

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

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ABSTRACT

This paper presents a computational model for encoding and inferential reuse of memories, based on novelty and familiarity principle. 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 an 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 [12]. The simulations following the functionality of the mammalian brain, that include memory or motivational features are

seldom implemented on a robot. The theoretical models of the hippocampus and basal ganglia, however, suggest neural solutions that incorporate those features, and produce results on a behavioral scale, although not in the range of the computational expense, affordable for robotics.

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 animate continuously gathers information about the surrounding world through experiencing sequences of events. The organisms, which are capable of making mental representation encode such subjectively experienced sequences (episodes). This capability arises with the availability of a limbic system (e.g. in mice).

The analysis and modeling viewed trough this aspect have the following feature. 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, memory for episodes copes naturally with the sensory, perceptual and behavioral character of learning of an embodied agent.

To be able to simulate the episode encoding, remembering has to be an intrinsic property of the learning model, instead of an external storage mechanism. To meet this standard, this paper uses a learning mechanism with asymmetric temporal association rule.

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 infor-

mation, 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 a central aspect of this work. Novelty is a known factor that gates learning in natural and artificial systems (for a recent review of on novelty detection in artificial systems see [15]). Definitions of novelty vary widely, due to the many perspectives within the considered multidisciplinary research area. Approaching the novelty and familiarity discrimination problem from the perspective of an embodied agent, has the following meaning: first, that novelty has to be considered in relation to behavior; and second, the information, that has to be judged for novel or familiar is derived by the experienced episodes of events.

The relation between novelty and behavior has received much attention by experimental neuroscientists[3][9][10]. 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, capable of one-trial learning and in the same time a degree of selectiveness of the content and importance of the encoded information is available.

In this study, novelty is considered as only gating factor for forming episodic memories during learning and familiarity as a mechanism for inferential use of episodic memories while behaving in a unseen environment. Technically, the novelty and familiarity are reciprocal criteria. The base for this model is the hippocampal function, 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.

- Robots interact with the environment through a continuous stream of sensory information, eventually forming an internal representation and acting accordingly. The hippocampus processes information sequentially, combines various sensory and memory experiences in a representation that is possibly modulated by behavioral feedback.
- Many experimental studies suggest the involvement of the hippocampal formation in novelty and familiarity detection [11][18] and inferential reuse of old episodes [7][24].
- Extensive modeling has created a consistent computational framework that connects the internal hippocampal and spatial representations.
- Experimental evidence has shown that the pyramidal cells in hippocampal area CA1 code for spatial location in terms of environmental queues and memorized episodes; more-

over, it provides a novelty/familiarity distinguishment.

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. In addition, the place of the work done so far in the overall navigation model is given, and the connection between the different elements are made explicit.

I. HYPOTHESIS

It is widely known that the hippocampus encodes episodic memories. In particular, the CA1 area, to which projections of sensory-bound stimuli come together with formed episodes of recent memories is an area of interest [11][18][25]. Recent analysis of the data from rat experiments [25] has shown the bimodal 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 [11][18]. 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 Entorhinal 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.

The combination of the information from the learned episode from CA3 and the sensory-bound information coming directly from EC forms a representation that controls the upcoming behavior. At the same time the comparison between the two patterns produces a novelty signal which 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 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.

Our hypothesis is, 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 determines the future behavior, and indicates the familiarity/novelty of the upcoming information. It therefore determines what has to be remembered or forgotten.

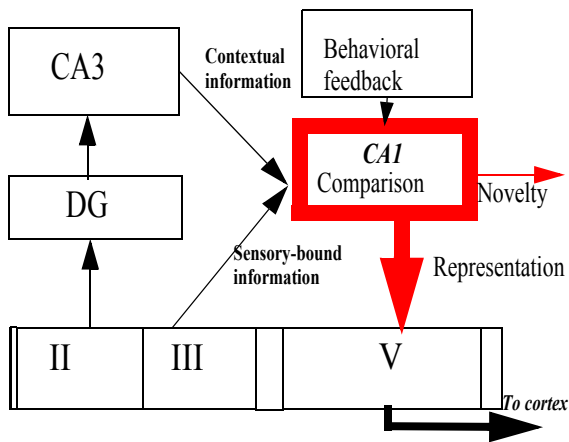


Figure 1. Working scheme, accentuating on the comparative role of the CA1 area. The sensory bound and episodic memory related representations are compared to indicate the familiarity.

Based on this hypothesis, we refine the computational scheme as shown in Figure 1. This scheme accentuates the CA1 area, as a physical component with comparative function: CA1 in this scheme provides two types of signals - one that will be further used to form a motor representation, and the other, that accounts for novelty.

