# Modelling directional firing properties of place cells

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**Abstract.** According to experimental data, hippocampal place cells are mostly directional when a rat is in radial or +-mazes, whereas most place cells are non-directional in open environments. Some studies have also reported both directional and non-directional cells in the center of plus or radial mazes [1, 2]. We hypothesize that place cells will be initially directional (responding to specific local views), and that directionality is reduced during exploration when the rat is not constrained in the direction of its movements (like in open fields or the center of mazes).

Even though place fields are maintained in darkness, vision is crucial for the creation of spatial representation in the hippocampus [3, 4]. In this paper we propose a feed-forward model of vision driven place cells which is able to correlate local views for different headings at the same place to produce place cells with reduced directionality when the agent is allowed exploring open environments. A first model is shown in which allothetic information consists in the distance and bearing angle to detected landmarks, then we introduce a model which is able to handle real visual stimuli based in gabor processing.

## 1 The Model

Several models for hippocampal spatial coding has been proposed, but quite a few have addressed the issue of the directionality of place cells. Notably, [5] propose a model for directional properties of hippocampal place cells based on a recurrent network of cells driven by "abstract" local views (consisting of allocentric coordinates and heading direction, presumably obtained by path integration and vestibular systems respectively). Their model is based in a similar hypothesis as ours, but they propose the recurrent dynamics as the unique responsible for the loss of directionality, and no model is presented on how the spatial representation can be obtained from sensory input.

Our model consists in a population of so-called View cells (VCs) which encodes sensory information from the environment (local views). In the rat brain, hippocampus receives highly processed input from sensory cortices through the Entorhinal cortex. The role of our view cells could be seen as analog in a functional way as the one played for rat's entorhinal cortex. Two different models of visual processing are presented in this paper. First, we describe a system where the local view is characterized by the distance and bearing of different landmarks
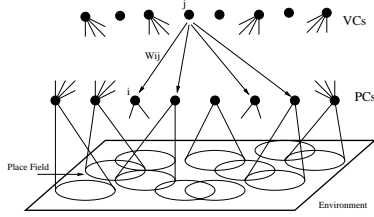
**Fig. 1.** Architecture of the model.

in its visual field. We will discuss then a model based on Gabor processing of real images. The details of both models are presented later on in this paper.

VCs project downstream onto a population of Place Cells (PCs). Unsupervised hebbian learning is applied on those projections to allow PCs to integrate information from local views into spatial coding.

$$\Delta w_{ij} = \eta \, r_i^{PC}(r_j^{VC} - w_{ij}) \tag{1}$$

PC activity is computed by linearly averaging the activity over its afferents. The ensemble activity of PCs population can be interpreted as the spatial location the agent employing *population vector coding* as in [6].

### 1.1 Landmark-based processing

Behavioural experiences suggest that hippocampal spatial representation is sensitive to the position of landmarks placed around the environment [7,3]. In this model, each view cell will encode the current local view using the current heading angle $(v_i)$ and the distance $(d_i)$ to an specific landmark $c_i$ (Fig 2 Left).

The activity of VCs, depend on the possibility of observe the same landmark at the same distance from the current position. (Fig 2 Right). The activity will be then computed using the following equation for all the bearing directions in the visual field.

$$r_i^{VC}(t) = \exp\left(-\frac{(d_i - |\overrightarrow{p}(t) - \overrightarrow{c_i}|)^2}{2\sigma_d^2}\right)[cos(\theta(t) - v_i)] \tag{2}$$
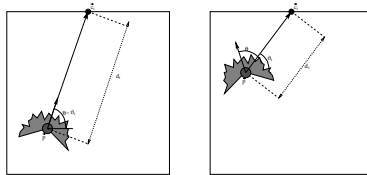


**Fig. 2.** Landmark-based view cells.

## 1.2 Gabor-based processing

To deal with real visual stimuli a vision system similar to [6] was implemented. A retinotopic grid is applied to the image and a set Gabor filters for different orientations and spatial frequencies are applied at each point. The set of Gabor responses, stored in a newly recruited VC, will code then for the current local view (Fig 3 Left).

At each new location, in order to perform self-localisation, the agent compares the current local view with those already visited, (stored in existing VCs). Given the fact that the same location will give different images according to the heading direction of the agent, local views must be aligned before perform the comparison. A mechanism of covert attention is used to perform this comparison.

