

Robots as Tool to Study the Robustness of Visual Place Cells

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ABSTRACT - In this paper, a model of *place cells* (PCs) built from precise neurobiological data is presented. The robustness of the model in real indoor and outdoor environments is tested. Results show that the interplay between precise neurobiological modelling and robotic experiments can promote the understanding of the biological circuitry and the achievement of very robust robot navigation algorithms. Short Term Memory (STM), soft competition and sparse coding are important for both landmark identification and computation of PC activities.

I. INTRODUCTION

Ethological studies of animal navigation show that a wide variety of sensors can be used by the animals to navigate and localize themselves. Among them, vision allows a very precise, robust and non intrusive way to navigate. Visual information can be used for taxon navigation (returning to a particular landmark) or to recognize a place from distant landmarks [Gould, 1986]. The different models of the biological navigation use the azimuth of the landmarks [Cartwright and Collett, 1983], or more rarely, their identity or a conjunction of the two [Arleo and Gerstner, 2000; Bachelder and Waxman, 1994; Gaussier et al, 2000]. In previous hippocampal modelization, the discovery of *place cells* (PCs) in the rat hippocampus and also in primates has emphasized the encoding of spatial

cognition and navigation by mammalian brain [O'Keefe and Nadel, 1978; Squire, 1992]. In a first model, proposed in 1994, we showed how the learning of few sensory-motor associations around a goal location was sufficient for a robot-like agent to exhibit a robust homing behavior [Gaussier and Zrehen, 1994] if the environment is simple (*i.e.* open field navigation with no need to plan a detour). A central hypothesis of our most recent model considers some aspects of hippocampus function are devoted to the detection and the fast learning of transitions between multimodal events [Gaussier et al, 2002; Banquet et al, 2005]. Hence, static PCs should exist prior the hippocampus. Model and experiments show robust PCs can be built by simple merging the *what* and *where* information coming from the visual system. We propose the merging could be performed as early as parahippocampus cortex (in the perirhinal and parahippocampus cortex: PrPh). The place recognition could be performed in the entorhinal cortex (EC: the main input to the hippocampus), and the dentate gyrus (DG: a substructure of the hippocampal system). Hippocampus proper (CA1/CA3) could be devoted to the learning of transitions. In this paper, we will analyze the parameters controlling the robustness of our PCs in real environments. We will show that going back and forth between robotics and neurobiological modelling can both help to obtain a more robust and faster place recognition for robotics applications and explain why short term memory (STM) and soft competition mech-

anisms are so important for the brain functioning.

II. MODEL DESCRIPTION

This section describes a biologically plausible model of the prehippocampal PCs tested on manifold robotic platforms (Koala, Labo3, Pioneer AT), evolving in open indoor and outdoor environments. Fig. 1 summarizes the processing chain. The model was first tested in an open indoor environment, with a trivial landmarks extraction method. The choice of the focal points was based on the detection of vertical contrast areas [Gaussier et al, 1997]. To be more efficient, a panoramic CCD camera using a conic mirror has been recently introduced. This camera allows one shot capture of a 360° panoramic image. To eliminate problems induced by luminance variability, the gradient image is the only visual input of the system (a 1500 × 240 pixels image extracted from the 640 × 480 pixels panoramic image which is originally circular). The gradient image is then convolved with a DOG (Difference Of Gaussian) filter to detect curvature points at low resolution (robust focal points). At last, a log-polar transform of the local views, extracted around each focal point, is computed to improve the pattern recognition when small rotations, and scale variations of the landmarks occur. The simulated visual system provides both a *what* information: the recognition of a 32x32 pixels snapshot in log-polar coordinates (that will be called local view) [Schwartz, 1980], and a *where* information : the azimuth of the focal point (absolute direction obtained with a compass or any simulation of a vestibular system). *What* and *where* informations are finally merged in a product space (a matrix of sigma-pi units [Rumelhart and Zipser, 1985] that stands in the model for the PrPh connectivity), with a STM that enables to remember the merging of previous inputs. At the beginning of the sequential exploration of a panorama, the STM of PrPh is reset. We suppose neurons in EC-DG learn and recognize the activity of several PrPh units as a pattern coding for an invariant representation of a place.

