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Efficient episode encoding for spatial navigation

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A method for familiarity mediated encoding of episodic memories for their inferential use in spatial navigation task is proposed. The method is strongly inspired by the state-of-the-art understanding of the hippocampal functioning and especially its role in novelty detection and episodic memory formation in relation to spatial context. The model is constructed on the presumption that episodic memory formation has behavioral, as well as sensory and perceptual correlates. In addition, the findings regarding hippocampal involvement in the novelty/familiarity detection and episodic memory formation, together with the existence of a straightforward parallel between internal hippocampal and abstract spatial representations are incorporated in the model. A navigation task is used to provide an experimental setup for behavioral testing with a rat-like agent. For this purpose, a framework that connects robot navigation and episodic memory representation is suggested. The computations are adapted for a real-time application. Simulation results show encoding of episodes and their use for navigation.

Keywords: Navigation; Novelty; Place cells; Episodic memory; Robotics

1. Introduction

Behavioral studies have found a convenient testbed in robotic simulations due to the embodied nature of both living organisms and robots. There are three systems that have to be considered in making this parallel: a sensory system, an action system, and a system that connects both. The connecting system can have arbitrary complexity, ranging from simple coupling between the sensing and action to a detailed model of integrative, perceptual, memory, attentional, and motivational processes.

Many spatial navigation tasks in robotics are inspired by navigation behavior of animals. Insects' behavior have been simulated in Leerink *et al.* (1995), Lambrinos *et al.* (2000), Svennebring and Koenig (2004),

and Wehner *et al.* (1996). Insects' navigation is mainly reactive in nature, while the behavior of mammals is memory and purpose driven (McNaughton 1989, Muller *et al.* 1991, Schmajuk *et al.* 1993, Burgess *et al.* 1994, Blum and Abbott 1996, Prescott 1996, Touretzky and Redish 1996, Trullier and Meyer 1998, Balakrishnan *et al.* 1999, Foster *et al.* 2000).

We propose a model suitable for simulated or embodied behavior that facilitates inferential reuse of experienced memories. Many models in computer science and robotics exploit the characteristics of the semantic memory – memory for facts. Actually, animals and robots gather continuously information about the surrounding world through experiencing episodes of events. Higher organisms can encode such subjectively experienced episodes, so their further actions are determined to a big extension of these remembered episodes. Therefore, memory determined behavior that we model relies on the neural mechanisms

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underlying episode formation. Episodic information encoding is inspired by the hippocampal modeling and with this respect our work is most closely related to Burgess *et al.* (1994), Foster *et al.* (2000), Touretzky and Redish (1996), Trullier and Meyer (1998).

We understand episodic memory as including event information within its temporal relatedness and directionality, as modeled in theoretical studies. To confine the theoretical neural modeling studies with the behavioral setup, we argue that episodic memory copes naturally with the sensory, perceptual, and behavioral character of learning of an embodied agent. The memory has to be flexible in both: encoding and retrieval. Flexibility, as opposed to exact storage, puts forward the need to selectively store the incoming perceptual information, judging what is new, or what is very similar to an experienced one. The criterion of familiarity determines the behavioral choice in the retrieval phase.

Discrimination of novelty and familiarity is therefore a central aspect of this work. Novelty is a known factor that gates learning in natural and artificial systems (Marsland 2003). The relation between novelty and behavior has received much attention by experimental neuroscientists (Knight and Nakada 1998, Bevins and Bardo 1999, Lisman and Otmakova 2001, Moses *et al.* 2002, Li *et al.* 2003, Kemp and Manahan-Vaughan 2004), but there is not enough evidence to build a good computational model. The hippocampus is a brain structure where episodic and perceptual information come together, and where environmental novelty is signaled. Therefore we develop a novelty method that is inspired from hippocampal functioning and we optimize it for robotics implementation. Novelty detection is related to experienced episodes rather than a novel place in the environment, as in other robotic studies (Pfeifer and Scheier 1999, Barakova and Zimmer 2000).

The base for this model is the hippocampal functioning, since the hippocampus can effectively perform the following functions in parallel: episodic memory encoding, and novelty judgment, in relation to spatial behavior.

