A neural-dynamic architecture for behavioral organization of an embodied agent

Yulia Sandamirskaya[*], Mathis Richter[†], Gregor Schöner[‡]
Institut für Neuroinformatik, Ruhr-Universität Bochum
Universitätstr. 150, 44780 Bochum, Germany
Email: [*]yulia.sandamirskaya@ini.rub.de,[†]mathis.richter@ini.rub.de,[‡]gregor.schoener@ini.rub.de

***Abstract*—How agents generate meaningful sequences of actions in natural environments is one of the most challenging problems in studies of natural cognition and in the design of artificial cognitive systems. Each action in a sequence must contribute to the behavioral objective, while at the same time satisfying constraints that arise from the environment, the agent's embodiment, and the agent's behavioral history. In this paper, we introduce a neural-dynamic architecture that enables selection of an appropriate action for a given task in a particular environment and is open to learning. We use the same framework of neural dynamics for all processes from perception, to representation and motor planning as well as behavioral organization. This facilitates integration and flexibility. The neural dynamic representations of particular behaviors emerge on the fly from the interplay between task and environment inputs as well as behavioral history. All behavioral states are attractors of the neural dynamics, whose instabilities lead to behavioral switches. As a result, behavioral organization is robust in the face of noisy and unreliable sensory information.**

I. Introduction

Consider a typical task that could be accomplished by a robot equipped with an arm, a gripper, and a vision sensor: for instance, the task to grasp an object. This task may be segmented into chunks, which we will call elementary behaviors (EBs): (1) find the object in the visual array, (2) open the gripper, (3) move the end-effector toward the object, and finally, (4) close the gripper. The order of the EBs in this sequence is constrained by the physical characteristics of the robot, for example the need to move the camera in order to locate the object prior to the arm movement or to open the gripper before the end-effector arrives at the object. The order may also be effected by the specifics of the task. Thus, the task 'push the object' involves the same EBs as the task 'grasp the object', but in a different order. The sequence may also depend on the particular situation during the task execution, for instance, on whether the gripper is closed or open at the beginning of the sequence or on whether the object is in view or not.

How such behavioral sequences are produced is relevant both for the design of architectures controlling robotic actions as well as for modeling sequential behavior of humans and animals. One may distinguish three different mechanisms of sequence generation. The first emphasizes serial order in which the elements or actions in the sequence are in an arbitrary but fixed order as in dialing a telephone number or in a routine coffee-making sequence. The second mechanism relies on an analysis of the behavior in terms of rules of behavioral organization which guide decisions about the next actions, adequate in a particular situation for a given task and body of the agent. The third mechanism is responsible for elaborating or planning sequences which lead to a particular goal state. Recently, we have introduced a model for the first type of sequences [1], which we will review briefly in this section. The third type of sequence generation is addressed in the literature on planning, dynamic programming, and reinforcement learning [2], [3]. In the present work, we focus on the second type of sequence generation mechanisms, in which a logic of action drives behavioral organization.

The term behavioral organization originates in work on behavior-based robotics, which arose as a contrast to more classical approaches to the control of robotic action that consisted of elaborate planning based on thorough or complete information about the world. In behavior-based robotics, the controller is coupled to the sensory information available to the robot from moment to moment. In a given environment, a particular behavior emerges from decisions about the next actions that are based on local sensory information. The complexity of the representational structures within the controller is minimized [4], [5]. Early work on the behavioral organization in robotics yielded architectures that could control navigating robots, which had to pursue several tasks, such as obstacle avoidance, exploration, or home-base visiting [6], [7], [8]. Scaling up these control systems to complex tasks and environments is a major challenge ([9], [10], see [11] for a review of several architectures in this domain). These architectures were somewhat flexible through their coupling to sensory inputs, but they were not shown to scale up to complex tasks involving several effectors and sensors, in which an explicit representation of the constraints of behavioral organization is needed.

A representation for such constraints, or rule-like relationships, has been suggested in the domain of modeling human and animal action selection [12], [13]. Here, the elementary behaviors correspond to abstractly represented 'schemes', which may be activated or not. Behavioral organization is expressed by links between these schemes and the resulting architectures may account for the generation of complex behavioral sequences. However, these architectures were not coupled to real behaving systems and the interface to a possible sensory-motor implementation of the schemes is underspecified. In other words, a gap exists between the units within these high-level architectures and actual concrete behaviors, which a real robot could execute.