The activity of a PC results from the computation of the distance between the PrPh pattern learned and the current PrPh pattern (the distance is computed only on the recruited neurons). Thus, the activity of the k^{th} PC can be expressed as follow:

$$P_k = \frac{1}{l_k} \left(\sum_{i=1}^{N_L} \omega_{ik} \cdot f_s(L_i) \cdot g_d(\theta_{ik}^L - \theta_i) \right) \quad (1)$$

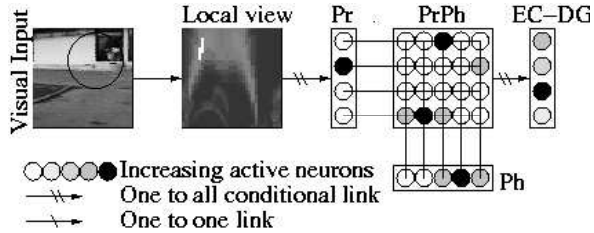


Figure 1: Block diagram of the architecture.

Our architecture is composed of a visual system that focuses on points of interest and extracts local views, a merging layer that compresses *what* and *where* information, and a place recognition layer.

with $l_k = \sum_{i=1}^{N_L} \omega_{ik}$ the number of landmarks used for the PC k , where $\omega_{ik} = \{0, 1\}$ expresses the fact that landmark i has been used to encode PC k , with N_L the number of learned landmarks, L_i the activity of the landmark i , $f_s(x)$ the activation function of the neurons in the landmark recognition group (Pr in the model), θ_{ik}^L the learned azimuth (coming from the PPC, Posterior Parietal Cortex, in rodents and primates) of the i^{th} landmark for the k^{th} PC, θ_i the azimuth of the current local view interpreted as the landmark i . d is the angular diffusion parameter which defines the shape of the function $g_d(x)$. At last. The role of $f_s(x)$ and $g_d(x)$ is to adapt respectively the dynamics of *what* and *where* groups of neurons. They are defined as follow:

$$g_d(x) = \left[1 - \frac{|x|}{d \cdot \pi} \right]^+ \\ f_s(x) = \frac{1}{1-s} [x - s]^+$$

where $[x]^+ = x$ if $x > 0$, and 0 otherwise .

In the following, we will show that, surprisingly, the optimization of our model both for indoor and outdoor navigation leads to propose a more plausible model.

III. INTEREST OF SOFT COMPETITION

In this section, it will be illustrated, for the specific problem of landmarks encoding, the interest of a more biologically plausible model than a simple WTA (Winner Take all) at the level of local views recognition to increase the generalization aptitude of the place fields.

A first approach to recognize a place is to suppose each local view corresponds to a single landmark. When the robot is moving from a place P_A to a

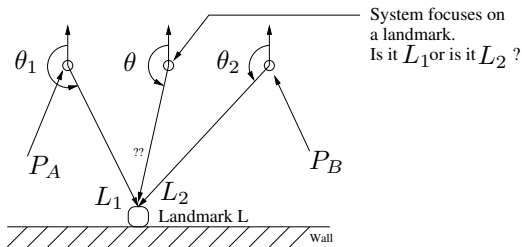


Figure 2: Learning PCs using the same landmark seen from two different points of view.

During navigation, two interpretations of the same landmark can compete and bias place recognition.

place P_B , a given landmark L can be perceived as two distinct visual patterns (L_1 or L_2). Hence, in P_A , the landmark L should be recognized by the neuron L_1 and by L_2 in P_2 (see Fig. 2).

