (O’Keefe & Nadel, 1978). Neurophysiological and behavioral experiments suggest that rats and primates use cognitive maps for navigation, whereas most insects have to rely on more basic navigation strategies. The cognitive maps referred to here are based on the following principles: *place cells* are neurons found mainly in the hippocampus of rats, their activation is dependent on the location of the rat within its environment (O’Keefe & Nadel, 1978); *head direction cells* are neurons whose activity is dependent on the orientation of the rat’s head within the environment (Taube, Muller, & Ranck, 1990); *place fields* are areas in the environment where a particular place cell has the strongest activation.

The evidence for cognitive maps in animals has inspired roboticists to implement those biological findings to allow for stable and adaptive navigation behavior in mobile robots coping with (partly) unknown and ever-changing environments. Franz and Mallot (2000) introduced a categorization scheme of navigation strategies, which is now widely accepted by many researchers. Their navigation scheme is a modification and extension of the navigation scheme by Trullier et al. (1997), and different from the scheme by Redish (1999) which mainly categorized rodent navigation based on the watermaze task. Following Franz and Mallot’s scheme, navigation strategies can be categorized into two types: Local navigation and wayfinding. What distinguishes the two is that in local navigation, the only information the agent has to keep track of is how to find its way back to the home position, whereas for wayfinding, a more general knowledge about the world, including the representation of several places in memory is required. Examples for local navigation are aiming and guidance. Guidance behavior has been intensely studied in the form of visual homing on the desert ant *Cataglyphis* (Wehner & Räber, 1979; Wehner, Michel, & Antonsen, 1996), and formalized into a model by biologists and roboticists (Cartwright & Collett, 1987; Lambrinos et al., 2000). Guidance navigation involves remembering the geometric relation of the goal position to a certain spatial constellation of objects or landmarks that can be detected from this position. Moving in a way to attain this constellation brings the agent to its goal. Rodents use a combination of different navigation strategies, both local strategies and wayfinding, depending on their internal state and the available sensory information.

An example for the advantage of combining different navigation strategies can be found in Figure 2. A virtual agent is put on the left side of the arena in Figure 2 left, with the task of finding the goal marked on the right. The direct way to the goal is blocked by an obstacle, and there is an additional obstacle or landmark on the upper right. Visual homing or aiming alone does not work in this case. If the agent had cre-

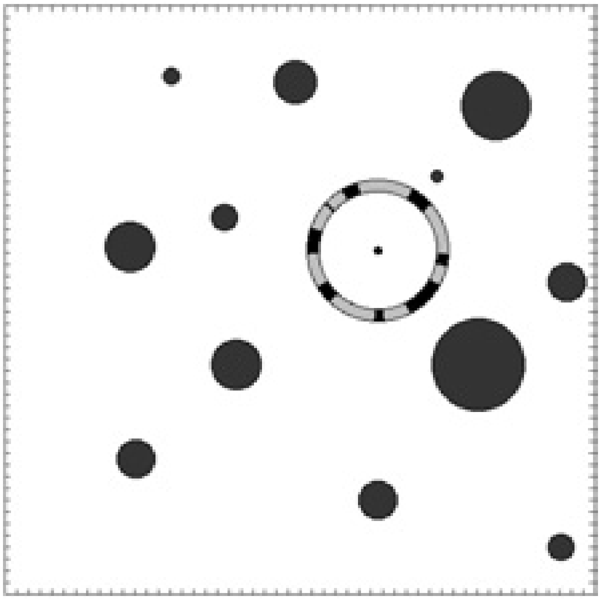

Figure 3 Virtual environment for the robot navigation experiments. The environment consists of a plane with 12 cylinders (shown from above) of different size. The ring shows an example of an omnidirectional view in this environment with a projection of the landmarks.

ated a cognitive map with place fields as depicted in Figure 2 center, it is possible to use visual homing to navigate from place field to place field as demonstrated in Figure 2 right.

