

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

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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 within the visual array, (2) open the gripper while (3) moving 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 (it’s camera and arm geometry, it’s gripper mechanics), by the specifics of the task (the sequence of behaviors would differ if the task were to “push the object”), and by the particular environmental situation (the sequence of behaviors would differ depending on whether the gripper is closed or opened at the beginning of the sequence and whether the object is in view or not).

Even for such a simple task, the constraints may be analyzed in terms of a logic of action, which can be expressed as rules of the behavioral organization of the EBs. Thus, the third EB, “move end-effector”, cannot be executed until the first one, “find object”, has terminated and the location of the object of interest has been identified. The second EB (“open gripper”) may run concurrently with the EB “find object”, but should precede the third EB (“move end-effector”), whereas the fourth EB (“close gripper”) must be at the end of the sequence. Again, the structure of the sequence that corresponds to this task depends on the agent’s embodiment (its sensors and

motors), on the task’s specifics, and on the moment-to-moment environmental situation as the sequence unfolds.

Such rule-like relationships between EBs are relatively easy to capture in abstract representations of behaviors such as the verbal descriptions provided above, or by programming the EBs in separate software modules. However, early efforts to design architectures that control action selection in robotic agents [1], [2], [3], [4] have revealed, that scaling up hand-crafted control systems to complex tasks and environments is a major challenge. The autonomous development of the control architectures has been envisioned as a solution to this problem [5], [6], [7]. First efforts to autonomously learn action policies have invoked principles of reinforcement learning (e.g., [8]), used neuronal networks (e.g., [9]), and exploited analogies with human language learning (e.g., [10]). A behavior-based approach uses a relatively simple fixed scheme of behavioral organization but achieves learning through belief estimation [11]. Another line of related work draws on analogies with the function of the basal ganglia [12], [13], [14], [15].

Our goal here is to provide a firm conceptual basis for how behavioral organization may be integrated with perceptual, cognitive, and motor processes so that noisy sensory signals and time-varying, unpredictable environments can be accommodated. Openness to learning is a constraint, although we do not yet directly address learning processes here.

We build on the dynamical systems approach which has been successfully used to capture natural developmental processes [16]. Within this approach, development may be understood as the gradual change of the parameters of a dynamical system that models the processes controlling behavior. Instabilities in the dynamics mark qualitative changes in behavior and the emergence of new functions. In Dynamic Field Theory (DFT), a neurally-grounded variant of the dynamical systems approach that uses dynamic neural fields (DNFs) [17], the development of spatial and visual working memory, motor planning, and perception may be understood [18], [19], [16]. Moreover, 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 [20], [21], [22], [23]. Thus, the framework of DFT provides a means to design architectures that generate robotic behavior and are grounded in neural and behavioral findings about learning mechanisms and natural development.

DNFs are continuous-time dynamical systems of activation fields, defined over continuous metric spaces of characteristic parameters [24]. The stability of the behaviorally relevant states of DNFs arises from the homogeneous interaction pattern within a neural field and makes behavior robust and reproducible in the presence of noisy, time-varying, and incomplete sensory information. In the DFT framework, instabilities separate qualitatively different attractor states of the neural dynamics, which correspond to particular percepts, motor intentions, or decisions. A sequence of attractor states separated by instabilities may be generated, when transitions between the attractor states are initiated by a neural system that detects and stabilizes a representation of the condition for the sequential transition [22].

Here, we explore how the DFT framework may be extended to accommodate rules of behavioral organization that guide the selection of the most appropriate next action. Expressing these rules by means of neural dynamics makes it possible to consider multiple constraints in selection decisions – constraints arising from perceptual inputs, from the current task, and from the specifics of the agents’ motor and sensory systems. The neuronal dynamics stabilizes these decisions, which may therefore be initiated by time varying and fluctuating sensory information. Controlled switches between different stable states enable robust transitions between different behaviors. The formulation of the complete architecture within the DFT framework opens the possibility of learning from experience through well-known neuronal mechanisms. In particular, the Hebbian learning mechanism and the related mechanism of the memory trace may both operate online, concurrently with the ongoing behavior.

