Towards Collaborative Robots as Intelligent Co-workers in Human-Robot Joint Tasks: what to do and who does it?

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Abstract

Recently there has been an increasing demand for collaborative robots able to interact and cooperate with people in several human environments, sharing physical space, and working closely with humans in joint tasks. Endowing robots with learning and cognitive capabilities is a key for natural and efficient cooperation with the human co-worker. In particular, these abilities improve and facilitate the use of collaborative robots in the joint assembly task, especially in smart manufacturing contexts. In this paper, we report the results of the implementation of a neuro-inspired model - based on Dynamic Neural Fields - for action selection in a Human-Robot join action scenario. We test the model in a real construction scenario where the robot Sawyer selects and verbalizes, at each step, the next part to be mounted and outputs an appropriate action to insert it, together with its human partner. The two-dimensional Action Execution Layer allows the representation of the components object and action in the same field. The results reveal that the robot can compute valid decisions for different workspace layouts and for situations where there are missing pieces.

1 Introduction

Robots are today an increasingly important part of the modern world, not only because they are a fundamental tool in many industries, but also due to their ability to assist humans in hazard environments and dangerous tasks. Recently, many robotic companies (e.g. Universal Robots, Kuka, ABB, Fanuc, Rethink Robotics) have been broadly advertising and selling a new generation of robots known as "Collaborative Robots". However, this designation is misleading. What is really meant is that these are a category of robots that can be used without fencing and that can work around humans without any additional safety devices. It does not mean that these are robots able to engage in proactive joint action with someone to achieve a common goal, which is exactly the ultimate purpose of collaborative robots [12]. Having them work directly with humans could speed up all kinds of processes – e.g. joint construction tasks – in which a human and a robot work together to assemble objects from their parts. The integration of robotic partners in human-dominated areas, such as in industrial settings, will only likely to be accepted by their biological colleagues if they allow for natural and efficient cooperation on a true peer-to-peer level. A person working with a robot should not be required to learn new forms of interaction. Thus, for fluent interaction and for building trust, the robot should actively contribute to the work and continuously communicate its reasoning and decisions to its human co-workers [1].

In the scope of several EU and national projects, our group has been developing and testing a cognitive control architecture for natural Human-Robot Interaction inspired by neuro-cognitive principles governing Human-Human Interaction in shared tasks like for instance joint assembly paradigms [4, 7]. Central to our approach, we apply the theoretical framework of Dynamic Neural Fields (DNFs), that has been proven to provide key processing mechanisms for applications in cognitive robotics, such as working memory, decision making, action selection, and learning processes [6].

Here, we present a cognitive control architecture for human-robot joint action that implements a flexible and dynamic coordination of actions and decisions among the teammates. It is formalized by a coupled system of dynamic neural fields representing a distributed network of local but connected neural populations with specific functionalities. The architecture was implemented and tested on the collaborative robot Sawyer (from Rethink Robotics) in the context of a specific task example consisting of a thrusters/pipes assembly task (**Figure 1**) composed by a Base (BA), four bottom-parts - Green (G), Orange (O), Pink (P) and Yellow (Y) - and four parts that are inserted in the top - Blue (B), Light Blue (LB), Light Green (LG) and Red (R). The pipes are distributed across different workspaces limiting the pieces reachable by each coworker. Sawyer must select, at each step, the most suitable action to take and communicate it to its teammate to achieve a coordination of actions to assemble each piece.

The remainder of the paper is structured as follows: Section 2 describes the cognitive architecture and its layers; Section 3 presents the construction task, the robotic platform, and the experimental setup; Section 4 is a description

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of the DNF models and its formulations; Section 5 presents the experimental results; and the paper ends with a discussion and future work in Section 6.

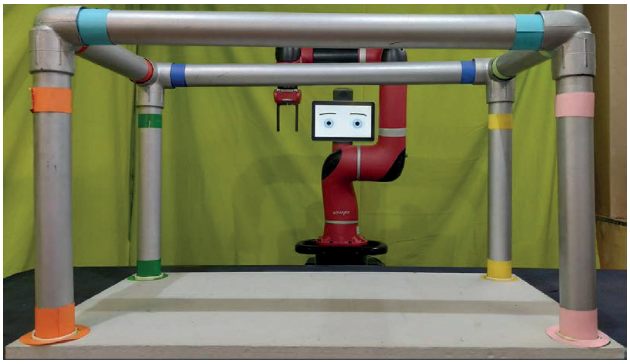

Figure 1 Robot Sawyer and Construction task

2 Cognitive Control Architecture for joint action

The cognitive architecture displayed in **Figure 2** is implemented using Dynamic Neural Fields. It is formed by different pools of neurons across several DNF-layers that encode task-relevant information about object location, action goals, and context in the form of self-sustained activation patterns. These patterns are triggered by input from connected populations and evolve continuously in time under the influence of recurrent interactions.