4 Cognitive Map Learning Model

Here we present a model that allows an agent to build a topological map of places that can be enhanced with additional metric information after an exploration and learning phase. A review of different map building and path planning strategies can be found in Meyer and Filliat (2003).

4.1 Exploration and Learning

In this section, a cognitive map model inspired by place cells is presented. An example with an agent that learns how to navigate in a virtual environment using this model is shown. During an exploration phase, the agent has the task of learning a map of the environment using its internal neural structure such as place cells and lateral weights. The usefulness of the cognitive map for a specific environment depends on the exploration and map learning strategy.

The environment consists of a plane with 12 cylinders of different diameter (see Figure 3). The agent is equipped with a compass and omnidirectional one-dimensional view with a resolution of 90 pixels. The visual information of the agent is always rotated according to the compass value so that for a given place the view is the same and does not depend on the current orientation of the agent.

The agent starts with a given number of place cells which are initialized at the beginning with random weights w to the visual input v. It performs random exploration tours within the environment, avoiding bumping into the obstacles. At each step, the current view is taken, resulting in a certain neural activation a in the place cell layer:

$$a = f(vw) = \tanh(vw) \qquad (1)$$

f is a sigmoid function, the view vector v and the weight vectors w are normalized. The place cell with the highest activation for a particular view is called the winner cell.

At each step, the weights w of the winner cell (2) and those of the previous winner cell (3) are updated using a Kohonen learning rule and then normalized:

$$\Delta w = \eta_1(v - w) \qquad (2)$$

$$\Delta w_{\_} = \alpha\eta_1(v - w_{\_}). \qquad (3)$$

The lateral weights w_l between the winner place cells at time t and $t - 1$ are updated using a Hebbian learning rule:

$$\Delta w_l = \eta_2 a_w^t a_w^{t-1}(1 - w_l). \qquad (4)$$

A decay factor is then applied to all lateral connections: $w_l = \delta w_l$.

Since two views at different positions could look similar (perceptual aliasing), the activation of the place cells also depends on their connectivity to previously active cells. We can include the strength of the connection:

$$c^t = \beta_1 w_l a^{t-1} \qquad (5)$$

and also the movement direction of the agent:

