FAMILIARITY GATED LEARNING FOR INFERENTIAL USE OF EPISODIC MEMORIES IN NOVEL SITUATIONS - A ROBOT SIMULATION

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ABSTRACT

This paper presents a method for familiarity gated encoding of episodic memories for the purpose of their inferential use in a spatial navigation task. 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. A navigation task is used to provide an experimental setup for behavioral testing with a rat-like agent. The model is build on three presumptions: First that episodic memory formation has behavioral, as well as sensory and perceptual correlates; second, hippocampal involvement in the novelty/familiarity detection and episodic memory formation, experimentally supported by neurobiological experiments; and third, that a straightforward parallel exists between internal hippocampal and abstract spatial representations. Some simulation results are shown to support the reasoning and reveal the methods applicability for practically oriented behavioral simulation.

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 last 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.

Most of the models of biologically inspired robotic systems are build by simulating insect-like behaviors, for a review see [14]. The simulations following the functionality of the mammalian brain, that include memory or motivational features are seldom implemented on a robot without a severe simplifications. The theoretical models of the hippocampus and basal ganglia, however, suggest neural solutions that incorporate those features, and produce results on a behavioral scale, often not in the range of the computational expense, affordable for a realistic robotics task [1][4][5].

The objective of this paper is to propose a model suitable for simulated or embodied behavior, that facilitates inferential reuse of experienced memories. Therefore, internal memory is a necessary feature of the proposed model. In addition, the model has to satisfy requirements coming from the behavioral setup as well as requirements that concern memory reuse.

An animat continuously gathers information about the surrounding world through experiencing sequences of events. Higher organisms can encode such subjectively experienced episodes, so their further actions are determined to a big extend of these remembered episodes. Episodic memory formation is generally associated with the encoding in the hippocampus. Many models in computer science and robotics exploit the characteristics of the semantic memory - memory for facts; Actually, memory for events and their relatedness is the way higher organisms build their knowledge. Moreover, episodic memory copes naturally with the sensory, perceptual and behavioral character of learning of an embodied agent.

In addition, the memory has to be flexible in both encoding and retrieval. Flexibility, as opposite to exact storage puts forward the need to selectively store the incoming perceptual information, judging which is new, or very similar to the experienced one. The criteria of familiarity will determine the behavioral

choice in the retrieval phase.

The so narrowed scope puts forward memory based behavior, which includes recall of past events, distinguishment of what is novel at present, in order to perform selective encoding, and familiarity detection to facilitate the ability to infer appropriate behavior in a novel environment or for performing a novel task.

Therefore, discrimination of novelty and familiarity is another central aspect of this work. Novelty is a known factor that gates learning in natural and artificial systems [6][11][12][17]. The requirements of embodiment dictate that novelty has to be considered in relation to behavior.

The relation between novelty and behavior has received much attention by experimental neuroscientists[6][11][12]. The mammals, who are able to form episodic memories, and especially humans can remember some information for the whole life span. This fact suggests, that the episodic memory encoding is an efficient process, suitable for one-trial learning. It is generally related to the hippocampus - a brain structure developed in mammals.

The base for this model is the hippocampal functioning, since the hippocampus can effectively perform both functions together: episodic memory encoding, and novelty judgement, while, for instance, the organism is involved in spatial behavior task. Such model, adapted for a robotics task, has the potential to go beyond the state of the art robotic applications since it intrinsically accounts for the following aspects.

- 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. (The episodic memory encoding is the basis for the emergence of behaviors.)
- Navigation based to a great extend on encoded episodes, needs a criteria to guide the encoding and retrieval of the episodes and gate the emergent navigational behaviors. Familiarity is a natural criteria that gates learning in biological systems, and is related to the hippocampal functioning, along with episodic memory formation.
- Extensive modeling has created a consistent computational framework that connects the internal hippocampal and spatial representations. Keeping the skeleton and the physiological meaning we simplify the computations and extend to a relation between hippocampal, spatial and behavioral representation, mediated by familiarity.

