# Goal-directed Imitation for Robots: a Bio-inspired Approach to Action Understanding and Skill Learning ⋆

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**Abstract**

In this paper we present a robot control architecture for learning by imitation which takes inspiration from recent discoveries in action observation/execution experiments with humans and other primates. The architecture implements two basic processing principles: 1) imitation is primarily directed toward reproducing the goal/end state of an observed action sequence, and 2) the required capacity to understand the motor intention of another agent is based on motor simulation. The control architecture is validated in a robot system imitating in a goal-directed manner a grasping and placing sequence displayed by a human model. During imitation, skill transfer occurs by learning and representing appropriate goal-directed sequences of motor primitives. After having established computational links between the representations of goal and means, further knowledge about the meaning of objects is transferred ("where to place specific objects"). The robustness of the goal-directed organization of the controller is tested in the presence of incomplete visual information and changes in environmental constraints.

*Key words:* Imitation learning; Action understanding; Goal inference

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## 1 Introduction

There has been a growing interest in creating autonomous robots which are capable of developing motor and cognitive skills through real-time interactions with their environment. Recent research in movement learning suggest that trying to imitate an experienced teacher (e.g., a human) is a powerful means of speeding up the learning process (for reviews see [1,2]). Observing a "good model" may drastically reduce the state-action space which has to be explored in order to optimize the movements at hand. This form of social learning in robots is not restricted to movements. It may be complemented by acquiring more abstract knowledge such as, for instance, structurally new motor behaviors composed of a set of parameterized motor primitives. This requires that the learning process goes beyond an adaptation of variable parameters of pre-designed, task-specific representations. Instead, the control architecture should allow for developmental change to explicitly represent and memorize newly acquired knowledge.

In this paper we summarize results of an interdisciplinary project which aimed at exploring new ways of imitation and imitation learning in artefacts based on recent discoveries in cognitive psychology and neuroscience. The basic idea was to get new insights into the relevant functional mechanisms underlying imitation from behavioral and neuronal data. Central questions for robot imitation that we have addressed in our work concern "what to imitate" and how to solve the correspondence problem across dissimilar embodiments and task constraints [3]. Very often these differences do simply not allow for a matching on the level of movement trajectory or path. In the goal-directed theory of imitation proposed by Bekkering and colleagues [4,5] imitative behavior can be considered successful whenever the end-state of the witnessed action is reproduced. The means, on the other hand, may or not coincide with the observed ones. The emphasis on the goal of the action requires of course that the imitator understands the demonstrator's motor intention. The "matching hypothesis" forwarded by Rizzolatti and colleagues [6] based on their discovery of the mirror system states that an action is understood if its observation activates the motor representations controlling the execution of a similar goal-directed action ("motor simulation"). The proposed controller implements action understanding and goal-directed imitation as a continuous process which combines sensory evidence, contextual information, and a goal-directed mapping of action observation onto action execution. As a theoretical framework, we base our implementation work on dynamic fields [7,8] previously used to endow autonomous robots with cognitive capabilities [9–11].

The complete control architecture including vision, cognition and path planning is validated in variations of a paradigm in which the robot system learns to imitate a grasping and placing sequence displayed by a human model. The learning is accompanied by structural changes in the controller representing knowledge transferred from the human to the robot during imitation.

In Section 2 we briefly present the experimental setup. A detailed description of the control architecture follows in Section 3. Specifically, we focus on the bio-inspired "cognitive module". We sketch the dynamic field framework and the learning rule used to implement the cognitive capacities underlying imitation. Experimental results and discussion are presented in Sections 4 and 5.

## 2 Experimental Setup

For the robotics work we adopt a paradigm which has been developed to further investigate in experiments with humans the idea that actions are represented with respect to their end state (van Schie and Bekkering, in preparation). The paradigm contains an object that must be grasped and then placed at one of two laterally presented targets that differ in height. Importantly, the grasping and transporting behaviors are constrained by an obstacle in form of a bridge (see Fig. 1). Depending on the height of the bridge, the lower target may only be reached by grasping the object with a full grip and transporting it below the bridge. Placing the object at the higher target, on the other hand, may require combining a precision grip and a hand trajectory above the bridge.
The robot has to imitate the observed or inferred end state of a grasping and placing sequence displayed by a human model. The work was conducted on a robot platform consisting of an industrial 6-degrees-of-freedom robot arm (KUKA, Germany) on which a four-fingered anthropomorphic robot hand [12](GRAALTECH, University of Genova, Italy) was mounted. A real-time vision system provided the information about the scene parameters and the human hand motion.

## 3 The Control Architecture

Three interconnected modules (vision, cognition, path planning) define the robot control architecture (see Fig. 2).

### *3.1 Vision module*

The *vision module* provides the environmental variables of the task setting (Cartesian position of bridge, object and goals) by means of a semi-automatic calibrated stereo camera system. All outputs are stored in the general configuration structure, globally available for the other modules of the controller. The demonstrator's hand and the object are identified and tracked in real time on the basis of a chroma-space blob segmentation in the YUV color space using a monocular camera view. The hand tracking algorithm is based on a mutual information optimization approach [13] which maximizes the consistency between an observed image and postures of a hypothetic hand model (26-degrees-of-freedom). The algorithm has been proven to be robust under changes in lightning condition, data acquisition noise, and partial occlusion of the hand. Finally, the grasping behavior (full or precision grip), the hand trajectory (above or below the bridge), and the the placing goal (high or low) are classified on the basis of a distance measure relative to the respective object.