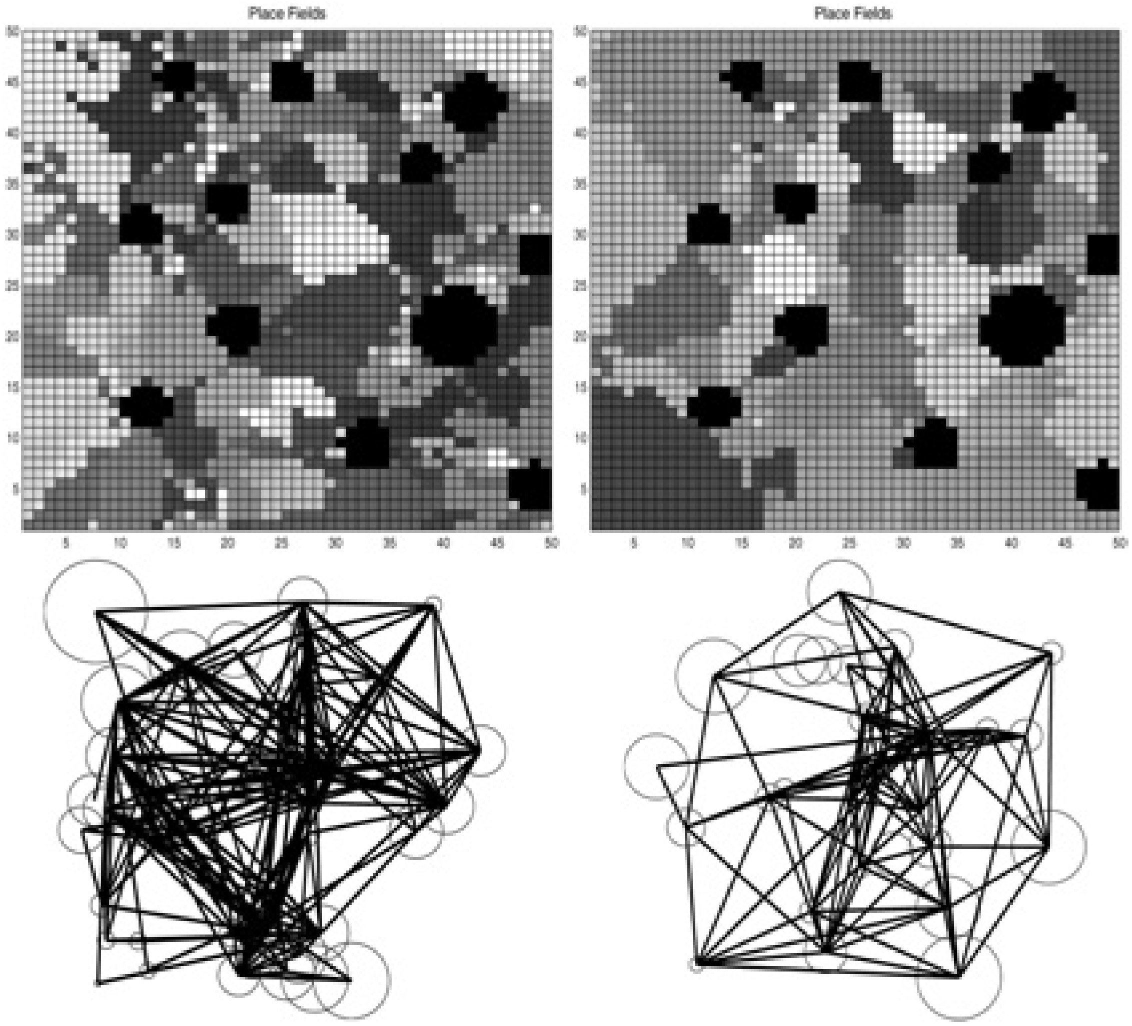

Figure 4 Top: Maps of the environment with black disks indicating obstacles, and gray shadings indicating the different place fields after the agent has explored the environment. Bottom: The centers of the place fields are interconnected as specified by the weights. Left: Random parameters. Right: Parameters are optimized by evolutionary strategies.

$$o^t = \beta_2 \cos(\gamma) a^{t-1} \tag{6}$$

where γ is the angle difference between the current and the stored orientation between two places. Information on the connection and the connection heading of two place cells representing adjacent places is—for simplicity—directly encoded, instead of being available through head direction cells:

$$a = f(vw + c + o). \tag{7}$$

Free parameters are the learning rates η_1, η_2, α and factors β_1, β_2 for the influence of connections c and orientation o.

In Figure 4 top, the place field representations after an exploration tour of the agent are projected onto the two-dimensional environment. Areas with the same grayscale value are represented by the same place cell. Figure 4 bottom shows the topological graphs corresponding to the place fields. The centers of mass of these place fields are shown with variable sized circles indicating the roundedness r:

$$r_p = \frac{1}{n}\sum_i (x_i - \mu_p)^2$$

where μ_p is the center of mass of the place field for place cell p, x_i a position on the grid where p is the win-