This paper is organized as follows: In Section I a hypothesis of how the novelty function of the hippocampus is accomplished and proposes a computational scheme accordingly. In Section II global framework is constructed that makes a parallel between robot's and hippocampal encoding; The framework and the scheme from the last two chapters is bridged to the computations, derived by theoretical findings in Section III to lay a ground for further modelling. The initial results are shown in Section IV. Section V offers a discussion of the state and the perspectives of this research.
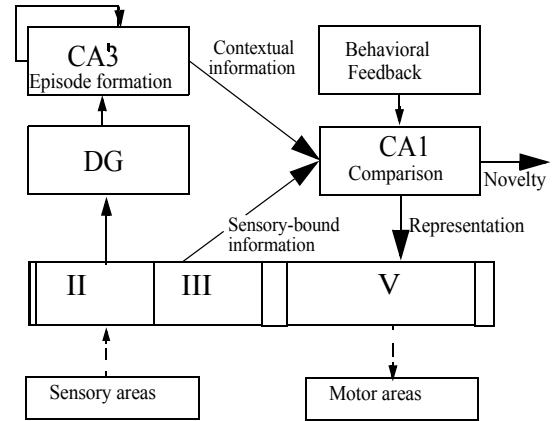

Figure 1. Working scheme, accentuating on the CA1 area. The sensory bound and memory representations are projected to CA1, also affected by the behavioral feedback.

I. HYPOTHESIS

It is widely known that the hippocampus encodes episodic memories [7]. The CA1 area, to which projections of sensory-bound stimuli come together with formed episodes of recent memories is an area of interest [13][20][27]. Recent analysis of the data from rat experiments [27] has shown the bi-modal structure of the theta rhythm, a brain rhythm which appears when exploratory behavior takes place. A possible reason for bimodality might be the different nature of information that comes at the same time to CA1 area - sensory and episodic, and the different time it needs to be projected to this area. Other studies suggest, the function of CA1 as a comparator [13][20]. There are slight variations of how exactly the comparison takes place, but in general they agree in the following mechanism:

The same sensory-bound pattern is transferred trough the direct and the indirect pathway from the Enthorinal cortex to CA1 area (Figure 1). During the indirect path the pattern passes DG and CA3 areas, where orthogonalization, and episodic memory encoding take place.

Our hypothesis is based on the evidences, that the CA1 area of the mammal hippocampus is one possible place where sensory and memory-related information comes together to form a representation. This representation, we hypothesize, determines the future behavior, and indicates the familiarity/novelty of the upcoming information. It therefore determines what has to be remembered or forgotten.

Based on this hypothesis, we define the computational scheme as shown in Figure 1. This scheme accentuates the CA1 area. The representation in CA1 is formed under the influence of the sensory- bound representation from EC area and the formed episodic memories on the basis of recent sensory history in CA3. The information from the learned episode from CA3 and the sensory-bound information coming directly from EC

forms the pattern that controls the upcoming behavior. At the same time the interplay between the patterns in CA1 and CA3 signals for novelty. This signaling indicates wether 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 CA1. However, for familiar stimuli, the pattern of the activity arriving from region CA3 via the Schaffer collaterals will dominate within region CA1, allowing output from region CA3 to drive neurons which had previously been associated with the particular activity pattern in region CA3.

Figure 1 outlines the entire computational flow for encoding within the behavioral setup of a simulated rat. It briefly introduces the sensory, motor areas and the connecting 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 trough 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. The sensory and behavioral part will not be further discussed in this paper.

Several studies have established the opinion, that the parahippocampal area is responsible for novelty detection and management, while the hippocampus is involved in encoding relational memory. Recently a series of new experimental and neuroimiging studies [15][22][23] [26][28] confirmed that the hippocampal formation contributes similarly to declarative memory tasks that require relational or familiarity processing. This confirms the plausibility of the proposed schematic representation.

III. EPISODIC MEMORY AND ROBOTICS FORMALISM

This paper features the familiarity based encoding mechanism as a part of a robotic simulation. Only those robotics related features that have relation to novelty and familiarity encounter will be discussed in the current paper. Approaching the novelty and familiarity discrimination problem from the perspective of an embodied agent implies that the information, that has to be judged for novel or familiar is derived by the experienced episodes of events.