The paper is organized as follows: in section 2 the hippocampal paradigm and the robotics task are confined in an unified framework. The computational model, following the proposed framework, is developed in section 3. Section 4 shows the episode encoding for memory-based navigation. A discussion of the state and the perspectives of this research is made in section 5.

2. Confinement of the robotics formalism and the hippocampal paradigm

Sensed information, together with the memory experiences, goals, and anticipations, form perception in the
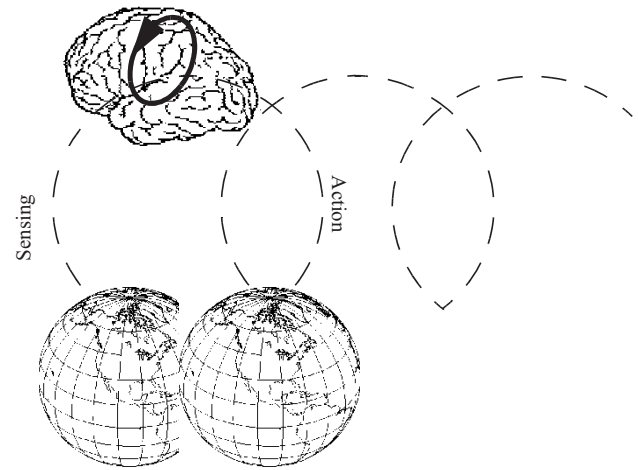
Perception/Behavior

Figure 1. Spiral model of organism–environment interaction.

brain which in turn determines the behavior of the animal (Pfeifer and Scheier 1999, Barakova and Lourens 2002). The expression of the behavior is a concrete action. This relation can be expressed as a cycle with two connecting points: the organism and the environment.

The organism gets sensory information from the environment, and acts upon it. The world changes continuously, so every other action is applied on an ever changing environment. The new sensation forms a perception in the changed mind, since the preceding percept might have changed the expectations, the understanding, the certainty of the mental representation etc., i.e. the brain has changed as well. Therefore, the interplay between perception and behavior connects two changing systems: the mind and the environment. If expressed graphically, this interplay can be represented by a spiral, as shown in figure 1. Since the difference between two perceptions is usually small, it is easy to reuse the old model of the world by only distinguishing what has changed, i.e. the novel part.

In addition to the external perception–action loop, that connects the organism and the environment, an internal loop associates the current environmental stimuli with the encoded memories (figure 1). One possible intersection point of the past and present of the two systems – the one that stays for the interaction between the organism and the environment and the other that is responsible for the changes within the organisms' brain – is to be found in the episodic memory.

Brain studies have shown that the hippocampus, area CA3 in particular, is primarily involved in episodic memory encoding (Bunsey and Eichenbaum 1996). Experimental evidence has also shown that pyramidal

cells in area CA1 code for spatial location in terms of environmental queues and memorized episodes. Others have shown an experience dependent expansion and shift in center of mass, relative to behavioral trajectory (McNaughton 1989), as well as finely-tuned responses to novel/familiar stimuli (Li *et al.* 2003, Moses *et al.* 2002).

The EC II and III are the areas, where spatial location signaling has closest relation to the sensory representation. The sensory-bound pattern is further transferred through the direct and the indirect pathways from the enthorinal cortex to CA1. During the indirect path the representation, comes from EC and projects to DG (not shown in figure 1) and CA3 area, where orthogonalization and episodic memory encoding take place. The direct pathway carries projections from EC to CA1, where no substantial processing takes place. Jensen and Lisman (1996), O'Reilly and McClelland (1994), and Vinogradova (2001) provide indirect evidence that the CA1 may have a comparative function in processing information that comes through these pathways.

Our hypothesis is based on the evidence that sensory, behavioral, and episodic memory information come together to form a representation in CA1 area of the mammal hippocampus. In addition, it is tuned by a behavioral feedback. This representation determines the future behavior, and indicates novelty. It would therefore determine what needs to be remembered and what can be forgotten.