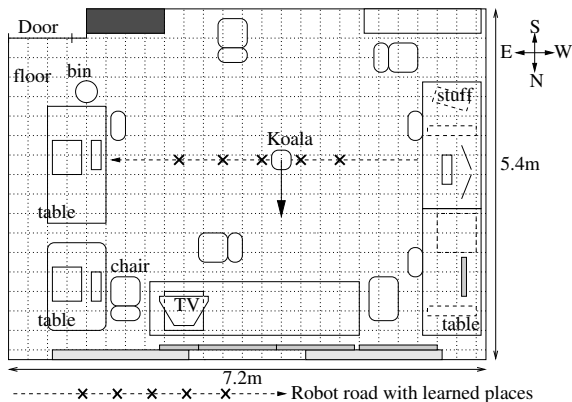


Figure 3: Room used for the experiment of the fig. 5. Crosses represent the learned positions.

A real example, in outdoor environment (see Fig. 4), illustrates two landmarks N and M learned respectively as L_1 and L_2 in place P_A , and as L_3 and L_4 in P_B . P_AP_B is 5 meters long. At the middle place P_C between P_A and P_B , the recognition level of each learned local view is given. We can see L_1 and L_3 (or L_2 and L_4) have almost the same activity level and that a strict competition induces a random choice of the winner, disadvantaging one of the two PCs.

As the PC activity results from the product between the recognition level of *what* and *where* information (see eq. (1)), allowing a single winner for *what* information is equivalent to impose a maximum azimuth error for all the other interpreta-

tions, even if others can be valid. It is also equivalent to consider that the landmarks corresponding to all the other interpretations are not present or not visible. Furthermore, the distance between learned prototypes shrinks with the increase in the number of encoded landmarks. Therefore, errors induced by a strict competition become more frequent (classical problem of clustering). It seems difficult and not really necessary to assign a single label to each local view. Trying to avoid the ambiguity of the sensorial information seems to be a mistake. Only the global behavior of the system matters [Gaussier et al, 2004; Maillard et al, 2005]. Instead of trying to perform an impossible choice, allowing multiple interpretations of the same view seems to bring a lot of advantages if the decision taking, here finding the more proximal place or deciding of the current movement, is able to manage this kind of coding.

A solution could come from fixing a recognition threshold (RT), under which the neurons would not discharge. But it could also be difficult to optimize this parameter. Moreover, the more the system encodes landmarks, the higher the number of neurons whose activity is over this RT will be (so most of these activities will correspond to noise). Another simple solution is to fix a maximum number of interpretations over a safety RT. All interpretations under this RT will be considered as wrong. If the system focuses on a non-learned local view, the RT should be able to inhibit a large number of neurons. In order to increase the dynamics of the landmark neurons output, the activity between RT and 1 can be linearly rescaled between 0 and 1. This is performed by the activation function $f_s(x)$, where s is in fact the RT. However, the distance between learned prototypes will decrease each time a new landmark is encoded. So, the maximal number of available interpretations has to be correlated with the number of encoded landmarks. The ratio $\frac{W}{N_L}$, with W the maximal number of winning interpretations and N_L the number of encoded landmarks, must be higher than a given confidence threshold according to the landmark encoding method. As example, Fig. 5 shows the place fields induced by a strict competition, versus a soft competition. In this experiment, five aligned places were learned in an indoor room (see fig. 3). Then, the robot went over the line and PCs activity was computed at each position. Generalization is largely increased by using a soft competition. Using a strict competition prevents place fields