The several pieces that form the construction task are dispersed into three different workspaces - Human, Robot, and Shared (**Figure 3**) - that are represented in the neural populations of the Object Memory Layer (OML). Input from the Vision System triggers activity in each field, marking the location of the pieces across the different workspaces. Information regarding what pipes the robot is (physically) able to insert is encoded in the Executable Tasks Layer (ETL). Task-related information concerning the sequential order of sub-goals is stored in the Sequence Layer (SL), where a continuous representation of achieved sub-goals (Past field) activates the next valid sub-goals (Present field). The knowledge about the sequential structure of the task is encoded in the synaptic connections between the Past and Present fields in SL. These connections have been previously learned (and reported in past work) from tutors' demonstrations memorized in a Short-Term Memory Layer (STM) to prevent the need for multiple demonstrations (for a complete review see [10, 5]).

The Action Execution Layer (AEL) is modeled as a two-dimensional neural field that integrates input from OML, ETL, and SL and implements the decision-making process regarding the selection of an appropriate goal-directed action. The goal-direct action is constituted by two parts:

1. the next part to be mounted, which is assumed to be color-coded;
2. what action is performed and who does it (e.g. Human Inserts, Robot Hands Over).

The selected action is represented as a bump of activity emerging in the two-dimensional neural field expressing the complete decision-output that triggers the corresponding motor control action and it is verbalized by the robotic system.

3 Experimental Setup

The dynamic control architecture has been implemented in Sawyer and validated using a scenario in which the robot acts as an assistant/co-worker during a joint construction task. Sawyer consists of an articulated arm with 7 degrees of freedom and 1.26 meters reach, designed to perform collaborative tasks [9]. The LCD that sits on its top displays animated eyes capable of representing different emotions that endow it with a humanoid appearance and make it appealing to work with, contributing to a more natural and user-friendly interaction. The information about object color/type is provided by the head camera system. As a concrete application scenario, a task consisting of building a structure of eight different-colored thrusters/pipes (Figure 2) was selected. The task was segmented into eight subgoals, where inserting each pipe on top of the Base corresponds to one sub-goal. The pieces are distributed through the three workspaces displayed in Figure 3. Besides selecting the next pipe to be inserted, the robot also needs to select the best suitable action to take, considering the end purpose (insert a piece in a given place), which will depend on two factors:

1. **Who should grab the next piece?** - Sawyer can grab pieces from the Robot and Shared Workspaces. The Human can reach pieces in the Human and Shared Workspaces;
2. **Who should insert the piece?** - Due to its physical constraints, the robot can only reach the placing location of the Green, Orange, and Yellow pipes - information encoded in ETL. The other parts are assumed to be inserted by the Human.

Four different actions can be taken to insert each pipe, which will depend on the location of the piece and on the ability of the robot to insert each piece in the structure:

- **Robot Inserts (RI):** Pipes placed in the Robot or Shared Workspaces and which insertion is executable for the robot - Sawyer grabs and inserts the piece;
- **Human Inserts (HI):** Pipes placed in the Human or Shared workspaces that the robot is not able to reach and insert - Human grabs and inserts;
- **Robot Hands Over (RHO):** Pipes placed in the Robot Workspace that cannot be inserted by the robot - Sawyer grabs the piece and hands it over to the Human co-worker that performs the insertion;
- **Human Hands Over (HHO):** Pipes placed in the HumanWorkspace that can be inserted by the robot - Human grabs the piece and hands it over to Sawyer that performs the insertion (reducing the workload of the Human partner).

