

Independent component analysis forms place cells in realistic robot simulations

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Abstract

It has been argued that the processing of sensory information in the entorhinal-hippocampal loop involves independent component analysis (ICA) on temporally concatenated inputs. Here, we demonstrate that ICA in a realistic robot simulation on a U-shaped track forms place fields similar to those found in rat experiments *in vivo*.

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1. Introduction

It has been argued that the processing of sensory information works by maximizing information transfer (see, e.g., [1,4] and references therein). This led to the suggestion that the underlying algorithm that forms receptive fields is independent component analysis (ICA) [2] on temporally concatenated inputs [8] in V1 and also in the hippocampus (HC) [11]. Recently, Lőrincz and colleagues proposed a reconstruction network model of the loop formed by the hippocampus and the entorhinal cortex (EC). This model of the EC–HC loop uses information-maximization principles, too [10,12]. According to the model, the loop is an auto-associative network, which derives a comparator signal by reconstructing the input at the superficial layers via the hidden representation at the EC deep layers [10]. ICA arises in a natural fashion in the model: top-down reconstruction requires the maximization of information transfer to the top, that is, to the hidden layers. Details of the model and some falsifying predictions can be found in [10,13].

A brief summary of the model is depicted in Fig. 1. In the model, both the direct connections from EC layer III to the CA1 field, as well as the perforant path perform ICA. ICA

transformations are determined up to permutations of the components. The ambiguity arising by the *two* ICA transformations is resolved by the loop structure: the two ICA transformations can match each other if they apply different learning rules. It has been suggested that the fast natural gradient learning of Amari occurs in the EC layer II to CA3 to CA1 pathway, whereas the Bell–Sejnowski learning rule operates in the EC layer III to CA1 direct connections [10].

Here we report our results about place cell formation in complex robot simulations. It is an extension of our previous modelling efforts [11]. In the present simulations (i) the position of the robot changes in a quasi-continuous manner, (ii) sensory information is rich: it models whiskers, visual information, and peripheral motion sensors (iii) no allocentric information is utilized, (iv) path generation is realistic, and (v) inputs have considerable amount of noise-like sudden changes.

2. Methods

An open source Khepera simulator was used (<http://yaks.ida.his.se/>) and a U-shaped track was constructed. Details of the track are shown in Fig. 2. Sensory information included ‘whiskers’, the wide angle proximity sensors of Khepera, ‘peripheral motion detectors’, the angular speed of the wheels, and ‘visual information’, the 64 pixel activities of the linear pixel array camera (the turret) of the Khepera.

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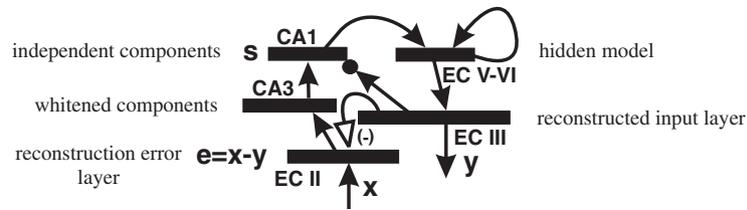


Fig. 1. EC–HC reconstruction network. Hidden model of the loop is formed at the deep layers of the EC (EC V–VI) by the hidden representation and the predictive recurrent collaterals at the layer. Input enters at layer EC II. Reconstructed input is formed at EC III by deep layer to superficial layer synapses. Input and reconstructed input are compared and form the reconstruction error at EC II. This error enters the dentate gyrus (not shown) and the CA3 field. The CA3 field has whitened (decorrelated and normalized) outputs. Independent components are formed at the CA1 field. Direct EC III–CA1 connections serve top-down attentional biasing of bottom-up information, and possibly denoising. Notations: x : input; y : reconstructed input; s : ICA representation. (For more details, and for some falsifying predictions, see e.g., [10,12,13].).

