

Learning Through Imitation: a Biological Approach to Robotics

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Abstract—Humans are very efficient in learning new skills through imitation and social interaction with other individuals. Recent experimental findings on the functioning of the mirror neuron system in humans and animals and on the coding of intentions, have led to the development of more realistic and powerful models of action understanding and imitation. This paper describes the implementation on a humanoid robot of a spiking neuron model of the mirror system. The proposed architecture is validated in an imitation task where the robot has to observe and understand manipulative action sequences executed by a human demonstrator and reproduce them on demand utilizing its own motor repertoire. To instruct the robot what to observe and to learn, and when to imitate, the demonstrator utilizes a simple form of sign language. Two basic principles underlie the functioning of the system: 1) imitation is primarily directed toward reproducing the goals of observed actions rather than the exact hand trajectories; and 2) the capacity to understand the motor intentions of another individual is based on the resonance of the same neural populations that are active during action execution. Experimental findings show that the use of even a very simple form of gesture-based communication allows to develop robotic architectures that are efficient, simple and user friendly.

Index Terms—Bioinspired robotics, chain model, human-robot interaction, imitation, mirror system, spiking neurons.

I. INTRODUCTION

ONE OF THE peculiarities of humans is their capacity to easily interact with other individuals to attain knowledge and learn new skills. In order to do so individuals effortlessly, and generally unconsciously, monitor the actions of their partners and interpret them in terms of their meaning and outcomes [1], [2]. Additionally, key characteristics of the executed actions are extracted, adapted and integrated into the observer's motor repertoire in a rapid and efficient way. Surprisingly, this ability seems to be present already at birth. In fact, it has been demonstrated that few days old infants, both humans [3] and monkeys [4], are able to imitate both facial and manual gestures executed by other persons, without having seen neither their own faces nor those of many other adults. Thus, the capability to map perceived gestures onto one's own repertoire was concluded to be innate and contradicted Piaget's ontogenetic account of imitation [5].

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A consistent number of studies has demonstrated that animals are also able to engage in various types of social behavior that involve some form of cooperation and coordination among individuals [6]–[9]. The existence of true imitative behavior in the animal kingdom is still in debate [10]–[12], however, social learning can be found in a variety of species providing clear benefits over other forms of learning [13], [14].

These results lead us to think that there exists a common low level neural mechanism or structure, more complex and developed in humans and less in other animals, that underlies social interaction and action understanding.

In recent years, imitation has received great interest from researchers in the fields of robotics because it is considered a promising learning mechanism to transfer knowledge from an experienced teacher (e.g., a human) to an artificial agent. In particular, robotic systems may acquire new skills without the need of experimentation or complex and tedious programming. Moreover, robots that are able to imitate could take advantage of the same sorts of social interaction and learning scenarios that humans readily use, opening the way for a new role of robots in human society: not confined in laboratories and industrial environments anymore, but being teammates in difficult or dangerous working situations, assistants for care needing people and companions in everyday life.

This paper describes the implementation of the Chain Model [15], [16], a biologically inspired model of the mirror neuron system, on an anthropomorphic robot. The work focuses on an interaction and imitation task between the robot and a human, where motor control applied to object manipulation is integrated with visual understanding capabilities. More specifically, the research focuses on a fully instantiated system integrating perception and learning, capable of executing goal directed motor sequences and understanding communicative gestures. In particular, the goal is to develop a robotic system that learns to use its motor repertoire to interpret and reproduce observed actions under the guidance of a human user.

The rest of the paper is structured as follows. Sections II and III provide a brief description of the functioning of the mirror neuron system from the neurophysiological point of view and its computational counterpart, i.e., the Chain Model, respectively. Section IV describes the reference experimental paradigm and its adaptation to the current architecture, while Section V concentrates on the robotic control system, which consists of a humanoid robot with a seven degrees of freedom arm and a Firewire vision module. Section VI reports the result of the teaching by demonstration task, both on the neural network and on the robot behavior side. Finally, the conclusions and discussions are presented in Section VII.

II. THE MIRROR NEURON SYSTEM

In a series of key experiments, researchers at the laboratory of Rizzolatti [17]–[19] discovered that a consistent percentage of neurons in the premotor cortex (area F5) become active not only when monkeys execute purposeful object-oriented motor acts, such as grasping, tearing, holding or manipulating objects, but also when they observe the same actions executed by another monkey or even by a human demonstrator. These types of neurons have been termed “mirror neurons” to underlie their capacity to respond to the actions of others as if they were made by one self.

Neurons with the same mirroring properties have been subsequently discovered also in the inferior parietal lobule (IPL) of the monkey, more precisely in areas PF and PFG [20], [21]. Interestingly (and surprisingly), the firing rate of the large majority of motor and mirror neurons were found to be strongly modulated by the final goal of the action. More specifically, neurons that are highly active during a grasping-to-eat action fire only weakly when the sequence is grasping-to-place and vice versa, even if the sequence contains common motor acts (e.g., reaching and grasping) [21], [22].

These findings have contributed to a review of the concept about the degree of interplay between different brain areas: it is now clear that the parietal cortex is actively involved in the execution and interpretation of motor actions and that most of the motor and mirror neurons (both in parietal and premotor cortex) encode also higher cognitive information such as the final goal of action sequences.

An important distinction between the two mirror-endowed areas, which at first sight may seem to be two duplicates, is that while F5 appears to contain the hand motor vocabulary [24], i.e., it codes detailed movements such as “precision grip”, “finger prehension” or “whole hand grasp”, in IPL the motor act representation is more abstract with neurons encoding a generic “grasp” or “reach” or “place”, rarely including parameters such as speed or force. In this view, it appears that the parietal cortex provides the premotor cortex, to which it is strongly interconnected, with high level instructions, which are then transformed in F5 into more concrete (i.e., low level) motor commands integrating, for example, details about object affordances (provided by neurons in the intraparietal sulcus), and then the primary motor cortex resolving the correct muscle synergies. The inferior parietal area receives strong input from the superior temporal sulcus (STS) which in turn is connected to visual areas. There is a striking resemblance between the visual properties of mirror neurons and those of a class of neurons present in the monkey [25], [26] anterior part of STS. Neurons in this area are also selectively responsive to hand-object interactions, such as reaching for, retrieving, manipulating, picking, tearing and holding but they are not mirror neurons, as they do not discharge during action execution.

