Serial order in an acting system: a multidimensional dynamic neural fields implementation.

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***Abstract*—Learning and generating serially ordered sequential behavior in a real, embodied agent that is situated in a partially unknown environment requires that noisy sensory information is used both to control appropriate motor actions and to determine that a particular action has been successfully terminated. While most current models do not address these conditions of embodied sequence generation, we have earlier proposed a neurally inspired model based on Dynamic Field Theory that enables sequences in which each action may take unpredictable amounts of time. Here we extend this earlier work to accommodate heterogeneous sets of actions. We show that a set of matching conditions-of-satisfaction can be used to stably represent the terminal condition of each action and trigger the cascade of instabilities that switches the system from one stable state to the next. A robotic implementation on a vehicle with a camera and a simple robot arm demonstrates the stability of the resulting scheme.**

I. Introduction

Action sequences form the core of human behavior. The question of how serially ordered sequences are learned, initiated, and produced in the form of fluent and flexible behavior is fundamental to understanding human cognition. A large number of models address the problem of serial order in language [1], speech [2], spelling [3], [4], action planning [5], and in sensori-motor tasks [6]. In most of these models, individual actions are represented symbolically, sensory input is highly preprocessed and delivers categorical information about the state of the environment and of the acting system, and the performance of the sequence in time is reduced to an a-temporal advance from one state to a successor state. Even in models using neural dynamics or distributed neural representations [7], [8], [9], [10], actions are idealized, neglecting that they may take finite and variable amounts of time to terminate and may achieve their goals only partially.

This level of abstraction matches the strategy of many experimental studies of the serial order, in which the complexity of the individual actions in a sequence is limited such as in keyboarding or reading tasks [1], [11], [12]. When actions are simple and fast and involve highly familiar perceptual or motor states, errors of serial order are the most frequent failures and can be studied in isolation providing access to how serial order is represented. But would this remain true in more natural settings in which more variable, object-oriented motor actions must be performed to achieve goal states in the environment? When the successful completion of each individual action requires careful monitoring and potentially correction, serial order errors may no longer be the main bottleneck of sequence generation. Instead, the sensory motor grounding of sequence generation may become relevant. This has not been much studied in adults, whereas these considerations are quite natural in children, who begin to produce well-ordered sequences of actions only relatively late, around two years of age [13], [14], [15]. The capability of producing action sequences may depend on cognitive capacities such as keeping in memory choices and order, but also on the capacity to coordinate actions in time, and to achieve the sensory-motor goals of each step. That the sensory-motor capacities constrain cognitive development has been broadly recognized since Piaget and is at the core of the Dynamical Systems perspective of development and the embodiment stance [16].

Three particular, yet fundamental problems arise when sequence generation is considered in an embodied system. First, in the face of highly variable sensory information, neural states representing and controlling actions need to be *stable*. Because the duration of an individual action in a sequence can be unpredictable, this stability needs to include the neural representation of where in a sequence the system currently is. Second, in order to proceed along a sequence of actions, the stable state corresponding to a particular action must be *destabilized* autonomously once the goal of that action has been achieved. Third, actions and perceptual states are not, generally, categorical in nature but require *graded neural representations* to achieve smooth and flexible behavior in complex natural environments.

To address these issues of embodied sequence generation, largely neglected in the existing theoretical literature, we recently established a model for sequence learning and production based on neural attractor dynamics [17]. The framework of Dynamic Field Theory (DFT) [18] offers the means to address the constraints of embodiment through the notion of attractor states of the neural activation fields which can be induced by noisy sensory input and can be coupled to error-prone actuators. The embodied nature of DFT models can be demonstrated by implementing these models on real robots situated in structured environments. Apart from a proof of concept, robotic implementations help generate ideas for un-

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derstanding how natural developing systems learn and develop through interaction with their environments.