The term "episodic memory" is used differently by the researchers. In definition, given in [8], which extends the widely accepted definition of Tulving [25], the episodic memory has event specific, sensory-perceptual details of recent experiences that lasted for comparatively short periods of time (minutes to hours).

To make this definitions more transparent for the purposes of our model, lets clarify that perception includes sensing, as well as memory, anticipation, behavioral goals, etc. [2]. Further in this text sensing and perception will be distinguished, so that sensing implies the external (sensory-bound) patterns, while the perception is the combined representation, formed by the sensory, memory and eventually top-down behavioral or attentional influence.

Basing our reasoning on the idea that the organism - environmental interaction is a continuous and inseparable process [2][21], we argue, that episodic memory has also behavioral correlates:

- There is not a clear separation between action and perception [2][21]. Every sensory-perceptual event causes behavior, which in turn either changes the environment or reflects the changes that occurred independently of its action;
- Episodic memory is formed during specific experienced sequence of events, and every event consists of sensing, binding the sensed information into a coherent perception, acting accordingly;
  - Episodic memory formation takes short time slices, possibly determined by changes in goal-processing. Goal and action processing are tightly related.
  - Episodic encoding consists of organizing abstract knowledge defined by the goals active during experience.

The encoding of episodes takes place in CA3 area, while the representation, that guides the goal-oriented behavior is formed in CA1 area. The overall processing, naturally includes the contextual temporal information and accounts for novelty, and efficient encoding.

The computational approach that has been taken in this work requires a formalization of the episodic memory task. Let us assume that an episode E evolves under the action of the following competing influences: sensory s, perceptual p and behavioral a.

$$\frac{dE}{dt} = f(s + p + a) - \alpha E \qquad (1)$$

where f denotes a functional dependence, and αE is a self inhibitory term.

For a robotic framework it is feasible to consider discrete processing. Therefore an episode E is a set of n discrete events occurring in a temporal order e_t, $(t \in [1,...,n])$ defined by a considerable difference in the event representations.

$$E = \{e_t\}, t \in [1,...n] \qquad (2)$$

A single event e is defined by s, p and a,

$$e = \{s, p, a\} \qquad (3)$$

where the sensory component s introduces the influence from the external world and constitutes by feedforward connections; perceptual component p represents the internal influences, and is performed by the lateral connections; the behavioral component a represents the influence, that the previous action has brought on the current event. All three components can be multidimensional vectors. The change from one to another

event requires a change in at least one component, that is bigger than an internal threshold, indicating the detection of a novel event.

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.

IV. BIOLOGICAL LEARNING

This model follows the information flow as suggested in the scheme of Figure 1. It is widely known that particular cells in the rat hippocampus fire when the rat is at particular location of the environment [19]. Because of that feature, this cells are called also place cells. If the rat moves trough the environment, at every particular place a number of place cells fire. Cells that code for places in nearest vicinity fire most strongly, while the cells that code for more distant location fire less. The activity of the place cell firing can be modelled by a Gaussian 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, containing of the active place cells in vicinity of the animate. The activity of each cell can be represented in the following way:

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

where c_i is the location in the space of the center of the cell i 's place field, r is the position of the simulated rat, and σ represents the width of the place field. s corresponds to the sensory representation within a single event, eq. (3).

The sensory as well as behavioral signals are encoded into a 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 fields centers. Figure 2 shows two single 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 pathway.
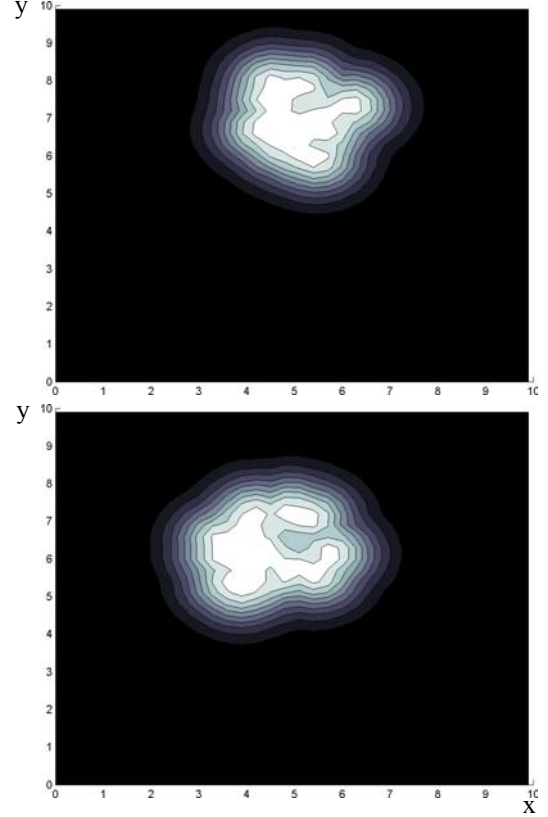

