Distance coding strategies based on the entorhinal grid cell system

Zsófia Huhn a, Zoltán Somogyvári a, Tamás Kiss a, Péter Erdi a, b

Abstract

Estimating and keeping track of the distance from salient points of the environment are important constituents of the spatial awareness and navigation. In rodents, the majority of principal cells in the hippocampus are known to be correlated with the position of the animal. However, the lack of topography in the hippocampal cognitive map does not support the assumption that connections between these cells are able to store and recall distances between coded positions. In contrast, the firing fields of the grid cells in the medial entorhinal cortex form triangular grids and are organized on metrical principles. We suggest a model in which a hypothesized ‘distance cell’ population is able to extract metrics from the activity of grid cells. We show that storing the momentary activity pattern of the grid cell system in a freely chosen position by one-shot learning and comparing it to the actual grid activity at other positions results in a distance-dependent activity of these cells. The actual distance of the animal from the origin can be decoded directly by selecting the distance cell receiving the largest excitation or indirectly via transmission of local interneurons. We found that direct decoding works up to the longest grid spacing, but fails on smaller scales, while the indirect way provides precise distance determination up to the half of the longest grid spacing. In both cases, simulated distance cells have a multi-peaked, patchy spatial activity pattern consistent with the experimentally observed behavior of granule cells in the dentate gyrus.

1. Introduction

Behavioral experiments have shown that rodents (Siegrist, Étienne, Boulebs, Maurer, & Rowe, 2003), cats (Pouet, Thinus-Blanc, & Chapuis, 1983) and chimpanzees (Menzel, 1973) are able to learn the layout of their environment, make detours and find shortcuts if they face obstacles or have to cross unknown areas while they navigate. To achieve these metric navigation tasks, the animal has to possess metric information, i.e. distance among places and direction from specific points in the environment. Orientation of the animal is coded by head direction cells that were first discovered in the dorsal presubiculum (Rank, 1984) but was later found in many other brain regions, including thalamus (Taube, 1995), mammillary nucleus (Stackman & Taube, 1998), retrosplenial cortex (Chen, Lin, Green, Barnes, & McNaughton, 1994), striatum (Wiener, 1993) and layer III of the entorhinal cortex (Sargolini et al., 2006). However, neurons representing distance from specific points have not been described yet.

The majority of principal cells in the hippocampus are place cells that show spatially correlated activity, representing specific positions of the environment. In the CA3 region of the hippocampus, there is a significant number of lateral cross connections between principal cells, therefore, a natural assumption of computational models (Trullier & Meyer, 2000) was that the connection strengths between CA3 place cells could represent distances between positions. However, place cells are not topographically organized, they randomly re-map in a new environment, therefore distance between positions represented by any two place cells is not constant, it depends on the environment. This makes hard to implement metrics by the CA3 recurrent collaterals, since the connection strengths in the whole connection system should be re-organized in each environment for correct distance representation.

The attention has been recently drawn to the medial entorhinal cortex (MEC) layer II pyramidal cells (Fyn, Hafting, Treves, Moser, & Moser, 2007; Fyn, Molden, Witmer, Moser, & Moser, 2004; Hafting, Fyn, Molden, Moser, & Moser, 2005; Moser, Kropff, & Moser, 2008; Sargolini et al., 2006) that show a topographic organization. These grid cells were shown to be active on the vertices of triangular grids tessellating the plane and each cell is characterized by the spacing (spatial periodicity), orientation and the 2 dimensional phase value of its grid (Fig. 1C). The cells were found to be topographically organized along the dorsoventral axis of MEC according to their spacing value. This grid cell system is...
considered as an explicit example of metric space representation in the central nervous system (Jeffery & Burgess, 2006; Moser & Moser, 2008), and according to the present view (Fuhs & Touretzky, 2006; Guanella, Kiper, & Verschure, 2007), the function of grid cell system is to perform path integration. These properties make the grid cell system a possible source of metric information.