In the DFT sequence generation model, actions are represented as attractor states of neural dynamics. The stability of these states enables them to resist perturbations and persist over variable durations as an action is realized. The graded nature of the neural field representations makes it possible to represent the graded, low-level sensory information. The transitions between subsequent states of a sequence arise from instabilities, which occur in the dynamics of the neural fields controlled by a neural representation of a condition of satisfaction (CoS) that signals successful completion of an intended action.

It is an important limitation, that the first DFT model was only designed to generate sequences of actions that could be characterized by the values of a single metric dimension represented in a neural field. In an exemplary implementation, that dimension was the color of objects that a robot vehicle needed to search for in a particular order. Here we address the question of whether the principles of neural field attractors and their instabilities can be extended to produce sequences of heterogeneous actions that may require the specification of a set of different parameters. This requires addressing how the condition of satisfaction, the driving force behind sequence learning and production in our framework, may be neurally represented when it depends on different graded aspects of actions and perceptual signals. We demonstrate how a neural representation of serial order may be associated with distributed multimodal neural representation of actions and perceptual states. The model is implemented on an autonomous robot vehicle that carries a camera and a simple robotic arm. We demonstrate how sequence learning and generation with flexible timing emerges in a simple robotic scenario that involves different categories of motor behaviors that rely on different actuators and sensors.

II. The Architecture

In order to represent heterogeneous sequences in the DFT sequencing architecture, we separate the ordinal dimension, which reflects the serial order of sequence elements, from the metric motor dimensions. Thus, a set of discrete dynamic nodes represents the ordinal positions of actions in a sequence. Their bistable dynamics with lateral inhibition guarantees that only one node can be active at a time. A second layer of memory nodes ensures activation of the correct successor at each transition.

The ordinal nodes project onto a number of neural fields that represent actions. The connection weights in these projections constitute the memory for the sequence and are learned within a single demonstration of the action. Localized peaks in the action fields impact on the motor system of the agent, shaping attractors of the motor dynamics, and thus specifying a particular action. The stability of the neural field dynamics guarantees that the impact on the motor dynamics is sustained as long as needed for current action goal to be achieved.

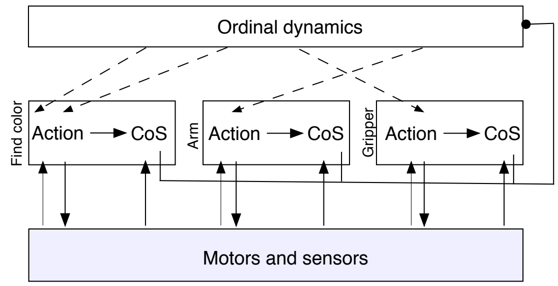


Fig. 1. The sequencing architecture including action systems specific to the robotic implementation.

For each action modality, a condition of satisfaction (CoS) neural field is defined. Localized input from the active regions of action fields makes the CoS field sensitive to sensory input signaling successful accomplishment of the action. Positive activation in the CoS field triggers a cascade of instabilities that bring about the sequential transition to the next action.

An overview of the architecture for the present robotic implementation is given in Figure 1. We briefly describe the dynamics of the three main parts of the architecture, relegating the detailed mathematics to the Appendix.

A. Ordinal nodes

The ordinal positions in a sequence are represented by a set of dynamic neural nodes. Each ordinal node has a self-excitatory connection which generates a bistable dynamics. The mutual inhibition among ordinal nodes allows only one node to be active at any particular point in the sequence. The active node provides input to the action fields through modifiable connection weights. When the final state of the action is reached, the ordinal set is inhibited by input from the condition of satisfaction system. A memory node associated with each ordinal node keeps the ordinal information during the transition phase and facilitates activation of the next ordinal node once the ordinal system is released from inhibition.

