Learning Sensorimotor Transformations with Dynamic Neural Fields

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Abstract. The sensorimotor maps link the perceived states to actions, required to achieve the goals of a behaving agent. These mappings depend on the physics of the body of the agent, as well as the dynamics and geometry of the environment, in which the behavior unfolds. Autonomous acquisition and updating of the mappings is crucial for robust behavior in a changing real-world environment. Autonomy of many architectures, which implement the learning and adaptation of sensorimotor maps, is limited. Here, we present a neural-dynamic architecture that enables autonomous learning of the sensorimotor transformation, involved in looking behavior. The architecture is built using Dynamic Neural Fields and is implemented on a robotic agent that consists of an eDVS sensor on a pan-tilt unit.

1 Introduction

Behavior of a biological or artificial cognitive agent may be understood in terms of the sensorimotor transformations, which map the perceived states of the environment and the agent's body onto actions, leading to accomplishment of the agent's goals. These transformations, or mappings, may be segregated into more or less independent modules based on the available sensory and motor modalities, which can be organized according to different goals, pursued by the agent [2]. Critically, the mappings between the sensory states and the actions change constantly, because of the changes in the agent's body, as in the case of a developing and aging human, or changes in the environment. Therefore, learning and adaptation of the sensorimotor maps is essential for flexible and robust generation of purposeful behavior in a real-world environment [9].

A possible mechanism to learn and update a mapping was introduces by Kohonen early on in his work on Self-Organizing Maps (SOMs) [7]. Using the mathematical mechanism of SOMs, several architectures have been introduced, which enable learning of sensorimotor mappings, involved in modeling forward and inverse models in robotic control [12, 6, 4, 17]. Other architectures for adaptive control based on learning sensorimotor mappings use learning in multilayer neural-networks [13], incremental memory-trace update on the map based on experience [10], or error-driven learning rules (for a classical example, see [8]).

This and much more work on adaptive robotic control emphasize the importance and feasibility of learning and adaptation of the sensorimotor mappings. However, all these methods share a subtle, but critical limitation, which is hindering their application outside restricted scenarios. This limitation is the lack of autonomy. For instance, in training a SOM or a neural network in an adaptive controller, robotic actions are generated by sending random commands and observing sensory states when each action is finished. Both the command and the sensory state are stored in a data vector, which is used – in most cases offline – to drive the self-organization algorithm. The autonomy of the learning process is limited here, because the mechanisms of autonomous selection, initiation, monitoring, and termination of the actions are not included in the models. The moments in time, when it is appropriate to update the map are not detected autonomously from the sensory flow. These problems of coupling of the learning processes to the perceptual and motor systems have to be solved in order to enable learning along with behavior in a real-world robotic scenario.

Autonomy of cognitive processes and their development is central in the dynamical systems approach to modeling human cognition [16]. Dynamic Field Theory (DFT) is a particular flavor of the dynamical systems approach, which has been successful in application of the cognitive models to control of robotic behavior [14, 11, 19]. The core element in this framework are the Dynamic Neural Fields (DNFs) – activation functions defined over topological spaces, which characterize the state of the behaving agent and its representation of the environment. Localized activity peaks emerge as stable solutions of the dynamics of DNFs and represent salient characteristics of the perceived states, as well as the goals of the upcoming motor actions.

Here, we demonstrate how the framework of DFT can be applied to learning the sensory-motor transformations involved in looking behavior. We explore how autonomous learning may be enabled in this framework along with autonomous perception and action generation. The actions are initiated and terminated autonomously based on emerging representations of intentional states. The learning process is triggered autonomously when a match between the intended and the actual sensory state is perceived and its representation is stabilized in the condition-of-satisfaction neural-dynamics. We present here an implementation of the learning architecture in a robotic system using a pan-tilt camera unit.