Figure 2. Samples of sensory patterns, as represented in CA1 area. They denote a unique position-pattern_of_activity relation in 2D space.

The same patterns are also projected to CA3 area and therefore take also the itinerary of the indirect pathway. We assume the same hebbian learning rule between EC and CA1 as well as between EC and CA3. (Eq. (5)).

$$\Delta w_{ij}^{CA-EC} = \alpha_1 g(EC_i CA_j - w_{ij}^{CA-EC} CA^2_j) \tag{5}$$

where α_1 is learning rate, notation $CA\text{-}EC$ shows the starting and destination layer of the connection (coming from EC, reaching CA layer) the indices i and j denote neurons on the input and output layer, correspondingly. The CA layer is not denoted as CA1 or CA3, because the learning rule is used for EC-CA1 as well as EC-CA3 learning. The term $-w_{ij}^{CA-EC} CA^2_j$ of Eq. (5) is needed due to internal instability of the Hebbian rule.

In EC-CA3 area the predominant are the topological connections - the simulation is done as the neurons from the first (EC) layer project to a topologically correspondent area, in a way that every input neuron is connected to 20% of the output neurons. Differently, the learning between EC and CA1 area is done on the self-organizing principle, since the connectivity between those two layers is full. The lateral inhibition connections, denoted as LI (Eq.(6)), have a sharpening effect on the transmitted to the CA areas activations.

$$\Delta w_j^{LI-CA} = \alpha_2 g(L\dot{I} \cdot CA_j - \alpha_3 w_j^{LI-CA} CA_j^2) \qquad (6)$$

where α_2, α_3 are learning rates, g is a gating factor,

The biological and computational plausibility of the learning process performed in Eq. (5),(6) have been shown previously in [24] where the learning parameters choices is explained in detail.

By far, the representation made within the layer denoted as CA3 has not the intrinsic capacity for temporal association. This quality is obtained by applying a hebbian rule with asymmetric time window over the neurons within the CA3 lattice, since in CA3 layer lateral connections exist between the neurons. Note, that this learning is not affected by the lateral inhibitory connections, denoted as LI in Eq. 6. It concerns the learning due to the excitatory lateral connections only. The asymmetric time window has been simulated to correspond to the experimental measurements as found by [29], see also [16]. Due to computational difficulties it has been scaled symmetrically in the interval [-1 1]. The lateral excitatory learning rule is adapted from the initially proposed by Dayan and Abbott rule [9], so that it fits to the practical constrains of the asymmetric time window function - Eq.(7).

$$\Delta w_t = \sum_{\tau = 0}^{bound} ATW(\tau)v(t)u(t-\tau) + ATW(-\tau)v(t-\tau)u(t) \qquad (7)$$

where ATW stays for the asymmetrical time window function, the one shown in Figure 3, v and u are correspondingly the post, and presynaptic lateral neurons, and *bound* is the time window size.
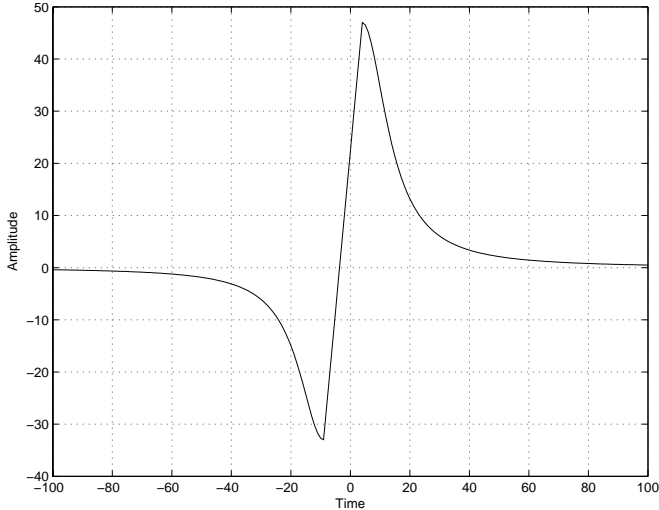