Based on this hypothesis, we define the computational scheme as shown in figure 2. The scheme aims to confine the hippocampal functioning with the robotics formalism, therefore the model is not neurophysiologically precise. The modeled areas are denoted as superficial EC, CA1, CA3 to indicate this imprecision. This scheme accentuates on the superficial CA1 (SCA1) area. The representation in SCA1 is formed under the influence of the sensory-bound representation from the superficial EC (SEC) area and the formed episodic memories on the basis of recent sensory history in the superficial CA3 (SCA3) area. The information from the learned episode from SCA3 and the sensory-bound information coming directly from SEC forms the pattern that controls the upcoming behavior. At the same time the interplay between the patterns in SCA1 and SCA3 signals for novelty. This signaling indicates whether encoding has to take place, or the episode is familiar already. Subsequently, during recall, the perforant path input initially has a stronger influence on activity in SCA1. However, for familiar stimuli, the pattern of the activity arriving from region SCA3 via the Schaffer collaterals will dominate within region SCA1, allowing output from region SCA3 to drive neurons which had previously been associated with the particular activity pattern in region SCA3.
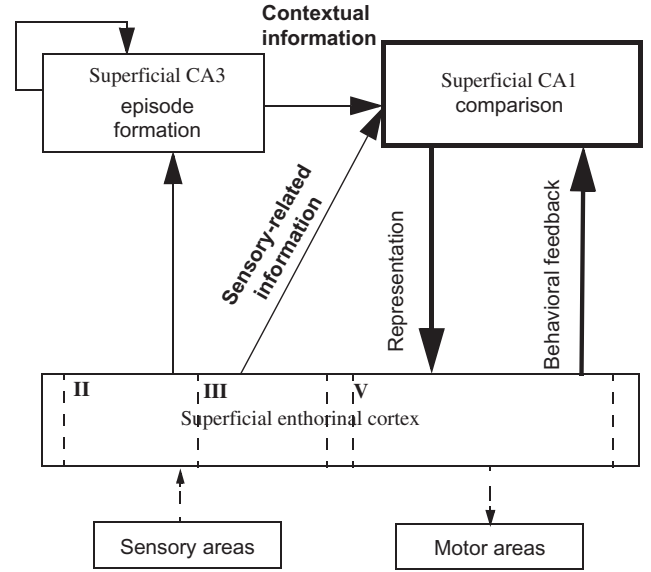

Figure 2. Computational scheme based on the assumed functionality of the hippocampal formation. CA1–3 denote resemblance with areas 1–3 of cornu ammonis within the hippocampus. The scheme accentuates on the comparative role of the CA1 area. The sensory bound and episodic memory related representations are projected to CA1 area, where novelty/familiarity are signaled. The areas are denoted as superficial CA1, CA3 or EC to indicate that modeling may not be biologically precise.

We formalize the functioning for the purposes of a robotics task by assuming that the representation D in SCA1 evolves under the action of sensor input, memory (for episodes), and behavior, denoted by S, E, and B, respectively.

$$\frac{dD}{dt} = f(S + E + B) - \alpha I, \tag{1}$$

where f denotes a functional dependence, and αI is a self-inhibitory term. For a robotic framework it is feasible to consider discrete processing. Therefore, formally D is a set of n discrete events d, defined by a considerable difference in the event representations. A single event d, that is expressed by a specific firing pattern in SCA1 area is defined by s, e, and b. In formula

$$d = \{s, e, b\} \tag{2}$$

where the sensory component s introduces the current influence from the external world and constitutes by feedforward connections. The episodic memory component e represents the temporal impact of the sensory patterns, and is constituted by the lateral connections. The behavioral component b represents the influence that the previous action has caused on the current event.

All three components are multidimensional vectors. A novel event is determined by a change in at least one component, that is bigger than an *a priori* known internal threshold.