The existence of these neurons is of particular importance because it indicates that mirror neurons do not directly perform visual processing but they receive an already view-invariant description of the interaction between effectors and objects observed in a scene. In other words, the signals arriving to IPL correspond to the motor content extracted from the visual input.

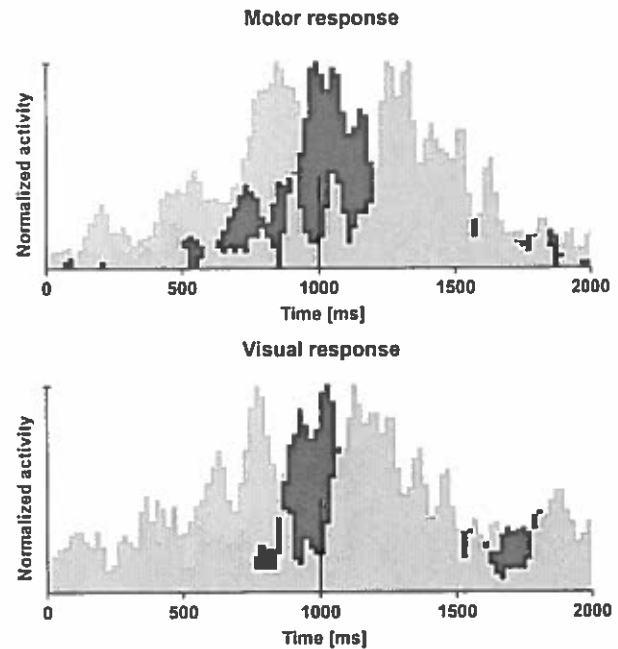


Fig. 1. Activity of three mirror neurons recorded in the monkey IPL during the execution of a “reaching, grasping, bringing to the mouth” sequence (upper panel) and during the observation of an experimenter performing the same action (lower panel). Histograms were synchronized with the moment in which the monkey or the experimenter touched the piece of food ($t = 1000$ ms). Different colors indicate different motor acts. Modified from [23].

In this sense, the information transmitted from STS to IPL is the result of a “translation” of a visual input into a “motor format” that can be understood and processed by motor and mirror neurons.

In the last decades a great number of brain imaging studies and electrophysiological experiments have provided evidence for the existence of a mirror neuron system in the human brain (for a review see [27], [28]). In particular, the link between STS and IPL, as well as the circuit between premotor areas and parietal areas, has been demonstrated to exist also in humans [29], [30] both directly [31] and indirectly [32], [33]. Furthermore, it has been shown that also in humans the observation of actions performed by others elicits a sequential pattern of activation in the mirror neuron system that is consistent with the proposed pattern of anatomical connectivity [34], [35].

III. THE CHAIN MODEL OF THE MIRROR SYSTEM

In recent years, there has been an increasing interest in modeling the mirror neuron system and action recognition mechanisms [36]–[38] and sensory–motor couplings [39], [40]. In particular, the Chain Model [15], [16] addressed these questions in detail both at the system and at the neuronal level. Its key hypothesis, supported by a growing body of experimental findings [21], [41], [42], is that motor and mirror neurons in the parietal and premotor cortices are organized in chains encoding subsequent motor acts leading to specific goals (see Fig. 2). The execution and the recognition of action sequences are the result of the propagation of activity along specific chains. More

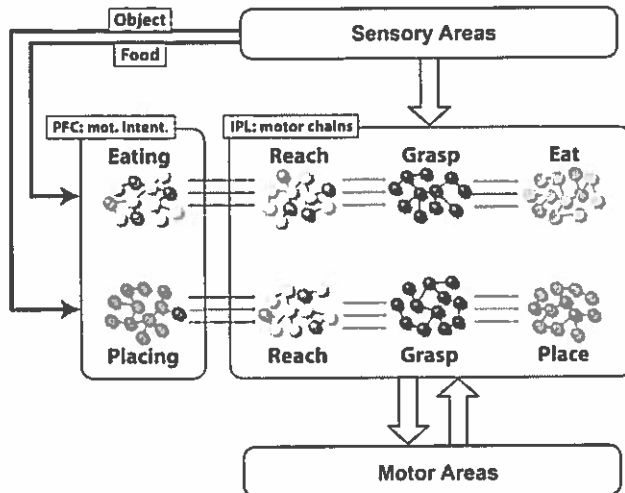


Fig. 2. Scheme of the fronto-parietal circuit with two neural chains. Each neuronal pool in the chains receives input from the preceding and projects to the following pool, moreover it is connected to the motor areas, and receives from sensory areas. The prefrontal area contains the intention pools (“Eating” and “Placing”) which integrate the information from sensory areas and then provide the activating input to the chains.

precisely, if we consider for example a “grasping to place” sequence, the first motor pool that is activated is the one in the parietal cortex encoding a reaching movement. This activity is immediately propagated to the premotor cortex, which computes finer details about the movement, integrating information from other sensory areas, and in turn propagates activity to the motor cortex where motor synergies are computed and transmitted to the spinal cord. At the same time, each area back-propagates an efferent motor command to its higher level area, the function of which can be interpreted as a “confirmation” of the execution of the command, and contributes to the sustainment of the activity in the receiving pool as long as the motor act is executed. When the motor act is completed or is hindered from execution no efferent copy is back-propagated and the activity in the originating pool rapidly decreases (for a detailed description see [16]). In addition to this “downward” propagation, part of the activity is also transmitted to the pool encoding the subsequent motor act (in this case grasping). This pool does not immediately start to fire because the input from the previous pool contributes only partially to its activation and in order to reach the threshold level it needs additional input from sensory and proprioceptive areas. Importantly, due to their “duality”, the same mechanism for action execution is employed for recognition in chains composed of mirror neurons. More precisely, during the execution of actions, mirror neurons behave exactly as ordinary motor neurons, while during observation specific subpopulations of mirror neurons resonate when the observer sees the corresponding motor acts (e.g., reaching, grasping, placing, etc.) being executed by another individual. These feedback signals from resonating mirror neurons trigger the activation of neurons in PFC encoding intentions attributed to others. In this case neurons in primary motor cortex are not active.