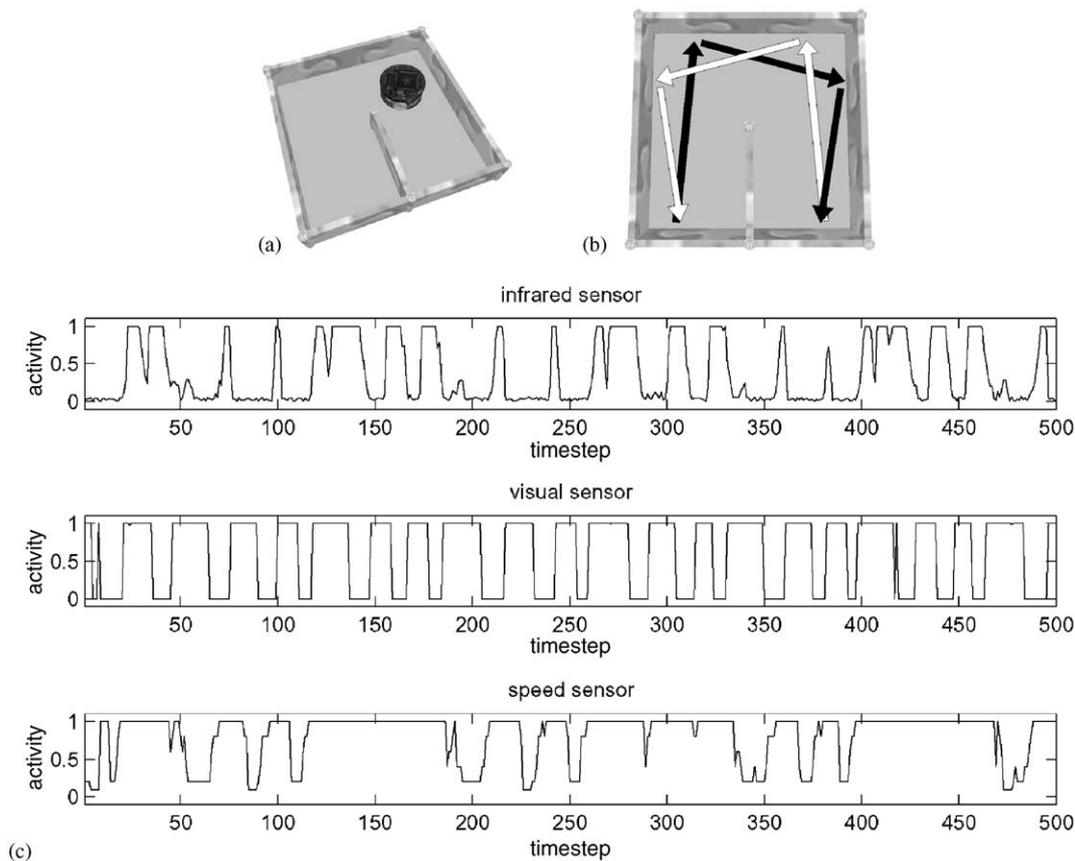


Fig. 2. Robot and track, trajectories and sensory information: (a) Khepera and its track; (b) typical trajectories; and (c) sensors: ‘whiskers’ (wide angle infrared sensors), visual sensors (camera pixels) and ‘peripheral motion sensors’ (angular speed of wheels). Full length is about three round trips.

More details are provided in Fig. 2. Sensory information was temporally concatenated: in each instant, the input was extended by the six preceding sensory inputs. This type of sequence formation is a reasonable assumption, because of the long propagation delays of the dendrites of CA3 pyramidal cells [11]. For detailed arguments see, e.g., [14]. This temporally *embedded* representation was the input of ICA. We applied the FastICA algorithm [9], because it has no adjustable parameters. This choice comes at a price: FastICA output may hold both negative and positive codes. We maintained positive coding by doubling the output dimension and splitting the output into positive

and negative parts after the ICA transformation. An internal representation of 30 dimensions was developed by FastICA.

Receptive fields were sampled at 100×100 grid points during the motion of the robot. We experienced that no further improvement can be achieved by increasing the number of sampling points. Even for relatively long runs, some of the grid points had low number of samples. The sampling method described in [3] was applied: if a grid point had a low number of samples (< 50), then samples were collected from the smallest circle around that point containing at least 50 points. 40,000 samples

were used in total, which consists of ≈ 500 full-length trajectories.

3. Results and discussion

Firings of all ICA neurons became direction and position sensitive. Four typical receptive fields are shown in Fig. 3. Our ICA neurons usually produced large signals at a few (and in many cases at a single) points of the track, although only partial information about the environment was available. One can understand this by recalling that ICA separates (the temporal) information chunks as much as possible. The receptive fields are similar to those found in rats on U-shaped tracks [5].

The information that we used for ICA in the simulation had no allocentric components. The simulation demonstrates that place cells can be formed in linear tracks in the absence of such information. Allocentric information is generally thought to be essential for generating the localized hippocampal receptive fields found in rats while exploring open spaces. However, such information makes the formation of place cells trivial in both in linear tracks and two-dimensional labyrinths. We think that the inverse question could be of relevance concerning the role of the EC–HC loop: can this loop structure enable the formation of non-body centered, non-head centered representation, which is locked to the environment?