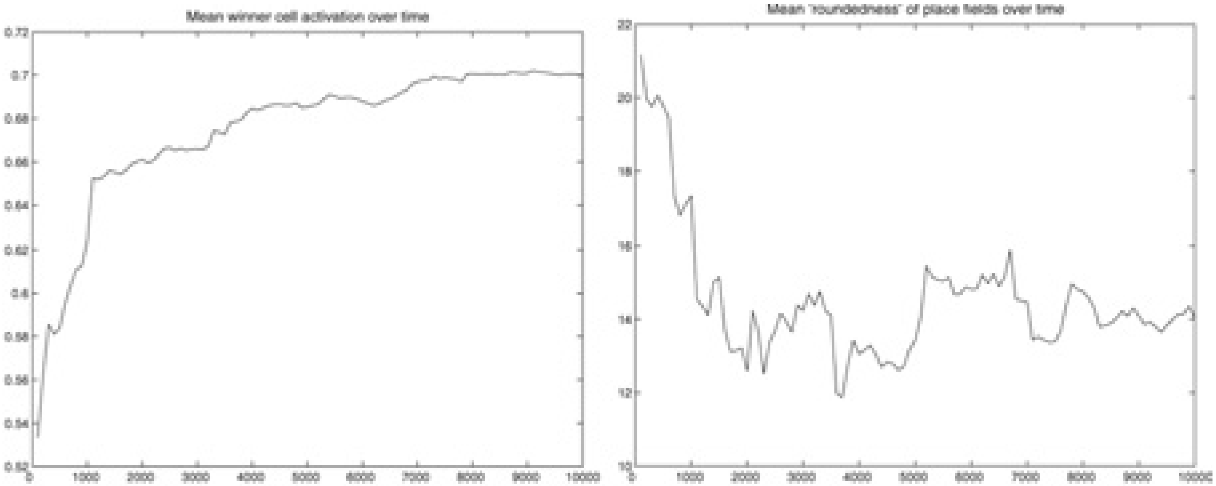

Figure 5 Left: Average activation of the winner neuron for each grid position over time during the exploration and learning phase for one agent. Right: Average roundedness measure for each place field over time.

ner cell (place cell with highest activation), and *n* the number of these positions. This is a measure for the variance in distance between each grid point belonging to the place field and the center of mass. Connections are drawn between the centers of mass of connected place cells. A map is well suited for navigation purposes when it contains many, roughly circular place fields with connections between regions that are adjacent and can be traversed.

Although the agent does not have a metric map itself, it is able to extract some metric information from the topological map when it contains some additional information like orientation of the connections. Examples of the application of such algorithms are the spring force model (Hafner, 2000a) or the relaxation algorithm (Duckett, Marsland, & Shapiro, 2002). These algorithms assign each place cell to a position on a two-dimensional plane and use iterative methods to optimize the spatial layout of the cells.

In Figure 5 left, the average activation of the winner place cell for each grid position is shown for 10,000 steps of the agent exploring the environment. Here, the place cell activation $a = \tanh(vw)$ is calculated purely from the visual input v and the neural weights w without the context (previous positions of the agent) being taken into account. The average winner activation converges to a value of about 0.7 in the given environment with optimized free parameters for the learning algorithm. Figure 5 right shows the development of the place fields in terms of the roundedness factor.

4.2 Optimizing Learning Parameters with Evolution Strategies

The learning strategy described in Section 4.1 has been optimized using Evolution Strategies (ES) to adapt the parameters p of the learning algorithm:

$$p = [\eta_1, \alpha, \eta_2, \delta, \beta_1, \beta_2].$$

The fitness function $f = f_1 \cdot f_2$ consists of the product of a measure f_1 for the regions (the roundedness of the place fields), and a measure f_2 for the connections (between adjacent place fields), which is a mixture of positive fitness for adjacent place fields whose place cells are connected and negative fitness for connected place cells whose place fields are not adjacent. Alternative fitness functions could be used such as the correlation between metric and graph distance for all connections.

The evolution ran on the same randomly generated path through the environment for each individual in a generation. The number of place cells was chosen to be 50 and the evaluation ran for 3000 steps for each individual. One generation contained 12 individuals, the evolution strategy (Rechenberg, 1973) used roulette wheel selection with 1-elitism, real valued coding and an adaptive mutation rate.

The evolved learning parameters of the cognitive map in Figure 4 right are $\eta_1 = 0.045$, $\alpha = 0.62$, $\eta_2 = 0.5$, $\delta = 0.998$, $\beta_1 = 0$, $\beta_2 = 0$.