In previous work, a dynamical systems architecture for behavioral organization was proposed in which dynamic neurons were coupled to implement behavioral rules [25], [26], [27], [28]. 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 (such as the possibility that a behavior would be rapidly switched on and off again). Specific solutions for many of these problems were found. Here we show that the intrinsic stability of states of the DNF dynamics solves many of the problems of the previous dynamical systems architectures in a principled fashion. In particular, we propose a set of dynamical primitives that both stabilize high-level representations of the intended goal of an EB and warrants robust switching between the EBs through a condition of satisfaction mechanism [22].

In the following section, we 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. Next, we demonstrate that switching between EBs is robust, stabilized through neuronal interaction. Signals that trigger behavioral transitions may be derived from low-level sensory input, thus reducing the demands made on sensory signals. We also show an example

of a complete architecture, including the perceptual and motor modules. We demonstrate how the elements of behavioral organization may be coupled to sensory-motor representations likewise formulated within the DFT framework and previously tested in robotic experiments [29], [21].

II. ELEMENTARY BEHAVIOR IN THE NEURAL-DYNAMIC FRAMEWORK FOR BEHAVIORAL ORGANIZATION

In the neural-dynamic architecture we propose, an elementary behavior (EB) is represented by an *intention* and a *condition of satisfaction (CoS)*, see Fig. 1. A particular *task* (e.g., “grasp an object”) 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. Furthermore, it sends activation to the associated CoS system, making it sensitive to the perceptual input that is characteristic of “goal state” of the EB. When the “goal state” is detected, the *CoS* system is activated and inhibits the corresponding intention, triggering an instability in its dynamics (see [22] for the detailed description of this mechanism).

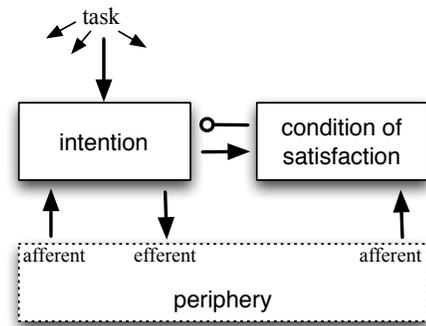
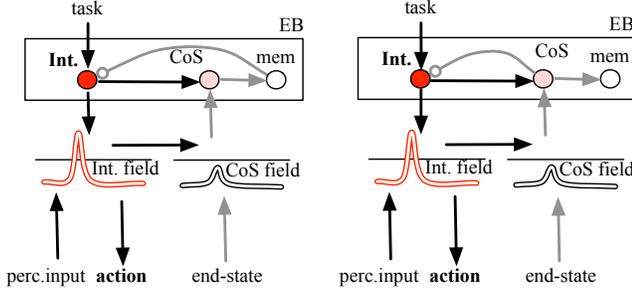


Fig. 1: Schematic representation of an elementary behavior within the neural-dynamic framework for behavioral organization.

In the dynamic neural field (DNF) implementation of the architecture, each intention is represented by a bi-stable dynamic intention node and a corresponding intention field (Fig. 2). While the intention node is the most abstract, high-level representation of the intention of a particular EB, the activation within the field is a more graded representation of the parameter of the intention. The intention node projects its activity onto the intention field through adaptable synaptic weights. The activity distribution within the intention field is thus defined by the connection weights from the intention node and, possibly, by the perceptual input to the intention field. This enables flexibility and coupling to the particular environmental context of the intention’s representation. The condition of satisfaction (CoS) of an EB is similarly represented by a bi-stable dynamical CoS node that is driven by activity in a CoS DNF. The CoS neural field is activated by perceptual input that overlaps with input from the intention field. The particular shape of the input from the intention field is encoded in the

connections between the intention field and the CoS field and represents the parameters of the goal state of the EB. The CoS node, activated by the CoS field, inhibits the intention node and thus triggers a transition to the next EB. 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.



(a) Single-action elementary behavior (b) Reactivating elementary behavior

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 CoS is deactivated) or (b) the CoS node (the EB is reactivated if CoS is deactivated).