The coupling of high-level, or cognitive, functions with perceptual and motor processes is taken seriously in the embodiment stance toward cognitive systems. The dynamical systems approach has been particularly successful in linking cognitive processes and their development to sensory-motor systems [14], [15]. Within this approach, cognitive functions are modeled as attractors of a dynamics that describes the temporal evolution of variables characterizing cognitive states and behavior. Development may be understood as the gradual change of the parameters of this dynamical system, which models the processes controlling behavior. Instabilities in the dynamics mark qualitative changes in behavior and the emergence of new functions. One of our goals here is to provide a conceptual basis for how rules of behavioral organization may be represented in this framework and may thus be integrated with perceptual, cognitive, and motor processes. Openness to learning is a constraint, although we do not yet directly address learning processes here.

In previous work, a dynamical systems architecture for behavioral organization was proposed in which dynamic neurons were coupled to implement behavioral rules [16], [17], [18], [19]. Although successful in the implementation of behavioral constraints, the particular dynamical mechanisms used in these earlier architectures rendered the design of these systems quite complex. A number of specific stability problems arose when behavioral switches were driven by fluctuating sensory inputs.

Here, we provide a new basis for the dynamical systems implementation of behavioral organization. In particular, we embed this implementation within the framework of Dynamic Field Theory (DFT), a neurally-grounded variant of the dynamical systems approach that uses dynamic neural fields (DNFs) [15]. DFT has been particularly successful in modeling the development of spatial and visual working memory, motor planning, and perception [20], [21], [14], but has also been established as a theoretical language for autonomous robotics [22], [23]. A number of architectures have been developed based on DFT to generate behavior in autonomous robots that are situated in physical environments about which they obtain partial information from noisy sensory inputs. These architectures model human behavior and, at the same time, realize useful robotic functions. An extension of the DFT framework with a mechanism for behavioral organization, proposed here, will increase the autonomy of such robotic architectures. The intrinsic stability of the states of the DNF dynamics solves problems of the previous dynamical systems architectures.

In the following section, we briefly review the main concepts of DFT. We then describe the neural dynamics of behavioral organization by laying out the structure of each elementary behavior and the dynamical couplings that express the constraints of behavioral organization. We illustrate how the behavioral organization dynamics may be coupled to perceptual and motor modules by presenting a complete architecture for an exemplary grasping task on Aldebaran's NAO robot. Finally, we present time-courses of the dynamics of modules of the architecture to demonstrate how the transitions between elementary behaviors are generated by sensory input signaling successful achievement of the objective of an elementary behavior.

II. Dynamic Field Theory (DFT)

The main concept of DFT is that a dynamic neural field describes the states of a (cognitive) system as an activation function, $u(x,t)$, defined over metric dimension(s), x. The activation function evolves in time according to Equation (1) [24]. The stability of the behaviorally relevant states of DNFs arises from an interaction pattern within the neural field, described by an interaction kernel, $\omega(x-x')$. The kernel has a shape of a Gaussian with a negative offset and expresses that nearby sites of a neural field excite each other and distant sites inhibit each other. Localized bumps of activation, or *peaks*, are units of representation in this framework. Their stability is the main property of the dynamics of neural fields, which makes the DNF representations robust against fluctuations in the (sensory) input.

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

In Equation (1), h is the negative resting level of the DNF, $f(\cdot)$ is a sigmoidal non-linearity shaping the output of the DNF, and I is the sum of external inputs to the DNF.

The stability of the solutions of this dynamics may be analyzed in some cases [24]. This stability is crucial when using this dynamics in modeling human cognition and linking the DNF architectures to sensory and motor systems [15].

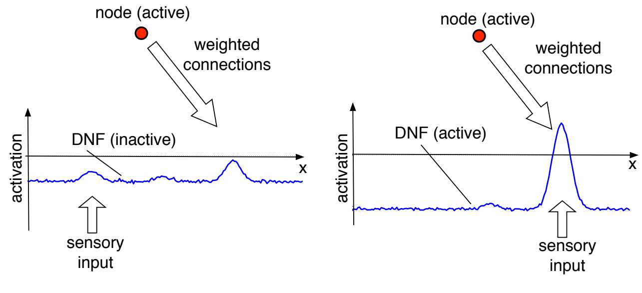
Our architecture for behavioral organization consists of a number of DNFs, all based on Equation (1), of different dimensionality of the underlying dimension, x. In the case when x has zero dimensionality, the DNF degenerates into a dynamical node, which only has self-excitation in place of the lateral interactions within the DNF.