The robot was placed on a U-shaped track (a). Size of the ‘labyrinth’ was 200 mm; diameter of the robot 55 mm. Sensory system of the robot had (i) two weak peripheral ‘motion detectors’ (the angular speed of the wheels), (ii) eight ‘whiskers’ (the wide angle infrared sensors of the robot, six at the front and two at the end), and (iii) a vision turret of 64 pixels. Detection range of the infrared sensors was cca. 40 mm; range of vision turret 100 mm with a frontal field-of-view of 36 degrees split evenly between 64 sensors. The output of a visual sensor was 1 if the wall was within range in its direction, and 0 otherwise. Visual inputs were affected by a small noise. Input: outputs of the 74 detectors. No other information, e.g., about the relative

topography was provided. The robot had a simple controller, which preferred to move along the central line of the track: it turned away from a wall when the short-range infrared detectors sensed the wall. If (rarely) a collision occurred, the robot turned about 100 degrees away from the wall. (b): typical trajectories. (c): sample sensory signals. In some cases the robot re-entered the same arm.

Our modelling efforts [10,12,13] are directed by the thought that the differences of the EC–HC function in mammals may originate from the differences of the sensory information, behavioral relevance, and the preprocessing steps before the information reaches the loop, but not from the alteration of the function itself. Our conjecture is based on the well-known critical involvement of the hippocampus and its immediate environment in learning and memory. It implies that place cell formation cannot be the major function of this area, because this function does not hold for primates. For example, CA1 in monkeys seems to contain cells which are sensitive to direct or indirect visual information [16]. We share the views that hippocampal neuronal activity can represent space in allocentric coordinates [6,15] and conjecture that this representation is *jointly* formed by the HC *and* the EC. Future work is needed to uncover the roles played by EC neurons. We need to understand the interplay between superficial layer EC neurons that encode large hexagonal grids [7] and the deep layer EC neurons that seem to encode pieces of the trajectories in linear tracks [5].

4. Summary

We have shown that ICA can form directional place cells in linear tracks from realistic sensory inputs. We have conjectured that the forming of more allocentric representation from less allocentric information is the function of the EC–HC loop. The falsifying theoretical question is whether reconstruction networks, similar to the model of the EC–HC loop [10,12], can promote the formation of allocentric representations or not.

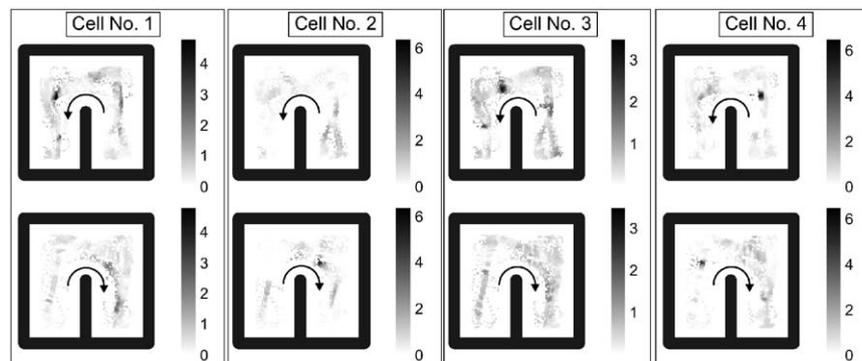


Fig. 3. CA1 receptive fields. Upper row: receptive fields when the traversed path leads from right to left (white arrows in Fig. 2(b)), lower row: receptive fields for the same cell when the robot moves from left to right (black arrows in Fig. 2(b)).

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Bálint Takács was born in 1976. He obtained his M.Sc. degree in Physics in 2000 and in Computer Science in 2002. He has won the Pro Scientia Award of the National Scientific Students’ Associations and is currently about to finish his Ph.D. studies in Computer Sciences in András Lőrincz’s group at the Eötvös Loránd University of Sciences, Budapest, Hungary. His main interests include functional modelling of biological neural systems, reinforcement learning, probabilistic learning methods and human–computer interfaces.



András Lőrincz has been affiliated with the Faculty of Informatics of the Eötvös Loránd University, since 1998. His research focuses on distributed intelligent systems and their applications in neurobiological and cognitive modelling, as well as medicine. He has acted as the PI of several international projects in collaboration with Panasonic, Honda FTR and the US Air Force in the fields of hardware–software co-synthesis, image processing and human–computer collaboration. He was awarded with the Széchenyi Professor Award, Master Professor Award, Széchenyi István Award and Kalmár Prize, in 2000, 2001, 2003, and 2004, respectively. He received his Ph.D. and C.Sc. degrees in experimental and theoretical solid-state Physics and Chemical Physics, respectively, and habilitated in laser physics based on his work on optimal control of quantum systems.