### *3.2 Cognitive module*

In the *cognitive module* decisions about the action goal and the means to achieve that goal are made. Its layered architecture is biologically inspired, as it represents the basic functionality of neuronal populations in interconnected brain areas known to be involved in action observation/execution tasks (for details see [14]). The core part consists of three reciprocally connected layers, STS, PF and F5, representing the mirror circuit. The fundamental idea is that within this circuit the matching of action observation and action execution takes place on the level of motor primitives that represent complete goal-directed actions such as, for instance, "grasping an object with a full grip"([6], see also [1] for an excellent overview in the context of robotics research). Motor primitives do not encode the fine details of the movement and thus provide a sufficiently abstract level of description for imitation learning across dissimilar embodiments. Concretely for the bridge paradigm, we distinguish two types of grasping primitives (precision grip (PG) and full grip(FG)) and two types of transporting primitives for avoiding the obstacle (below (BT) or above (AT) the bridge).
The visual description of the observed action is stored in STS. In the motor layer F5, the representations of the respective primitives become active both during action observation and action execution, that is, we assume that congruent mappings have already been learned in previous grasping or transporting trials. The representations in the intermediate layer reflect recent neurophysiological findings in brain area PF that suggest a goal-directed organization of action means in this area. Using a grasping-placing task, Fogassi and colleagues [15] described a population of grasping mirror neurons which showed a selective response in dependence of the final goal of the action to which the grasping act belongs. For the bridge paradigm, we abstract this finding by assuming representations of specific combinations of primitives (e.g., PG-AT) which allow achieving a specific goal. The two possible end states/goals, pa-

rameterized by their height relative to the bridge (spatial gap, Fig. 1), are explicitly encoded in layer PFC. The reciprocal connections between PFC and PF are learned during the imitation experiments. Beside the direct stimulation by the vision system (placed target), the goal representations in PFC may be influenced by two additional information sources: *i)* The task input represents memorized information about the number, identity (height) and probability of goals (for details of a computational implementation see [8]). It reflects the fact that in a known task setting the robot may engage in partial motor preparation even before the observation of the human model. *ii)* The second input represents object cues (e.g. color) which become associated with the goals during imitation.

### *3.2.1 The Dynamics of Decision Making and Learning*

Each layer of the cognitive module is formalized by a dynamic field [7,8] in which self-sustained patterns of excitation encode task specific information. We extend here previous work in which the field framework has been used to endow autonomous robots with cognitive capacities such as memory, decision making, and prediction (e.g. [9–11]). The layer dynamics is governed by the following equation:

$$\tau\frac{\delta}{\delta t}u(x,t) = -u(x,t) + h + \sum_i S_i(x,t) + \\ + f_1(u(x,t))\left[\int w(x-x')f_2(u(x',t))dx' - w_{inhib}\int f_2(u(x',t)dx'\right] \tag{1}$$

where $\tau > 0$, $h < 0$ and $w_{inhib} > 0$ are constants. The non-linear functions $f_i(u)$, $i = 1, 2$, are of sigmoid shape

$$f_i(u) = \frac{1}{1 + exp\,(-\beta_i(u-\theta_i))} \tag{2}$$

with threshold $\theta_1 > \theta_2$ and slope parameter $\beta_1 = \beta_2$. The excitatory connections, $w(x, x')$, are modelled as a Gaussian profile. The excitation patterns evolve under the influence of multiple information sources, $\sum_i S_i(x,t)$, representing summed excitation from connected layers and input from the vision module. The latter is modelled as gaussian functions of adequate intensity.
For the present work, we exploit some characteristic features of the field dynamics. First, the interplay of recurrent inhibition and excitation stabilizes non-uniform activation profiles and at the same time creates a competition between alternatives (e.g., type of grasping). Second, there is a threshold, $u_{TH}$, for triggering a self-sustained pattern. Weak external inputs (e.g., task input) may only bring the activation close to threshold. This "preshaping", however, may drastically alter the time course of the suprathreshold response

triggered by additional inputs. This, in turn, may affect the decision processes in connected layers.
Crucial for our approach to learning by imitation is that the control architecture may autonomously evolve during practice by developing new task-relevant representations. We apply a correlation based learning rule for the synaptic connections, $a(x, y)$, between any two neurons $x$ and $y$ in any two model layers that is compatible with the field format[16]:

$$\tau_s \frac{\delta}{\delta t} a(x, y, t) = -a(x, y, t) + \eta\, f(\bar{u}_1(x)) f(\bar{u}_2(y)) \tag{3}$$

where $\eta > 0$ and $\bar{u}_1$, $\bar{u}_2$ denote the equilibrium solutions of the relaxation phase in layer 1 and layer 2, respectively. Note that a transient phase of the dynamics could have been chosen as well without changing the results of the present study. Important for establishing a goal-directed organization of the control architecture is that an internally generated reinforcement signal representing a successful path planning toward the desired goal posture (see below) defines the time window for the learning. For simplicity, we have chosen a function which takes on the value 1 during the learning period and 0 otherwise. As a result, the metric for the learning appears to be defined by the similarity in the end state of the action[17].