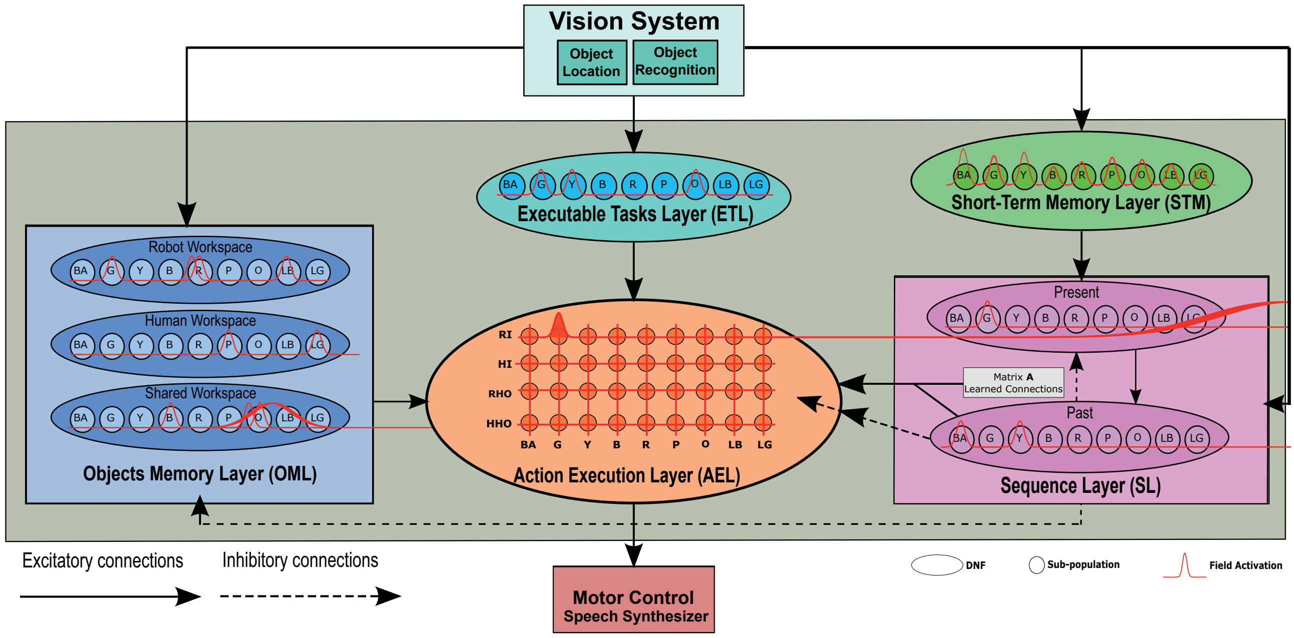

Figure 2 Schematic view of the Cognitive Control Architecture for joint action. According to the Present field, the next sub-goal should be the insertion of the Green pipe. The Green piece is placed on the Robot Workspace and, according to the information provided by the ETL, the robot can insert it. Therefore, the decision that will emerge in the AEL is: Robot Inserts (the Green pipe).

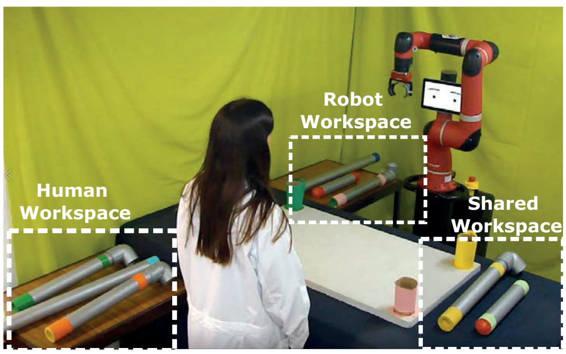

Figure 3 Illustration of the three workspaces: Human, Robot and Shared (working table).

4 Model Description

The models presented in this paper are inspired by previous research on natural and intuitive human-robot interaction [3, 11], based on Dynamic Neural Fields. The DNF-framework provides key processing mechanisms for applications in cognitive robotics, such as memory, prediction, and decision making [6]. DNFs are mathematically formalized by nonlinear integro-differential equations in which the activity of neurons is summarized into the activity function $u(x,t)$, which can be used to reduced computational complexity and can be mathematically analyzed. Task-related information is expressed in the form of bumps above a threshold level of neural activation representing specific sub-goals. Input from external sources, e.g., Vision, causes activation in the correspondent neural populations that remain active with no further external input due to recurrent excitatory and inhibitory interactions.

The mathematical implementation of each layer is based on the Amari equation [2], formalized as follows:

$$\tau \frac{\partial u(x,t)}{\partial t} = -u(x,t) + h + s(x,t) + \int w(x-y) f_0[u(y,t)]dy, \tag{1}$$

with $u(x,t)$ being the activation of a neuron x at the time t and $s(x,t)$ being the total amount of input given. The parameters $\tau > 0$ and $h < 0$ are the time constant and the field resting level to witch u converges in the absence of external input, respectively. Those sub-populations of neurons can either excite or inhibit each other, following a pattern defined by the type of interaction kernel w. The function f_0 is used as a gating function to ensure that only neurons with activity above a specific threshold level contribute to the interaction. Next, follows an explanation of the layers that form the cognitive architecture.

4.1 Short Term Memory (STM)

Figure 4 illustrates an example of an STM pattern. Each bump of activity represents an event triggered through excitatory input from the Vision System. The strength of each memory representation reflects the time elapsed since each event was observed (e.g., blue pipe inserted), resulting in an activation gradient from the first to the last sub-goal observed. This way, the STM layer can store a sequence of sub-goals observed by the robot, which is later used to train the synaptic weights of the network that stores task-related information in SL [10, 5].

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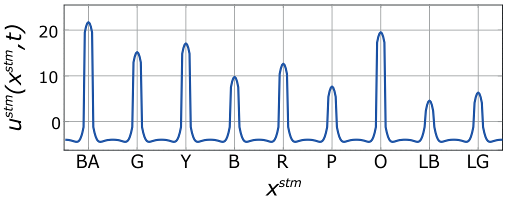

Figure 4 Example of an STM activation pattern.