The memory component consists of encoded episodes of events (memory with a temporal reference) E as formed in SCA3. E is a set of n discrete events occurring in a temporal order e_t, $t \in [1, \ldots, n]$, defined by a considerable difference in the event representations:

$$E = \{e_t\}, \quad \text{where } t \in [1, \ldots, n]. \tag{3}$$

Learning of an episode means that associations can rapidly be formed among items presented in temporal proximity. This is especially valid for events, or routes, where the temporal order is of importance. Therefore by episode learning the order or the temporal association has appeared important rather than or along with another common feature, and this has influenced the encoding. So, the events that have been learned as an episode will tend to be recalled together and after each other, even if presentation order is changed. In addition, the following two dependencies between the temporally related connections are important: contiguity and asymmetry. Contiguity means that stronger associations are formed between stimuli that occur near each other in time than between those that are separated by a larger interval. Asymmetry determines that the forward associations are stronger than backward associations.

Figure 2 outlines the entire computational flow for encoding within the behavioral setup. It briefly introduces the sensory and motor areas connecting the memory system, restricted to the hippocampus. There are feedforward and feedback/recurrent information flow. In feedforward track, the environmental sensory information is gathered and transferred to the hippocampus and through its direct and indirect pathways to CA1; the episodic memory system encodes history of sensory information, before projecting to CA1; the navigation system, associated with the motor/behavioral functionality uses the combined representation in CA1. The feedback behavioral influence has its impact on the internal hippocampal representation. The feedback coupling is also present in the temporal processing for episode formation.

3. Computational model

It is widely known that particular cells in the rat hippocampus fire when the rat is at a particular location of the environment (O'Keefe and Nadel 1978). Because of this feature, these cells are also called place cells. If the rat moves through the environment, at every particular place a number of place cells fire. Cells that code for places in the nearest vicinity fire most strongly, while the cells that code for a more distant location fire less. The activity of the place cell can be modeled by a Gaussian formula for the open environments, where place cells show non-directional firing. Therefore, the movement of a simulated rat at every place of the environment is characterized by a particular pattern of firing. The activity of each cell, which corresponds to the sensory representation of a single event, is as follows:

$$s_{i,t}(r) = -\frac{\|r - c_i\|}{\exp(2\sigma^2)} \tag{4}$$

where c_i is the location in the space of the center of the cell's i-th place field, r is the position of the simulated rat, and σ represents the width of the place field.

The sensory signals are encoded into constellations of the active place cells. The unique pattern of activity corresponds to a certain position r in the environment. The level of activity of every place cell depends on the distance between the rat position and the place field centers. For the purpose of real-time processing we have taken the smallest convex contour of the place cell representation. Figure 3 shows two activation patterns from the rat route. They represent patterns of activation in the simulated EC area. These patterns are dependant on the external-world and are further transmitted through the direct and the indirect pathways.

This model follows the information flow as suggested in the scheme of figure 2. In a previous study we have used a biologically plausible learning rule that accomplishes the computations between and within the areas EC, CA1 and CA3, as shown in figure 4. The activity of EC area is projected to areas CA1 and CA3 after Hebbian adaptation on fan-out connections, shown in figure 4(a). The activation affects also the inhibitory neurons within CA1 and CA3 lattices. The inhibitory neurons in turn affect the rest of the lateral neurons, as shown in figure 4(b). Lateral excitatory connections and the temporal learning mechanism promote the episode formation in area CA3, shown in figure 4(c). The representations in CA1 and CA3 areas that are caused by the feedforward projections from EC differ considerably because of the different connectivity between areas EC and CA3 and areas EC and CA1. While the connections between areas EC and CA3 are assumed to be predominantly topological fann-out with a small spread, the EC is fully connected to CA1.

