A robotic model of reaching and grasping development

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***Abstract*—We present a neurorobotic model that develops reaching and grasping skills analogous to those displayed by infants during their early developmental stages. The learning process is realized in an incremental manner, taking into account the reflex behaviors initially possessed by infants and the neurophysiological and cognitive maturation occurring during the relevant developmental period. The behavioral skills acquired by the robots closely match those displayed by children. The comparison between incremental and non-incremental experiments demonstrates how some of the limitations characterizing the initial developmental phase channel the learning process toward better solutions.**

***Index Terms*—reaching, grasping, developmental robotics, humanoid, incremental learning.**

I. INTRODUCTION

MODERN theories of motor development assume that the child's interaction with the environment plays a crucial role and that learning can be characterized as an exploratory process involving variation and selection of behavioral strategies and the discovery of affordances [1], [2], [3], [4], [5], [6], [7], channeled by maturational and developmental constraints [8], [9], [10]. Modeling this developmental processes requires the use of embodied and situated agents that acquire their skills while interacting with an external environment [11]. The agents engage in a strategic learning process to discover and adopt different ways of achieving the desired states, experiencing at the same time a vast array of physiological maturations leading the exploratory process toward promising directions.

We aim to demonstrate how a developmental process of this type can be realized in the context of a well-defined behavioral capacity: the development of reaching and grasping behaviors in infants from 2 to 18 months of age. During this period infants display a transition from sweeping and unsuccessful arm movements toward primitive imprecise reaching and grasping behaviors and then a second transition leading toward integrated and effective reaching and grasping behaviors [12], [13], [14], [15], [16].

The development of reaching and grasping behaviors in infants constitutes one of the most deeply studied areas of motor control, for which a large amount of empirical data is available (see section Incremental Training). An additional interest to the topic stems from the field of robotics, where the design of robots able to develop human-like reaching and grasping skills represents an open challenge [17] and a necessary step in order to emulate higher cognitive processes [18], [19]. A historically important quest is to understand the control of several interdependent degrees of freedom (DOFs) [20], thus overcoming the redundancy of the system (i.e. there is an infinite number of trajectories and postures to reach a given target position).

The main aim of this study is to provide a neurorobotic model able to acquire reaching and grasping capabilities analogous to those displayed by infants from 2 to 18 months of age that integrates into a single framework a large set of the empirical observations reported in the literature. The model should be able to reproduce the qualitative changes occurring during successive developmental phases such as the emergence of motor babbling behaviour [7], [15], [21], [22], the freezing and then defreezing of the distal DOFs [23], [24], the integration of multimodal information [25], and overall the nonlinear pattern of skills acquisition that characterizes child development [16], [26], [27]. This model allows us to study the role of the maturational constraints [10] (i.e. modifications affecting the architecture of the robot's neural controller and the robot's perceptual capacities) on the behavioral skills developed by the robot. This has been realized by carrying out and analyzing a series of comparative experiments, which could not be performed on humans, in which the maturational constraints have been systematically manipulated. The experiments and analysis reported extend significantly previous related studies [2], [28], [29] with respect, in particular, to the temporal extension of the developmental period studied and to the amount of empirical data taken into consideration.

II. THEORETICAL ASSUMPTIONS

Our aim is to build a psychologically accurate model displaying behavior analogous to that shown by infants during their early developmental stages. We intend to design the simplest possible model that incorporates all the aspects that play a key causal role for the production of human-like behavior and abstracts from all the other characteristics. In the chosen domain, we hypothesize that the following aspects and modeling choices constitute essential prerequisites:

A. *Embodiment.*

The morphological and sensory-motor characteristics of the agent play an essential role in adaptive behavior [11]. For this reason we carry out our experiments by using a humanoid robot (the iCub) that matches to a good extent the characteristics of human infants in term of morphology, kinematic structure, and DOFs. Moreover, we design the sensory-motor

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Fig. 1: The simulated setting (Left) is derived from experiments carried out on infants (Center and Right) reported in [16] and [30].

system of the robot by taking into account the empirical data regarding infants' maturation/development.