The prefrontal cortex, which encodes intentions and task relevant information, implements the early chain selection mechanism, while sensory and temporal areas provide the necessary

input to guide the propagation of activity within specific chains during action unfolding.

From a motor control point of view a chain structured network seems to be a very advantageous solution for the execution of learned actions because it avoids the need of higher level mechanisms that constantly generate and control the motor sequences. In case of the existence of an external supervising structure, which could be the PFC, this would need to receive and process low level information from sensory and proprioceptive areas, evaluate the state of the system, execute a step of the sequence and wait for the result. The burden would be so high that it would not be able to execute any other function in the meantime. Nevertheless, this highly cognitive control mechanism is utilized during learning when a situation is new, the sensory input unfamiliar, and the outcome unpredictable. In this case, initially greater attention is required to execute the correct moves, but once the sequence is well learned it is possible to execute it in an almost automatic way. An additional advantage of “hardwired” chains is that it permits a “smooth” and automatic execution of motor sequences (see Luria’s “kinetic melody” [43]) because the activation of one pool prepares the following one already before the new act has to be executed.

IV. EXPERIMENTAL PARADIGM

To evaluate the imitative behavior and learning capabilities of the proposed goal-directed neural system, we adapted to a human-robot interaction scenario a paradigm that has been originally developed for experiments with monkeys [21]. The original experiment consisted of two conditions, one “motor” and one “mirror,” each one with two types of tasks. In one condition a monkey had to observe an experimenter reaching and grasping either a piece of food or a metal cube, and then bringing it to the mouth or placing it into a container, respectively. In the other condition the monkey had to perform the described actions itself.

In the present work, we modified the original paradigm by replacing the piece of food and the metal cube with two colored polystyrene blocks. Additionally, the robot’s mouth was replaced by a box at the height of its “stomach,” and the “eating” goal with the “taking” goal, which in this case consisted in placing the object inside the “stomach.” Finally, the “placing” action corresponded to placing the object on a green target area on the table. The choice of this type of substitution was motivated by the consideration that eating and taking are somehow similar because they both recall the concept of possessing an object, while placing clearly does not. To this we want to underline the fact that it is important that the goals of the two sequences are conceptually different even if they both actually consist in placing two objects (food or cube) in two different locations (the mouth or the table): the distinction takes place on the conceptual (goal) level and not on the motor level.

V. SYSTEM ARCHITECTURE

The architecture implemented on the robotic platform is a combination of modules that use classic algorithms, such as the image processing engine and the robot arm controller, and modules that use biologically inspired neural networks, such as the

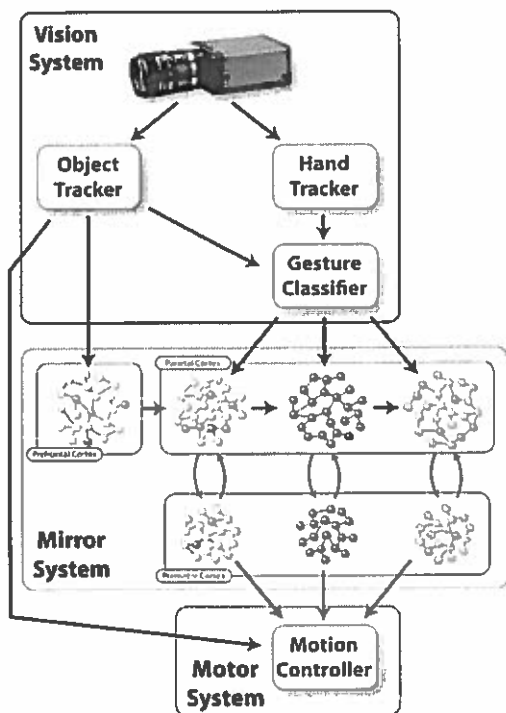


Fig. 3. Schematic representation of the various system components and their interconnectivity. For sake of simplicity only one neural chain has been represented (in this case a reaching, grasping, taking chain). Lighter and darker colors represent excitatory and inhibitory neurons, respectively.

action recognition and imitation circuits. Fig. 3 depicts the different modules and how they are connected to each other (for sake of simplicity only one IPL chain is represented with its downstream premotor neurons). In the following sections we describe each component and how it functions in detail.

A. The Robot

We used the anthropomorphic robot “AROS” [44] as an experimental test bed to validate our model. This robot is composed of a torso fixed on a rigid metallic support structure, one arm with a gripper, and a head with a Firewire vision system (see Fig. 4). The arm is the Amtec 7-DoF Ultra Light Weight Robot [45] which, in the present configuration is mounted horizontally with the base attached to the “backbone” of the support structure (thus forming the shoulder), and allowing a 1 meter working radius. The end effector is the gripper provided by Amtec. It has two parallel sliding “fingers” and the closing force can be regulated via the PC interface thus allowing to grasp fragile objects.

A 3 GHz computer is interfaced to the Amtec’s hardware controller through a dedicated CAN Bus. Amtec provides software libraries that allow an easy and transparent control of each joint motor. Moreover, these libraries also contain all the necessary functions that compute the inverse kinematics, thus allowing the user to easily work in Cartesian space.

B. Image Processing

The robot’s vision system consists of a Firewire camera with a resolution of 640×480 pixels in YUV format at a frame rate of 30 fps. The image processing is based on several modules