To adapt the computations for a robotics task, several simplifications of the biologically plausible learning process are made. The topology preserving learning between the EC and CA3 layer does not have substantial contribution to that formed in CA3 representation so
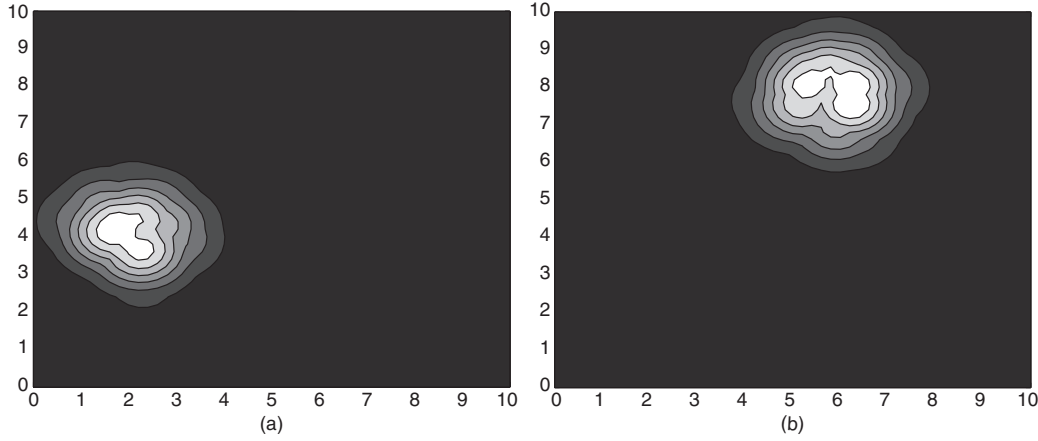
Figure 3. Samples of sensory patterns, as represented in CA1 area. They denote a unique position pattern of activity relation in 2D space.
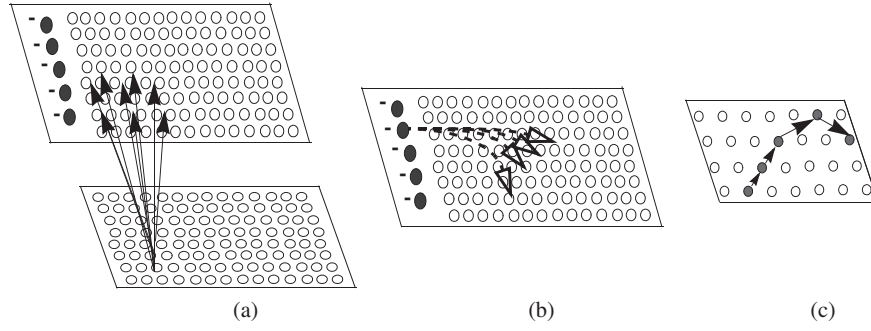

Figure 4. Stages of the biological learning process. (a) Afferent excitation. (b) Lateral inhibition. (c) Episode formation.

that it can influence the robot performance. In contrast, the self-organizing process between EC and CA1, and the temporal association learning within the CA3 layer are essential.

Therefore, the learning process ignores the plasticity of EC to CA3 connections. The lateral connections within area CA3 are of primary importance for the learning process, since they provide the intrinsic capacity for temporal association. This quality is obtained by applying a Hebbian rule with an asymmetric time window over the neurons within the CA3 lattice, where the lateral connections are present.

The asymmetric time window has been simulated to correspond to the experimental measurements as given by Zhang *et al.* (1998), Markram *et al.* (1997). The lateral excitatory learning rule is adapted from the initially proposed by Dayan and Abbott (2001), so that it fits to the practical constraints of the asymmetric time window function.

$$\Delta w_t = \sum_{\tau=0}^{bound} ATW(\tau)v(t)u(t-\tau) + ATW(-\tau)v(t-\tau)u(t)$$

(5)

where ATW is the asymmetrical time window function (figure 5), v and u are correspondingly the post, and presynaptic lateral neurons, and *bound* is the time window size. The first term under the sum can be explained as long-term potentiation. The second term causes long-term depression and is therefore equivalent to the effect of the inhibitory connections in the network.

The representation in the superficial CA1 area is dependant on the afferent connectivity. A biologically plausible learning rule between the layers, however, is replaced by an algorithm that includes competitive Hebbian learning and vector quantization (Bunsey and Eichenbaum 1996, Lambrinos *et al.* 2000). The interchangeability of the two algorithms is justified by the following experiment. The evolution of the network outputs for both algorithms was examined. The plots of the output evolution in time are shown in figure 6.