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The scheme in Figure 1 demonstrates the computational flow for encoding within the behavioral setup of a simulated rat. To put it into the right perspective the global view of the overall system is shortly outlined. In feedforward manner, first environmental sensory information is gathered; Next, the perceptual/episodic memory system (that takes the computational steps as shown in Figure 1) encodes the sensory information and prepares for the corresponding behavior; Third, the navigation system, associated with the motor/behavioral functionality uses the produced episodic representation. The behavioral feedback has its impact on the internal hippocampal representation. 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 neuroimaging studies [13][17][21] [24][27] 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

Episodic and autobiographical memories have intrinsic relation to sensory, perceptual, and behavioral events.

The term “episodic memory” is used differently by the researchers. Here the episodic memory will be understood in the line of meaning proposed by Tulving [23], and developed by Conway [5]. The episodic memory notion, as used in the hippocampal studies has some differences. By a definition, given by Conway [5], which extends the widely accepted definition of Tulving [23], the episodic memory has event specific, sensory-perceptual details of recent experiences that lasted for comparatively short periods of time (minutes to hours).

Exploiting the idea, that the organism-environmental interaction is continuous and inseparable process[1] we argue, that episodic memory has also behavioral correlates:

- There is not a clear separation between action and perception. 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 encoding consists of organizing abstract knowledge derived from goals active during experience.
- Episodic memory formation takes short time slices, possibly determined by changes in goal-processing. Goal and action processing are tightly related.

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 .

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

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 , ($t \in [1, \dots, n]$) defined by a considerable difference in the event representations.

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

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

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

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. The distinguishment among sensory and perceptual influences is very delicate, since the perception includes sensory as well as memory related, anticipatory and behavioral correlates. In our notation an artificial division is made which assumes that perception is a result of an internal state changes only.

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. MODEL OF THE BIOLOGICAL LEARNING PROCESS

This model follows the information flow as suggested in the scheme of Figure 1. It is widely known that the cells in the rat hippocampus fire when the rat is at particular location of the environment. Because of that feature, these cells are called also 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 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:

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

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, which represents the pattern of activation of the simulated EC area. These patterns are dependant on the external-world and are further transmitted through the direct pathway.

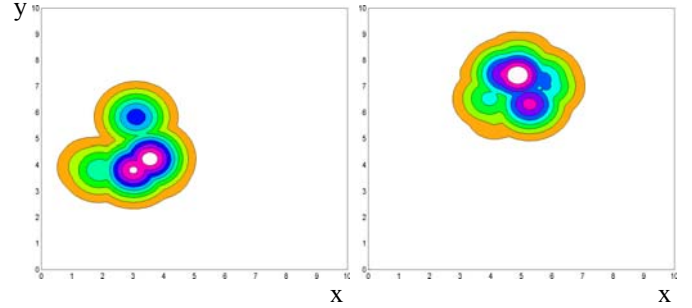


Figure 2. Samples of sensory bound patterns.

The same patterns are projected to CA3 area and therefore take also the itinerary of the indirect pathway, where they participate in the formation of episodes. The representation, projected to CA1 area through the indirect pathway is formed within a network structured as a two layer lattice of neurons, corresponding to the EC and CA3 layer. The feedforward connections from a EC area, that contain patterns as the ones shown in Figure 2, to the superficial CA3 area are trained through a modified hebbian rule as shown in Eq. (5).

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

where α_1 is learning rate, notation $CA-EC$ 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 $-w_{ij}^{CA-EC} CA_j^2$ of Eq. (5) is needed due to internal instability of the Hebbian rule.

The predominant are the topological connections - the simulation is done as the neurons from the first layer project to a topologically correspondent area, in a way that every input neuron is connected to 20% of the output neurons. The lateral inhibition connections, denoted as LI have a sharpening effect on the transmitted to CA3 area activations. Eq.(6), i.e. they promote self-organization.

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

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 [22] 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 lateral connections only. The asymmetric time window has been simulated to correspond to the experimental measurements as found by [28], see also [14]. Due to computational difficulties it has been scaled symmetrically in the interval [-1 1]. The lateral learning rule is adapted from the initially proposed by Dayan and Abbott rule [6], so that it fits to the practical constrains of the asymmetric time window function - Eq.(7).

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

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.

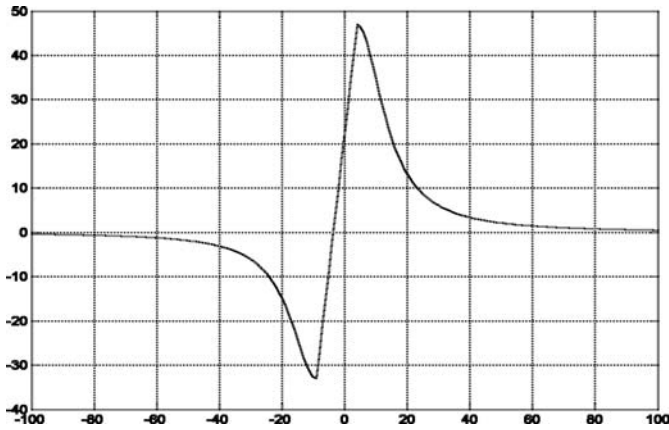


Figure 3. Asymmetrical time window function based on experimental studies.