Figure 3. Asymmetrical time window function based on experimental studies.
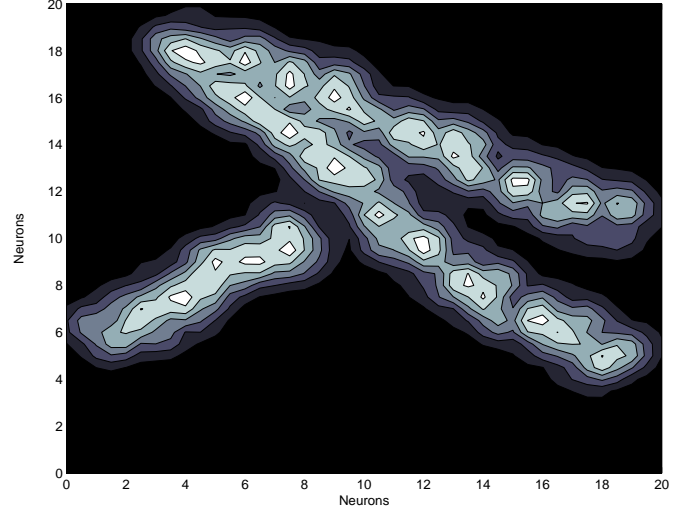

Figure 4: Episodes, formed after Hebbian learning with lateral inhibition. Every input pattern activates multiple neurons. The actual path corresponds to the neurons, activated at highest.

In summary, modified Hebbian learning mechanism with 20% projections between the EC-CA3 layers and inhibitory connections to promote topological self-organization. The EC-CA1 full connectivity promotes a different learning outcome - the topological projections are lost, the self-organization takes place.

Within CA3 layer, temporal association results in a formation of episodes. A plot of a sample learned episodes performed by the set of equations (5-7) is shown in Figure 4. The result of this learning process corresponds to the perceptual contribution p of the proposed event definition Eq. (3). Behavioral influence is represented by a neuromodulator-like gating signal:

$$\Delta a_i^{CA} = \beta g\left(\frac{CA_i}{CA^d} - 1\right) \qquad (8)$$

where β, CA_i, CA^d denote correspondingly the learning rate, current, and desired state of CA1 output. Due to the scope of this paper, this influence will not be elaborated further on.

V. Familiarity gated spatial encoding

The encoding of episodes takes place in CA3 area, while the representation, that guides the goal-oriented behavior is formed in CA1 area. We assume, that the two representations - in CA1 and in CA3 area act together for the novelty detection and behavioral choice. The CA1 representation determines the action selection and signals for novelty, while CA3 supplies it with contextual information.

The computational scheme, that illustrates the hypothesized functionality is as follows. Two simultaneously active neural networks, corresponding to CA3 and CA1 area perform the

major computations. The neurons in CA3 area account for temporal aspect and the formation of episodes, the representation in CA1 area is prone to detect novelty in the temporal context of CA3. The two representations are physically and computationaly connected.

The pattern that reaches CA1 area via the direct pathway is organized on pattern similarity, not on a topological principle. The same projected pattern from the EC area reaches areas CA1 and CA3 within a small time interval, and the connection between the currently most active neurons in these two areas is strenghtened also. This automatically activates the complete episode to which the pattern in CA3 area belongs, and therefore the contextual information from this episode is transferred to CA1 area.

For familiarity detection, the network build on the basis of the proposed computational scheme is simplified. The Hebbian learning followed by a lateral inhibition mechanism is replaced by a modification of the competitive Hebbian learning algorithm of [10][18], which makes a single neuron to represent an input pattern. Moreover, a map representation, derived by a Hebbian learning is inefficient for a practical navigation task since a vast number of place cells are required to organize a map. It is necessary to organize the map so that it becomes fine-grained at frequently visited places to coarse at rarely visited areas. This organization problem is elegantly solved by the proposed algorithm.