### *3.3 Path planning*

For generating overt behavior, the abstract motor primitives represented in layer F5 have to be translated into the right kinematics. We employ a global planning method in posture space which is inspired by the wave expansion network approach[18]. In the network, the locally interconnected nodes represent stored postures, that is, n-dimensional arrays of joint angels $\Theta_i = (\theta_{i1}, \ldots, \theta_{in})^T$, $i = 1, \ldots, N$, where $N$ represents the number of network nodes covering the workspace $W$. Each node $\Theta_i$ is connected with its $k$ nearest neighbors $\Theta_j, j = 1, \ldots, k$ defined by the euclidian metric $\|\Theta_i - \Theta_j\|_2$. The connection weights $w_{ij}$ are assumed to decrease exponentially with distance. Starting with an external activation of a set of goal postures $P_G$, activation spreads in each time step to inactive nodes by summing the excitation from the active neighbors (there is no interaction between already activated units). When the wavefront reaches the node corresponding to the initial posture, the activation dynamics is stopped. The sequence of postures defining a suitable path from the initial state to the goal state is then found by back propagation in time along the maximum excited nodes. Inverse kinematics is used to define three distinct sets of goal postures $P_{G^i}, i = 1, 2, 3$, associated with the Cartesian location of the object to be grasped, $X^1$, and location of the two placing targets, $X^2$ and $X^3$, respectively.

Moreover, additional information from the vision and the cognitive module of the control architecture is integrated before starting the wavefront operations. Posture nodes which are impossible due to the obstacles are inhibited. The forbidden set $P_O$ of all inhibited nodes is found by explicitly testing for spatial overlap in Cartesian space between the to-be-assumed posture and the bridge obstacle, $O_B \subset R^3$, using forward maps ($f(\Theta_j) \not\subset O_B$, $j = 1, \ldots, N$). Moreover, the ensemble of nodes which can become part of the wavefront is further constrained by the motor primitives in F5. For instance, we use again forward maps to check whether a particular node $\Theta_j$ represents "all links of the robot arm in a high position" as required by a trajectory above the bridge. This preselection of a set of compatible postures, $P_{F5}$, restrict the global planning process to the subset $P_{F5} \cap P_O = \emptyset$.
The integration of prior information together with the inherent parallelism of the wavefront operations makes a real-time path planning for artefacts with higher degrees of freedom possible. Finally, the path for the full grasping and placing behavior is described by the temporal sequence $\{\Theta_j, j \in (t_i \cdots t_g \cdots t_p)\}$, where $\Theta_{t_i}$ represents the initial posture and $\Theta_{t_g}$, $\Theta_{t_p}$ the postures at the time of grasping and placing, respectively.

## 4 Experimental Results

A set of imitation experiments within the bridge paradigm has been performed which differ in the amount of visual information available to the robot and in task constraints. The aim was 1) to exemplify what kind of knowledge may be transferred from the human to the robot by autonomously developing new representations, and 2) to illustrate the advantages of a goal-directed organization of the control architecture in terms of robustness.

### *4.1 Copying the means*

In the first set of experiment, a complete visual description of the teacher's actions in terms of the grasping and transporting behavior exists and the vision system identifies the placing goal. Although the robot has the knowledge how to grasp, transport and place objects in its motor repertoire, it does not know how to combine under the constraints of the bridge paradigm the specific motor primitives to achieve the same end state. One strategy could be trying to copy the primitives displayed by the human demonstrator. The visual description of the observed motions in layer STS resonates via the matching mechanism in the mirror circuit with the congruent motor representations of the robot. If the covert path planning toward the desired goal-posture turns out to be successful, the observed action sequence becomes associated with the goal representation in layer PFC by the learning procedure described above. Fig. 3 illustrates the result of this learning by imitation in an example in which the robot copies the demonstrated precision grip and the trajectory above the bridge to place the object at the higher goal. In the various layers of the neural field model, the task specific information is encoded by non-uniform activity profiles representing a steady state of the dynamics.

### *4.2 Discerning motor intention*

The second set of experiments has been designed to reflect a major challenge for all robotics systems cooperating in cluttered environments with other agents. Due to occluding surfaces, for instance, only partial visual information about the action displayed by the partner may be available and the observing robot has to infer the action goal. The proposed control architecture implements the idea that a goal-directed motor simulation together with the integration of prior task knowledge underlies the capacity of discerning motor intention. Consistent with this view, it has been recently reported that mirror neurons may fire under appropriate experimental conditions (e.g., with additional contextual cues) even if the goal of the motor act is hidden from view [6]. In the concrete example shown in Fig. 4, only the demonstrator's grasping of the object with a full grip is observable. However since the robot is familiar with the task, links between goal representations and associated goal-directed sequences have been established in previous trials. In addition, the constant task input results in a pre-activation below threshold, $u_{TH}$, of all task-relevant representations. As a result of the robot's "expectation" about possible goals and means, the evolving activation in STS encoding the observed FG-grip is sufficient to trigger first the sequence FG-BT and subsequently the representation of the associated lower goal (Panel B in Fig. 4). As shown in Panel C, the robot shows its action understanding by combining a full grip and a trajectory below the bridge to reproduce the inferred end state.