The DNFs of different dimensionality may be coupled to each other through the term $I(x,t)$ if they share one or several dimensions. This coupling may be one-to-one, or may be weighted. Fig. 1 shows a dynamical node coupled to a DNF through weighted connections. Activation of the node is transferred to the field and induces a localized activity bump there, which, however, does not reach the activation threshold (Fig. 1a). When this input overlaps with the sensory input in the neural dimension, a localized peak of activation emerges in the DNF, stabilized by the lateral interactions within the DNF (Fig. 1b).

In the following section, we present the building blocks of the DFT behavioral organization architecture.

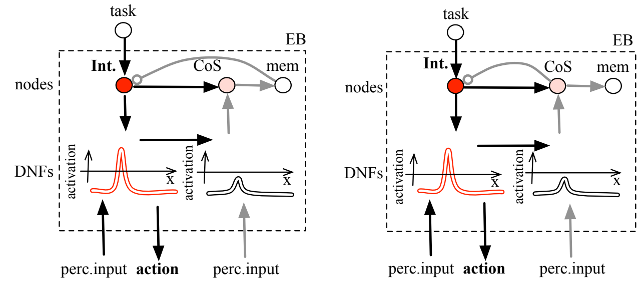
III. Elementary behavior in the neural-dynamic framework for behavioral organization

In the neural-dynamic architecture we propose, an elementary behavior (EB), such as 'find object' or 'move end-



(a) (b)

Fig. 1: Dynamics of a DNF coupled to a dynamical node and to sensory input: (a) The active node provides input to the dynamic neural field, which is not sufficient to induce an activity peak in the field. (b) When the location of the sensory input overlaps with the localized input from the node, a stable activity peak emerges in the DNF in a detection instability.



(a) (b)

Fig. 2: Structure of an elementary behavior: the intention node is activated by task input and pre-activates the condition of satisfaction (CoS) node. Both nodes are connected to neural fields that represent metric parameters of the intention and the CoS, respectively. The memory node, activated by the CoS node, holds memory for the accomplished EB. The intention node is inhibited by either (a) the memory node (the EB stays inhibited when the CoS is deactivated) or (b) the CoS node (the EB is reactivated if the CoS is deactivated).

effector', is initiated by the activation of an *intention* node ('Int.' in Fig. 2) and an intention DNF connected to it, which represents the perceptual and motor parameter(s) of the EB. The location of the activity peak within an activated intention DNF is defined by the connection weights from the intention node to the intention DNF and, possibly, by the perceptual input to the intention DNF. Thus, the specific contents of an intention DNF (i.e., the parameters of an EB) may also be induced by an environmental input. For instance, the target location of the end-effector for the 'move end-effector' EB may be derived from the camera input rather than encoded in the top-down connections from the intention node.

The *task* node (Fig. 2) represents the current overall task (e.g., 'grasp an object') and if active, this node activates the intentions of all EBs that contribute to this task. An activated intention affects the sensory-motor systems (*periphery*) of the agent and thus controls its behavior. The *condition of satisfaction (CoS)* DNF detects a match between the input it receives from the intention DNF and the perceptual input. The particular shape of the input from the intention DNF is encoded in the connections between the intention field and the CoS field and represents the parameters of the goal state associated with a particular intention. The match is detected when the perceptual input corresponds to the expected end-state of the EB. When the expected end-state is detected, the CoS field is activated and, consequently, the CoS node is activated and inhibits the intention of the EB, triggering an instability in the dynamics of the architecture and transition to the next elementary behavior (see [1] for a detailed description of this mechanism). A memory node that is associated with the CoS node holds the memory about the EBs that have been accomplished in the context of a particular task.

Now, as we have introduced the basic dynamics of an elementary behavior (its most high-level, 'intentional' part), we introduce the essential elements of behavioral organization that enable rule-based coupling between elementary behaviors. Afterward, we proceed with the sensory-motor part of the behaviors.