4.2 Sequence Layer (SL)

The SL consists of two interconnected DNFs that reflect changes in the task observed by the robot. The Past field behaves as a “working" memory of the state of the task while the Present field marks observed or predicted sub-goals. The experiments conducted in this work took place after Sawyer had learned the sequential structure of the multi-order task encoded in the form of a matrix of synaptic weights connecting Past to Present fields (see [11]).

4.3 Object Memory Layer (OML)

The OML encodes information regarding the different workspaces modeled as DNFs that work as a dynamic memory of the pieces in each workspace. Input from the Vision System generates bumps of activity in the subpopulations encoding the colored pipes in each workspace. The Base is always placed in the SharedWorkspace (working table). When a pipe is inserted, the inhibitory connection from the SL-Past field marking achieved sub-goals suppresses the sub-populations in the OML fields corresponding to the pieces already inserted. **Figure 5** exemplifies the profile of each workspace and their corresponding fields at a middle step of the construction. The Base is the first sub-goal inhibited in the OML since it is already placed in the table when the construction starts. Then, with the insertion of the Pink, Yellow, Green, Orange and Light Green pipes, all of the corresponding populations of neurons are inhibited. Consequently, there are only peaks of activity in the Red, Blue and Light Blue that are placed in the Robot, Human and Shared Workspaces, respectively.

4.4 Executable Tasks Layer (ETL)

The joint action scenario requires Sawyer to actively collaborate with his teammate in assembling the task. Considering its physical limitations (such as reachable distance) and the characteristics of the pieces, Sawyer is only able to insert the Yellow, Green and Orange. Therefore, the ETL field presents the multi-bump pattern depicted in **Figure 6**, where the active sub-populations represent the pieces that can be inserted by Sawyer. The robot cannot fully insert pipes on the top of the structure (Red, Blue, Light Blue and Light Green) since two hands are needed to insert those. In that case, the robot can either instruct the human to insert or assist him by handing over the pieces. From the remaining pieces, the only one out of the robot’s reachability is the Pink. For the purpose of this work, the ETL was manually encoded. However, for future work, it would be possible to use information from the Vision System to automatically calculate what pieces are reachable for the robot.

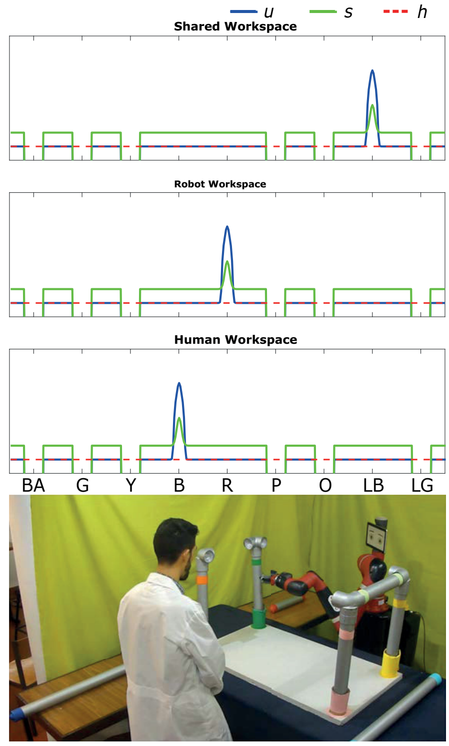

Figure 5 Human, Robot and Shared Workspaces: Layout of the pieces and corresponding OML fields at a middle step of the construction.

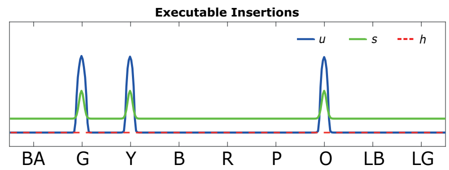

Figure 6 Executable Tasks Layer activation profile.

4.5 Action Execution Layer (AEL)

The AEL is modeled as a two-dimensional field representing the components “color” and “action” of the output decision of the system. Input from the SL contributes to the activation of the field corresponding to the color of the next piece. The dimension “action” receives input from the OML and ETL which triggers activation in the region of the field corresponding to the action selected by the system. The activity that appears in both dimensions results in a two-dimensional bump, giving information regarding what is the piece that should be placed next in the structure and each one of the four motor actions suits the scenario the best.