In the current local view, a measure of salience is computed, and the most salient location is attended to. The deployment of attention corresponds to aligning both the current view, and the view stored in the VC, so as make the most salient spots coincide. Once the views have been aligned the activity of the VC population is computed by comparing the features of the current and the stored views. This comparison is performed only in the overlapping region ($\Omega$) of both views. The activity of the VC corresponds to the mean distance between the current local view features and those stored in the VC (Fig 3 Right).

$$r_m^{VC} = \exp\left( -\frac{\left( \frac{1}{|\Omega|} \sum_{n \in \Omega} |w_{mn} - x_n| \right)^2}{2\sigma^2} \right) \tag{3}$$
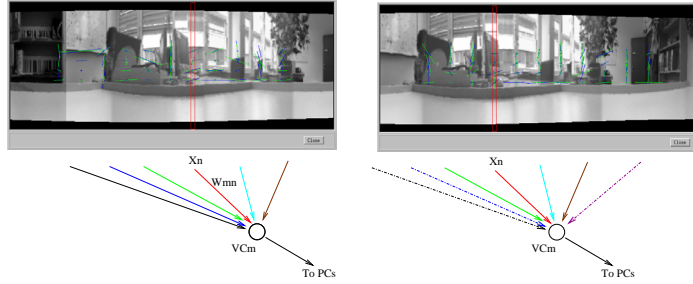


**Fig. 3.** Encoding local views. *Left.* When a new VC is created, visual features are stored in the weights $w_{mn}$. *Right.* VC Activation. Once the most salient location is attended to (red arrow), the activity is computed using only the features in the overlapping area (solid arrows).

## 2 Results

The model was tested with a simulated autonomous agent in two environments, a 80x80cm open field, and a +-maze with 40cm-long arms. The visual field of the agent was 180°. After exploration, the directionality of place cells activity was quantified with the same measure index as in [2, 5] [1].

$$D = \max_{\theta} \frac{|r(\theta) - r(\theta + 180°)|}{r(\theta) + r(\theta + 180°)} \qquad (4)$$

Fully directional cells will have a directionality index D= 1, whereas D=0 corresponds to an omnidirectional cell. According to our hypothesis the constraint in the rat movements in the arms of the maze will preserve the directionality of place cells whereas, in the open field and in the center of the maze the directionality will be reduced. Our results are consistent with this hypothesis.

The results for the landmark-based visual system are shown in the figures 4 and 5, the results obtained with the Gabor-processing of real world visual stimuli is shown in the figures 6 and 7. In the left we present the receptive fields of a typical place cell. The right histogram shows the fraction of cells who present a given directionality index D. Comparing both figures we can see that place cells in the open field are less directional than those obtained when exploring the maze.



(a)  (b)
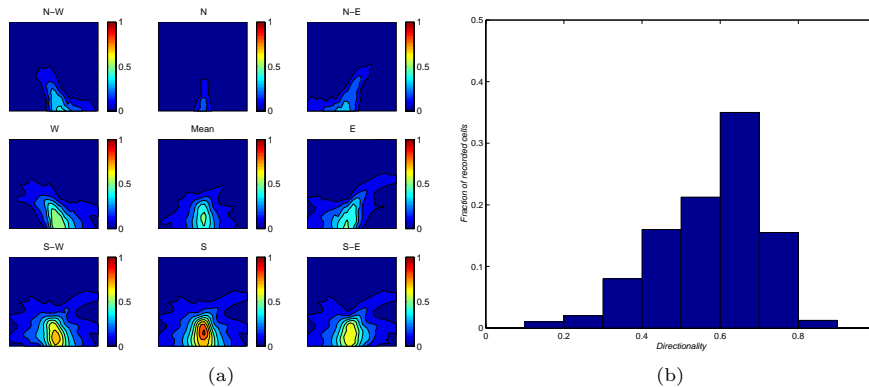
**Fig. 4.** Exploring a +-maze (landmark-based visual system). (a) Receptive fields of a "recorded" place cell (D= 0.84) for different heading directions. The plot in the center corresponds to the average of activity over all directions. The other plots show the activity for specific heading directions. (b) Directionality Histogram.