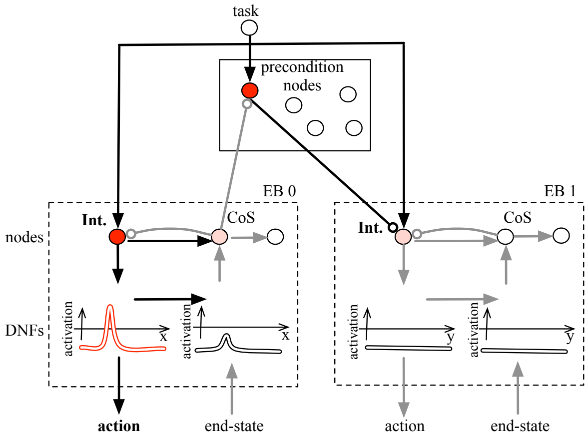
IV. Elements of the Behavioral Organization

In the DFT framework, dynamic neural fields (DNFs) represent different perceptual, motor, or cognitive parameters of the neural states and of the behavior of an agent. Different DNFs may be coupled through synaptic connections, so that activation of one DNF is propagated to another DNF, affecting its dynamics. Simple rules of behavioral organization may already be represented in this direct coupling between DNFs that represent different perceptual and motor systems. However, to enable flexible switching between different couplings, the rules of behavioral organization must be represented by neural dynamics that may be activated or deactivated. The dynamical *precondition* and *competition* nodes presented next serve this function.

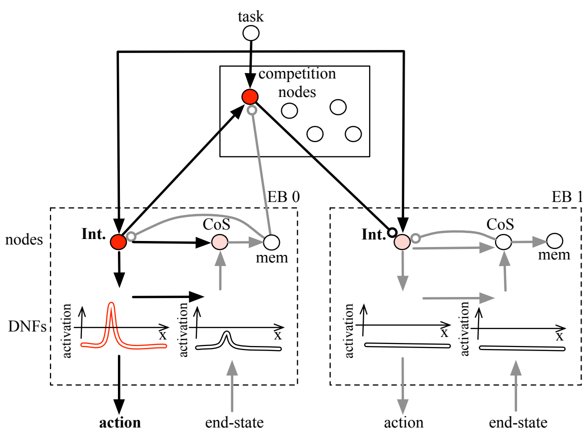
A. Precondition

A precondition relationship (see Fig. 3a) between two EBs prevents one of them from being activated until the other has been completed. In our architecture, this relationship is represented by a *precondition node* that, if activated by the task input, inhibits the intention node of the second EB (EB1 in Fig. 3a). When the precondition node is in turn inhibited by the activated CoS node of the first EB (EB0 in Fig. 3a), EB1 is released from inhibition and can be executed. The precondition node can alternatively also be inhibited by the memory node of EB0. In this case, EB1 may be activated independently of EB0 further in the behavioral sequences (i.e., the activity of the CoS of EB0 may cease if the sensory input to the CoS field changes).

Preconditions can also be expressed with a dependence on the sensory system itself (e.g., a perceptual neural field,



(a) Precondition coupling between two elementary behaviors



(b) Competition coupling between a two elementary behaviors

Fig. 3: Coupling of two elementary behaviors through a (a) *precondition node* and a (b) *competition node*. Filled circles are activated nodes, half-transparent nodes are pre-activated nodes, arrows mark excitatory connections, and lines with circles are inhibitory connections.

as described in Section V), so that the intention of EB1 is only activated when a particular state of the environment is perceived.

B. Competition

Another possible relation between EBs is competition, which may be uni- or bidirectional. An implementation of a uni-directional competition is illustrated in Fig. 3b. Here, the intention node of EB1 is inhibited by a *competition* node as long as the intention node of EB0 is active. The inhibition is released once the CoS of EB0 is met.

C. Logical conditions

Activation of an EB may depend on a combination of preconditions, or competitive conditions. In the neural-dynamical framework, different logical connections can be expressed between these conditions: 'AND', by a node that sums several inputs with an activation threshold set to be activated only if all inputs are present; 'OR', by a node that is activated by any single one of its inputs. By pairwise coupling of such *inter-neurons*, complex logical conditions can be represented in the dynamical structure with the stabilizing properties of the neural-dynamics that we use. However, such complex conditions are rarely relevant for real-world tasks.