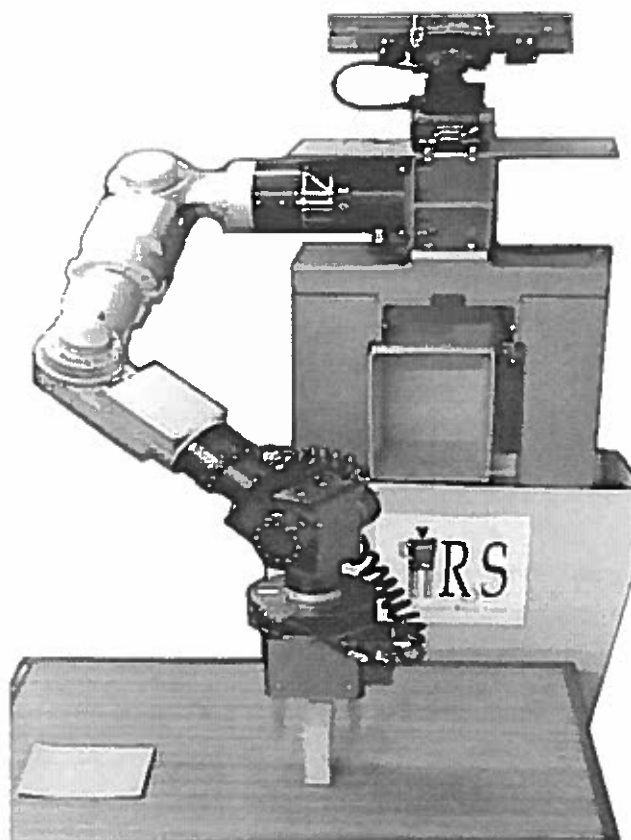


Fig. 4. The anthropomorphic robot “AROS” utilized in this study. It is endowed with a 7-DoF Amtec arm and a Firewire color camera.

that process the incoming images each one extracting specific features.

We want to underline the fact that the general rationale behind the development of the following algorithms was to minimize computational complexity in order to obtain real-time functioning, nevertheless trying to maintain acceptable performances.

In order to function correctly the system requires an initial training phase during which the image properties and the hand’s and objects’ shape and color descriptors are learned. The first step consists in the construction of a background model. It is important to note that in this setup the robot’s head and the camera view-field are fixed thus allowing it utilize very common and efficient background subtraction algorithms [46]. To this aim the Y, U and V components of each pixel of the reference view (i.e., the working area without objects or people) are modeled as Gaussian random variables, and during an initial period of 5 seconds (150 frames) their average value and their standard deviation are calculated and stored. This allows to estimate the probability of each pixel of a new image as being part of the background or not. In this implementation we have chosen as a membership criterion that a pixel of a given image is part of the background only if $|I(x, y) - I^{bg}(x, y)| < 2\sigma(x, y)$ for all channels (Y, U, V).

The second step is the color classification of the hand and the objects by means of a lookup table. The training data is obtained by placing one at the time the hand and the objects in the center

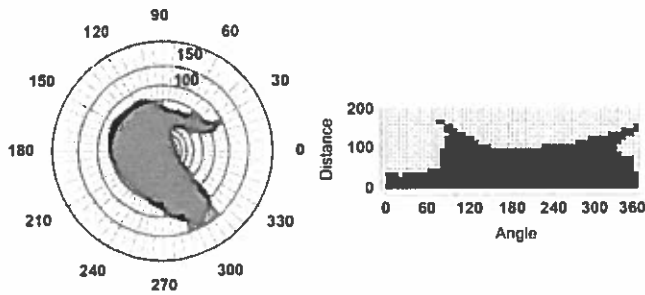


Fig. 5 Left: “whole-hand grasping” posture shape extracted from a video frame, and its down-sampled log-polar representation. Right: Log-polar representation of the hand posture.

of the camera view field and, after having digitally removed the background, by labeling in a lookup table the identified colors as “belonging to the object” or not (in this phase the hand is treated as an object). This procedure is repeated several times for each item in order to obtain a more complete and robust color description. The color classifications of each object and of the hand are stored in separate lookup tables. In order to reduce the memory requirements for the lookup tables, the chrominance components U and V of each pixel are normalized to 80, while the luminance component Y is normalized to 5 (thus obtaining a 32 kB lookup table).

The third step consists in the storage of hand postures. The procedure is the following. The hand with the desired posture (for example grasping) is shown in the center of the view field and is then extracted from an image by means of the segmentation techniques described above. The resulting silhouette is then translated to its center of mass and then converted into a down-sampled log-polar representation [47]. In our implementation we used a 72×50 (angular \times radial) representation, covering a circle of 250 pixels in diameter with a 5° resolution (see Fig. 5). This procedure is repeated for all the hand postures that one wants to store and is also utilized during the experiment to recognize observed actions.

The striking advantage of this representation is that hand rotations in the Cartesian plane correspond to translations along the angular axis in the log-polar space, while expansions and contractions (caused by changes in the hand elevation) correspond to translation along the radial axis. This allows to utilize a simple and fast Boolean comparison algorithm between the current hand posture and the database of stored postures.

Before starting the experiments the camera is calibrated using a planar checkerboard grid placed at different orientations in front of the camera [48].

During the experimental phase for each incoming frame first motion segmentation and then color segmentations are applied in order to identify and extract the hand and the objects in the scene. Thereafter, the position and orientation are calculated for each object and for the hand, and the latter is furthermore converted into the log-polar representation to be matched with the items in the hand posture database.

In parallel, the coordinates of the objects, when needed, are used by the motion controller to plan the reaching and placing movements.



Fig. 6 Three “Command signs” used by the demonstrator to interact with the robot. Left: “Beginning of sequence”, middle: “End of sequence”, right: “Execute sequence”.

The developed segmentation and recognition algorithms have proven to be very fast and sufficiently accurate for the task.

C. Recognition of Motor Acts

From an operational point of view a gesture can be defined as the evolution of the configuration and the kinematic parameters of the hand in time. As mentioned above, the image processing module provides, at each time step, information about the hand posture type and its position and orientation in space, as well as that of all the objects in the scene. Given the fact that the aim of this work was not to develop algorithms for automatic action segmentation, we have manually defined criteria that identify the single motor acts relevant to this task.