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[1] $r(\theta)$ corresponds to the activity of the place cell when the rat is heading the direction $\theta$).
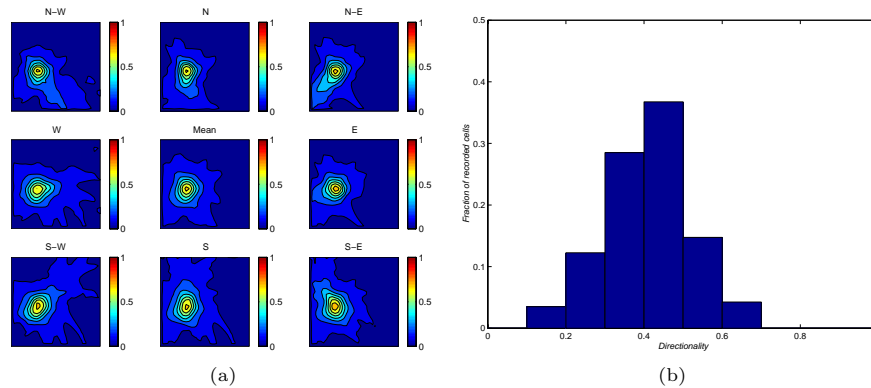
**Fig. 5.** Exploring an open field (landmark-based visual system). (a) Receptive fields of a "recorded" place cell (D= 0.16) (b) Directionality Histogram.

Comparing the obtained results we observe that real stimuli produces larger receptive and more directional fields than the landmark based approach, in both linear tracks and open environments. That can be explained because of different spatial location can provide similar visual information to the agent (*perceptual aliasing*). In our future work, other sensory modalities, as well as path integration information (intrinsically non directional) will be integrated to the model in order to obtain more refined place fields.

# References

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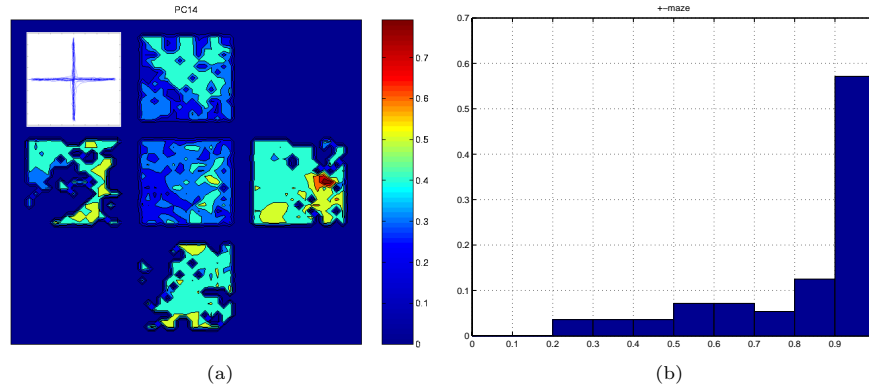
**Fig. 6.** Exploring a +-maze (Gabor-based processing). (a) Receptive fields of a "recorded" place cell (D= 1) for different heading directions. (b) Directionality Histogram.
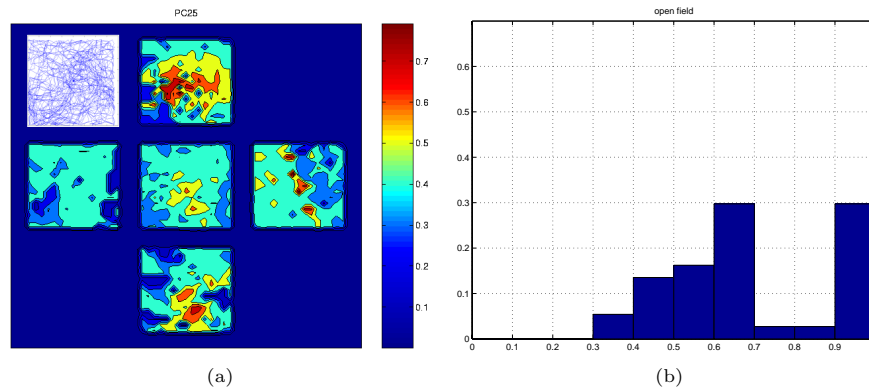


**Fig. 7.** Exploring an open field (Gabor-based processing). (a) Receptive fields of a "recorded" place cell (D= 0.62) for different heading directions. (b) Directionality Histogram.