However, due to the periodic nature of their spatial code, extraction of the distance information from these cells is not straightforward, further computations are necessary to perform this task. In this paper we extend the analysis of our previously proposed model that generates metrics via grid cells (Huhn, Somogyvári, Kiss, & Erdi, 2009). This model system has to solve two tasks: first, it should refer to or address two positions, between which distance is measured, second, the distance between these points should be decoded from the activity pattern of the grid cell system. In our model, the general task of estimating the distance between any two positions in the environment was simplified so that the position of the animal is compared to an already visited and stored significant position. The distance of the animal from this origin is encoded by the populational activity of hypothesized ‘distance cells’ (DCs) that receive input both directly and indirectly (through inhibitory cells) from the grid cell system. We study two variants of the general model: in one of them, the direct input is dominant, while in the other one it is negligible and distance cell activity is mainly determined by the indirect input. Distance coding capabilities and the estimation precision of the two model variants are analyzed in this paper.

2. Model

The general model architecture is the following: grid cells innervate both DCs and feed-forward inhibitory neurons (FFINs) projecting to distance cells, and a competition among distance cells is executed by feed-back inhibitory cells (Fig. 1A, B). Each distance cell and feed-forward inhibitory neuron is innervated by grid cells that share a common spacing, i.e. has a scale equaling this spatial periodicity and each inhibitory neuron projects to a distance cell that has the same scale. The two variants of this model only differ in the feed-forward connections from grid cells to the inhibitory neurons and DCs: in model A (Fig. 1A) the effect of the feed-forward inhibitory cells on DCs is assumed to be negligible while model B (Fig. 1B) assumes that distance cell activity is principally determined by the indirect effect through the inhibitory cells while direct excitation from the grid cells is not taken into account.

The grid cell firing pattern is similar to a triangular lattice so that grid cells fire at the vertices of the grid and are silent elsewhere (Fig. 1C). Each grid cell can be characterized by three properties (Hafting et al., 2005): the spacing, orientation and a two dimensional phase of its grid. In the numerical simulations 110 spacings were randomly distributed in the $S \in \{0.3 \ldots 1\}$ m interval following an exponential distribution and 1000 grid cells were simulated for each spacing value, resulting in a total number of 110,000 grid cells. This number is in accordance with data about the number of cells in the upper layers of the entorhinal cortex (Andersen, Morris, Amaral, Bliss, & O’Keefe, 2007). For each grid cell, orientation and phase values were chosen randomly. To represent the grid cell activity in our model we applied the cosine grating model (Blair, Welday, & Zhang, 2007), which was used for computational efficiency and was not intended to represent an accurate biological model of grid cell firing activity. Thus, the location dependent firing rate of a given grid cell is calculated as

$$G^{x,y}F(r) = \xi(r) \cdot \exp \left[ 0.3 \left( \frac{3}{2} + \sum_{k=1}^{3} \cos (\alpha_k \cdot (\frac{x}{5} - p)) \right) \right] - 1 \quad (1)$$

where $S$ is the spacing, $\Theta$ is the orientation and $p = (x_0, y_0)$ is the phase shift of the grid and $r = (x, y)$ is the position of the rat in the arena. Cosine gratings were oriented according to the three vectors $\alpha^x_1$, $\alpha^y_1$, $\alpha^x_3$ that had angles $\Theta - 30^\circ$, $\Theta + 30^\circ$ and $\Theta + 90^\circ$, and an equal length of $4\pi / \sqrt{3}$. $\xi(r)$ is a random noise term taking values from a uniform distribution in the $[1 \ldots 1.15]$ interval realizing multiplicative noise of 7.5% on average. The sum of the three cosine functions ranged from $-3/2$ to 3, so the value of $G(r)$ varied between 0 and $\sim 3.3$. Note, that the radius of a grid cell’s subfields increase with the spacing of the grid cell.
Grid cells sharing a common spacing innervated the same postsynaptic cell (DC and feed-forward inhibitory neuron). The summed input from these grid cells is

\[ D^f(r) = \sum_{\Theta} \sum_{p} C^{\Theta,p}(r) w^{\Theta,p}, \]  

where \( D^f(r) \) is the net input of the postsynaptic cell with scale \( S \), \( C^{\Theta,p}(r) \) is the activity of a grid cell with spacing \( S \), and \( w \) is the synaptic weight matrix.

Synaptic weights were assumed to be set by a one shot learning rule: when the animal occupies an emotionally significant place, i.e. the origin, synapses between grid cells innervated by them get long-term potentiated (Abe, Niikura, & Misawa, 2003; Nakao, Matsuyama, Matsuki, & Ikegaya, 2004), and synaptic weights become proportional to the firing frequency of the presynaptic grid cell in the origin (Blaise & Bronzino, 2003). This corresponds to Hebbian learning if firing activity of different DCs is assumed to be equal in the origin. According to these assumptions the synaptic weights stored the presynaptic firing rates at the important place:

\[ w^{\Theta,p}(R) = C^{\Theta,p}(R), \]  

where \( R \) is the position of the origin. In our simulations, the origin was chosen to be the central point (coordinates: 0, 0) of a 20 × 20 m sized rectangular arena (Fig. 3, cross).