### *4.3 Goal directed imitation*

The third set of experiments illustrates that the learned link from the mirror circuit to the goal representation is crucial. The bar of the bridge is removed for the human but not for the robot (Panel A in Fig. 5). Because of this change in the environmental constraints, the demonstrator now uses a full grip for placing the object at the higher target. For the robot, a direct matching on the level of motor primitives would result in a collision with the bridge. As shown in the snapshot of the field model in Panel B of Fig. 5, the decisions in layer F5 represent the motor primitives PG and AT previously associated with the higher goal (compare Fig. 3). This choice is the result of a primacy of the goals over the means implemented in the control architecture. The goal representation is triggered by direct input from the vision system. Through the learned links to layer PF, it biases the decision processes in the mirror circuit, thus overriding the direct mappings from the visual motion description in STS. Technically, we exploit here differences in time course with the goal representation being processed faster in a known task setting compared to the representations in STS (for a detailed discussion of the biological context see [14]).

### *4.4 Learning object meaning*

If an observed action is understood, that is, connections between action goal and action means have been established, further knowledge associated with that action may be transferred by imitation. We tested in a variation of the basic bridge paradigm the autonomous development of representations that relate object cues to specific goals. Fig. 6 illustrates as a simple example the effect of a learned association to object color processed by the vision system. After a series of imitation trials, human and robot share the knowledge about object meaning: a yellow object has to be placed at the higher goal and a blue object at the lower goal. As a consequence, a simple presentation of a specific object (blue or yellow) will automatically trigger the associated goal and the action means to achieve that goal.

## 5 Discussion

We have presented a control architecture for imitation and learning by imitation which is strongly inspired by recent insights about the processing principles underlying these capabilities in humans and other primates. In general, our approach emphasizes the role of factors in imitation which are usually considered cognitive such as goal inference or decision making. The experiments with the robot system illustrate that an organization of imitative behavior toward reproducing the end-state/goal of an observed action complements purely motor approaches which focus on a matching on the trajectory or path level[2,17]. The primacy of the goal over the action means implemented in the control architecture allows coping with differences in embodiment and task constraints known as the correspondence problem in robot imitation [3]. Most importantly, learning to understand the meaning of a particular action enables the robot to reuse the stored information in new contexts and to acquire more abstract knowledge associated with that action (e.g., object meaning).

Action understanding is also a prerequisite for more efficient interactions in, for instance, joint robot-human tasks since predictions about the outcome of the partner's action is frequently required.
The idea that the movement production system is essentially involved in action understanding has been proposed in the context of robotics research before (for review [2]). For instance, Demiris and Hayes [19] used internal forward models known from motor control theory to predict the sensory consequences of observed actions in an imitation task. However, the questions how to cope with differences in embodiment, task constraints or even motor skills have not been systematically addressed. In principle, the control architecture proposed here allows for learning to understand an action which is not strictly in the repertoire of the robot since the metric for the learning is defined by the end state of the movement[17]. The only condition is that the observed goal state is known to the robot and may be achieved by using proper means. Subsequently, the correlation based learning rule (Equation 3) will establish connections in the mirror circuit between the proper motor primitives and the visually classified hand motions represented in layer STS[14].
In the present imitation paradigm, the goal-directed sequence is still relatively simple as it combines only two motor primitives. In a joint effort with our experimental colleagues we are currently testing the learning of more complex sequences composed of a richer set of existing movement primitives (e.g., a sequence composed of two grasping and placing behaviors). Conceptually, the implementation work does not require any changes in the overall control architecture. However, some modifications in the field dynamics (Equation 2) and the learning dynamics (Equation 3) have to be introduced. First, to prevent from a competition between motor primitives belonging to the same category (e.g., grasping) but to different parts of the sequence, the representations should be transient in nature. A straightforward solution is to add a "forgetting dynamics" which results in a destabilization of the self-sustained activation profiles[10]. Second, to allow for an explicit representation of the temporal order of primitives in layer PF a predictive Hebbian learning rule [16] should be use.

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## References


[1] S. Schaal, Is imitation learning the route to humanoid robots, Trends in Cognitive Science, Vol. 3, No. 6, June(1999) 233-242.

[2] S. Schaal, A. Ijspeert, A. Billard, Computational approaches to motor learning by imitation, Phil. Trans. R. Soc. Lond. B Vol. 358 (2003) 537-547.

[3] A. Alissandrakis, C.L. Nehaniv, K. Dautenhahn, Imitation with ALICE: Learning to imitate corresponding actions across dissimiliar embodiments, IEEE Transactions on Systems, Man, and Cybernetics- Part A: Systems and Humans, Vol. 32 (2002) 482-496.

[4] H. Bekkering, A. Wohlschläger, M. Gattis, Imitation of gestures in children is goal-directed, The Quartely Journal of Experimental Psychology, Vol. 53A (2000) 153-164.

[5] A. Wohlschäger, M. Gattis, H. Bekkering, Action generation and action perception in imitation: An instantiation of the ideomotor principle, Phil. Trans. R. Soc. Lond. B., Vol. 358 (2003) 501-515.