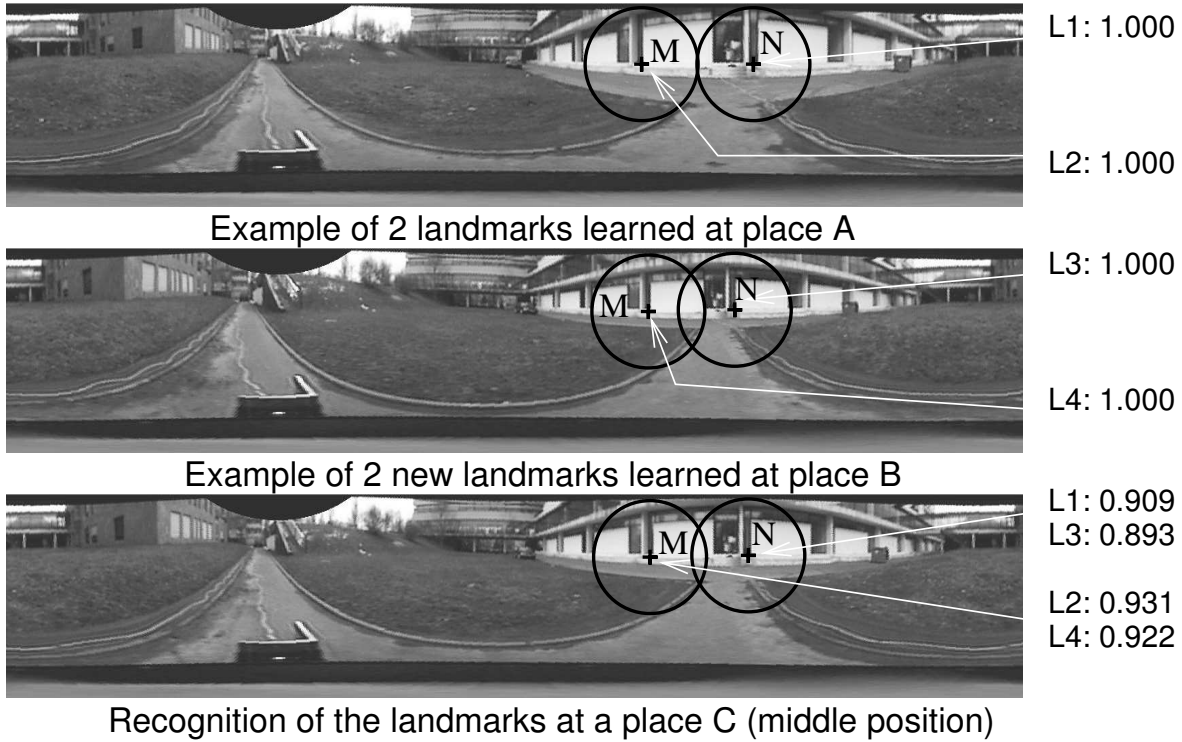


Figure 4: Learning and recognition of the same landmark by several neurons. The same landmarks M and N has been learned, for two proximal places (5m distant), as different visual patterns (upper figures). Hence, in the middle of the two places (lower figure), the landmarks have two valid interpretations. In place C, the activity level of " L_2 and L_4 " for the landmark M and the activity level of " L_1 and L_3 " for the landmark N are much lower than the valid interpretations of M and N (lower than 0.82).

from overlapping (see Fig. 5). This sparse coding solution allows place fields extension far from the center of the learned place, without reducing the precision in its center, as can be seen in biological EC place cells. This result shows another facet of the interest of sparse coding in biological systems.

IV. INFORMATION COMPRESSION

While local views are being extracted (*what* information), PrPh merges their interpretations with their absolute azimuth (*where* information). Our first idea to merge these informations was to use a product space by means of a neural matrix of $N_L \times N_A$ neurons, in which each neuron is linked to one of the N_L landmark neurons and one of the N_A azimuth neurons. Activity of the PrPh neurons was given by the product: $S_{ij}^{PrPh} = S_i^L \times S_j^A$, with S_{ij}^{PrPh} the activity of ij^{th} neuron in PrPh,

linked to the output S_i^L of landmark neuron i and to the output S_j^A corresponding to the azimuth j of landmark i .