The activation of the bi-stable dynamical nodes in this architecture follows the dynamics:

$$\tau \dot{u}(t) = -u(t) + h + c_{exc} f(u(t)) + I(t), \quad (1)$$

whereas the dynamic neural fields' (DNF) activation evolves in time according to equation [24]:

$$\tau \dot{u}(x, t) = -u(x, t) + h + \int f(u(x', t)) \omega(x - x') dx' + I(x, t). \quad (2)$$

Here, $u(\cdot)$ is the activation of the node or the field, x is the metrical parameter(s) of the neural fields, h is the negative resting level, $f(\cdot)$ is a sigmoid non-linearity, $\omega(x - x')$ is a Gaussian-shaped kernel, characterizing the lateral interactions in the neural field (local excitation and global inhibition), and I is the sum of external inputs to the node or to the field. The thorough analysis of this dynamics may be found elsewhere [24], [17]. These two equations govern the dynamics of all nodes and neural fields in our architecture, which are coupled to each other through the term I . The connection weights of the couplings may be adapted by a Hebbian learning.

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

III. ELEMENTS OF THE BEHAVIORAL ORGANIZATION

In the DFT framework, the 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 and affects its dynamics. Thus, simple rules of behavioral organization may already be represented within graded sensory-motor representation of the DFT framework. 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

The precondition relationship between two EBs (EB0 and EB1 in Fig. 3a) expresses the fact that the second EB of the two cannot be activated unless the first EB 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 its turn, inhibited by the activated *CoS node* of the first EB (EB0 in Fig. 3a), EB1 is released from inhibition. Alternatively, the precondition node can also be inhibited by the *memory node*. In this case, EB1 may be activated further in the behavioral sequences independently of EB0 (the activity of the CoS of EB0 may cease if the sensory input to the CoS field changes).

The precondition node may also be directly connected to a sensory system (e.g., a perceptual neural field described in Section IV), so that the intention of EB1 is activated when a particular state of the environment is perceived, independent of the EB that created this particular state.

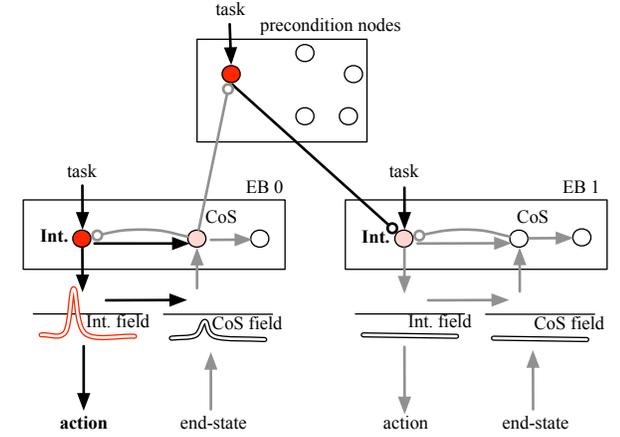
B. Competition

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

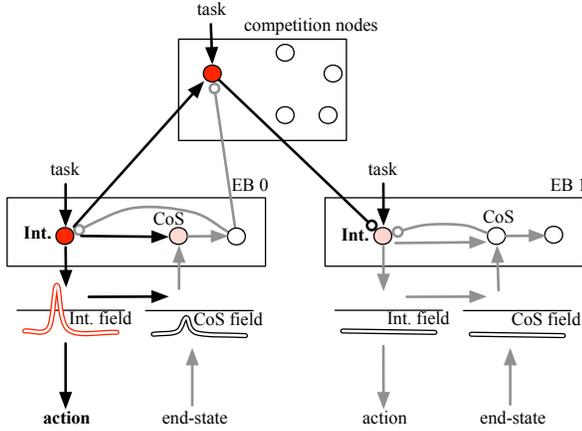
Depending on the dynamical regime of the *competition node*, the decay of activity of EB0's intention may be sufficient for the competition node to be deactivated (the CoS node is not involved then). When the competition node is inhibited by the *memory* of EB0, the competition will not be activated when EB0 is reactivated later in the behavioral sequence; the competition is specific to the first occurrence of the two EBs.