2 Methods: Mathematical framework and the dynamical architecture

2.1 Dynamic Neural Fields

The dynamics of populations of biological neurons can be described by a continuous differential equation, which abstracts away the discreteness and the spiking nature of individual neurons, Eq. (1) [18, 5, 1]. Moreover, this equation can be formulated not in the space of the network of physical neurons but, instead, in the functional space of behavioral parameters, to which the neurons respond according to their tuning curves. In this formulation, an architecture of coupled dynamic neural fields is still related to neural activity in real brains, but expresses the dynamics of a neural system in functional, behavioral terms:

$$\tau \dot{u}(x,t) = -\, u(x,t) + h + \int f(u(x',t))\omega(|x'-x|)dx' + I(x,t). \qquad (1)$$

In Eq. (1), $u(x,t)$ is the activation of a dynamic neural field (DNF) at time t; x is one or several behavioral parameters (e.g., color, pitch, space, or velocity), over which the DNF is spanned; τ is the relaxation time-constant of the dynamics; h is the negative resting level, which defines the activation threshold of the field; $f(\cdot)$ is the sigmoidal non-linearity shaping the output of the neural field when it is connected to other fields or self-connected; the latter connections are shaped by the "Mexican hat" lateral interaction kernel, $\omega(|x'-x|)$, with a shot-range excitation and a long-range inhibition; $I(x,t)$ is the external input to the DNF from the sensory systems or other DNFs.

The dynamics of a DNF (Eq. (1)) has an attractor, determined by the external input, $I(x,t)$, the resting level of the field, h, and the strength of lateral interactions, specified by the kernel, $\omega(|x-x'|)$. A distinctive type the attractor of a DNF is a localized activity peak, which may be "pulled up" by the lateral interactions from a distributed input with inhomogeneities. Such peaks of activation are units of representation in Dynamic Field Theory [15]. Because of the stability and attractor properties of the DNF dynamics, cognitive models formulated in DFT may be coupled to real robotic motors and sensors and were shown to generate cognitive behavior in autonomous robots [14].

Intentionality in DFT. In order to enable autonomous activation and deactivation of dynamical attractor states in DNF architectures, each behaviorally relevant component consists of two dynamic neural fields: an intention and a condition-of-satisfaction DNF. The intention DNF is coupled to motor systems of the agent and drives its behavior by setting attractors in the low-level motor dynamics. The condition-of-satisfaction DNF receives a sub threshold input from the intention DNF and is activated by the sensory input, which matches the expected final state of the intended action. An active CoS field inhibits the intention DNF and therewith terminates the current behavior. After a brief transition instability, in which the CoS field looses its activation, the next action is selected driven by the external (bottom up) or internal (top-down) input to the intention DNF [11].

Learning in DFT. The basic learning mechanism in the DFT is the formation of memory traces of positive activation of a DNF. The memory trace is coupled back to the DNF and facilitates its activation at previously activated locations. Two DNFs may be coupled through a higher-dimensional memory structure, similar to a weight matrix in the standard neural networks. In DFT, such weight matrix is adapted through the mechanism of memory trace formation: similar to the Hebbian learning process, the coupling is strengthen between locations in two

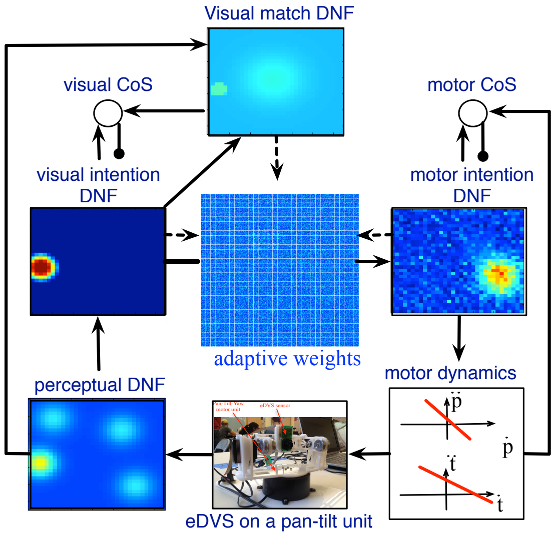

Fig. 1: The DNF learning architecture: the eDVS provides a visual input to the perceptual Dynamic Neural Field (DNF), which in its turn drives the visual intention DNF, and, through an adaptive mapping, the motor intention DNF. Visual and motor condition-of-satisfaction (CoS) nodes control the action-perception flow, and the visual match DNF detects moments, when the mapping should be updated.