[6] G. Rizzolatti, L. Fogassi, V. Gallese, Neurophysiological mechanisms underlying the understanding and imitation of action, Nature Reviews, Vol. 2 (2001) 661-670.

[7] S. Amari, Dynamics of pattern formation in lateral-inhibitory type neural fields, Biological Cybernetics, Vol. 27 (1977) 77-87.

[8] W. Erlhagen, G. Schöner, Dynamic field theory of movement preparation, Psychological Review, Vol. 109 (2002) 545-572.

[9] G. Schöner, M. Dose, C. Engels, Dynamics of behavior: Theory and applications for autonomous robot architectures, Robotics and Autonomous Systems, No. 16, (1995) 213-24.

[10] E. Bicho, P. Mallet, G. Schöner, Target representation on an autonomous vehicle with low-level sensors, The International Journal of Robotics Research, Vol. 19, No. 5, May (2000) 424-447.

[11] M. Quoy, S. Moga, P. Gaussier, Dynamical Neural Networks for Planning and Low-level Robot Control, IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, Vol. 33, No. 4, July (2003) 523-532.

[12] A. Caffaz, G. Casalino, G. Cannata, G. Panin, E. Massucco, The DIST-Hand, an Anthropomorphic, Fully Sensorized Dexterous Gripper, in: IEEE Humanoids Boston, M.I.T., USA, Sept., 2002.

[13] A. Viola, W.M. Wells III, Alignement by Maximization of Mutual Information, in: $5^{th}$ IEEE International Conference on Computer Vision, Cambridge, MA, 1995, 16-23.

[14] W. Erlhagen, A. Mukovskiy, E. Bicho, A dynamic model for action understanding and goal-directed imitation, Submitted.

[15] L. Fogassi, P.F. Ferrari, B. Gesierich, S. Rozzi, G. Rizzolatti, Parietal lobe: from action organization to intention understanding, Science, In press.

[16] P. Dayan, L.F. Abbott, Theoretical Neuroscience, The MIT Press, 2001.

[17] A. Billard, Y. Epars, S. Calinon, S. Schaal, G. Cheng, Discovering optimal imitation strategies, Robotics and Autonomous Systems, Vol. 47 (2004) 69-77.

[18] A. Kassim, B.V.K.V. Kumar, The wave expansion neural network, Neurocomputing, Vol. 16 (1997) 237-258.

[19] J. Demiris, G. Hayes, Imitation as a dual-route process featuring predictive and learning components: A biologically plausible computational model, in: Imitation in Animals and Artifacts, Dautenhahn, K. and Nehaniv, C.L. MIT Press, Cambridge MA (2002) 327-361.

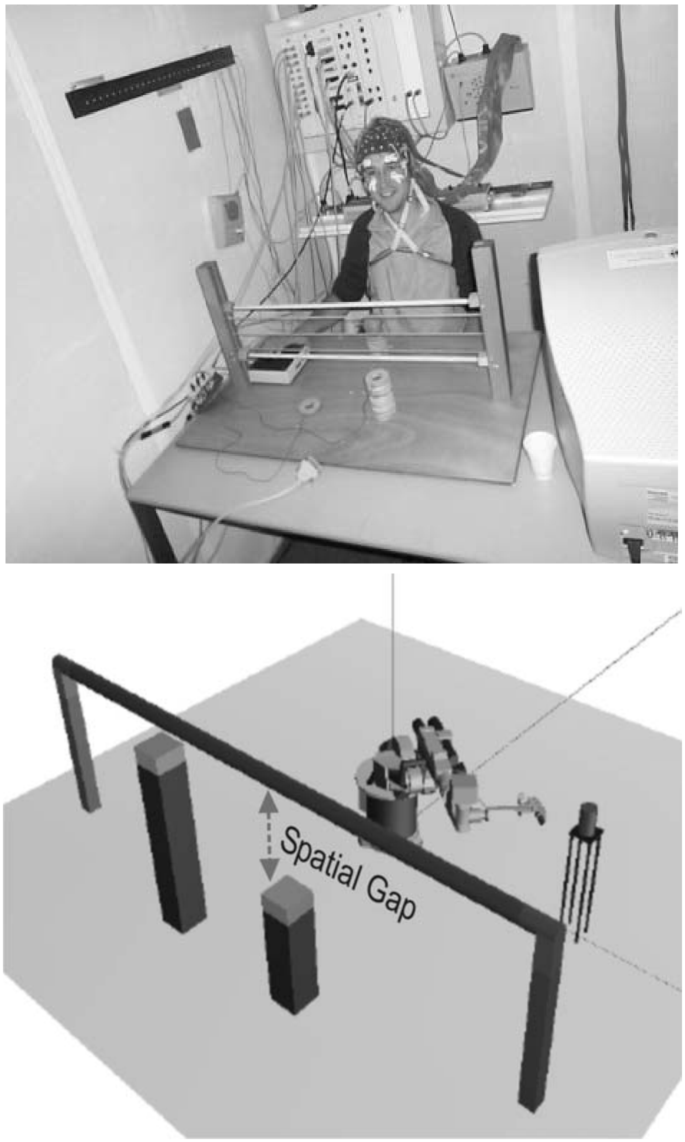


Fig. 1. Bridge Paradigm.