C. Logical conditions

Activation of an EB may depend on a combination of preconditions, or competitive conditions. Different combinations of logical conditions are possible and may be implemented in the neural-dynamical framework: ‘‘AND’’ by a node that sums several inputs with a activation threshold set to be



(a) Precondition coupling between two reactivating elementary behaviors



(b) Competition coupling between a single-action elementary behavior and a reactivating behavior

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

activated only if all inputs are present, “OR” by a node, that is activated by either of its inputs. By pairwise coupling of such *interneurons*, complex logical conditions can be represented in the dynamical structure with the stabilizing properties of the neural-dynamics that we use. For the real-world tasks, however, such complex conditions are rarely relevant.

IV. 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 the complete DNF architecture capable of producing behavioral sequences that correspond to different tasks. The

particular task is specified by introducing the task inputs to different intention, precondition, and competition nodes.

The tasks we have looked at are within a table-top scenario with a robot equipped with an arm with a gripper and a pan-tilt camera unit. Fig. 4 presents a 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, used to detect objects on the table-top, or the location of the end-effector. The arm module implements a dynamical system that controls the arm movement. The gripper module simply generates the “close” and “open” commands on the gripper hardware and outputs the current gripper’s opening. The pan/tilt module implements a dynamical system that controls the rotation of the camera head.

The next layer consists of perceptual neural fields that represent in a graded fashion the sensory information. In particular, three neural fields are relevant for our scenario: a color-space field represents 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 end-effector to the position specified by 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. Each intention field is coupled to a corresponding CoS field, as described in Section II, and each CoS field receives a perceptual input from either one of the perceptual neural fields, or directly from the sensors, and stabilizes the detection decision if the input from the intention field overlaps with the input from the perception.

The intention and CoS fields are coupled to the intention and CoS nodes, as described in Section II, and are also coupled through particular precondition nodes (no competition nodes are involved for the tasks in the present scenario, the lateral competition within DNF is sufficient to prevent simultaneous activation of the EBs “close gripper” and “open gripper” that are intrinsically in conflict with each other).

V. RESULTS

At this point, our results are primarily proofs of concept. We illustrate that the architecture does perform the sequential activation of behaviors in a stable fashion consistent with the designed behavioral rules. We also explore the different kinds of organizational constraints that can be expressed within our framework.

The connectivity within the neural-dynamic architecture expresses a particular coupling structure between the neural-