Such a coding of the *what* and *where* information is correct, but uses too many resources and is not biologically plausible. The ratio between the number of active neurons in the PrPh matrix and the number of neurons that are really used by EC-DG is globally $\frac{N_L \times \bar{n}_a}{N_L \times N_A} = \frac{\bar{n}_a}{N_A}$ where \bar{n}_a is the average number of different azimuths under which a landmark can be seen. For a good precision, N_A has to be high enough (for instance 90 neurons coding for 360°). Thanks to generalization, the same landmark does not need be encoded for too close azimuths. So \bar{n}_a can be small (3 different azimuths of a given landmark seems to be a reasonable value). In this case, the ratio between neurons used in EC and active neurons is $\frac{3}{90}$.

For the purpose of information compression, it is not necessary for the PrPh matrix to have more

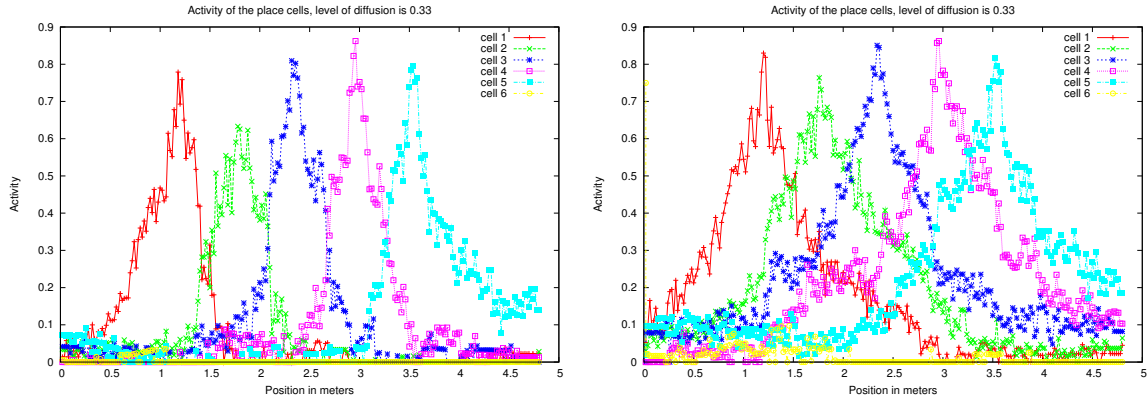


Figure 5: Place fields induced by a strict or a soft competition (indoor env.). PC activities are computed every 2 cm over a line of 4.8 m long (see fig. 3). Places have been learned every 60 cm. Left figure shows place fields induced by a strict competition. Right figure shows place fields induced by a soft competition. A strict competition at the level of the landmark recognition does not allow a good generalization and place fields to overlap.

columns than the maximum number of different azimuths under which a landmark can be learned (correlated to \bar{n}_a , such as $2 \times \bar{n}_a$). But if the connectivity remains unchanged, azimuthal precision is lost. So, in order to avoid a loss of place field azimuthal precision, each neuron of the matrix can be linked to a subset of the neurons in the azimuth group (not only a single input neuron). In this way, the same landmark will not be encoded on different azimuths unless these azimuths are significantly different. This property is directly derived from the neighborhood connectivity. At last, the precise azimuths can be encoded by the connections between PrPh neurons and the azimuth neuron group Ph. Thus, our merging matrix has fewer columns (6 columns avoid a landmark to be encoded with different azimuths that are closer than $\frac{360}{6} = 60^\circ$), whereas the azimuthal precision remains the same (90 neurons coding for 360°). So the ratio between the number of neurons used by EC and the total number of neurons in PrPh is now: $\frac{\bar{n}_a}{6} \ll \frac{\bar{n}_a}{90}$. Moreover, there is no active neurons that has not been used by EC.