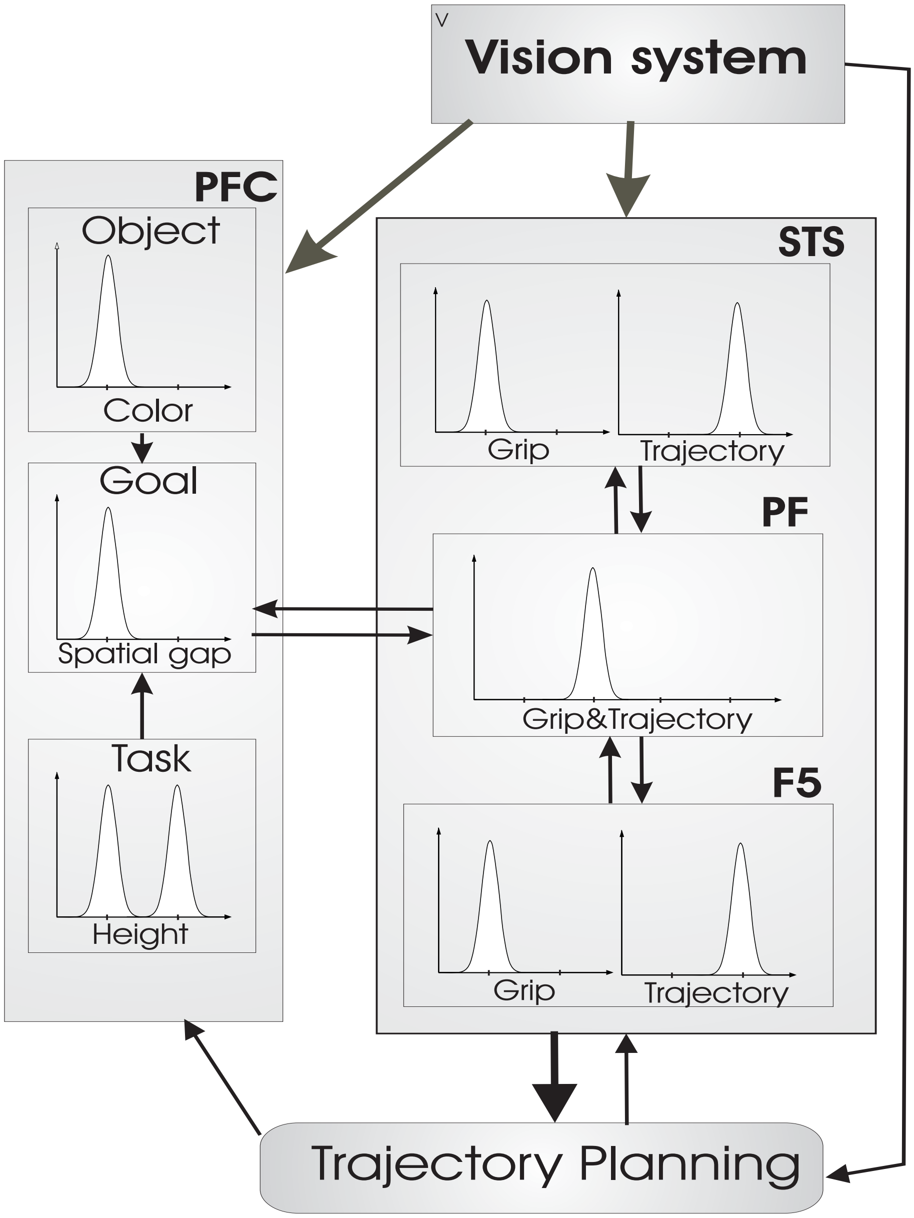


Fig. 2. Robot control architecture.