In summary, modified Hebbian learning mechanism with 20% projections between the layers and inhibitory connections to promote topological self-organization form the episodic samples. A plot of a sample learned episode performed by the set of the explained rules is shown in Figure 4.

The result of this learning process corresponds to the perceptual contribution of the proposed event definition p . Behavioral influence is represented by a neuromodulator-like gating signal:

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

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.

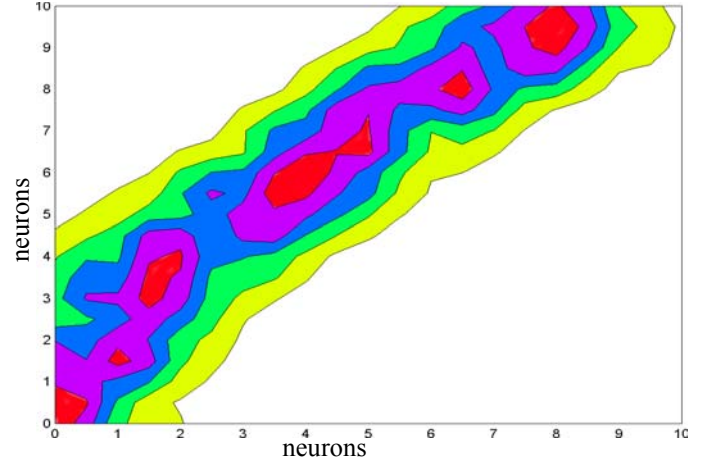


Figure 4. An episode, formed during a single run.

V. NOVELTY DETECTION AND THE HIPPOCAMPAL PARADIGM

The two representations, the sensory bound representation of the direct pathway, and the episodic representation of the indirect pathway, come together in CA1 area, where the comparison (novelty/familiarity judgements) takes place. Note, that at the same time, the CA1 area gets input from the current pattern of EC area and a pattern from CA3 area, which does not have processed yet (incorporated into an episode) the pattern that EC area currently projects.

The sensory bound patterns from the direct pathway are simplified in order to fit into the representation of the encoded episodes, some examples are shown in Figure 5.

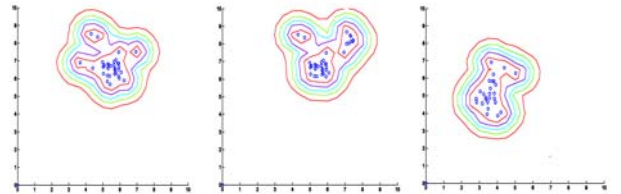


Figure 5. Some training patterns, based on the place field activation patterns.

For solving of the novelty problem, that will reflect the computations on the behavioral scale, the network build on the basis of the proposed computational scheme is simplified.

The hebbian learning followed by a lateral inhibition is replaced by a modification of the competitive hebbian learning algorithm [8][16], which makes a single neuron to represent a input pattern. 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 [1]. An on-line comparison of the incoming sensory-bound patterns with those encoded into the episodes. As a result of training the two episodes from the figure below have been distinguished: after the presentation of the third pattern,

the novelty signal gradually increases, which initiates encoding of a new episode.

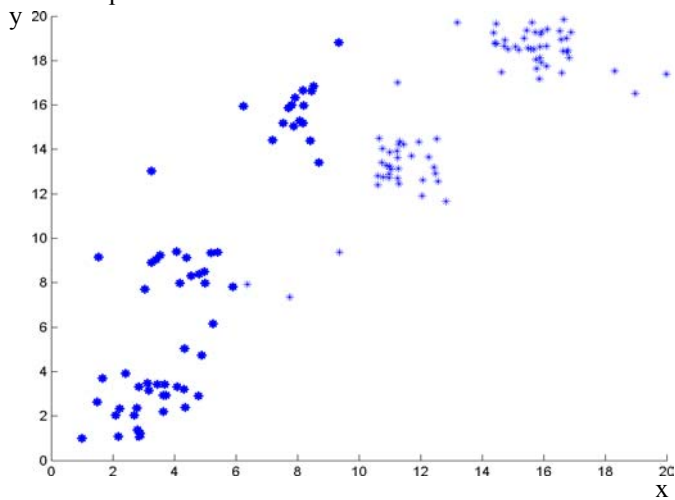


Figure 6. Learning of two episodes with an overlap. After the two trajectories show discrepancy, the novelty signal is issued.

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 (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. The reuse of memories on familiarity principle is in an experimental phase.

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. 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 novelty for episode formation that is to determine emergent behavior.

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