If we indicate the coordinates of the hand with $\mathbf{x}_H(t)$, of the object with $\mathbf{x}_O(t)$, of the placing target with $\mathbf{x}_T(t)$, of the demonstrator’s position with $\mathbf{x}_D(t)$, and the posture type with $P(t)$, the hand gesture definitions utilized in this work are the following:

- **Reaching** (to grasp): the hand has an open shape and the distance between it and an object decreases at every time step: $P(t) = \text{“open,”}$ $|\mathbf{x}_H(t) - \mathbf{x}_O(t)| < |\mathbf{x}_H(t-1) - \mathbf{x}_O(t-1)|$.
- **Grasping**: the hand is at a short distance d from an object and its shape varies from the fully open grasp to the almost closed grasp: $P(t-1) = \text{“open,”}$ $P(t) = \text{“grasping”}$, $|\mathbf{x}_H(t) - \mathbf{x}_O(t)| < d$.
- **Placing**: the hand is constantly at grasping distance d from an object and they move together both approaching the placing spot: $P(t) = \text{“grasping,”}$ $|\mathbf{x}_H(t) - \mathbf{x}_O(t)| < d$, $|\mathbf{x}_H(t) - \mathbf{x}_T(t)| < |\mathbf{x}_H(t-1) - \mathbf{x}_T(t-1)|$.
- **Taking**: the hand has a closed grasp shape and is constantly at grasping distance from an object, and their distance from the demonstrator decreases in time: $P(t) = \text{“grasping,”}$ $|\mathbf{x}_H(t) - \mathbf{x}_O(t)| < d$, $|\mathbf{x}_H(t) - \mathbf{x}_D(t)| < |\mathbf{x}_H(t-1) - \mathbf{x}_D(t-1)|$.

These criteria, although simple, have proven to produce good results, at the same time being an acceptable compromise between computational complexity and accuracy.

D. Human-Robot Interaction Through Gestures

A fundamental feature that has been integrated into the robotic system is the possibility to interact with it using visual commands in the form of specific hand postures. The use of a simple hand sign language allows the demonstrator to easily send the robot commands indicating what to learn and when to imitate it [49], [50]. This has proven to be a key requisite for the correct functioning of the experiment since the robot is

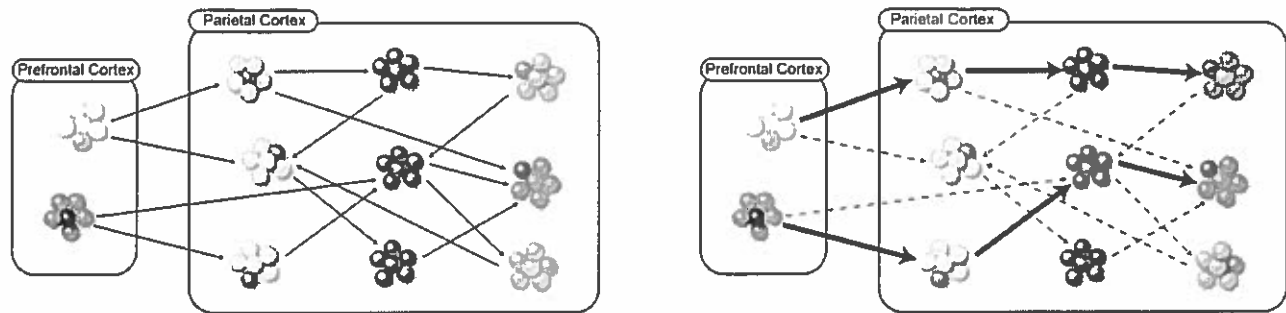


Fig. 7. Schematic representation of the organization of the network. Each layer contains pools composed of 80 excitatory and 20 inhibitory neurons (drawn as lighter and darker colors) neurons. Pools are initially connected randomly to each other (left panel) but through learning they form the correct chains.

never deactivated during the whole experimental session, nor any command is given manually through the controlling PC. The system, thus, continuously identifies motor acts that compose the two sequences to be learned when the demonstrator sets up the workspace, places the objects on the table before the beginning of the trial, and removes them after the trial is completed. Should the robot always be in “learning mode” it would recognize and build neural chains of sequences that are meaningless or even counterproductive for the experiment.

The “command signs” the demonstrator can utilize are shown in Fig. 6 and are: 1) “Beginning of sequence” (left panel) to instruct the robot that the sequence to be learned is about to start; 2) “End of sequence” (middle panel) when the robot should stop learning; and 3) “Imitate” to inform the robot that it should identify the cues in the scene and execute the corresponding sequence.

For the present experiment the system was trained to recognize 5 hand postures: “reaching,” “grasping,” plus the three “command signs.” In order to achieve an acceptable recognition rate (more than 85% of the frames) the “reaching” posture required two prototypes, while the “grasping” five. The low recognition level does not represent a problem because the neural pools integrate the input signals over longer periods of time, thus occasional misinterpretations are generally leveled out.

E. Neural Network Configuration

The cognitive architecture employed in this work has been developed with the aim of mimicking the mirror neuron circuit. To this end the neural network has been subdivided into three different layers: the prefrontal layer where goals are encoded, the parietal layer where sequences are recognized and stored, and the premotor layer which dispatches the motor commands to be executed (see Fig. 3, middle inset).

In this implementation neurons within each layer are grouped into pools of 100 identical integrate-and-fire neurons (see next section), of which 80 excitatory and 20 inhibitory [51], which are randomly connected to about 20% of the other neurons in the same pool, and the excitatory ones to about 2% of the neurons of other pools (also in other layers) (see Fig. 7). This type of configuration is known as “small-world” topology [52]. As a result, neuronal pools have a very high specificity concerning feature encoding with each prefrontal pool encoding only one of the possible action goals (“taking” or “placing”), and each

parietal and premotor pool encoding only one of the possible motor acts (“reaching,” “grasping,” etc...). This network structure was motivated by anatomo-functional evidence suggesting the organization of neural circuits into assemblies of cortical neurons, that possess dense local excitatory and inhibitory interconnectivity and more sparse connectivity between different cortical areas [53], [54]. Note that inhibitory neurons project only inside their pool, and help to provide stability and to avoid situations of uncontrolled hyperactivity (seizures). There is no direct competition between neural chains thus allowing the parallel activation of multiple hypotheses at the same time. The deactivation of a chain or an intention pool is caused by the sudden lack of its supporting external input (typically sensory or motor feedback) [16].

The projections between the parietal and the premotor layer were assumed to be genetically predetermined and have been set in such a way that neurons in each pool in the first are connected only to neurons within a single corresponding pool in the second, with the latter providing the motor feedback to the first. On the other hand instead, connections between parietal neurons and between prefrontal and parietal neurons are learned during the experiment.

Finally, the connectivity between neurons in the same pool is not plastic and the weights are calculated offline in the following way. Initially weights are set to random values (in this implementation in the order of 1 nA), thereafter they are iteratively selectively increased or decreased until all neurons fire at the desired average firing rate in response to a given input. In this implementation this rate was 100 spikes/s, a typical biological value [22].