The AEL is implemented as a 2d-DNF field $u(x^c,x^a,t)$, where x^c and x^a designate the dimensions “color” and “action”, respectively. The formulation can be generalized from the DNF equation (1), as follows:

$$\tau\frac{\partial u(x^c,x^a,t)}{\partial t} = -u(x^c,x^a,t)+h+s(x^c,x^a,t)+\varsigma_{stoch}(x^c,x^a,t) + \iint w(x^c-q,x^a-s)f_0[u(q,s,t)]dqds, \quad (2)$$

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where q and s represent the center distance within each dimension and w is a two-dimensional kernel function with global inhibition (see [8]), given by:

$$w(x^c - q, x^a - s) = A\left[e^{\frac{-\frac{1}{2}(x^c-q)^2}{2\sigma^2}} * e^{\frac{-\frac{1}{2}(x^a-s)^2}{2\sigma^2}}\right] - w_{inh}. \quad (3)$$

The equation is a convolution of two gaussian kernel functions with global inhibition w_{inh}. Using this type of kernel, the competition between sub-neuronal populations is enabled, from where only one localized bump of activity will evolve. Additionally, a noise function ς_{stoch} is applied to force the competition between neurons with identical input value.

4.5.1 Input to the AEL field

The AEL receives input from two main sources, contributing to the dimensions x^c and x^a:

$$s(x^c, x^a, t) = s(x^c, :, t) + s(x^a, :, t). \quad (4)$$

$s(x^c, :, t)$ results from the propagation of activity from the SL that encodes the sequence of sub-goals and the inhibitory connections from past/achieved sub-goals. $s(x^a, :, t)$ is mathematically computed from the information received from the OML and ETL, according to the connections displayed in **Figure 7**. The connections were pre-defined to compute the expected action-output.

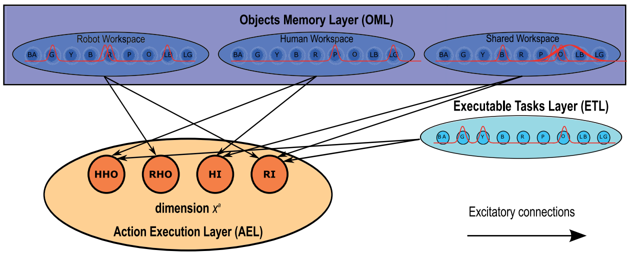

Figure 7 Excitatory connections from OML and ETL to AEL.

5 Experimental Results

During the experiments, two different workspace layouts were used (**Figure 8**). At each step of the construction, the robot verbalizes to its co-worker the result of the selected decision (active region in AEL) and then generates the corresponding motor action. Following the task sequence information previously acquired and stored in the synaptic weights in the Sequence Layer, the expected construction order should be: Yellow→Pink→Orange→Light Green→Green→Red→Blue→Light Blue.

5.1 Test number 1: Layout A

Figure 11 illustrates the results of the first experiment [1]. In the beginning, the pipes are placed in the workspaces

[1] A video of this experiment can be found at `https://youtu.be/XQwAz1PCuHw`.

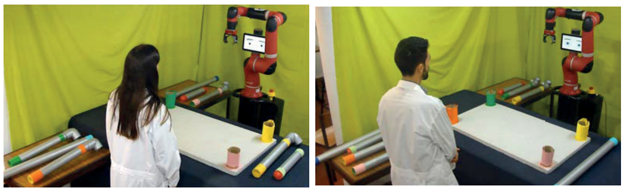

Figure 8 Distribution of the pipes according to Layout A (left) and B (right)

according to Layout A. Following the SL, the Yellow is the first pipe to be inserted. Since it is placed in the Shared Workspace and marked in ETL as a piece that Sawyer can insert, Sawyer verbalizes "I think I should grab and plug the Yellow thruster", informing his teammate that the robot will grab and insert the Yellow pipe (Figure 9a).
Next, Yellow triggers the next sub-goal, which is placing the Pink piece. The AEL activation profile in this step is displayed in **Figure 10**. Note that the sub-populations in the dimension "color" have a small pre-shape of activity - except for the ones encoding past sub-goals (Base and Yellow) - due to the OML connection informing about available pieces in the workspaces. Pink is placed in the Robot