More precisely, at the beginning, all the connection weights are set to 0. Neurons are recruited when a couple landmark-azimuth is encountered: simultaneous activation of a landmark neuron i and an azimuth neuron $a(i)$ triggers the learning of the corresponding synapses in PrPh. The weight of the connection between the Π neuron recruited in PrPh and the corresponding azimuth neuron $a(i)$ is set to 1 (the connection to the landmark neuron

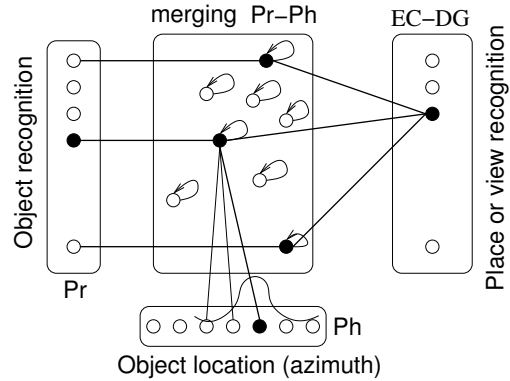


Figure 6: Merging connectivity of PrPh. Each neuron is linked to one landmark neuron and a neighborhood of azimuth neurons. Only one connection from this neighborhood is set to 1.

i is also set to 1). As only one connection from Ph has been learned (that means $a(i)$ has a single value), azimuthal precision is preserved. Finally, unused neurons can be pruned to further foster the performances.

This architecture is absolutely equivalent to the full matrix, but is faster. It uses less memory and is more biologically plausible than the former architecture. Once again, a more plausible model leads us to a more efficient and faster system.

V. STM IN PrPh FOR OUTDOOR ENVIRONMENT

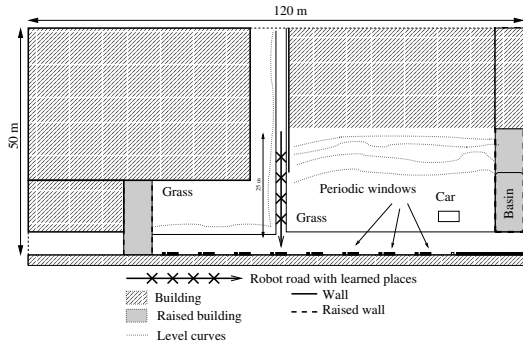


Figure 7: Environment used for the experiment of the fig. 8. Crosses represent the learned position.

The functioning of the STM in PrPh can also be criticized. Indeed, in our first indoor experiments, the number of visual cues was much higher and the stability of the features points was much better than in outdoor environments. The PrPh activity was reset before the analysis of each new panorama (curves of Fig. 5 illustrate this method). Unfortunately, the outdoor experiments of place fields formation led to highly unstable place fields. Variability was so high that even at the position of a learned place, the PC activity could be very low (left curves of Fig. 8). However, it seems that averaging activities curves or interpolating the local maximum would induce better results and fight against the lack of performance of the landmark extraction system.

Indeed, the study of the neural network while running shows that the main problem is the high variability in the number of learned local views the system focuses on step after step. Because the images are too complex, the mechanism to control the focus of the attention is unable to guaranty the focus on learned landmarks (low probability to retrieve them and therefore to recognize them). The question was then: how would it be possible to store integrated information for a while, in order to fight against the lack of robustness of the focus system? Obviously, mammals need not to see, step after step, every visual cue in their environment, to be able to navigate. Seeing only a few visual cues from time to time seems enough to navigate without ambiguity. The existence of a real STM at the level of PrPh would allow to remember what was seen in the previous iterations, and could explain why

mammals do not need to verify step after step the position of each landmark. STM in PrPh was already used to store landmark-azimuth associations during exploration of the visual inputs. PrPh was reset before the analysis of each new panorama. However, there is no need to reset so often the PrPh matrix. Informations merged in PrPh should remain valid for a while after their integration.

Hence, PrPh STM was increased in order to deal with the sparse or the incomplete exploration of the visual environment. By means of a STM in PrPh, the place fields become robust and allow a good generalization (see fig. 8). On Fig. 8, we can also see that in outdoor environment, the place field are really larger than in indoor environment. These experimental results confirm the mathematical model which predicts that the size of the place fields grows proportionally to the landmarks distance. For instance, in Fig. 8, the place fields have a useful diameter of about 25 meters, which is almost the size of the environment (the result was of the same kind in indoor environment).