V. The Overall Architecture: Coupling to the Sensory-Motor Representations

The neural-dynamic mechanisms of behavioral organization must be linked to low-level representations that are directly coupled to sensors and motors of the agent. To illustrate how this coupling can be achieved in the DFT framework, we introduce a complete DNF architecture capable of producing behavioral sequences that correspond to different tasks. A particular task (e.g., 'grasp the object' or 'point to the object') is specified by introducing task inputs to different intention, precondition, and competition nodes.

The tasks we have looked at are within a table-top scenario involving a NAO robot, which is equipped with two arms with grippers and a pan-tilt camera unit. Fig. 4 presents the DNF architecture that guides the behavior of the robot.

On the lowest level, several modules are implemented that are responsible for the actual robotic movements or constitute the physical sensors: the camera module grabs images from the color camera and outputs unprocessed color distribution maps over the image, which are used to detect objects on the table-top, or monitor the location of the end-effector. The pan-tilt module implements a dynamical system that controls the rotation of the camera head. The arm module implements a dynamical system that controls the arm movement. The gripper module generates the 'open' and 'close' commands on the gripper hardware and outputs the current gripper's opening angle.

The next level consists of perceptual DNFs that represent sensory information. In particular, three neural fields are relevant for our scenario: a color-space field holds the color distribution over the visual space, the end-effector-space field represents the spatial representation of the end-effector's location, and the spatial target location field is the spatial projection of the color-space field.

The perceptual fields are reciprocally coupled to the three intention fields: the 'color' field representing the intention to search for the color of the target object, the 'move end-effector' field representing the intention to move the end-effector to the position specified by the location of the activity peak within this field. The location of the peak is determined by the input from the spatial target location field. The gripper field represents the intention to set the gripper to a particular opening angle. Each intention field is coupled to a corresponding CoS field, as described in Section III, and each CoS field receives a perceptual input from either one of the perceptual DNFs, or directly from the sensors. The dynamics of the CoS fields dynamics stabilize the detection decision (see [15] for discussion of modeling elementary cognitive