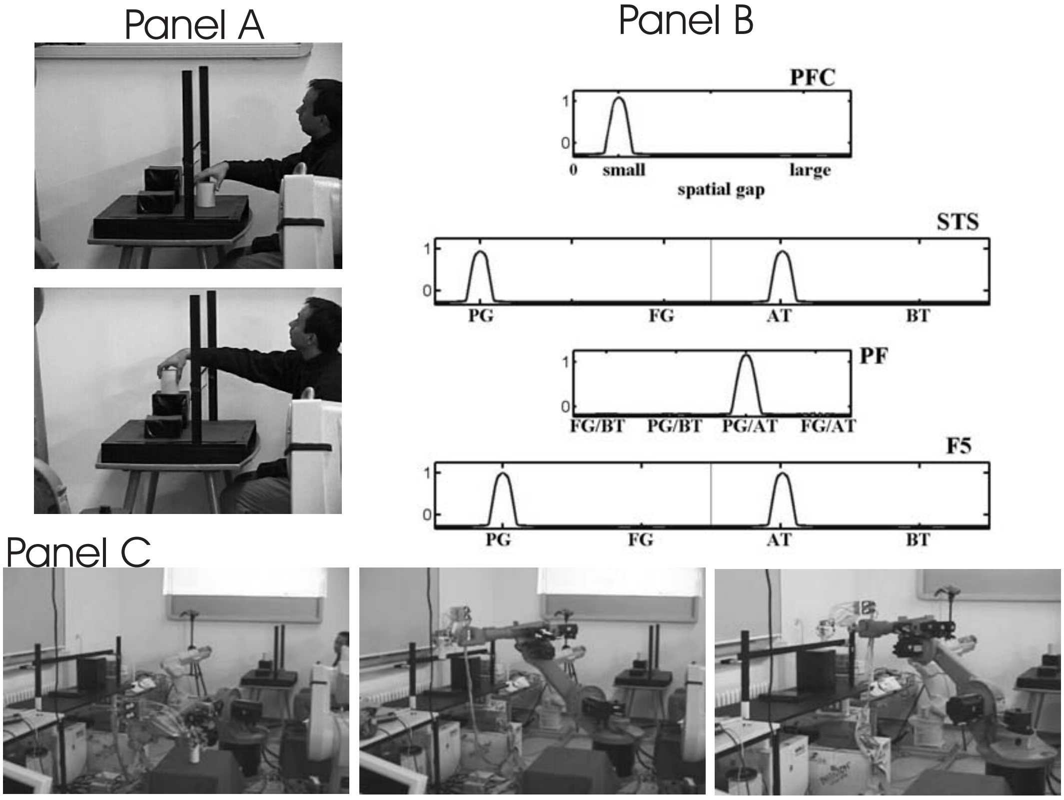


Fig. 3. Copying the means. **Panel A**: The teacher shows a complete grasping-placing sequence, here precision grip (PG) followed by a transport above the bridge (AT). **Panel B**: Cognitive module. The peaks of activation in layer F5 represent the means (motor primitives) selected by the robot to reproduce the same goal. **Panel C**: The robot reproduces the observed end-state using the same means.

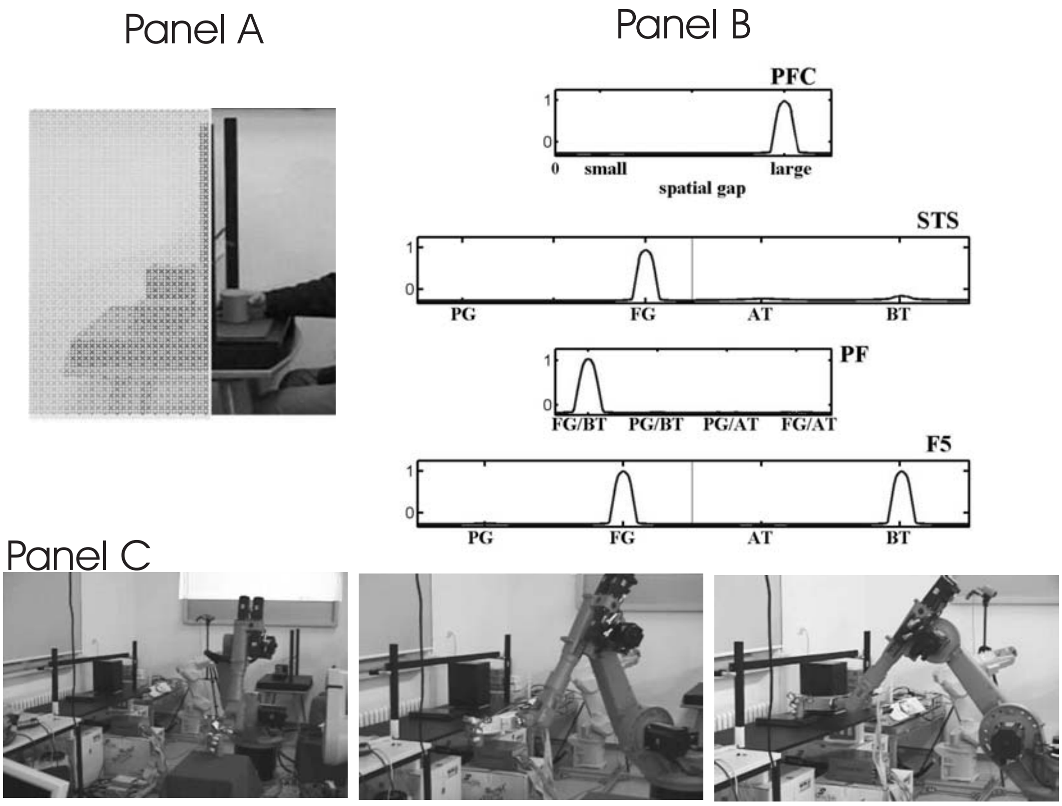


Fig. 4. Inference task. **Panel A**: Only the grasping behavior is observable. **Panel B**: The stable state in layer PFC of the field model represents the inferred goal (here lower goal). **Panel C**: To reproduce the inferred end state the robot combines a full grip (FG) followed by a trajectory below (BT) the bridge as represented in the motor layer F5 in Panel B.