Thus, this kind of PC allows a homing behavior and generalization of the sensory-motor learning over a very important distance. Moreover, our PCs are incompatible with the features of PCs found in the hippocampus proper (CA1/CA3 region). Our results confirm that simple navigation tasks could be performed by broad prehippocampal PCs, and that hippocampal PCs could be built from a strong competition between these cells (in our model, CA3/CA1 neurons predict transitions between the current place and the next possible places).

VI. PERSPECTIVES AND CONCLUSION

In this paper, it was shown that the interaction between robotics and neurobiology leads to introduce more biological plausibility in our model, to increase performance of the system, and to explain the importance of STM and soft competition in the brain functioning.

Our results also suggest that, even in outdoor environment, no Cartesian map is required for a robust navigation. However, as visual information is sometimes limited, idiothetic information could help to disambiguate the recognition of complex environments, and allothetic information could help maintaining a coherent idiothetic space representation [Arleo and Gerstner, 2000; Redish and Touretzky, 1997]. But we claim, as

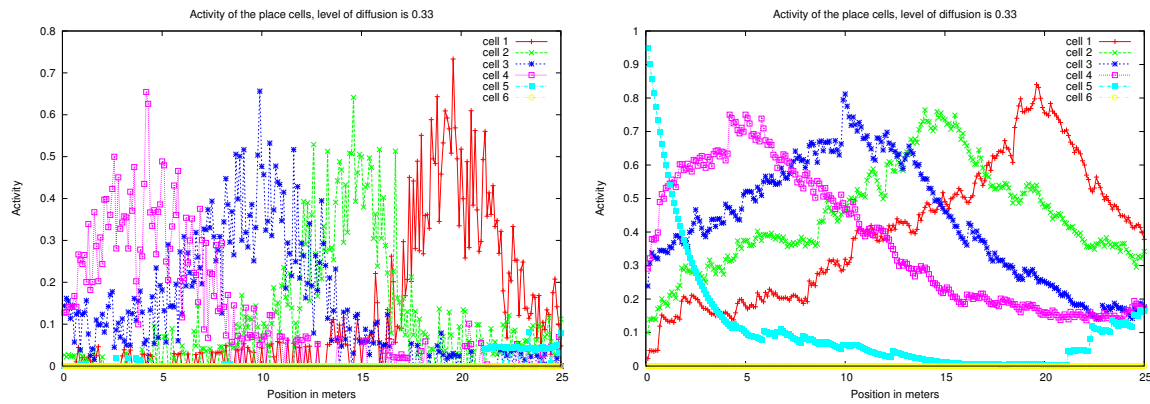


Figure 8: Place fields with and without STM (outdoor env.).

PC activities are computed every 10 cm over a line of 25 m long (see fig. 7). Places have been learned every 5 m. Soft competition is used at the level of the landmark recognition. Left figure shows unstable place fields. Right figure illustrates the interest of a STM. In outdoor environment, the useful diameter of the place fields is about 25 m.

opposed to other models of hippocampal function [McNaughton et al, 1996], that visual information is preponderant. Outdoor experiments have also shown the interest of a more sophisticated attentional system, that would help identifying and retrieving more robust landmarks. Finally, other visual cues like apparent size or distance deduced from parallax effects, color and textures information, will be taken into account for a better characterization of the landmarks.

Videos are available on http://www.etis.ensea.fr/~neurocyber/Videos/index_videos.html

ACKNOWLEDGMENT

These researches are supported by the Delegation Generale pour l'Armement (DGA), project no 04 51 022 00 470 27 75. We particularly thank G. Desilles for his useful collaboration.