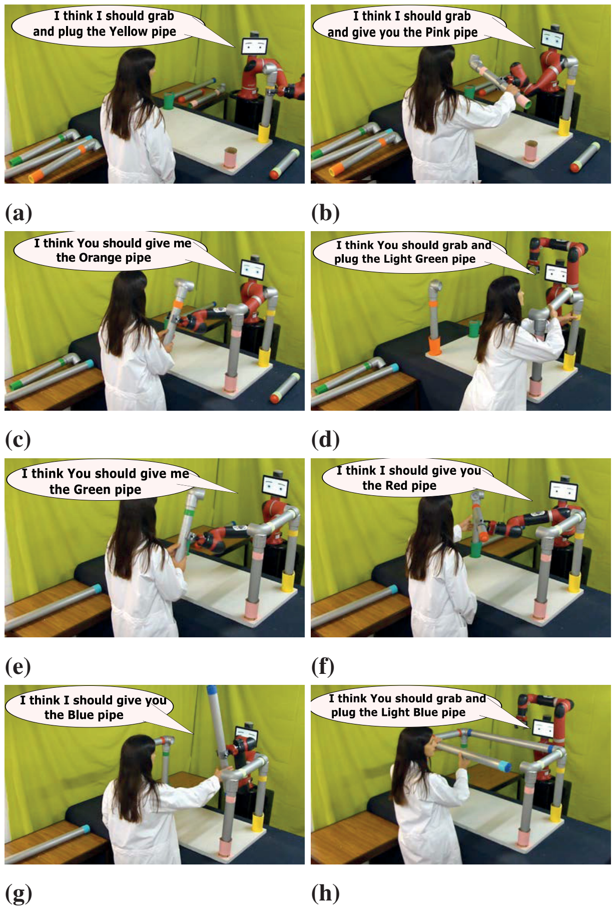

Figure 9 Test number 1 - Snapshots illustrating the sequence of actions during the first trial.

Workspace, but its insertion is not an executable action for Sawyer. Therefore, in the dimension "action," the active population corresponds to "Robot Hands Over". Consequently, Sawyer decides to grab and pass the Pink pipe to

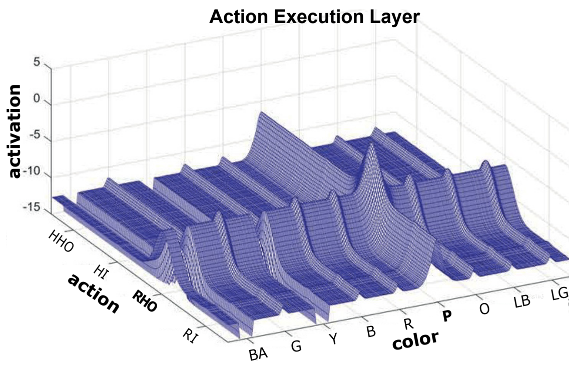

Figure 10 AEL activation profile in the second step of the construction. Sawyer's decision is to grab and hand over the Pink thruster (P) to its Human co-worker (RHO).

its co-worker that makes the insertion (Figure 9b). The same happens in the steps illustrated in Figures 9f and 9g. Next, follows the Orange piece placed in the Human Workspace but which insertion can be done by Sawyer. Therefore, Sawyer requests its co-worker to grab and pass it so the robot can perform the insertion: "I think you should give me the Orange thruster" (Figure 9c). The same action is taken in the step illustrated in Figure 9e to insert the Green. The fourth step consists of inserting the Light Green pipe. Since it lays on the Shared Workspace and the robot cannot insert it, Sawyer requests its co-worker to grab and insert it on his own: "I think You should grab and plug the Light Green thruster"(Figure 9d). The same action is selected in the last step of the construction to insert the Light Blue (Figure 9h).

5.2 Test number 2: Layout B

A new experiment was conducted to validate the architecture for a different layout (Layout B - Figure 3) to verify if the robot would be able to output correct decisions[2]. **Figure 11** shows a sequence of snapshots describing the actions selected at each step of the construction. Here, the Yellow pipe lays on the RobotWorkspace so Sawyer grabs and inserts the piece in the structure, as expected (Figure 11a). However, since the Pink thruster lays on the human's side and the robot cannot insert it, Sawyer instructs: "I think You should grab and plug the Pink thruster" (Figure 11b). The experiment continued until the construction was finalized. The decisions that emerged in the AEL were correct and in accordance with the location of each thruster, following the expected sequence of sub-goals.

5.3 Test number 3: What if there is a missing piece?

This experiment had the purpose of evaluating the robot's response when an item is missing (Green pipe removed from Layout A) and its implications in the development

[2]A video of this trial can be seen in `https://youtu.be/nI6yCEVWJVI`.