In summary, a modified Hebbian learning mechanism with 20% projections between the EC-CA3 layers and inhibitory connections promotes topological self-organization. The EC-CA1 full connectivity promotes a different learning outcome – the topological projections are lost, and self-organization takes place.
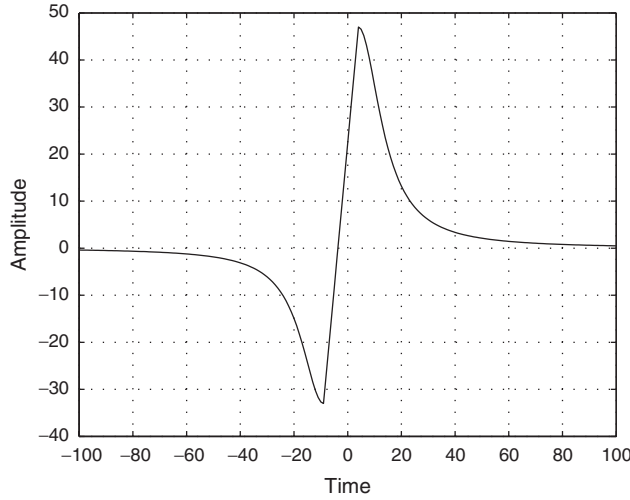
Figure 5. Asymmetrical time window function based on experimental studies.

The result of this learning process corresponds to the episodic contribution e of the proposed event definition given in equation (2).

The actor–critic model of O'Reilly and McClelland (1994) most closely resembles the behavioral part of the organism–environment interaction. At any moment t, the embodied animate is able to choose an action on the environment, as well as environment provides it with feedback. In the case considered here, the simulated animate† can choose from 8 possible actions, the directions of movement on an 8-connected discrete grid. For a robot, in practice, they are restricted to 3, since the robot will rarely take turns bigger than or equal to 90°. The critic is the feedback influence, that reaches area CA1 in this model. The actor–critic mechanism regards the actions of the animate that are directed to finding a particular goal.

The familiarity gating is entirely performed in the feed-forward track and is considered purely as a function of the hippocampal formation. The goal oriented behavior will be used only for illustration of the animate behavior, and not to optimize its performance. The mechanism of actor–critic optimization, based on place cells representation is suggested in Foster $et\ al.$ (2000).

A mechanism of actor–critic optimization, based on place cells representation is suggested in Foster $et\ al.$ (2000). It refers to place cells formation in CA3 area.

Critic b indicates the behavioral feedback

$$b(r_{CA1}) = \sum_i w_i f_i(r_{CA1}) \qquad (6)$$

where r is the animate's position, w_i is the weight between the output cell and the i-th place cell as formed in area CA1. The critic learns the value function by updating the weights (of the critic) by

$$\delta(t) = R(t+1) + \Upsilon b(r(t+1)) - b(r(t)). \qquad (7)$$

This reduces the prediction error, that drives learning. Constant Υ denotes a discounting factor and R is the reward at time $t+1$.

At the experiments shown below, the actor makes use of 8 action cells $a_j, j \in [1, \ldots, 8]$. At position r, the activity of the each action cell is:

$$a_j(r) = \sum_i v_{ji} f_i(r_{CA1}) \qquad (8)$$

where a_j is the j-th action cell, and v is the adaptive weight between the action cell and the i-th place cell. The first step for the movement direction is taken randomly with a probability, P_j. However, the next movement direction is chosen in a random way, but the possibilities are restricted according to the choices made in the previous movements $P_j(t-1)$ and $P_j(t-2)$, so there is not a random walk-like trajectory, but smoother orbits with eventual sudden turns.

The actor weights are adapted according to:

$$\Delta v_{ij} \propto \delta_t f_i(r_t) g_j(t) \qquad (9)$$

where $g_j(x) = 1$ if action j was chosen at preferred time $t = t_p$, and 0 otherwise.

Once a learned episode has been encountered, the animate follows the episode instead to continue optimizing its path on the basis of experienced rewards.