B. Action fields and synaptic projections

The action fields are dynamic neural fields defined over characteristic dimensions of actions. During sequence generation, the active ordinal node projects its activation through the modifiable connection weights onto the regions of the action field, that were active at this particular ordinal position during learning. A self-stabilized peak induced by the ordinal input controls the robotic action by setting attractors for the sensory-motor dynamics.

Action fields also receive perceptual input about the characteristic action parameter of an ongoing or demonstrated action. This input is critical during sequence learning, when it induces a localized, self-stabilized peak of activation in the action field that represents a demonstrated action. The connection weights linking the active ordinal node to the region of positive activation of the action field are upweighted according to a Hebbian learning rule.

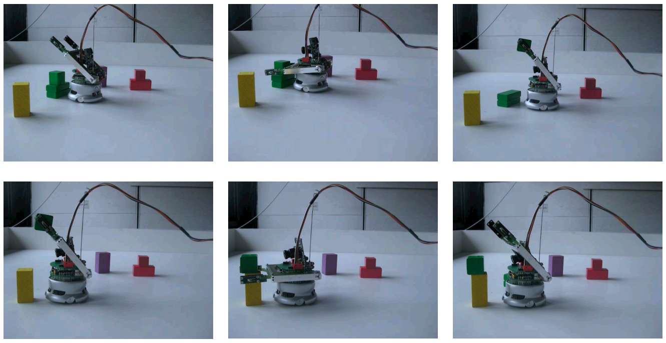


Fig. 3. The robotic scenario.

C. Condition of satisfaction fields

For each action in a sequence, its condition of satisfaction (CoS) is defined. The CoS dynamic fields are spanned over metric dimensions that characterize the terminal states of the actions. The CoS fields receive localized inputs from active regions of the action fields. The mapping between the action fields and CoS fields could be learned from previous experienced, but was assumed given in the current implementation. The action field input preactivates its CoS field so that the CoS is sensitive to perceptual input that matches the expected terminal state of the action. When such a terminal state is detected, a self-stabilized peak in the CoS field is induced, that then inhibits the ordinal system. This suppresses activity in the ordinal system and thus removes the input the ordinal system provided to the action fields. As a result, the peak in the action field becomes unstable and decays. This removes the previous input to the CoS field, pushing that system through the same instability and leading to the decay of the peak in the CoS field. This transition, finally, removes inhibitino from the ordinal set, and the next ordinal node becomes activated. This cascade of instabilities separates the different ordinal positions in a sequence both during sequence learning and production.

III. Robotic implementation

In order to demonstrate learning and production of action sequences in an embodied setting, we describe an exemplary implementation of the architecture on a mobile robot vehicle of the Khepera type.

A. The scenario

In the learning phase of the scenario, a teacher demonstrates arbitrary sequences of alternating movements or colors to the robot. After learning, the robot is put in an arena in which colored blocks have been distributed. The first node of the ordinal set is activated by a "go" signal and the robot performs the learned sequence.

In this scenario, three action modalities are considered: search of objects of a given color, lifting movement of the robotic arm, and opening of the robotic gripper. The three metric parameters, characterizing the three action modalities - color, arm height and gripper opening - span the three neural dimensions over which the action fields are defined.

The particular sequence, described in the following is "find green - lower arm - close gripper - lift arm - find yellow - lower arm - open gripper", which results in the grasping of a green block, its transportation to a yellow block and its depositing there (Figure 3).

B. Implementation

1) Teacher interaction: During learning, graded sensory input specifies the demonstrated action. Additionally, the teacher specifies the intended action modality by pressing buttons in a GUI. That signal provides a homogeneous activation boost that raises the resting level of the cue action field. Thus, for instance, specifying "color" boosts the color action field so that the color of the block that is currently present in the robot's visual array induces a localized peak of activation. Similarly, specifying "arm" boosts the arm-pose field and a peak is built at the location that represents the sensed current elevation of the robot's arm. Specifying "gripper" activates the gripper field in the same manner.