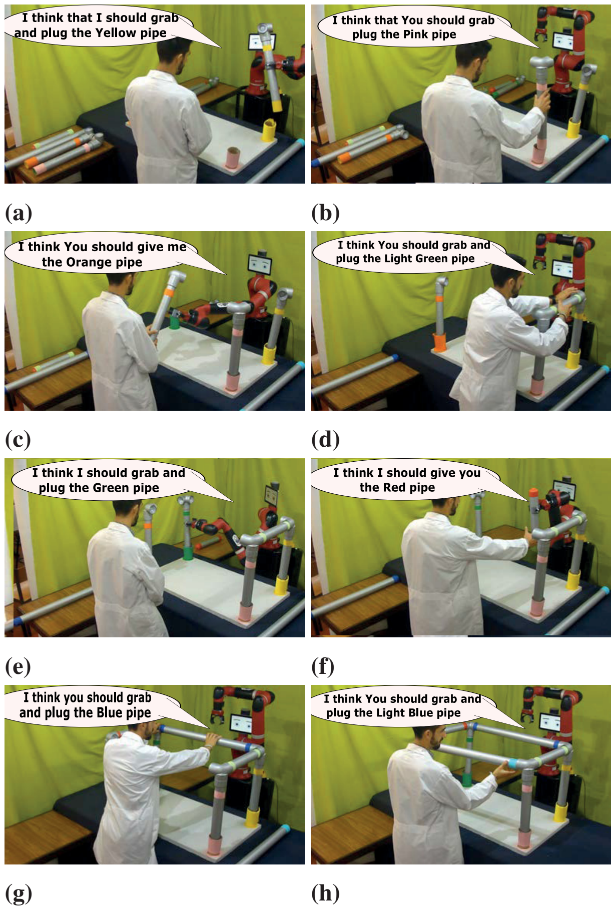

Figure 11 Test number 2 - Snapshots illustrating the sequence of actions during the second test.

of the task[3]. Therefore, the sub-population encoding the Green piece has no activity in any of the OML fields (**Figure 12**). The first four steps of the construction were the same used in the first test. Sawyer and its human co-worker followed the same steps illustrated in Figures 9a-d to insert the Yellow, Pink, Orange and Light Green thrusters. After that, following the learned sequence, the Green piece should be the next piece inserted. However, Green is not available in any of the workspaces. The AEL activation profile after inserting the Light Green thruster is depicted in **Figure 13**. Since the sub-neuronal population encoding the Green piece did not receive input from the OML, the pre-shaped activation is too low compared to other sub-populations. Therefore, the winning decision goes to the Light Blue that had already received excitatory input triggered by the Pink and Orange sub-populations. After placing the Light Blue, only two pieces remain in the workplace: Blue and Red. However, they cannot be placed in the structure without inserting the Green first. **Figure 14** illustrates the result of the decision process at this step. None of the available items in the workspaces received enough input to evolve as a bump of activity in AEL. As a result, from the input received from the OML and SL, the system recognizes that the structure is not yet completed. The absence of activity in AEL, combined with

[3]A video of this trial is available at `https://youtu.be/Q01ZqSpotfs`.

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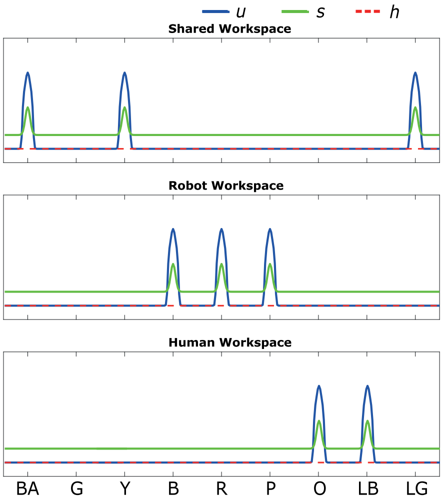

Figure 12 Test number 3 - Activation profile of the OML fields at the beginning of the construction. The Green pipe is missing from the workplace.

the previous information, leads the robot to realize that there is a missing item. Therefore, the construction cannot

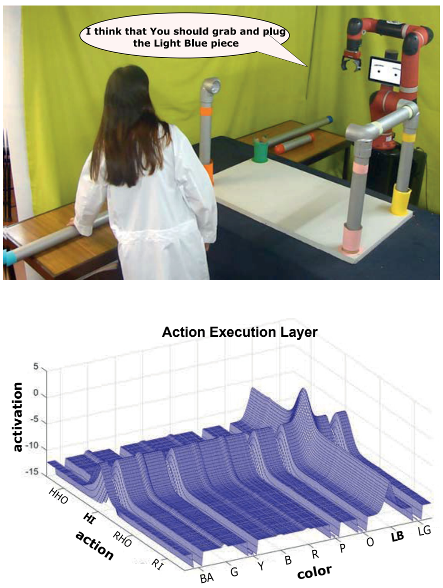

Figure 13 Sawyer's decision in the fifth step of the construction.

be completed and the robot verbalizes "I cannot complete the structure, please bring the missing thruster" to alert its coworker. To continue the task, the human co-worker brings the Green piece and places it in her workspace, triggering a peak of activity in the sub-population encoding the Green. Subsequently, the input from OML causes activation in the corresponding sub-population of AEL, and the model retrieves the insertion of Green as the next sub-goal (**Figure 15**). The task continued with the insertion of the Red and Blue thrusters.

The final sequence used in the task was the following: Yellow → Pink → Orange → Light Green → Light Blue → Green → Red → Blue

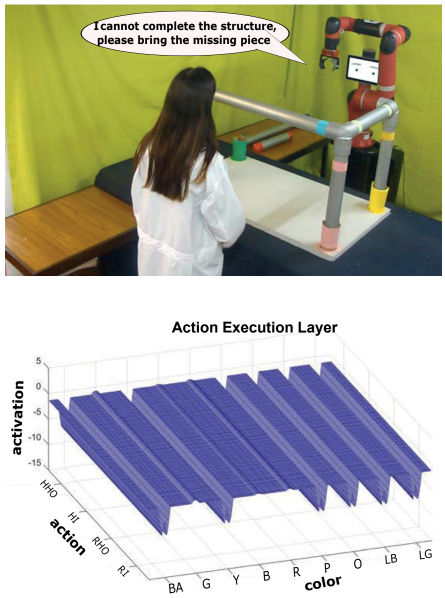

Figure 14 Sawyer's decision in the sixth step of the construction.