Feed-back inhibitory neurons realized a competition among distance cells so that only the DC receiving the highest net excitation was assumed to remain active in every spatial location.

Simulations were done in Matlab (version 7.3.0.298) on Linux operating system.

3. Results

The task that the model has to execute is to represent the distance of the animal from the origin by the population activity of distance cells. In model A, the activity of a DC depends on the summed input received from its presynaptic grid cells, since effects from FFINs are assumed to be negligible. The constrain that a DC receives input from grid cells of a given spacing \( S \) results that the net input of the DC changes periodically with the distance from the origin, creating concentric rings around it (Fig. 3A). A DC is exposed to large excitation, when the animal’s distance from the origin is around an integer multiple of the scale of the DC (\( \sim n \cdot S \)) (Fig. 3A, black rings). The alignment of the grid cell activity maxima deteriorates as the animal moves farther from the origin, which results in decreasing local maxima of the input to a given DC. At a given distance, the net input to the different DCs changes quasi-periodically as a function of the scale of the DCs (Fig. 2A). Due to the competition among grid cells only the DC receiving the largest excitation remains active. Therefore, if there is an unambiguous correspondence between the distance and the scale of the active DC, the identity of the active distance cell would encode the distance of the animal from the origin. Fig. 2B and C demonstrates that in the distance range of effective coding (2.5–10.5 m, Fig. 2B, dashed vertical lines), at most positions, the active DC’s scale is around the distance to be estimated. However, in some cases, the largest input targets DCs of lower scales (Fig. 2B, circled points), which makes the distance code ambiguous and decreases the estimation precision of the system. The standard deviation from the linear fitted in the effective coding range by least squares method is 84 cm. Note, that up to ~2.5 m distance the scale of the active DC equals the highest spacing of the grid system (10 m) which makes this system unable to estimate distances in this regime. The reason for this failure on short distances is that the diameter of one subfield of a grid cell increases with increasing spacing and the wider the receptive fields of a grid cell is, the less sensitive for small displacements from origin it is.

In model B, feed-forward excitation from grid cells to DCs are assumed to be negligible so DC activity is determined by the feed-forward inhibitory neurons. Again, the DC receiving the largest net input in any positions will be active, that is the one receiving the lowest inhibition from FFINs. Due to the learning rule, a FFIN receives small inputs at locations where the distance from origin is an integer multiple plus half of the DC’s scale (\( n \cdot S + S/2 \)) (Fig. 3A, white rings). At a given position, the smallest excitation targets the inhibitory cell the scale of which approximately equals twice of the distance from origin (Fig. 2A), therefore the active DC’s scale is similarly twice of the distance to be estimated. This distance code is unambiguous in the 0.15–5.5 m distance regime (Fig. 2B, C) and the standard deviation from the fitted line is 38 cm.

In summary, (i) the smallest distance that can be estimated by model A is around one fourth of the highest grid spacing (~2.5 m), while model B is able to encode distances as small as the half of the minimal spacing of the grid system (~0.15 m), (ii) the upper bound of distance estimation ability equals about the largest spacing of the grid system in model A, while it is around the half of the maximal spacing in model B, (iii) in the distance ranges of effective coding (2.5–10.5 m for model A and 0.15–5.5 m for model B), model B has a significantly smaller estimation error than model A.

So far our model assumed a clearly convergent projection from grid cells to their postsynaptic cells: each grid cell innervated only one DC and FFIN while one postsynaptic cell received connections from several grid cells with the same spacing. In the followings we introduce divergence as well assuming that a grid cell innervates more than one DCs and FFINs so that a given cell receives innervation from all the grid cells with similar spacings. We tested the tolerance of the model, i.e. the size of effective coding range and the average error of the distance estimation, to the increasing number of neighboring grid spacings innervating one DC/FFIN. Fig. 2D shows that although the range of effective coding is slowly decreasing, the estimation precision is increasing with the increasing divergence. In case of model A, for a slight increase of divergence, the estimation error is significantly reduced, it becomes approximately one third of the error compared to the model assuming no divergence. This suggest that there is an optimal degree of divergence, which is large enough to significantly decrease the estimation error for both model A and B, but not so large that would cause a remarkable decrease in the effective range size. In our simulation this was reached by the cases when each DC/FFIN received connections from grid cells with approximately five different (but neighboring) spacing values.