2) Perception and motors: The robot's color camera provides perceptual input to the color-search modality. Color extraction is performed through a color-space neural field, which models early stages of visual processing (see [17] which employed the same method). The search for colored objects is accomplished by an attractor dynamics of the heading direction of the robot, as described in [19].

The arm of the Khepera robot can be lifted and lowered. This movement is controlled by a one-dimensional neural field defined over the dimension "arm elevation". For a robotic arm with several degrees of freedom, the corresponding field can be defined over the three spatial dimensions the specify the spatial position of the end-effector. A localized peak of activation in the arm field sets an attractor for the dynamics of arm movement. During learning, the sensed current position of the arm sets a localized sensory input to the arm action field. That input may induce a peak if the teacher specifies "arm" as the action modality to attend to.

The robotic gripper consists of two bars which can be closed or opened. The action field is defined over the dimension "gripper opening". A peak in that field initiates either the "closeGripper()" or the "openGripper()" commands (only these two options exist for the Khepera's gripper), depending on where along that dimension the peak is centered relative to the current gripper position. During learning, a graded sensory signal reflecting the current opening of the gripper is fed into the action field inducing a peak, whose location represents the action at that ordinal position.

In this implementation, the CoS fields for the color, arm and gripper modalities are defined over the same dimensions of color, arm elevation and gripper opening. For color, the sensory input to the field is derived from the central portion of the robot's field of view; consequently, the CoS field is activated when an object of the searched color is close to the robotic camera and centered in view. The arm and gripper CoS field are activated when a match is detected between the

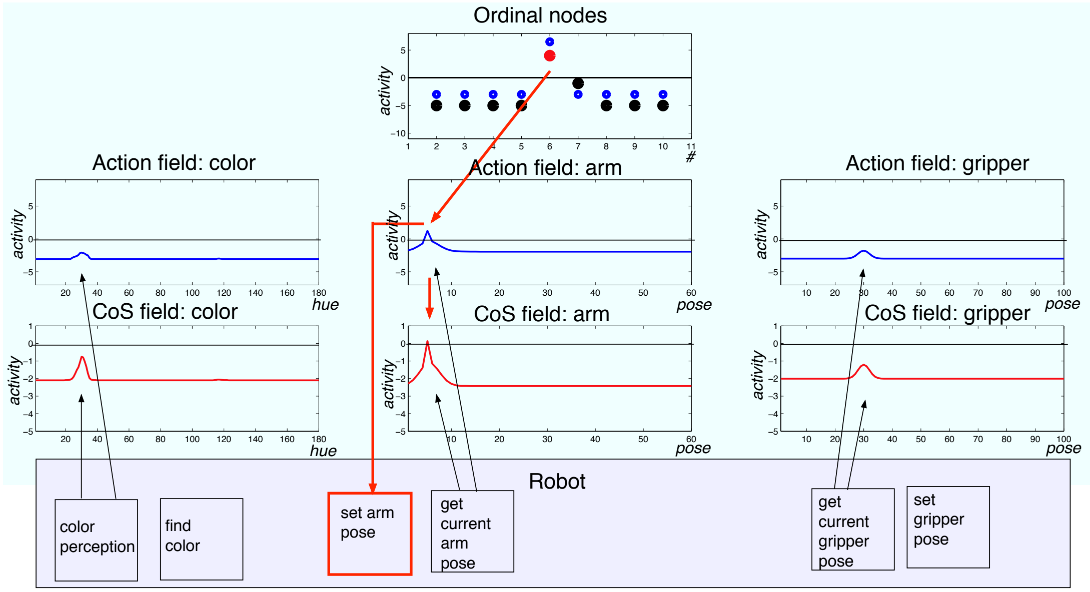


Fig. 2. Snapshot of the dynamics of the model. See text for details.

attractor position for the corresponding movements and the actual position of the arm and the gripper.