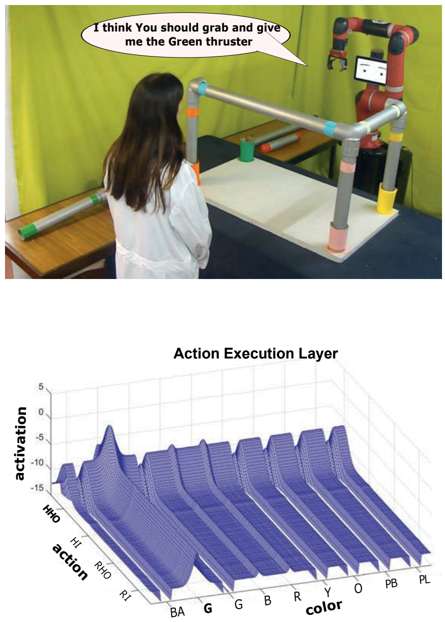

Figure 15 New decision in the sixth step of the construction.

6 Discussion

The experiments conducted validated the cognitive control architecture for different workspace layouts confirming that it outputs correct decisions taking into consideration the information provided by the different layers. The context dependent mapping from observed features onto appropriate actions allows the robot to cope with dynamically changing joint action situations, including different human partners. The benefit of this new model architecture is that, instead of stopping when facing an unpredictable situation, the system takes advantage of the task knowledge to continue and generates a different decision, which brings greater flexibility for the joint cooperation. Important for the coordination is the verbalization of what the robot 'thinks' should be done, i.e. informing what part should be used next, what action should be done over the selected part, and who should do it. The model architecture proposed in this paper was tested in a concrete joint assembly task. However, this architecture is easily adapted and implemented on other different joint tasks, especially in smart manufacturing contexts. Future work will evaluate this model architecture in different join action scenarios.

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8 Literature

[1] Ackerman, E. (2019). A Robot That Explains Its Actions Is a First Step Towards AI We Can (Maybe) Trust - IEEE Spectrum.

[2] Amari, S.-i. (1977). Dynamic of pattern formation in lateral-inhibition type neural fields. *Biological Cybernetics*, 27:77–87.

[3] Bicho, E., Erlhagen, W., Louro, L., and Costa e Silva, E. (2011a). Neuro-cognitive mechanisms of decision making in joint action: A human-robot interaction study. *Human Movement Science*, 30(5):846–868.

[4] Bicho, E., Erlhagen, W., Louro, L., Costa e Silva, E., Silva, R., and Hipólito, N. (2011b). A dynamic field approach to goal inference, error detection and anticipatory action selection in human-robot collaboration. In *New Frontiers in Human-Robot Interaction (Advances in Interaction Studies)*, pages 135–164.

[5] Cunha, A., Ferreira, F., Erlhagen, W., Sousa, E., Louro, L., Vicente, P., Monteiro, S., and Bicho, E. (2020). Towards endowing collaborative robots with fast learning for minimizing tutors' demonstrations: What and when to do? In *Robot 2019: Fourth Iberian Robotics Conference*, volume 1092, pages 368–378.

[6] Erlhagen, W. and Bicho, E. (2006). The dynamic neural field approach to cognitive robotics. *Journal of Neural Engineering*, 3(3):R36–R54.

[7] Erlhagen, W. and Bicho, E. (2014). A dynamic neural field approach to natural and efficient human-robot collaboration. *Neural Fields: Theory and Applications*, pages 1–487.

[8] Ferreira, F. (2014). *Multi-bump solutions in dynamic neural fields : Analysis and Applications*. PhD thesis, University of Minho.

[9] Rethink Robotics (2018). Sawyer collaborative robot.

[10] Sousa, E., Erlhagen, W., and Bicho, E. (2014). On observational learning of hierarquies in sequential tasks: A dynamic neural field model. In *Computational Models of Cognitive Processes*, pages 196–210.

[11] Sousa, E., Erlhagen, W., Ferreira, F., and Bicho, E. (2015). Off-line simulation inspires insight: A neurodynamics approach to efficient robot task learning. *Neural Networks*, 72:123–139.

[12] Wiese, E., Metta, G., and Wykowska, A. (2017). Robots as intentional agents: Using neuroscientific methods to make robots appear more social. *Frontiers in Psychology*, 8:1663.