Fig. 3B and C show the firing pattern of DCs in model A and B (with no divergence), respectively. Due to the winner-take-all mechanism among DCs, concentric rings of net input on postsynaptic cells of grid system (Fig. 3A) were transformed into disjoint patches at a distance from origin approximately equaling the scale (model A) or half of the DC’s scale (model B). These firing activity patterns are similar to the behavior of granule cells in the dentate gyrus region of the hippocampus (Jung & McNaughton, 1993; Leutgeb, Leutgeb, Moser, & Moser, 2007).

4. Discussion

In the short history of grid cells, most papers discuss their possible role in navigation in connection with hippocampal place representation. Up to now these articles attributed more or less the same role to the grid cell system: being involved in path integration it facilitates the creation of place cells in the hippocampus even in the absence of allocentric information (Fiete, Burak, & Brookings, 2008; Franzius, Vollgraf, & Wiskott, 2006; Fuhs & Touretzky, 2006; Rolls & Kesner, 2006; Solstad, Moser, & Einevoll, 2006). It
Fig. 2. Distance encoding. (A) Net input from grid cells to their postsynaptic cells (distance cells and feed-forward inhibitory neurons) with different scales at three different distances from the origin. At 2 m distance (upper graph) the highest input targets the cell with the largest scale (filled arrow), while the lowest input is received by cell with scale \( \sim 4 \) m that is approximately twice of the distance (empty arrow). This makes DCs of model B (but not model A) able to encode this distance. In case of 4 m distance (middle graph) model B is still working, since the lowest input is received by inhibitory neuron with scale around 8 m. The highest input is received by a cell the scale of which is smaller than the distance to be encoded, reflecting an incorrect encoding in model A. However, note, that most of the distances in the \( \sim 2.5 - 10.5 \) m range are correctly encoded in model A. When distance from origin is 8 m (lower graph), model B is not able to encode the distance, while model A is working properly, the largest excitation is received by a DC that has a scale approximately equaling 8 m. (B) The scale of the active DC as a function of the animal’s distance from origin. In model A (upper graph) small distances can not be encoded by the DCs, since the DC with the largest scale is active at any distances in the \( \sim 0 - 2.5 \) m range. In the \( 2.5 - 10.5 \) m range, the active DC’s scale equals the distance to be estimated in most of the cases (points lying near the \( \sim x \) line i.e. thick line), however there is a significant amount of positions where distance encoding is not correct (circled points). In model B (lower graph), distance encoding is correct up to \( \sim 5.5 \) m, i.e. approximately half of the largest scale. Points are dispersed near to the \( \sim 2x \) linear (thick line) reflecting that each distance is represented by the DC with scale approximately equaling twice of the distance. In the range of effective coding (between vertical dashed lines) linear was fitted by the least squares method (thin lines). The standard deviation of the points in the above range from this line is significantly smaller for model B than for model A. (C) Scale of the active DC in every positions of the rectangular arena for model A (upper subfigure) and model B (lower subfigure). (D) Distance estimation in case of divergence, i.e. when grid cells innervate more then one DCs and FFIs. Distance estimation is enhanced both for model A (left graph) and model B (middle graph) when each postsynaptic cell receives innervation from grid cells of five different but neighboring spacings: points in the range of effective coding (between vertical dashed lines) are less dispersed than in (B). With the increasing divergence (number of grid spacings innervating the same postsynaptic cell), the range of effective coding slowly decreases, however, the estimation error (standard deviation from the fitted linear in the effective range) is significantly decreasing both for model A and B (right graph).