Figure 2 shows a snapshot of the sequence generation dynamics. The fifth ordinal node is active here and projects onto the "arm" action field through the neural connections. The ordinal input induces an activity peak in the action field, and the arm elevation value $pose \approx 5$ is set as attractor for the arm movement. When the CoS field detects the arm elevation of $pose \approx 5$, an activity peak arises in the CoS field and starts to inhibit the ordinal nodes. The "color" and "gripper" action and CoS fields also receive perceptual input from sensors of the robot here, but this input alone is not sufficient to induced peaks in those fields.

C. Results

Figure 4 presents the time courses of activity of the eight ordinal nodes and the three action fields during learning (Figure 4(a)) and production (Figure 4(b)) of the sequence "find green - lower arm - close gripper - lift arm - find yellow - lower arm - open gripper". During learning, the teacher demonstrates the actions to the robot by naming the modalities of interest and triggering the needed actions. The demonstrated actions are detected in the action fields at times that are marked with arrows on the Figure 4(a). Lightly shaded regions mark regions in the action fields with positive activity. These regions are associated with the currently active ordinal node by quickly adaptable neural weights. The CoS is activated shortly thereafter by perceptual input that signals the accomplished action. The CoS signal inhibits the ordinal set (top row on the Figure 4) and triggers an instability, after which the next ordinal node is activated. The next action, demonstrated by the teacher is associated with this node.

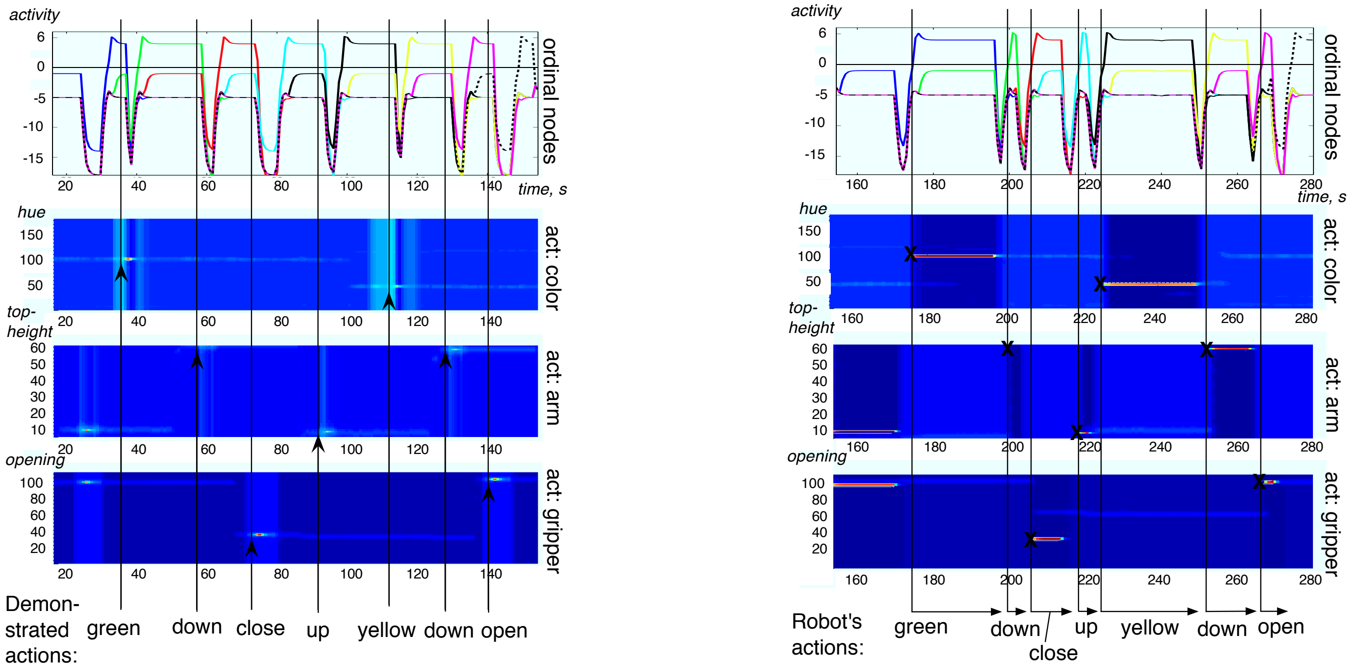
After learning, the robot is put into the arena, in which colored objects may be distributed in a different spatial arrangement. A "go" signal brings the robot into its initial state (gripper is high and opened) and activates the first ordinal node. A stable peak of activation emerges in the "color" action field (dark red region on the Figure 4(b)). This peak represents the color-search action for however long it takes to locate, center and approach an object of the specified color (with $hue \approx 100$, green, here). The CoS field detects that an object of the specified color is sufficiently close and centered, builds a peak, and inhibits the ordinal set. This triggers the ordinal transition, a cascade of instabilities leading to the activation of the second ordinal node. The second action, "arm lowering" is performed by the robot, its termination again being controlled by the CoS field and pertinent sensory input. The rest of the sequence is acted out in the same manner. The robot picks up the green block and delivers it to the yellow one.