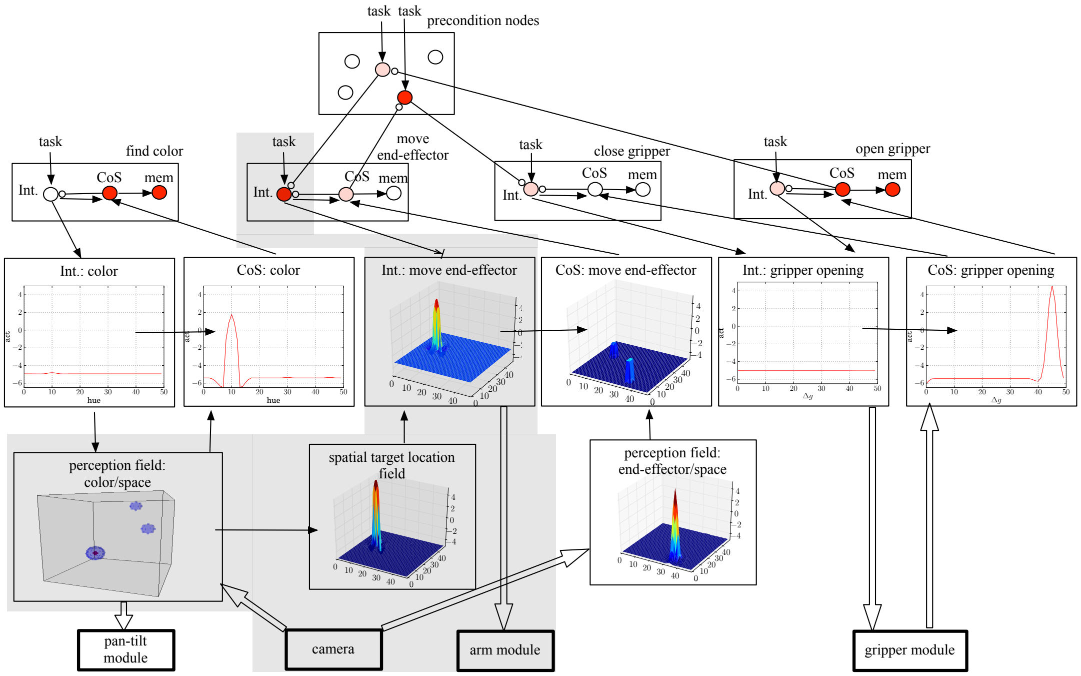


Fig. 4: Behavioral architecture for the ‘grasp’ task, ordered in functional layers. The top layer consists of a pool of precondition nodes, which can couple elementary behaviors. The second and third layer from the top depict the EBs the grasp task consists of (i.e., ‘find color’, ‘move end-effector’, ‘open gripper’, and ‘close gripper’) and the intention and CoS field they are linked to, respectively. Next is the perceptual layer, where the intentions of different EBs are coupled to sensory input to form perceptual representations. The sensory input comes from the lowest layer, consisting of the sensory-motor system. The shaded gray area denotes a part of the architecture that is currently active: the intention node of the ‘move end-effector’ EB is forming a peak in the EB’s intention field in conjunction with localized activation from the perceptual system, which provides the spatial target of the end-effector.

functions within DFT) if the input from the corresponding intention field overlaps with the input from the perception.

In the next section, we illustrate that the architecture performs the sequential activation of behaviors consistently with the designed behavioral rules, while being guided by input from real sensors and being coupled to motors. For that, we describe a complete architecture, which implements rules of behavioral organization, perceptual systems, and motor dynamics on a NAO robot.

VI. Results

The connectivity within the neural-dynamic architecture expresses a particular coupling structure between the neural-dynamic subsystems, which corresponds to the particular scenario, or set of tasks. For instance, within the architecture presented in Fig. 4, the behavioral sequences that correspond to the tasks ‘grasp an object’, ‘push an object’, ‘point at an object’, ‘lift an object’, and ‘transport an object’ may be generated. The tasks differ in the precondition and competition nodes involved, as specified by the task input; the rest of the connectivity between the dynamical nodes and fields is shared between these tasks.

In Fig. 4, a snapshot of the architecture is presented. Here, two EBs are already completed: the ‘open gripper’ EB and the ‘find color’ EB: their CoS nodes and memory nodes are activated. The currently active EB is the ‘move end-effector’ EB: the intention node of this behavior is active and a peak of suprathreshold activation is present in the ‘move end-effector’ intention field. This peak is induced, on the one hand, by the homogeneous input (boost) from the intention node and, on the other hand, by the localized input from the spatial target location field, which is coupled to the perceptual color-space field and receives the spatial projection of this field as input.

Activity within the ‘move end-effector’ intention field impacts on the robotic *arm module*, setting the location of the peak as an attractor for the dynamics that controls movement of the end-effector of the robotic arm.

The perceptual neural field ‘end-effector/space’ represents the current location of the end-effector of the robotic arm, as perceived by the visual sensor. This field provides input to the CoS ‘move end-effector’ neural field. When the location of the peak of positive activation in the perceptual field ‘end-effector/space’ overlaps with the location of the input from the intention field to the CoS field, a peak emerges in the CoS ‘move end-effector’ field that signals the successful completion of the elementary behavior: the end-effector is then perceived to be at the desired location (at the object of interest). The activated CoS node of the EB ‘move end-