DNFs, which are activated simultaneously. The learning process is functionally robust if the coupling is updated only when the behaviorally relevant states are active. In the looking architecture, presented next, we combine the elements of intentionality with learning dynamics to demonstrate autonomy of learning processes in DFT.

2.2 The DFT closed-loop looking architecture

Fig. 1 shows the DNF architecture, which both generates the autonomous looking behavior of the pan-tilt camera system and enables adaptation of the sensory-motor mapping to produce correct motor commands that move the camera toward visual targets. The architecture consists of the following dynamical structural modules.

Visual system. In the architecture, an embedded dynamic vision sensor (eDVS) [3] asynchronously generates events, which represent those pixels in the current field of view, for which the observed temporal contrast changes, e.g. because of moving objects in an otherwise static scene. Such events, generated by the hardware, provide positive input to a perceptual DNF (pDNF), in which peaks of suprathreshold activation are built at those locations where salient moving pixels are concentrated. The pDNF is input-driven, i.e. activity peaks decay if input ceases and are not sustained, new moving input induces new peak(s).

The pDNF provides input to the visual intention DNF (viDNF), in which self-sustained activity peaks may be formed. A peak in this field represents the target for the next saccade and has to be sustained for the time of the saccade, although the object representation moves in the visual field because of the camera motion. The viDNF is inhibited by the visual CoS, which signals that the saccadic movement is successfully accomplished. The viDNF is also inhibited by the motor CoS to a weaker extent, so that a new peak may be built in this field after an unsuccessful saccade, which failed to center the target.

Motor system. A peak of positive activation in the viDNF induces an activity peak in the motor intention DNF (miDNF) through a matrix of adaptive weights, which map locations in the viDNF to locations in the miDNF. The learning mechanism, active in this coupling structure will be described in the section on Sensorimotor transformation.

Activity peaks in the miDNF set attractors for the motor dynamics of the looking behavior according to Eq. (2):

$$\tau p\ddot{a}n(t) = -\, p\dot{a}n(t) + \xi_{pan}(t), \quad \tau t\ddot{i}lt(t) = -t\dot{i}lt(t) + \xi_{tilt}(t), \tag{2}$$

where $\xi_{pan}(t)$ and $\xi_{tilt}(t)$ are attractors for the rate of change of the pan and the tilt of the camera head unit, set according to Eq. (3):

$$\begin{aligned} \xi_{pan}(t) &= c_1 \iint k f(u_{mot}(k,l,t))dkdl, \\ \xi_{tilt}(t) &= c_2 \iint l f(u_{mot}(k,l,t))dkdl. \end{aligned} \tag{3}$$

Here, k and l are the two dimensions of the miDNF, which correspond to the pan and tilt velocities, respectively. The ξ_{pan} and ξ_{tilt} are estimations of the location of the activity peak in the miDNF along its two dimensions; c_1 and c_2 are scaling constants.

A peak in the miDNF sets a non-zero attractor for the pan and tilt velocities. As long as the velocity variables approach this attractor, the camera moves. When the attractor is reached, the motor CoS node, Eq. (4), is activated and inhibits the miDNF. When activity in the miDNF ceases, the motor attractors are set to zero (according to Eq. (3)).

$$\tau \dot{v}_{cos}(t) = -v_{cos}(t) + h_{cos} + c_{exc} f(v_{cos}(t)) + c_m f_{\iint}(u_{mot}) + c_a f_{diff}. \tag{4}$$

In Eq. 4, $v_{cos}(t)$ is activation of the motor CoS node for either pan or tilt movement; $f_{\iint}(u_{mot}) = \iint f(u_{mot}(k,l,t))dkdl$ is the peak-detector for the miDNF; $f_{diff} = f(0.5 - |\xi_{pan} - p\dot{a}n|)$ is a detector, activated when the state variable for the pan or the tilt dynamics reaches the respective attractor; c_m and c_a are scaling constants for these two contributions, c_{exc} is the strength of self-excitation of the motor CoS node.

Following the dynamics of Eq. (2-4), the "saccades" are produced with different horizontal and vertical amplitudes depending on the location of the activity peak in the miDNF.