Note the flexible timing of the actions both during learning, when the timing is controlled by the teacher, and during production, when the duration of actions depends on the current situation in the arena.

IV. Discussion

In this paper we extended the DFT model of sequence generation to heterogeneous sequences involving different motor and perceptual modalities. This is an important step toward an approach to sequential behavior in natural settings in agents with rich behavioral repertory.

Stability of the functional neural states is the critical property of the model that enables the agent to connect to noisy and unreliable sensory information. Stability is in conflict with the need to transition among the sequential stages and is, therefore, absent from most of dynamical models of sequence generation [20], [21], [9], [10]. We overcome this conflict by introducing the concept of a condition of satisfaction, a stable neural representation of the terminal state of an action.



(a) Learning

(b) Production

Fig. 4. Time-courses of the dynamics of ordinal nodes and the three action fields during learning and production of a multimodal sequence.

This mechanism makes it possible to execute sequences in environments in which the durations of individual actions are unpredictable and the signal for a sequential transition must be extracted autonomously from noisy sensors. Our extension of the model required enabling the condition of satisfaction system to represent graded aspects of actions, that are specified by graded sensory information controlling the sequential transitions during learning and production.

Neural inspiration for model comes from findings of a separate neural substrate for the ordinal position of an element in a sequence, along with the neural representation of the motor characteristics of the associated movements [22], [23]. The condition of satisfaction system may be thought of as a potential reward mechanism. Together with the ordinal nodes, the condition of satisfaction system resembles the mechanisms of action selection hypothesized to reside in the basal ganglia [24], which project onto the distributed neural representations of actions and perceptual states. In our model, the adjustable neural weights hold the memory for each element of a sequence. These weights are established from a single exposure to a sequence element. Such fast learning is possible due to the explicit segregation of ordinal position within the ordinal layer and stands in contrast to the extensive learning required in models of serial order that are based on distributed and overlapping representations of the order along with motor and perceptual features [7].

With the introduction of multiple motor modalities, the sequence generation model touches on the problem of behavioral organization, the coordination of multiple different behaviors in time. At this point, the model sidesteps this issue. Within the model, different motor modalities do not interfere or interact. In the implementation, the three action systems link to different effector systems and degrees of freedom of the robot. Their simultaneous initiation, represented by co-existing peaks in the different action fields, is allowed. The actions “move gripper”, “close gripper” and “search for red”, for instance, can all be active at the same time. Integrating principles of behavioral organization would require a form of hierarchical organization, in which actions within a sequence may consist of an organized ensemble of sub-actions. One direction in which we would like to develop our approach would be to autonomously learn such organizational rules as something like a grammar of action. The fundamental mechanism established here for sequence generation in a stable neuronal dynamics may also provide a framework for how heterogeneous sequences of actions may be produced that lead to a given goal.