is also often assumed, that grid cells perform path integration, thus change their firing rate according to the movement of the animal (Burgess, Barry, & O’Keefe, 2007; Fuhs & Touretzky, 2006; Guanella et al., 2007). There are two major mechanisms of grid cell models generating path integration (Welinder, Burak, & Fiete, 2008): attractor networks (Fuhs & Touretzky, 2006; Guanella et al., 2007) and oscillatory interference networks (Burgess et al., 2007; Hasselmo, 2008). The latter was originally developed to account for the phase precession of place cells (Huhn, Orban, Erdi, & Lengyel, 2005; Lengyel, Szatmary, & Erdi, 2003). Since hippocampal independent phase precession has been shown to be present in grid cells (Hafting, Fyn, Bonnaive, Moser, & Moser, 2008), oscillatory inference models can be naturally applied to the modeling of grid cells. In almost every model in the literature, firing pattern of grid cells is transformed to hippocampal place representation through competition among place cells receiving the summed activity of grid cells. In DC, more plausible place field activity pattern emerges if theta oscillation and phase precession are also taken into consideration (Motter & Yamaguchi, 2008). It was also shown, that the grid cell system provides a very effective way for position encoding: the necessary number of grid cells is increasing logarithmically with the linear size of the environment (Fiete et al., 2008).

However, the organization of the hippocampal place cell system is not topographic, therefore the metrical information, which is clearly present in the grid cell system, is lost in this way. For this reason, computational models dealing with the role of the hippocampal system in navigation of mammals attributed a limited role to place cells, where learned connections between them store only the topology of the environment, but do not or minimally provide information on metrical relations (Foster, Morris, & Dayan, 2000; Trullier & Meyer, 2000). This topological representation is able to support such a spatial navigation strategy, where a movement direction is associated to a given place during learning, however, this strategy can not account for many higher order navigation strategies, such as shortcut or detour finding in unknown areas. The ability of shortcut and detour finding is common among mammals and generally requires information...
about metric relations, distances and directions of the significant places in an environment (Trullier, Wiener, Berthoz, & Meyer, 1997).

We propose that distance information, necessary to perform these navigation tasks, is extracted from the entorhinal cortical grid cell system and distance information is stored in the populational firing activity of hypothesized distance cells that are innervated by grid cells. According to the architecture of our model, the hypothesized distance cells have to be located in the EC or downstream towards the CA3 region. As grid cells in the EC layer II project directly to the dentate gyrus of the hippocampus, we propose that distance cells can be most likely identified with the principal cells of dentate gyrus, the granule cells. In accordance with this, experimental findings support the view that the second stage of metric generation is related to dentate gyrus. Gilbert, Kesner, and DeCoteau (1989) have developed a behavioral paradigm to study spatial pattern separation in rats: animals were trained to learn, which of two objects covered a baited food-well. The experiments revealed that lesions of the DG (but not the CA1) result in an inability of the animal to correctly separate spatially nearby locations (Gilbert, Kesner, & Lee, 2001), suggesting that the DG plays a specific role in distance determination. In another experiment (Goodrich-Hunsaker, Hunsaker, & Kesner, 2008), dorsal DG lesioned rats have been shown to spend more time exploring the non-displaced objects than the metrically displaced objects, in contrast to control rats that behave conversely (Buhot, Foreman, Poulet, & Save, 1992); this suggests that the dorsal DG is required to generate a metric representation and mediate metric memory. These observations can be explained by assuming that DG performs pattern matching (Treves & Rolls, 1994). One of the main conclusions of our modeling study is that pattern matching on the grid cell system results in a distance measure if some basic assumptions are fulfilled.

Our grid model relies on three main assumptions on the entorhino-hippocampal network:

First, it assumes, that grid cells with different spatial frequencies projects to different postsynaptic population, i.e. granule cells and inhibitory interneurons of DG. This is in good agreement with the known anatomy of the perforant path projection, where the dorsolateral-to-ventromedial axis of the medial entorhinal cortex corresponds to the dorsal-to-ventral axis of the hippocampus (Fyhn et al., 2004). Furthermore, it is also known, that the dorsoventral gradient in the spatial scale of the grid fields (Hafting et al., 2005) is conserved in place field sizes of hippocampal place cells (Jung, Wiener, & McNaughton, 1994). However, the entorhinal cortex-gyrus dentatus projection is probably more dispersed than assumed by the basic model, in which each granule cell and inhibitory cell is innervated by grid cells that all have the same
grid spacing (Dolorfo & Amaral, 1998). Therefore, we tested the behavior of the model assuming that a given DC and FFIN receives connections from grid cells of several similar spacings. We found that a slight increase in divergence significantly decreases the average estimation error of the model, thus, taking into account anatomically realistic projection distribution even approved the coding capabilities of the system, although at the slight expense of the size of the distance range in which the estimation works (Fig. 2D).