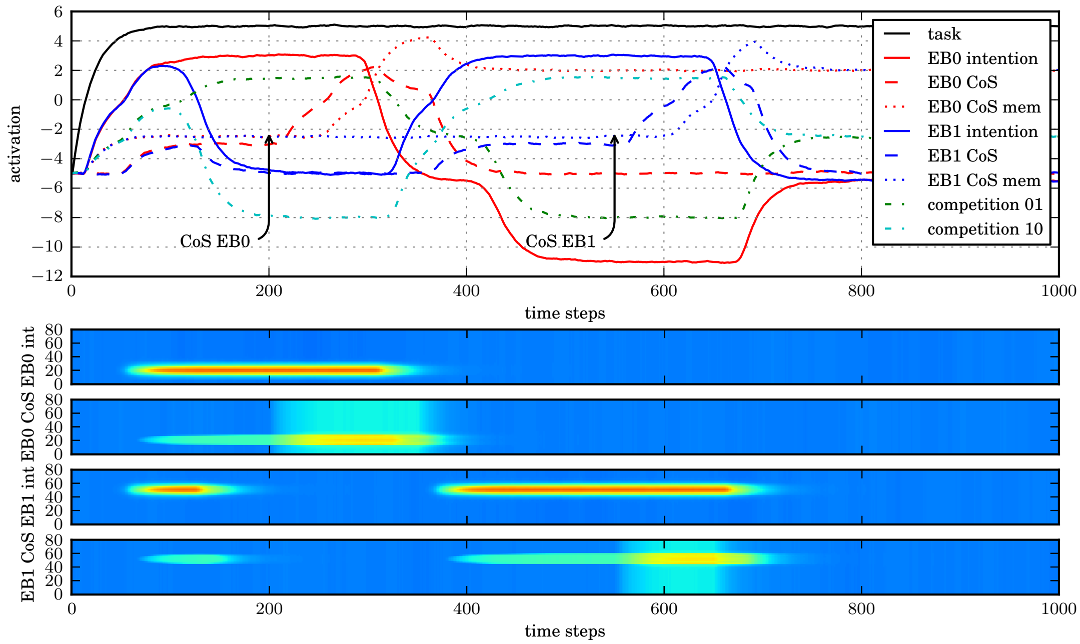


Fig. 5: Time-courses of activation for the elements of two EBs that are in competition. The line plot shows the development of the activation of all dynamical nodes involved in the task over time. The lower plots show the activation of the intention and CoS fields of both EBs over time, where the y-axes are the feature dimensions of the fields; activation in the fields is encoded by a color-map—red color being positive and blue negative activation. At time steps 200 and 550, a completion of the respective behaviors EB0 and EB1 is simulated by boosting their CoS fields, leading to the completed EB to be deactivated. In the first case, the deactivation of EB0 leads to EB1 to become active, as the inhibiting competition node, 'competition 01', is deactivated.

effector' inhibits the precondition node connected to it. This releases the inhibition on the intention node of the EB 'close gripper'. The activated intention node of this EB eventually impacts on the motor gripper module and the gripper is closed around the object—the task is completed.

The shaded region in Fig. 4 marks the currently active behavior, which is represented by activation in the following structures: the intention 'move end-effector' node and the corresponding intention dynamic neural field (DNF), the spatial target location DNF and the perceptual color-space DNF, coupled to the camera input, the visual input from the camera, and the dynamics that controls the arm movement. These dynamical structures, activated concurrently, constitute a 'functional system'—the part of the cognitive architecture active during a particular activity, or elementary behavior, which is a segment of the sequence on the functional level. Here, the exact activity pattern depends on top-down input, propagating from the task node through the coupling structure between the nodes and fields down to the motors. Additionally, it depends on bottom-up input, coming from the sensory surface.

The signal for the transition to the next EB is detected in a bottom-up stream from the sensory surface to the CoS node and its memory node. The detection decision is stabilized by the neural representations and ensures the robust switching. One such sequential transition is depicted in Fig. 5, where a transition between two elementary behaviors, coupled through competition nodes, is shown resolved in time.

VII. Conclusions and Outlook

We presented a neural-dynamic architecture for behavioral organization and showed how it may be integrated with grounded sensory-motor and cognitive processes within the DFT framework. We illustrated how this architecture generates sequences of elementary behaviors in which the transition to and the selection of the subsequent behavior depend on task constraints and sensory inputs. In this picture, elementary behaviors are represented by patterns of activation distributed across a broad variety of dynamic neural fields (i.e., intention fields, condition of satisfaction fields, perception fields, and motor fields), dynamic neural nodes (i.e., intention nodes, condition of satisfaction nodes, and competition and precondition nodes), and motor dynamics. These patterns emerge from the interplay of top-down and bottom-up activation streams along connections coupling the different dynamical structures. The connections may be learned based on standard learning rules.

Clearly, we have only made the first steps toward a comprehensive system of behavioral organization. Experience with implementations in more complex scenarios will give us feedback about how complete our set of elements of behavioral organization is. Scaling up the architecture to real-world scenarios, which include richer object representations and action repertories, will be an important step. Autonomous learning will then become a necessity and is a longer-term goal of our research program.

VIII. Additional material

The software package that implements the current architecture is written in Python and will be freely provided by the authors on request. The authors are also happy to provide additional figures and movies of the activation dynamics. This material will be available online when the paper is published.

Acknowledgment

The authors acknowledge the financial support of the European Union Seventh Framework Programme FP7-ICT-2009-6 under Grant Agreement no. 270247 – NeuralDynamics. This work reflects only the authors' views; the EC is not liable for any use that may be made of the information contained herein.

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