APPENDIX

The dynamics of the ordinal nodes and the corresponding memory nodes are described by the equations:

$$\tau \dot{d}_i(t) = -d_i(t) + h_d + c_0 f\big(d_i(t)\big) - c_1 \sum_{i' \neq i} f\big(d_{i'}(t)\big) + c_2 f\big(d^m_{i-1}(t)\big) - c_3 f\big(d^m_i(t)\big) - I_{\mathrm{C}}(t) \qquad (1)$$

$$\tau \dot{d}^m_i(t) = -d^m_i(t) + h_m + c_4 f\big(d^m_i(t)\big) - c_5 \sum_{i' \neq i} f\big(d_{i'}(t)\big) + c_6 f\big(d_i(t)\big) \qquad (2)$$

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The first three terms shape the bistable dynamics of the i^{th} *ordinal node*: the negative activation $-d_i(t)$ provides stabilizing properties, $h_d < 0$ is the resting level, c_0 is the strength of the self-excitatory term. $f(\cdot)$ is a sigmoid non-linearity shaping the node's output. c_1 is the strength of the mutual inhibition in the ordinal set; c_2 and c_3 are the strengths of couplings to the memory nodes. I_C is the input from the condition of satisfaction field, which signals the successful accomplishment of an on-going action.

h_m is the resting level of the *memory nodes*, c_4 is the strength of the self-excitation, c_5 is the strength of lateral inhibition, c_6 is the strength of the input form the corresponding ordinal node.

The dynamics of the *action fields* follows the equation:

$$\tau \dot{U}^A_j(x_j,t) = -U^A_j(x_j,t) + h^A + \int f\Big(U^A_j(x'_j,t)\Big) w(x_j - x'_j) dx'_j + \sum_{i=0}^{N_d} f\Big(d_i(t)\Big) M_i(x_j,t) + c^A_p I^A_p(x_j,t) \quad (3)$$

Here, the first three terms define the generic neural field dynamics with a negative resting level h^A, and the lateral interactions term. N_d is the number of ordinal nodes, activities of which, $d_i(t)$, are thresholded by a soft sigmoid function $f(\cdot)$ and then projected on the action field through the modifiable weights, $M_i(x_j,t)$, where j numbers the actions fields, and i numbers the ordinal nodes. c^A_p controls the strength of the perceptual input, $I^A_p(x_j,t)$, essential during sequence learning.

When an ordinal node is active (i.e. $f(d_i(t)) > 0$), its activation propagates to the action field, providing a localized input to this field. The shape of this input is defined by the *neural weights*, $M_i(x,t)$, which are modified during sequence learning according to a Hebbian-like rule:

$$\tau_l \dot{M}_i(x,t) = \Big(-M_i(x,t) + f\big(U_A(x,t)\big)\Big) \cdot f\big(d_i(t)\big) \quad (4)$$

The *CoS neural fields* evolve according to a dynamical equation:

$$\tau \dot{U}^C_j(y,t) = -U^C_j(y,t) + h^C + \int f\Big(U^C_j(y'_j,t)\Big) w(y_j - y'_j) dy'_j + T(x_j,y_j) * f\Big(U^A_j(x_j,t)\Big) + c_p I_p(y_j,t). \quad (5)$$

Here, the activity of the CoS field $U_C(y,t)$ is defined over the neural dimension, y. The transfer function $T(x,y)$ defines the mapping between the dimensions characterizing actions and their terminal states ($T(x,y) = \mathbf{1}$ in the implementation presented here). Positive activation in the action field (where $f\big(U_A(x,t)\big) > 0$) propagates to the CoS field through this mapping. The constant c_p controls the strength of the perceptual input $I_p(y,p)$, h_C is the resting level, and τ is the time-constant of the field's dynamics.

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