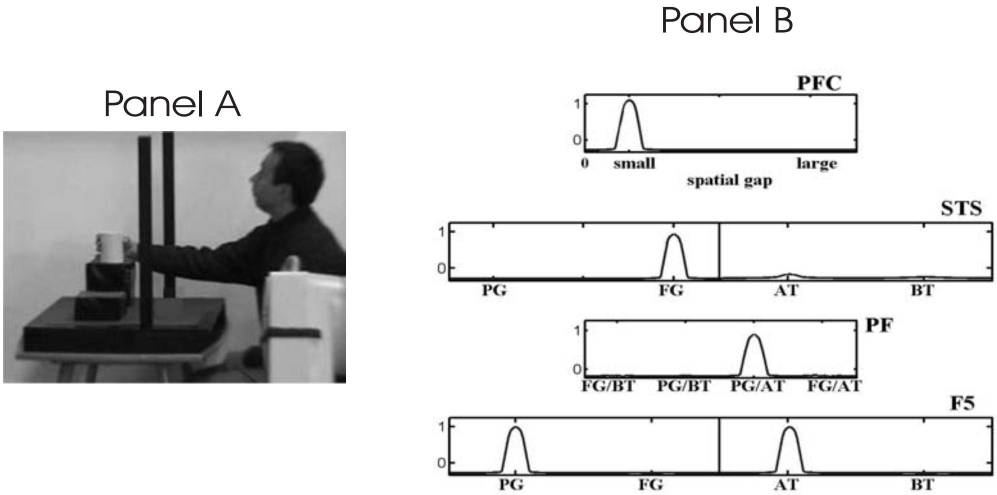


Fig. 5. Goal directed imitation. **Panel A**: Conflict in the grasping behavior, i.e. the teacher uses a full grip for placing the object in the higher goal position. **Panel B**: As shown in layer F5 of the field model, the robot decides to use a precision grip to reproduce the observed end-state.

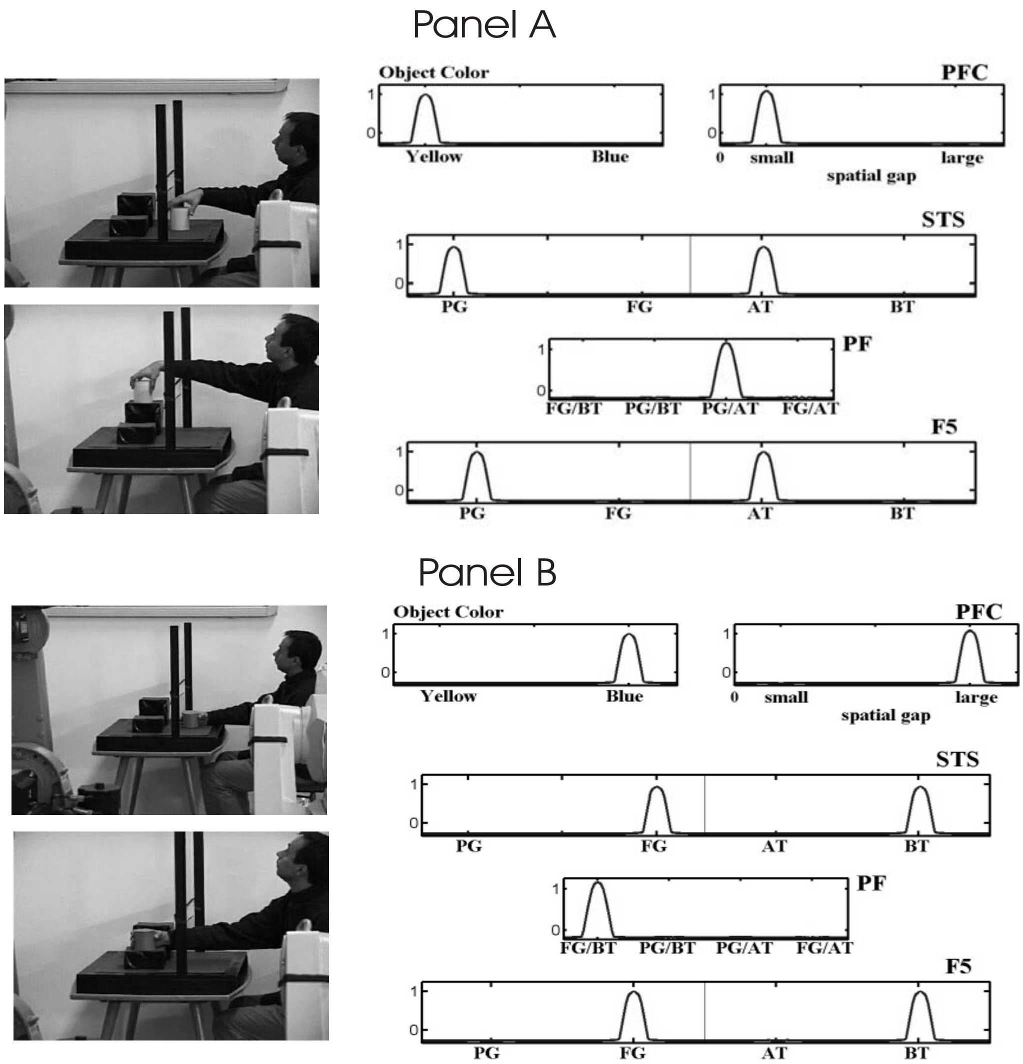


Fig. 6. Learned association of object color to specific goals. **Panel A**: A yellow object has to be placed at the higher goal. **Panel B**: A blue object has to be placed at the lower goal.