4. Results

The experimental setup that shows the applicability of the proposed episode encoding method for spatial navigation is set on a two-dimensional (2D) environment. Some target positions are set that can be reached by the robot. The robot is positioned at random places in the environment. The path of the robot from random initial position to a goal position is defined

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†An animate is defined as a simulated animal, a rat in our case.
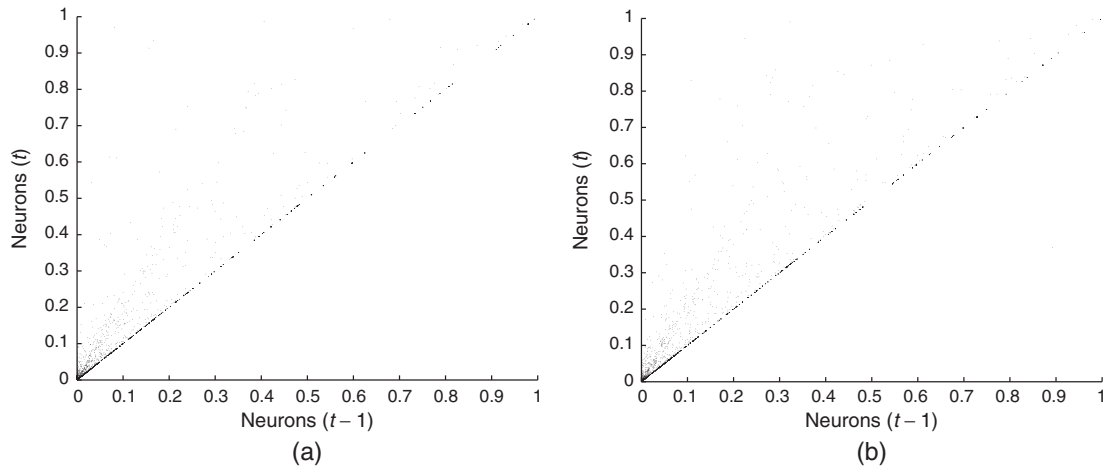
Figure 6.   Temporal evolution of the weights. (a) Biologically plausible algorithm. (b) Computationally efficient learning algorithm.
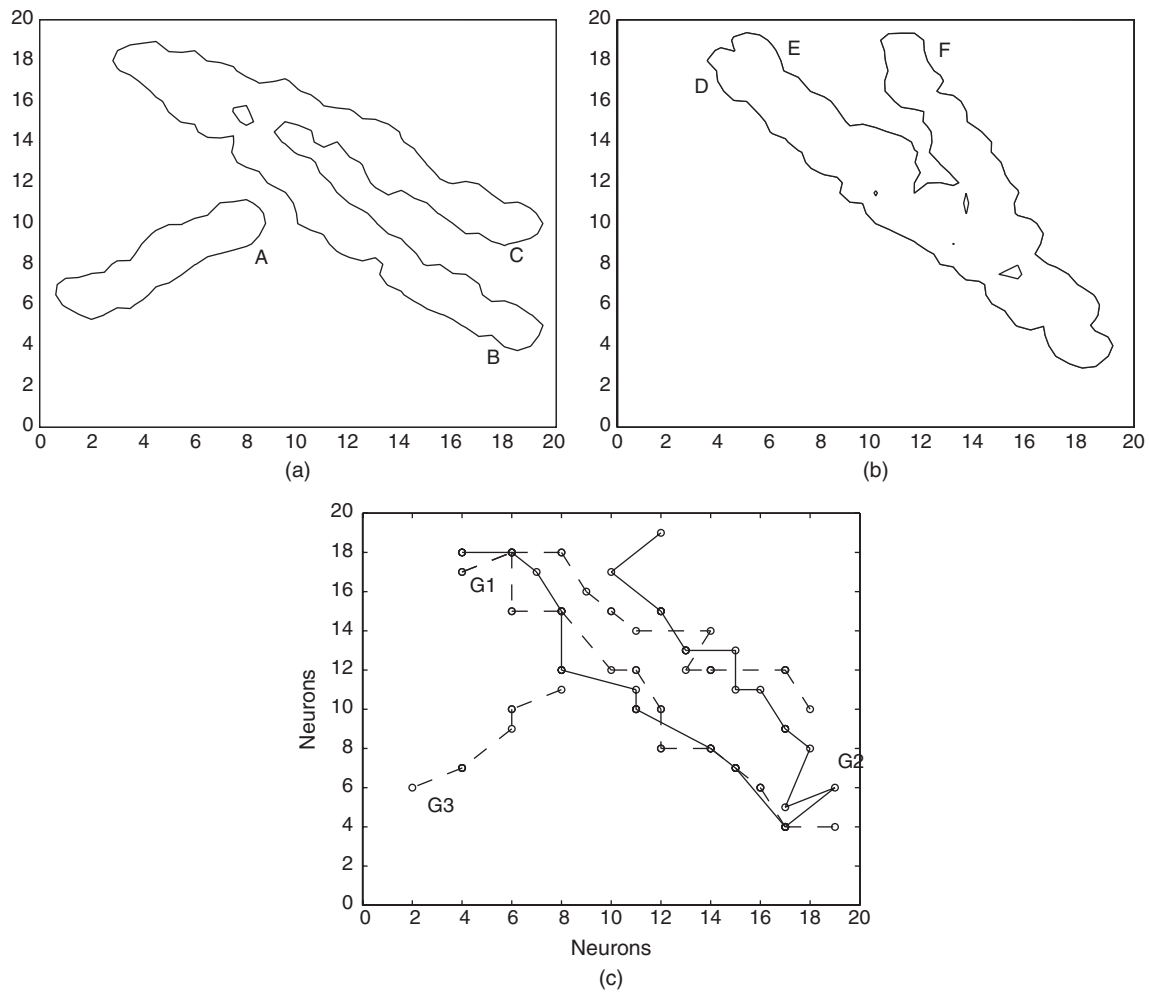