In the present implementation the IPL layer contains a total of 40 pools equally distributed among the four classes of elementary motor acts (reaching, grasping, taking and placing), while the PFC networks contains eight pools, half of which represent the “eating” goal and half the “placing” goal. Each of the IPL and PFC pools is initially connected to four IPL pools chosen randomly. The sparse connectivity of the network is very important because it avoids that, due to overlearning, all neurons eventually become strongly linked together. At initialization plastic interpool weights are given values randomly chosen between 0% and 5% of the firing threshold value w_{thr} (i.e., the connection strength that causes a highly active pool to highly activate the connected pool, 8 nA).

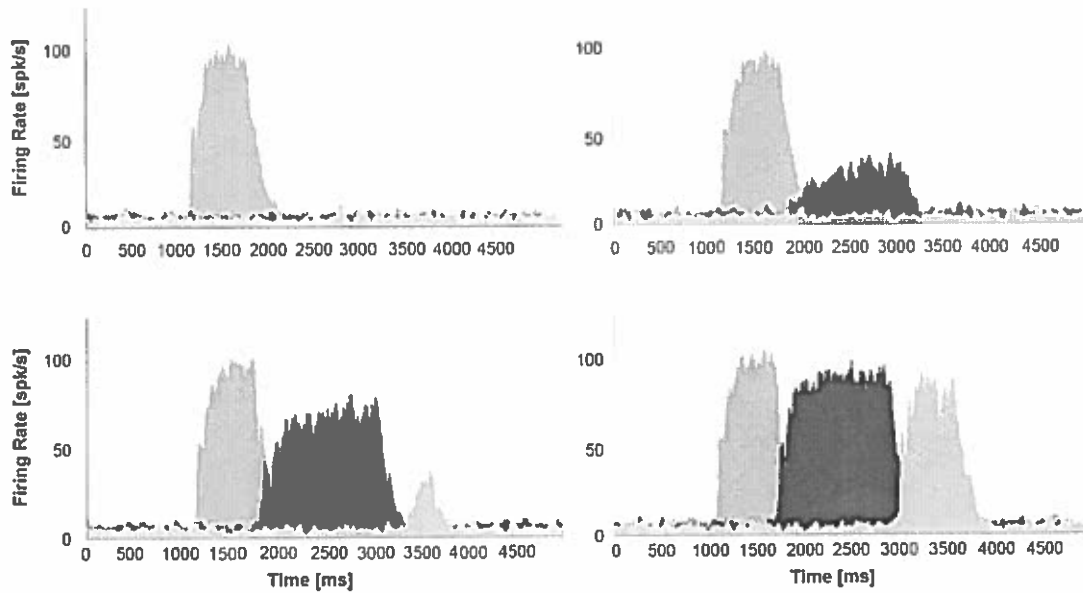


Fig. 11. Histograms of the mean firing rate of three neural pools during four different phases of the learning process: at the beginning, after 15 trials, after 27, and after 40 trials, respectively. Green represents the “reaching” act, the blue the “grasping” act and the orange the “taking” act.



Fig. 12. Three frames extracted from the “grasping to take” sequence executed by the robot. “Taking” consists in placing the object into the box inside the robot.



Fig. 13. Three frames extracted from the grasping to place sequence executed by the robot.

to be trained visually and then to be used to produce the corresponding motor sequence.

Fig. 12 shows three different moments of the imitation task performed by the robot, respectively: reaching, grasping, and taking. While Fig. 13 shows three images taken during the execution of the “reaching to place” sequence by the robot.

Important to note is that, once the system is correctly trained, it will produce no errors during imitation, as the error prone part of the learning is the construction of motor chains, while the

motor execution is obtained using classical and well established algorithms.

VII. DISCUSSION AND CONCLUSION

Imitation is a very efficient means for transferring skills and knowledge to a robot or between robots. What makes this form of social learning so powerful, in particular for the human species, is the fact that it usually relies on understanding the underlying goal of the observed action. In this view, a prerequisite for the development of more sophisticated imitating agents would be not only that they recognize the overt behaviors of others, but also that they are able to infer their intentions. An important consequence that directly derives from this capacity is that a skilled agent would be able to imitate an action even if it is partially occluded [63] or if the demonstrator accidentally produces an error during the execution of the action [64]. Moreover, such an agent would also be able to predict the outcome of new actions making use of his experience to mentally simulate the unfolding of the actions and their consequences.

Clearly, this cognitive capacity is crucial for any social interaction, be it cooperative or competitive, because it enables the observer to flexibly and proactively adjust his responses according to the situations.

Taking inspiration from recent neurophysiological studies on the mechanisms underlying these capacities we have developed a control architecture for humanoid robots involved in interactive imitation tasks with humans. In particular, the core of the system is based on the Chain Model, a biologically inspired spiking neuron model which aims at reproducing the functionalities of the human mirror neuron system. Our proposal of the functioning of the mirror system includes aspects both of the forward-inverse sensory-motor mapping and the representation of the goal. In our model, in contrast for example with Demiris’ architecture [39], the goal of the action is explicitly taken into

The image processing module sends targeted input to each pool according to the observed motor act: if reaching is observed only the neurons in the 10 reaching pools are activated; if grasping is observed only the 10 grasping pools are activated, and so on. Additionally, the information about the presence of one object reaches four of the PFC pools, and the information about the other object reaches the remaining four PFC pools.

F. Spiking Neuron Model

In the present implementation individual neurons are described by a leaky integrate-and-fire model [55]. Below threshold, the membrane potential $V(t)$ of a cell is described by

$$C_m \frac{dV(t)}{dt} = -g_L(V(t) - V_L) + I_{tot}(t) \quad (1)$$

where $I_{tot}(t)$ represents the total synaptic current flowing into the cell at time t , $V_L = -70$ mV is the resting (leak) potential, $C_m = 0.4$ nF is the membrane capacitance, $g_L = 20$ nS the membrane leak conductance and the membrane time constant is $\tau_m = C_m/g_L = 20$ ms.