Second, each granule cell and interneuron is assumed to be innervated by grid cells with different orientations. In the pioneering paper of Hafting et al. (2005) grid cells recorded from the same tetrode were shown to share the same grid orientation. However, simultaneously recorded cells from noncorresponding locations in the left and right entorhinal cortices do sometimes have different grid orientations (Hafting et al., 2005), suggesting that more than one orientations are represented in one brain. In another experiment, measurements were made from several locations along the dorsoventral axis of dMEC in one hemisphere (Barry, Hayman, Burgess, & Jeffery, 2007), and grid cells were found to have similar orientations (the largest difference in orientation between any two grids was 15 degrees, 25% of the maximally possible 60 degrees). However, grid orientation might show a gradient orthogonal to the dorsoventral axis (along which the spacing values increase), in which case differently oriented grids could be found along mediolateral or rostrocaudal axes. In conclusion, in order to decide whether our second assumption holds, the spatial distribution of grid orientations in the whole MEC has to be explored.

Third, we assume, that the grid cell synapses on the dentate granule cells and interneurons are potentiated in a one-shot manner when the animal occupies a significant place, and this potentiation is proportional to the presynaptic activity. This assumption is in accordance with the facts that the amygdala, which plays an important role in emotional arousal, can modulate synaptic plasticity at perforant path – DG synapses (Nakao et al., 2004) and that the strength of the long-term potentiation (LTP) indeed depends on the activation frequency (Blaise & Bronzino, 2003). A good candidate for the natural induction of LTP is the dentate EEG spike (Bramham, 1998) which is a large population activity occurring in the DG during awake immobility and slow wave sleep and is likely to be triggered by layer II cells of the entorhinal cortex (Bragin, Jandó, Nádasdy, van Landeghem, & Buzsáki, 1995; Penttonen, Kamondi, Silk, Acsády, & Buzsáki, 1997). Interestingly, these entorhinal neurons can generate population bursts (sharp potentials) during non-theta EEG pattern in cats which are abolished after amygdala lesion (Pare, 1995). The one-shot manner of our learning rule is in accordance with the theory that the hippocampus is responsible for episodic memory processes in higher mammals, as episodic memory requires fast, one-shot learning. In contrast to many navigational models that apply slow, incremental learning in order to form spatial representation (Chavarriaga, Strüsslin, Sheynikovich, & Gerstner, 2005; Káli & Dayan, 2000; Ujfalussy, Eros, Somogyvári, & Kiss, 2008), our model does not require a thorough exploration of the environment. The applied method of one-shot-learning and continuous comparison of the stored and actual patterns can be extended to other, non-spatial modalities as well.

These three assumptions, together with the known properties of the grid cell system, are enough to establish a system in the hippocampal dentate gyrus, which is able to continuously monitor the animal’s distance from a selected, salient point. The mechanism of distance encoding is the following: The one-shot learning stores the momentary activity pattern of the grid cell system in the significant position at the synapse of grid cells on the dentate gyrus neurons. Thus, the output activity of these postsynaptic cells is proportional to the dot product of the stored and the actual activity pattern of the grid cell system, representing the similarity between the two. Considering the periodicity of the grid activity, this similarity became high whenever the animal moves an integer multiple of a grid period and low at the midpoints between them. When the animal is at a given distance from the origin, all the cells with divisor scales of the actual distance are receiving high input in this way. Since the highest among the divisors is the dividend itself, the activated distance cell with the highest scale represents the actual distance. According to experimental data (Hafting et al., 2005) the subfield diameter of a grid cell is increasing with increasing grid scale and this property is reflected in our model (Eq. (1)). As a result of this, the correlation between grid cells is increasing with the increasing scale, thus the heights of the peaks as well as the depths of the dips in the synaptic activation of dentate cells are increasing with the scale. Therefore, the most activated dentate cell has the highest scale while the scale of the least activated one is the double of it. Therefore, decoding the distance from this activity pattern can be achieved simply by selecting the dentate cell receiving either the largest (model A) or the smallest (model B) net excitation from the grid system. Identification of the activity minimum requires a transformation into activity maximum by local feed-forward inhibitory interneurons in model B. In this case, the firing pattern of these inhibitory cells in DG should also show spatial selectivity, which is in accordance with experimental findings (Kubie, Muller, & Bostock, 1990; Marshall et al., 2002; McNaughton, Bernes, & O’Keefe, 1983). In both models, the distance cell receiving the largest net excitation can be chosen by a simple mechanism, by competition among DCs realized by feedback inhibition, which leaves only the most activated cell active. This mechanism, which is widely used in computational neuroscience (Rolls & Deco, 2002), can be theoretically performed by the DG, where feed-back inhibition (Acsády & Káli, 2007) can realize a strong competition among granule cells.