Figure 7.   Representation and encoding of episodes. (a) Three experienced episodes denoted by A, B, and C that reach two different goal locations. (b) Three experienced episodes (D, E, F) that reach a single goal location. (c) The encoded episodes, after presentation of all the experienced episodes, as shown in (a) and (b). The dashed lines show the encoded episodes that reach goals G1 and G3. The episodes D and E are perceived as the same episode, therefore only one of them is encoded. Experienced episodes B and D are composed by very similar locations, but they are experienced in an opposite order. Therefore, both episodes are encoded.

as an episode. The encoding of an episode depends on its familiarity. Episodes, that are considered as familiar are not encoded again. Figure 7 depicts several peculiarities of the episode learning method. Figure 7(a) shows episodes that reach two different goal locations, G1 and G3. Figure 7(b) depicts three episodes that reach a third location – G2. Since two of the experienced episodes on this plot are very similar as perceived by the algorithm, they are encoded as a single episode (figure 7c). Figure 7(c) shows the final encoding, after all these episodes have been presented to the network. The dashed line gives the episodes that reach goal G1 and goal G3. The solid line shows the encoding of the episodes, that reached goal position G2. Episode E is considered familiar, after episode D was learned. Episode B (from figure 7a) and episode D from figure 7(b) are very similar by encoding (this is not obvious in the particular learning trial). However, since the two episodes are encoded from a different direction, both episodes are encoded. From a temporal point of view this is obvious, although one could argue that the spatial order of the encoding is reversed only.

5. Discussion

This study aims to show the relevance of novelty/familiarity discrimination method for robotics exploration. The algorithm is based on the parallel between animal and robot exploration that was inspired by the operation of the rat hippocampus on a very coarse level. The embodied nature of an animal and robot makes this parallel useful, and the functional efficiency of the hippocampal encoding, while performing both tasks — episodic encoding and novelty detection — suggests an optimal computational scheme. The model is not biologically precise, but might be attractive from the perspective of functional behavior.

The impact of novelty is two-fold: it allows an efficient encoding in the exploration phase and it is a basis for flexible reuse of memories in the recall (exploitation) phase. The same computational paradigm is used in both cases, which makes it suitable for on-line applications. The obtained results show the applicability of the novelty-mediated memory encoding method for spatial navigation. The behavior and the underlying episodic encoding and retrieval process are analyzed together, so that the remembering of episodes provides contextual background for the behavior.

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