When the membrane potential $V(t)$ reaches the threshold $V_{thr} = -50$ mV a spike is generated and propagated to the connected neurons, and the membrane potential is reset to V_L [56]. Thereafter, the neuron cannot emit another spike for a refractory period of $\tau_{ref} = 3$ ms. All the parameters in this model have been chosen in order to reproduce as close as possible biological data.

The total input to a neuron n in a motor chain is given by

$$I_{tot}(t) = \sum_{i \in \text{pool}} W_{i,n} \cdot \delta(t - t_i) + \sum_{j \in \text{prev}} W_{j,n} \cdot \delta(t - t_j) + \sum_{k \in \text{ext}} W_{k,n} \cdot \delta(t - t_k) \quad (2)$$

where $W_{i,n}$ defines the strength of the connections arriving from neurons in the same pool, $W_{j,n}$ the connections from neurons in the previous pool or in PFC in case the neurons is part of the first element in the chain, while $W_{k,n}$ represents the strength of the input arriving from proprioceptive, sensory, or backprojecting motor areas ($W \approx 4$ nA).

G. Learning Rule

In the present model, learning takes place through the modification of the connections' strength between the neurons in two different pools. The implemented learning rule is the spike-timing dependent plasticity (STDP) [57], [58].

According to this rule the synaptic efficacy between two neurons is reinforced if the postsynaptic neuron fires shortly after the presynaptic neuron, while it is weakened when the presynaptic neuron fires after the postsynaptic neuron. The term $F(\Delta t)$, that takes into account the dependency of the synaptic efficacy change rate on the past activity the two neurons [59], [60], can be written as

$$F(\Delta t) = \begin{cases} A_+ \cdot \exp\left(\frac{-\Delta t}{\tau_+}\right) & \text{if } \Delta t > 0 \\ A_- \cdot \exp\left(\frac{\Delta t}{\tau_-}\right) & \text{if } \Delta t < 0 \end{cases} \quad (3)$$



Fig. 8 Three frames extracted from a "reaching, grasping, taking" sequence as seen by the robot "Taking," which consists in placing the object in the blue box, substitutes "eating" of the original experiment.



Fig. 9 Three frames extracted from the "reaching, grasping, placing" sequence executed by the demonstrator.

with $\Delta t = t_j - t_i$, where t_i and t_j are the time of occurrence of the presynaptic and postsynaptic spikes, respectively. A_+ and A_- determine the maximum amount of synaptic modification, and the parameters τ_+ and τ_- determine the ranges of prepost synaptic interspike intervals over which synaptic change occurs. Based on Song *et al.* [58] we have chosen $A_+ = 0.005w_{thr}$ (where $w_{thr} = 8 \cdot 10^{-9}$ is the value for which a single presynaptic spike leads to the firing of the postsynaptic neuron), $A_- = 0.9A_+$. Finally $\tau_+ = 8$ ms, $\tau_- = 10$ ms, (see also [61]).

Finally, the complete equation reads as follows:

$$\frac{dw_{ij}(t)}{dt} = -\gamma w_{ij}(t) + \eta S_j(t) \int_0^\infty F(s) S_i(t-s) ds \quad (4)$$

where $\gamma = (500 \text{ s})^{-1}$ determines the synaptic decay (i.e., the "forgetting" factor), η determines the learning speed, $S_j(t)$ and $S_i(t)$ are the pre and postsynaptic spike trains, respectively, ($S(t) = 1$ for $t = t_{spike}$), $F(s)$ is the above mentioned kernel function [62].

In order to keep the weights within an acceptable working range, we have imposed the following hard bounds: $w_{min} = 0$; $w_{max} = 0.2w_{thr}$.

VI. RESULTS

In this section, we present the results of the imitation experiments carried out on the robotic platform described above. The aim of the experiments was to verify the robot's capabilities in understanding, learning and imitating action sequences performed by a human demonstrator. Similarly to the monkey experiment, also in this case there two phases, the "observation" and the "imitation" phase, which are repeated several times until the robot is able to correctly perform the tasks.

After the robot is powered up and the calibration parameters are either loaded or newly obtained, the system is in the default "observation" mode and the demonstrator can comfortably set up the working area. Once he's finished he makes the "Beginning of sequence" sign (see Fig. 6, left), telling the robot to switch to "learning mode," and demonstrates one of the sequences to be learned, i.e., either "reaching, grasping and taking

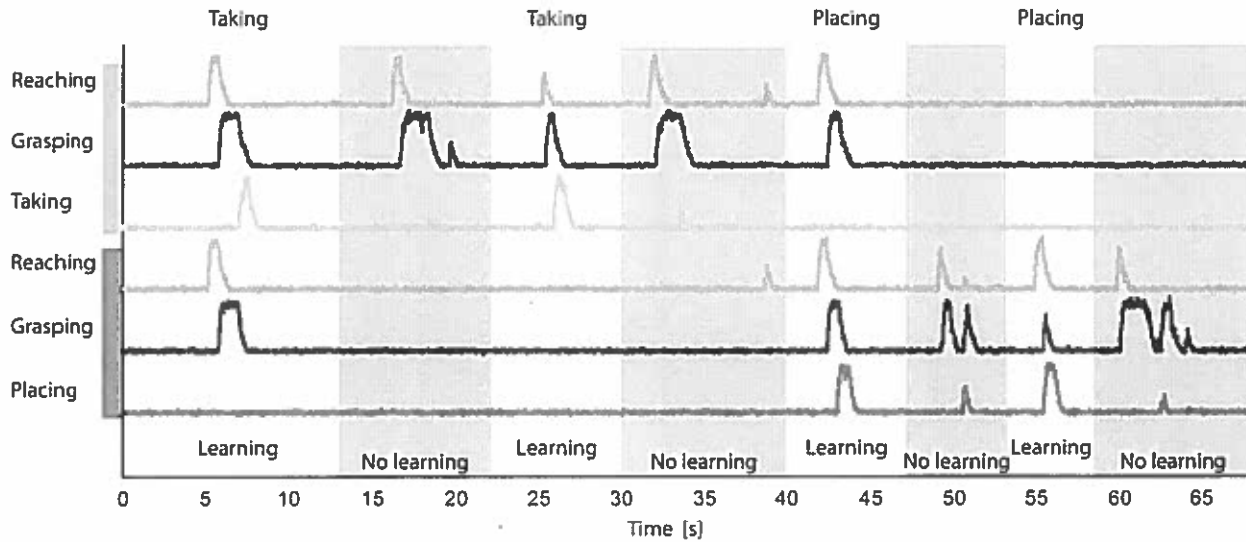


Fig. 10 Neural activity of six pools during various training phases. The first three will be linked to the yellow object and thus taking, and the last three to the red object and thus placing. White and gray zones indicate the learning and nonlearning periods, respectively.

one object” and “reaching, grasping, and placing the other object.” When the demonstrated sequence is completed, the experimenter shows the “End of sequence” sign (see Fig. 6, middle) in order to stop the robot from learning.