Sensorimotor transformation. Initially, the coupling between the viDNF and the miDNF is modeled by a random connectivity matrix. The coupling structure is updated directly after a successful saccade, when the (still active) location in the visual intention DNF and the (still active) location in the motor intention DNF correspond to a correct mapping. The strength of the memory-trace activation in the respective location in the coupling structure is updated according to a simple Hebbian-like learning rule ("fire together – wire together"), gated by the activity in the visual match DNF (vmDNF), Eq. (5).

$$\tau_l \dot{T}(x,y,k,l) = \lambda \int f(u_{match}(x,y))dxdy \cdot \\ \cdot\Big(-T(x,y,k,l) + f(u_{vis}(x,y)) \times f(u_{mot}(k,l))\Big) \quad (5)$$

The coupling structure $T(x,y,k,l)$ (time-dependence is omitted in the equation) between the viDNF, $u_{vis}(x,y)$, defined over image coordinates (x,y), and the miDNF, $u_{mot}(k,l)$, defined over motor coordinates, k (pan) and l (tilt), retains its values if the vmDNF, $u_{match}(x,y)$, is salient. If there is a positive activation in the vmDNF (i.e., the visual input from the target landed in the central part of the pDNF, see Fig. 1), the integral before the learning term shunts the change in the mapping to be non-zero. The learning equation sets an attractor for $T(x,y,k,l)$ at the values of positive correlation between the two intention DNFs, calculated as a sum between the output of the viDNF, expanded along the dimensions of the miDNF, and the output of the miDNF, expanded in the dimensions of the viDNF, augmented with a sigmoidal threshold function (this neural-dynamic operation is denoted by the $\times$ symbol in Eq. (5)).

3 The learning experiments

Fig. 2 (left) shows an exemplary time-course of the pan component of several saccadic movements. The upper plot shows the time-course of the pan-velocity variable, sent to the motors, and of the attractor for this variable. The middle plot shows the respective pan trajectory. In the lower plot, activation of the motor CoS is depicted. Fig. 2 (right) shows the sensorimotor mapping before learning and after several successful saccades. The 4D mapping is shown here as slices along the motor dimensions, arranged in the figure according to the visual dimensions. Before learning, the mapping is initialized as random connections tensor. After each successful saccade, one region in the 4D field, which corresponds to the overlap between activity peaks in the viDNF and miDNF, is updated (one such region is marked with the red circle; note the light-blue dots in the tiles in this region). After only a few successful saccades (nine shown here), a large portion of the 4D space of the mapping is learned (regions marked by the red circle and the red arrows), because of the finite size of activity peaks in the intention DNFs.

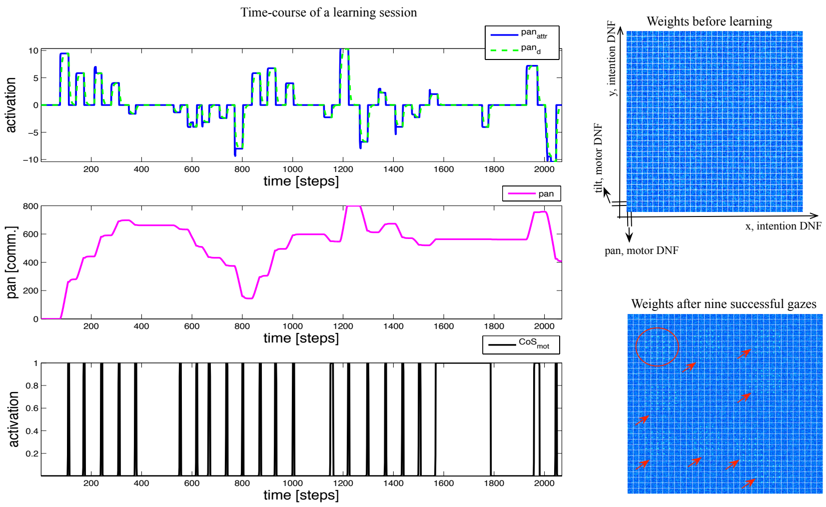

Fig. 2: **Left**: Exemplary time-course of a learning session. **Right**: The mapping between the visual and the motor intention spaces before learning (top), and after several successful "saccades" (bottom).