The connections between events within an episode are formed as an internal property of the learning process, that is a principle difference from existing models with temporal history encoding [3].

The sensory bound patterns from the direct pathway are also simplified to the smallest convex contour of the place cell representation (Figure 5).

An on-line comparison of the incoming sensory-bound patterns with those encoded into episodes takes place. To illustrate the results of the familiarity gating, two episodes with an overlap at their initial itineraries have been distinguished in the very beginning after short history of pattern presentation from the second episode. Figure 7.a shows the first encoded episode. The small circles denote the most active neuron from CA3 area by presentation of the patterns that form this episode. Figure 6.b illustrates the learning outcome after both episodes have been presented. The most active neurons are denoted with stars, so it is obvious, that the representations of both episodes does not overlap strongly. The first pattern is classified as familiar in both: the topologically organized superficial CA3 area and the organized on the pattern similarity CA1 area. However, the interepisode connections do not transfer activation patterns to the adjacent CA1 areas by the presentation of the next patterns, so the two episodes are encoded (i.e. the second episode is considered as novel).
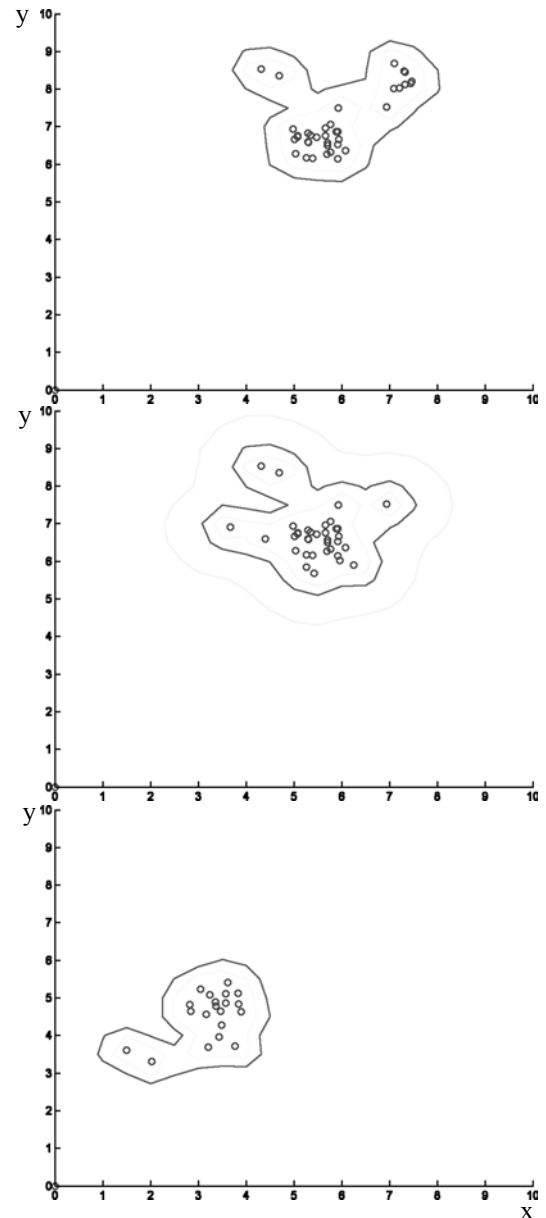

Figure 5.   Some training patterns, based on the place field activation patterns.