In the experiments shown here (see Figs. 8 and 9) the yellow polystyrene block has been chosen to represent food, while the red one represents the metal cube. The colors of the objects can be arbitrarily chosen by the demonstrator before the beginning of the learning phase, but they have to remain linked to the same sequence throughout all sessions otherwise the robot cannot learn a univocal cue-action association.

Fig. 10 shows an example of the time course of the activation of six neural pools during the presentation of two “reaching, grasping, taking” and two “reaching, grasping, placing” sequences. In this case, the learning rate parameter has been set to a value that allows one-shot learning. As can be noted, only after the complete presentation of the action sequence, the three upper pools will associate the taking sequence to the yellow object and the lower pools will associate the placing sequence to the red object. The zones with the white background indicate the time interval during which the robot is in learning modality, whereas the gray zones represent the period during which the robot is only observing (following a “End of sequence” command). At all times (also when the experimenter is preparing the work area for a new trial) pools of neurons corresponding to the recognized motor acts are activated by incoming visual signals, similarly to what is observed in visuomotor neurons in human and animal brains. However, during the “nonlearning” phases no synaptic modifications take place.

Important to note is the fact that simultaneously to the construction of the chains, the robot also learns from the demonstrator the association rules, i.e., the links from PFC pools to IPL pools, between the cues (the color of the blocks) and the corresponding action to be performed. After the learning phase is successfully completed the input signal from the PFC layer will only activate the taking chain when it sees the yellow object (which is linked to taking) and the placing chain when it

sees the red object. This behavior can be seen in Fig. 10 where in the first epoch (between $t = 0$ and $t = 12$ s) when the yellow block is on the table and the grasping-to-take sequence is shown, both chains are activated up to the “taking” act to which only the first chain responds completely. At the second presentation of the grasping-to-take sequence (from $t = 22$ to $t = 30$ s) the placing chain does not respond anymore because the yellow object now elicits only the activation of the taking sequence. The equivalent behavior can be observed for the grasping-to-place sequence in the subsequent learning windows (between $t = 40$ to $t = 42$ s, and between $t = 53$ and $t = 58$ s).

Fig. 11 shows the response of three neural pools (“reaching,” “grasping,” and “taking”) during the “Imitation” phase at different moments of the learning phase. From the increase of the firing rate of the three pools as learning proceeds, it is possible to recognize that there is a strengthening of neuronal connections. To correctly form the chains for the two tasks around 40 training epochs are necessary. It is possible to decrease this number by increasing the learning rate factor, nevertheless too high value cause the network to rapidly over-learn. Note that even if wrong or unclear examples are shown to the robot, the employed learning rule (eq. 4) on one side averages over the whole set of examples and on the other forgets old inputs. One of the notable results is the possibility, provided enough examples are shown, to train the system to a point where it makes no errors both in the recognition and in the recall phase.

A. Imitation

During the imitation phase, which starts when the demonstrator shows the “Imitate” sign, the robot has first to understand the goal of the task by analyzing the cues present in the scene (i.e., which block is present) and then, utilizing the previously learned neural chains, replicate the corresponding motor sequences. We recall that, due to the “duality” of their components, mirror chains are active both during observation and execution of motor sequences. This unique property allows them

account and embedded into the system through the use of dedicated structures (i.e., goal-directed chains). This is a key aspect of the learning process, which subsequently works as a prior to bias recognition by filtering out actions that are not applicable in the specific context or simply less likely to be executed.

The results shown in this paper demonstrate that the proposed architecture is able to extract important information from the scene (presence and position of the objects and the hand), reconstruct in real-time the dynamics of the ongoing actions (type of posture and gesture) and acquire all the necessary information about the task from the human demonstrator. Particularly important, in contrast to other existing models (for example [65]) is the fact that the recognition and execution of motor sequences do not take place in separate modules, but on the contrary they utilize the same neural circuit, and in case of identical actions the same exact mirror neuron chains are activated.

Finally, studies on infants have shown that, because of their little experience with the environment, context cues, and complex motor skills in general, parents tend to significantly modify and emphasize specific body movement during action demonstrations [66], [67]. They, for example, make a wider range of movements, use repetitions and longer or more frequent pauses, or simply shake or move their hands. This action enrichment, called "motionese," is assumed to maintain the infants' attention and support their processing of actions, which leads to a better and faster understanding. Not surprisingly, the adaptation in parental action depends on the age, and thus on the comprehension capabilities of the infants [68], with a progressive switch to the use of language as the children become older. In the case of humans teaching animals, this mechanism is rarely directly applicable. For example, when monkeys in a laboratory need to be trained, the standard procedure requires the demonstrator to take the animals' arm and hand and guide their movements from the beginning to the end. After each trial the animals need to be rewarded in order to increase in their brain the value of the motor sequence. The real difficulty in this type of teaching is not the possible complexity of the sequences, which the monkeys learn rather easily, but to be able to give them the reason and the motivation to execute the actions. Once the task is learned, the "Go" signal usually consists in lifting a barrier or showing a visual cue on a screen.

Although much more elementary, a human-like form of action highlighting has been utilized in this work demonstrating that the ability to communicate with robots using a simple form of sign language opens the possibility to build systems that are not as complex and error prone as those utilizing speech. In this view, we think that the results described in this paper may be a good starting point for the development of an artificial interpreter of body language, with the hope that a better comprehension of these lower level communication mechanisms may help on one side to develop smarter and more efficient human-robot interaction systems, and on the other to provide new insights on the mechanisms that, stemming from complex gestural capabilities, led to the evolution of human language [69].

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