This winner-take-all mechanism resulted in a multi-peaked, patchy firing activity pattern of DCs, which is in general agreement with the experimental observation that a significant portion of DG granule cells have multiple place fields in an open environment (Jung & McNaughton, 1993; Leutgeb et al., 2007). However, these fields have not been reported to have a circular arrangement yet, as would be suggested by our model. This contradiction might be resolved in the following ways. (i) The circular firing property should be observable only in experiments, in which distance measuring from specific locations is important for the animal (which is not the case in most of the experiments). An optimal experiment would be for example in which the rat has to execute navigation task in a large open environment, containing a food source at a fixed position to where the animal has to find its way from many different positions. (ii) Instead of analyzing single cell activity, the geometrical analysis of the population activity of granule cells would be optimal to reveal the hidden regularity of the distance cell firing patterns. (iii) As our model required only a relatively small number of distance cells (in the presented simulations 110 distance cell for the estimation of distance from one location), it does not exclude the possibility that most of the dentate granule cells behave as place cells, and only a small portion are distance cells.

Thus, according to our model, information on distances from specific places arises in the dentate gyrus, that projects to the CA region of the hippocampus. The question naturally arises: what is the distance information used for there? We hypothesize that distance cell activity might modulate the activity of CA3 place cells that encode the location of the animal, so that distance and position information would be associated. In this way, the distances of a position from the significant places of the environment become
a subset of those important properties that define the identity of a position. Identity of a position can be defined by means of local properties, such as local view, smell and availability of food or water etc. and by means of more global properties, such as distances or directions of important objects. All of these properties can serve the identification of a place, but can drive the animals too. In an advanced navigational system, the animal should be able to search for an actual aim based not only on its elementary needs such as hunger or thirst but also based on environmental topology or metrics. Topological search makes possible to find out those places that are available from a given location or from where the given location is available while metrical search helps to find those places that are close to or in a given distance from the referential points of the environment. Feed-forward association of these distances to positions makes possible this metrical search. An experimental finding supporting this view is that place cells can show goal dependent activity (Ainge, Tamosiušiūtė, Woerger, & Dudchenko, 2007).

Our network shares some common properties with the boundary vector cell (BVC) model of Hartley, Burgess, Lever, Cacucci, and O’Keefe (2000) and Barry et al. (2006). While the firings of BVCs mark the proximity of a boundary, activity of distance cells might be anchored to any location in the environment. Consequently, BVC fields should follow walls and thus tend to be elongated, while receptive fields of a distance cell are organized into patches on a ring around the relevant location. BVCs first were hypothesized (Barry et al., 2006; Hartley et al., 2000) and later they were found in the MEC (Solstad, Boccara, Kropff, Moser, & Moser, 2008). According to our theory, distance cells could be located either in MEC or in DG. Note that in a former model of Burgess, Recce, and O’Keefe (1994) place cell activity was based on hypothesized cells which are tuned to specific distances from two environmental cues. In our model, distance cells in DG are able to provide this type of information towards the CA regions in order to facilitate place cell formation.

In the present paper we introduced a model, which is able to keep track of the animal’s distance from one specific point. However, the proposed method could be extended easily to represent distances from more than one significant places or objects, by introducing parallel distance cell systems competing during learning. It is important to note that the number of grid cells does not have to be increased in order to represent distances from several origins. Only the number of required distance cells increases with the number of significant places, however the proposed model needs so small amount of DCs compared to the number of DG granule cells, that a vast number of DC systems (representing distances from different locations) can exist in the DG. We hypothesize that the several DC systems would be able to support many navigational systems and strategies such as self-localization and route planning.

Acknowledgement

Authors are grateful for the useful discussions held at the Budapest Computational Neuroscience Forum. The research was funded by the EU Framework 6 ICEA project (IST 027819). PE thanks the Henry Luce Foundation for general support.

References