Figure 7 illustrates the encoding by two episodes that are closely spatially related since most of the time the topological, similarity learning, as well as contextual connections are activated, the episode is encountered as familiar and encoding does not take place.
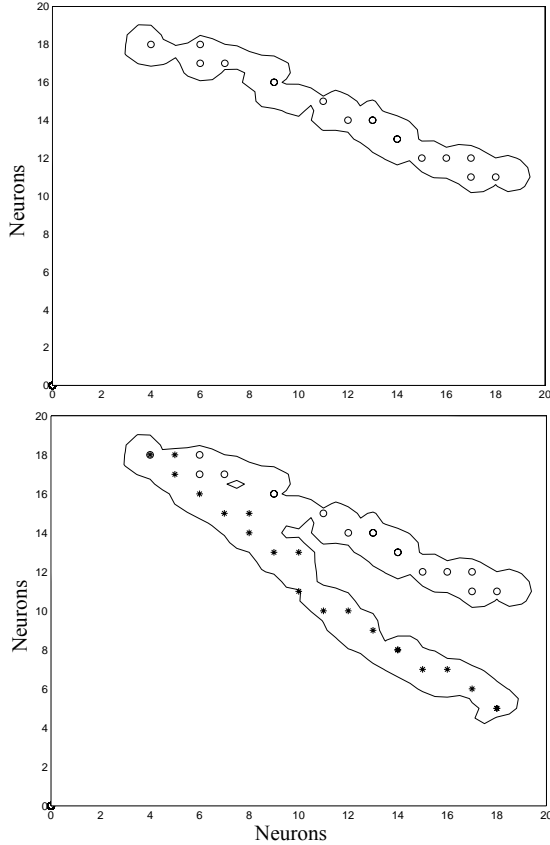
Figure 6.   Learning of two episodes with initial overlap. After the two trajectories show discrepancy, the novelty is signaled.

VI. DISCUSSION

This study aims to show the relevance of novelty/familiarity discrimination method based on the hippocampal modelling for robotics exploration. 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 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 possible on-line implementation. The paper accentuates on the methodological part and shows simulations of episodic memory encoding and novelty/familiarity detection, on which efficiency of the encoding process is based. Making the parallel between the robotics and episodic memory formalism we argue, that in addition to sensory and perceptual (memory and another internal factors related), behavioral influence contributes to episodic memory formation. The behavioral feedback, however is not a part of the simulations shown so far, and is to be described elsewhere. Novelty and familiarity principle is the only gating factor for encoding and recall at this stage of the work.
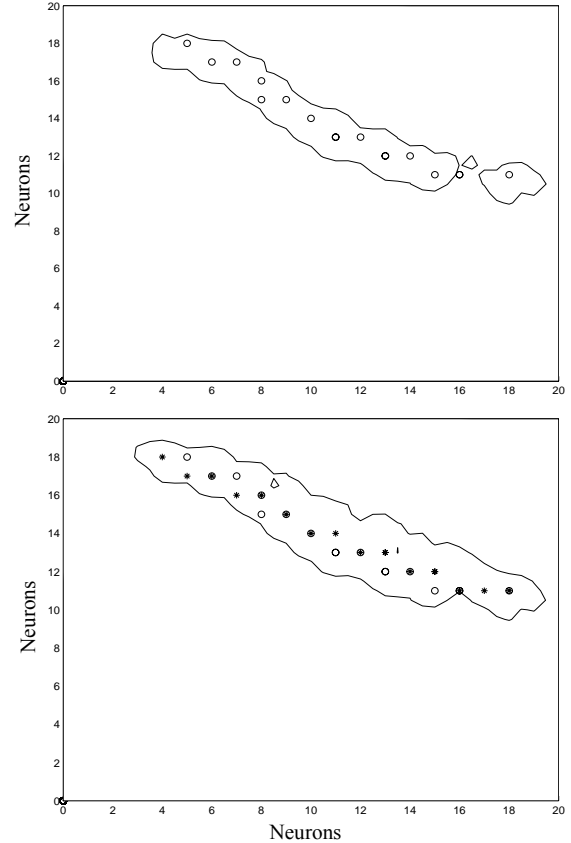

Figure 7.   Learning of two similar episodes. By episode formation, the representation of the second episode overlaps with the trajectory of the already existing episode. Encoding does not take place.

Including the behavioral feedback shall change this setting as goal oriented behavior and novelty will determine learning.

The method differs from the existing navigational models, that relate hippocampal modelling and robot navigation tasks, since it focuses on familiarity gated episode formation that is to determine emergent behavior Its merits for a robotics task, as shown by the experimental testing, prove that it can solve both representational problems of perceptual aliasing, learning in context, and concept formation for life-long learning.

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