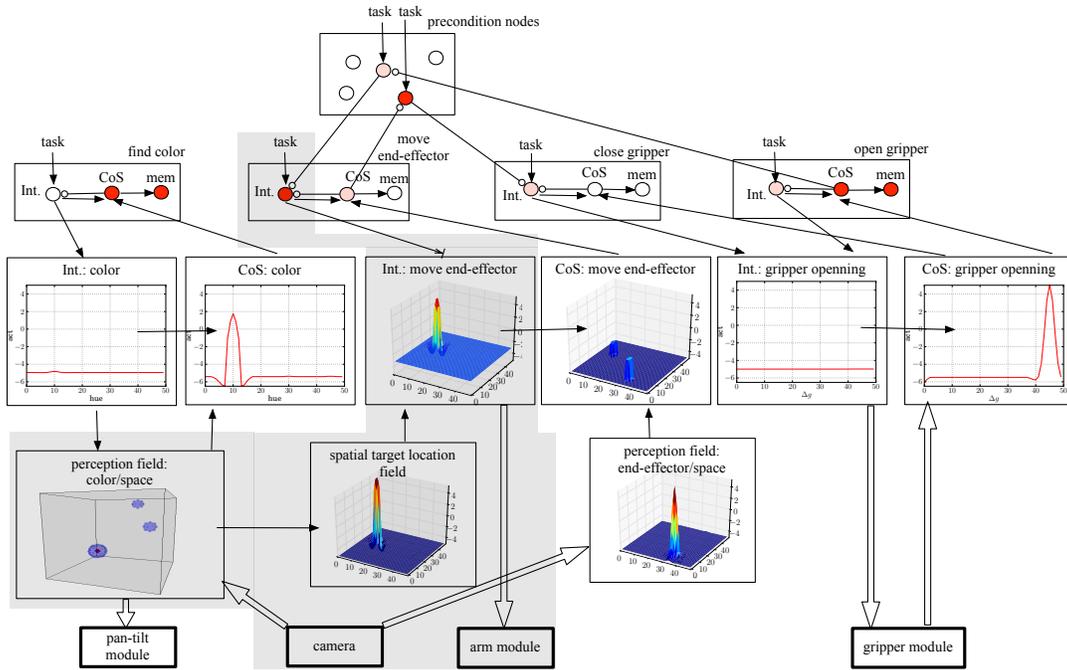


Fig. 4: Behavioral architecture for the “grasp” task

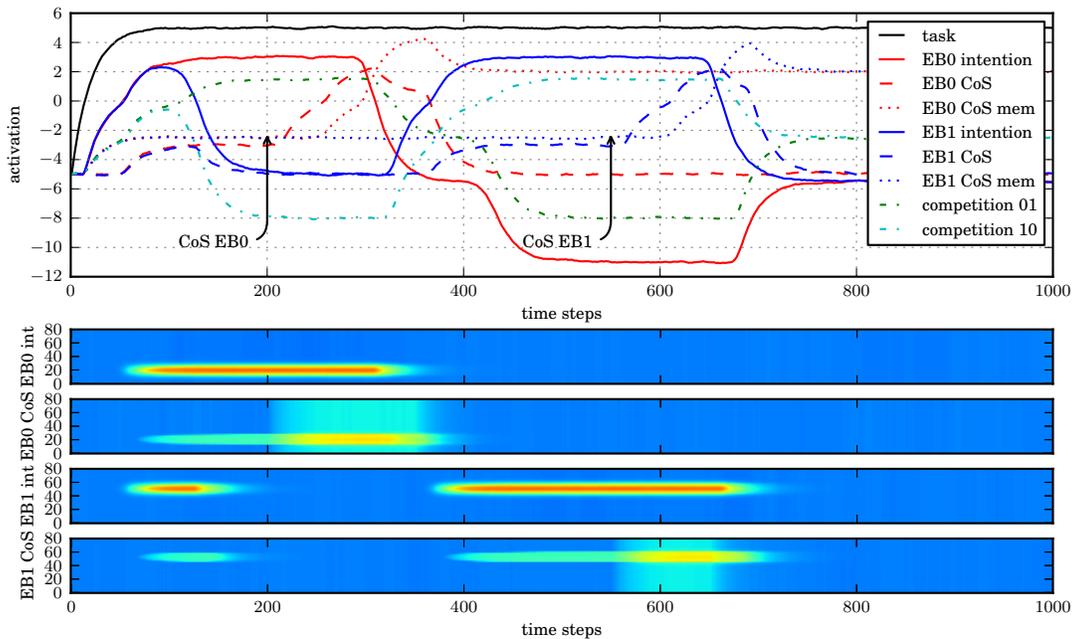


Fig. 5: Time-courses of activation within the neural-dynamic architecture for behavioral organization.

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, 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 accomplished: the “open gripper” EB and the “find color” EB: the CoS nodes and the memory nodes of these EBs 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, 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 will emerge in the CoS “move end-effector” field that will signal the successful accomplishment 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-effector” will inhibit 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 will eventually impact on the motor gripper module and the gripper will be closed around the object – the task will be 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 camera, and the dynamics that controls the arm movement. These dynamical structures, activated concurrently, constitute the elementary behavior. The exact activity pattern here depends on the top-down input, coming through the coupling structure between the nodes and the fields from the task node through intention node down to the motors, and on the bottom-up input, coming from the sensory surface. This representation of an EB emerges autonomously within the neural-dynamic architecture and is stabilized by the lateral interaction within neural fields and self-excitation of the nodes.

The signal for the transition to the next EB is detected in a bottom-up stream from sensory surface to CoS node and it’s 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.

VI. CONCLUSIONS AND OUTLOOK

We presented base mechanisms of a neural-dynamic architecture for behavioral organization and showed how these 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 (intention fields, condition of satisfaction fields, perception fields, motor fields), dynamic neural nodes (intention nodes, condition of satisfaction nodes, 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. These 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 will be an important step. Autonomous learning will then become a necessity and is a longer-term goal.

VII. 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 available online when the paper is published.

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