REFERENCES

[Arleo and Gerstner, 2000] A. Arleo and W. Gerstner. Spatial cognition and neuro-mimetic navigation: A model of hippocampal place cell activity. *Biol. Cybern.*, 83(3):287–299, 2000.

[Bachelder and Waxman, 1994] I.A. Bachelder and A.M. Waxman. Mobile robot visual mapping and localization: A view-based neurocomputational architecture that emulates hippocampal place learning. *Neural Networks*, 7(6/7):1083–1099, 1994.

[Banquet et al, 2005] J.P. Banquet, P. Gaussier, M. Quoy, A. Revel, and Y. Burnod. A hierarchy of association in hippocampo-cortical systems: cognitive maps and navigation strategies. *Neural Computation*, 17:1339–1384, 2005.

[Cartwright and Collett, 1983] B.A. Cartwright and T.S. Collett. Landmark learning in bees. *Journal Comp. Physiology*, 151:521–543, 1983.

[Gaussier and Zrehen, 1994] P. Gaussier and S. Zrehen. Navigating with animal brain : a neural network for landmark identification and navigation. In *Proceedings of Intelligent Vehicles*. Paris IEEE Press, 1994.

[Gaussier et al, 1997] P. Gaussier, C. Joulain, S. Zrehen, J.P. Banquet, and A. Revel. Visual navigation in an open environment without map. In *International Conference on Intelligent Robots and Systems - IROS'97*, pages 545–550, Grenoble, France, September 1997. IEEE/RSJ.

[Gaussier et al, 2000] P. Gaussier, C. Joulain, J.P. Banquet, S. Lepretre, and A. Revel. The visual

homing problem: an example of robotics/biology cross fertilization. *Robotics and autonomous system*, 30:155–180, 2000. 99:143–145, 1992.

[Gaussier et al, 2002] P. Gaussier, A. Revel, J.P. Banquet, and V. Babeau. From view cells and place cells to cognitive map learning: processing stages of the hippocampal system. *Biological Cybernetics*, 86:15–28, 2002.

[Gaussier et al, 2004] P. Gaussier, J.C. Baccon, K. Prepin, J. Nadel, and L. Hafemeister. Formalization of recognition, affordances and learning in isolated or interacting animats. In *From Animals to Animats: SAB'04*, pages 57–66, Cambridge, MA, 2004. MIT Press.

[Gould, 1986] J.L. Gould. The biology of learning. *Annual Review of Psychology*, 37:163–192, 1986.

[McNaughton et al, 1996] B.L. McNaughton, C.A. Barnes, J. Gerrard, K. Gothard, M. Jung, J. Knierim, H. Kudrimoti, Y. Qin, W. Skagges, M. Suster, and K. Weaver. Deciphering the hippocampal polyglot: the hippocampus as a path integration system. *Journal of Experimental Biology*, 119:173–185, 1996.

[Maillard et al, 2005] M. Maillard, O. Gapenne, L. Hafemeister, and P. Gaussier. Perception as a dynamical sensori-motor attraction basin. In *ECAL, in Press*. Springer-Verlag, 2005.

[O'Keefe and Nadel, 1978] J.O'Keefe and N. Nadel. *The hippocampus as a cognitive map*. Clarendon Press, Oxford, 1978.

[Redish and Touretzky, 1997] A.D. Redish and D.S. Touretzky. Cognitive maps beyond the hippocampus. *Hippocampus*, 7(1):15–35, 1997.

[Rumelhart and Zipser, 1985] D.E. Rumelhart and D. Zipser. Feature discovery by competitive learning. *Cognitive Science*, 9:75–112, 1985.

[Schwartz, 1980] L. Schwartz. Computational anatomy and functional architecture of striate cortex: a spatial mapping approach to perceptual coding. *Vision Res.*, 20:645–669, 1980.

[Squire, 1992] L.R. Squire. Memory and the hippocampus: A synthesis from findings with rats, monkeys, and humans. *Psychological Review*,