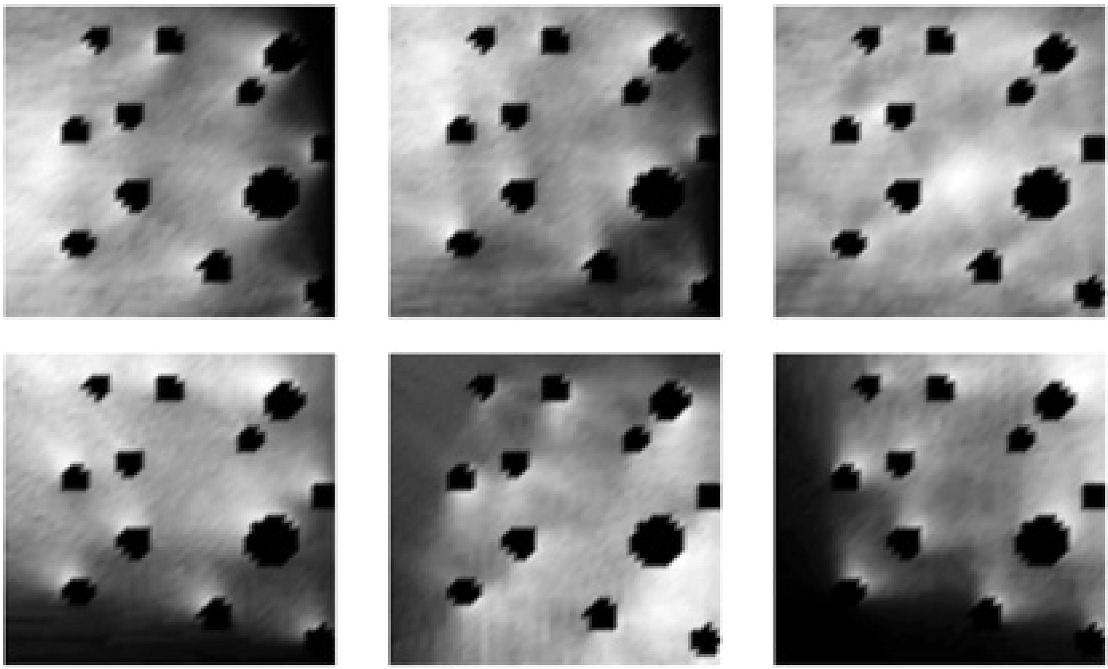

Figure 6 Activation of six different place cells after an exploration tour in the virtual environment. The black circles represent the obstacles. The activation is indicated by the brightness where white means a high activation of this cell for a given place and black a low one.

When comparing left and right panels of Figure 4, the influence of the evolved learning parameters can be easily seen. Contrary to the intuition about introducing β_1, β_2 to avoid the problem of spatial aliasing, they have been factored out during the evolutionary process. This is surprising, but might be explained by the fact that these factors play a role for an existing map and could be disturbing at the beginning when only a few connections are present.

4.3 Analyzing the Strategy

The cognitive map learning strategy can be analyzed both on a structural and on a behavioral level. In Figure 6, the activation of six different place cells is shown for each position of the agent within the environment after an exploration tour with ES-optimized parameters. One can clearly see that the place cells specialize for different regions (bright areas) and build their own distinct place fields. Please note that the activities indicated by different levels of brightness only depend on the position, but not on the previous position of the agent ($a = \tanh(vw)$). The obstacles have an effect on the place fields. It would be interesting to compare this effect with the influence of obstacles in the measurement of rat place fields (Muller & Kubie, 1987).

Another way to analyze the resulting cognitive map is to observe the behavior of an agent using this map. It is difficult to make quantitative statements with just one particular environment. One interesting effect could be observed, however: Asymmetry. The success rate of an agent navigating from place A to place B can be different than when navigating from place B to place A. The reason is the higher importance of correct connections to the goal place than to the starting place.

5 Discussion and Perspectives: Integrating the Proposed Model into the *aMouse* Architecture

5.1 Mobile Robot Experiments

The cognitive map learning strategy has already been successfully applied to the mobile robot Samurai which explored an unmodified office room and created a cognitive map of place cells (Hafner, 2000b). The sensory modalities of the robot are similar to those in the simulation presented in the previous chapter. The robot is equipped with a magnetic compass and an omnidirectional camera similar to the one of *aMouse* in Figure 1, built from a camera pointing towards a convex mirror. The grayscale camera image is transformed into a panoramic view by a polar transform, vertically averaged and normalized. Results were presented in Hafner (2000b) and show the different maps corresponding to different exploration tours within an office room. The parameters for these experiments had been hand-coded and not yet optimized using evolutionary algorithms.