4 Discussion

In this paper, we have presented a neural-dynamics architecture that enables autonomous learning of a sensory-motor mapping involved in looking behavior, generated with an eDVS camera mounted on a pan-tilt unit. We have demonstrated how learning accompanies autonomous generation of the looking actions from the low-level sensory input in a closed behavioral loop. We have combined stability of the Dynamic Neural Field representations with elements of the behavioral organization to enable autonomy of the learning process. This includes autonomy of selection of the visual target, initiation of the motor action, termination of the motor action, and decision to trigger the learning dynamics. Such autonomy is critical for implementation of algorithms for adaptation of sensorimotor mappings in real-world robotic scenarios, as well as for understanding autonomy of learning processes in biological cognition.

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References

1. Amari, S.: Dynamics of pattern formation in lateral-inhibition type neural fields. Biological Cybernetics 27, 77–87 (1977)
2. Brooks, R.A.: New approches to robotics. Science 253, 1227–1232 (1991)
3. Conradt, J., Berner, R., Cook, M., Delbruck, T.: An embedded aer dynamic vision sensor for low-latency pole balancing. In: Computer Vision Workshops (ICCV Workshops), 2009 IEEE 12th International Conference on. pp. 780–785. IEEE (2009)
4. Gaskett, C., Cheng, G.: Online learning of a motor map for humanoid robot reaching (2003)
5. Grossberg, S.: Nonlinear neural networks: Principles, mechanisms, and architectures. Neural Networks 1, 17–61 (1988)
6. Guilherme, G., Araújo, A.F., Ritter, H.J.: Self-organizing feature maps for modeling and control of robotic manipulators. Journal of Intelligent & Robotic Systems 36(4), 407–450 (2003)
7. Kohonen, T.: Self-organized formation of topologically correct feature maps. Biological cybernetics 43(1), 59–69 (1982)
8. Kuperstein, M.: Infant neural controller for adaptive sensory-motor coordination. Neural Networks 4(2), 131–145 (1991)
9. Maes, P., Brooks, R.A.: Learning to coordinate behaviors. In: Proceedings of the Eighth National Conference on Artificial Intelligence. pp. 796–802 (1990)
10. Metta, G., Sandini, G., Konczak, J.: A developmental approach to visually-guided reaching in artificial systems. Neural networks 12(10), 1413–1427 (1999)
11. Richter, M., Sandamirskaya, Y., Schöner, G.: A robotic architecture for action selection and behavioral organization inspired by human cognition. In: IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS (2012)
12. Ritter, H.J., Martinetz, T.M., Schulten, K.J.: Topology-conserving maps for learning visuo-motor-coordination. Neural networks 2(3), 159–168 (1989)
13. Saegusa, R., Metta, G., Sandini, G., Sakka, S.: Active motor babbling for sensorimotor learning. In: Robotics and Biomimetics, 2008. ROBIO 2008. IEEE International Conference on. pp. 794–799. IEEE (2009)
14. Sandamirskaya, Y., Zibner, S., Schneegans, S., Schöner, G.: Using dynamic field theory to extend the embodiment stance toward higher cognition. New Ideas in Psychology. Special Issue "Adaptive Behavior". (in press)
15. Schöner, G.: Cambridge Handbook of Computational Cognitive Modeling, chap. Dynamical systems approaches to cognition, pp. 101–126. R. Sun, UK: Cambridge University Press (2008)
16. Thelen, E., Smith, L.B.: A Dynamic Systems Approach to the Development of Cognition and Action. The MIT Press, A Bradford Book, Cambridge, Massachusetts (1994)
17. Toussaint, M.: A sensorimotor map: Modulating lateral interactions for anticipation and planning. Neural Comput. 18(5), 1132–1155 (5 2006), `http://dx.doi.org/10.1162/089976606776240995`
18. Wilson, H., Cowan, J.: A mathematical theory of the functional dynamics of cortical and thalamic nervous tissue. Biological Cybernetics 13, 55–80 (1973)
19. Zibner, S.K.U., Faubel, C., Iossifidis, I., Schöner, G.: Dynamic neural fields as building blocks for a cortex-inspired architecture of robotic scene representation. IEEE Transactions on Autonomous Mental Development 3(1), 74–91 (2011)