Since we are modeling the navigation skills of mice, inspired by their behavior and by findings of place cells in their hippocampus, the mobile robot should share some of the sensory–motor properties of a real mouse. This is partly true in the *aMouse* robot which is equipped with both visual and tactile sensors (whiskers). The cognitive map model presented in this paper has yet to be implemented on the *aMouse* robot. The following section outlines the challenges of extending the cognitive map model to sensory modalities other than vision.

5.2 Combining Visual and Tactile Information in Cognitive Maps

As vision is just one sensory modality available to rats when they are navigating (Save, Nerad, & Poucet, 2000), it would be advantageous to also supply the robot with additional sensory modalities, e.g., whiskers. The whiskers can serve as an alternative source of information when vision is temporarily not available, or in addition to improve localization.

Different sensory modalities can be combined in a cognitive map model. Touretzky and Redish (1996) designed a place cell activation model, which consists of the product $A = F_1 \cdots F_6$ of six Gaussians which represent different information cues. If one of the cues for the place cell activity becomes temporarily unavailable, e.g. when the light has been switched off, the corresponding term drops out of the equation. This was realized by including the width of the Gaussian into the term $F_i = \exp(-x_i/\sigma^2)$, which then became close to one.

The problem with integrating the different modalities in the same level into the cognitive map model is partly related to their different information structure. Visual cues are long-distance cues, whereas tactile cues can only be gathered in the direct vicinity of an object.

Strösslin, Krebser, Arleo, and Gerstner (2002) propose a model to combine visual and tactile information in a spatial learning task using gating networks. Their work is inspired by cells in the superior colliculus and has already been implemented on a Khepera robot with a grayscale camera and infrared distance sensors.

The cognitive map model presented in Section 4.1 will be extended to include tactile information from whiskers as they are used by rats for navigation. For this purpose, an artificial mouse robot, *aMouse*, has been designed and tested in different setups. It will serve as an ideal platform for the future cognitive map navigation experiments that will include both visual and whisker information.

6 Conclusion

We have presented a cognitive map model that can be used to create a spatial internal representation for autonomous agents during exploration tours and that has been tested both in simulation and on a mobile robot. The model is inspired by place cells in the hippocampus of rats, and reproduces some of the rat place cell properties, such as the shape and size of place fields. It lies on a high level of abstraction, representing the place cells as nodes of a topological graph. This work was originally inspired by the cognitive map algorithm by Schölkopf and Mallot (1995), but extends the restriction to mazes to a realistic open environment where arbitrary movements are possible. The algorithm results in sparse topological maps that can easily extended with metric information. Allothetic (vision) and idiothetic (movement) information is combined within the model (Arleo & Rondi-Reig, 2004).

Interesting results are the formation of place fields similar to those observed in rats, and the behavioral experiments. One problem which can be seen in Figure 4 is that of multiple place fields. Here, one place cell fires at two spatially separated regions within the environment. Being unaware of this can result in strange behavior. We know, however, that rats have to cope with the same problem. Evidence for multiple place fields have also been found in rat experiments.

The experiments on cognitive maps all rely on visual information and compass information so far. The next step is to include the tactile sensors (whiskers) into the model. The *aMouse* robot with omnidirectional vision and two active whisker arrays is an ideal experimental platform for integrating the two sensory modalities in the way shown above.

Acknowledgments

This work had been partly funded by the European project AMOUSE (construction of the active whisker array and the *aMouse* robot) and the SNF project on “Embodied AI.” The author is now working at Sony CSL Paris on the European project ECAGENTS. Thanks go to Miriam Fend and Max Lungarella for their work on *aMouse* and the artificial whiskers, and to Angelo Arleo for helpful discussion.

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