B. Situatedness.

Behavior is not only the result of the agent's characteristics but also of the interactions between the agent and the environment. This aspect is accounted for in our experiments by simulating the characteristics of the physical environment and of the robot/environmental interaction in detail, and by using a learning process and a control architecture that allow the robot to exploit sensory-motor coordination and more generally properties emerging from the agent/environmental interaction. Finally, we replicated as much as possible the characteristics of the experimental settings in which the behavior of infants was studied [16], [30], see Fig. 1. This allowed us to generate data more easily comparable with experimental data, and to produce testable predictions for infant motor learning.

C. Nervous system and learning process.

Here we refer to the formalism used to specify the agent's nervous system (or robot's controller) and the way in which it adapts. In the context of infant reach/grasp development modeling addressed in this paper, we implement the robot's controller with an artificial neural network and the learning process through a simple trial and error learning algorithm that is driven by the observed consequences of the robot's action (visual and tactile feedback). The neuromimetic controller is not intended to reproduce the detailed characteristics of the nervous system (at the level of the single neurons or at the level of the nervous system architecture) but to capture its essential features. More specifically, the fact that neural networks encode and process quantitative information, operate over time, display generalization properties, and constitute a suitable and biologically plausible medium for learning [31]. The learning algorithm driven by distal somatosensory feedback complies with empirical evidence suggesting that young infants acquire reaching and grasping skills through a self-learning trial and error process [7] rather than by imitation learning [28], [32]. For the same reason, in contrast with models of adult and skilled movement [33], [34], we do not assume learning of explicit forward or inverse models.

D. Incrementality.

The fourth and last key aspect is constituted by the incremental nature of the developmental process. Action development in newborn infants does not start from scratch,

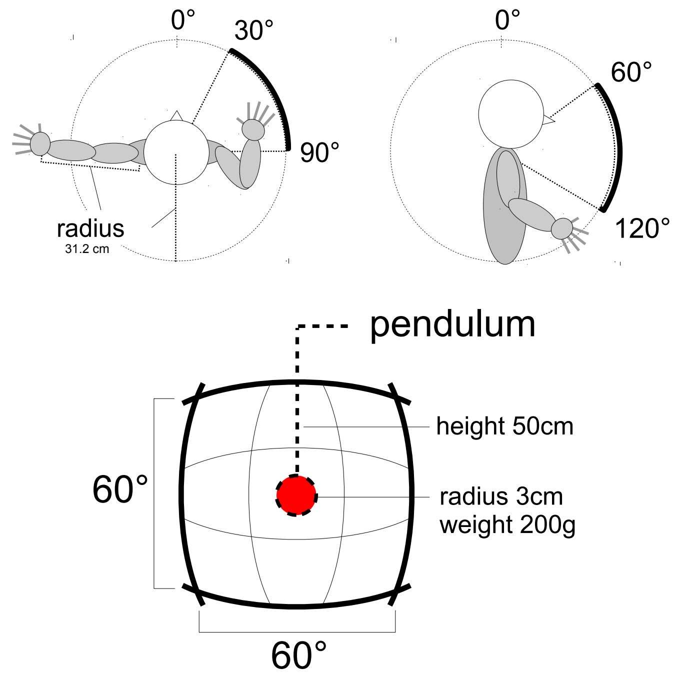

Fig. 2: The thick line in the three pictures shows the portion of the spherical surface in which the ball can be placed. To ensure a good spatial distribution over space of the target objects, the surface is virtually divided into 9 sectors.

as it is strongly influenced by pre-existing behavioral skills and by concurrent maturational processes. For this reason we provide the robots with two simple reflexes homologous to some of the reflexes initially possessed by infants: an orienting response [35] and a grasp reflex [36]. Moreover, we model the developmental process in a series of cumulative phases subjected to physiological modifications originating from tissues maturation [10] and cognitive modifications (e.g. increased ability to process visual information [37]).

III. Method and relation to the state of the art

A simulated iCub robot [38] is trained for the ability to reach and grasp a colored ball located in its peripersonal space. The experimental scenario in which we train the robot is derived from the experiments done with children of about 4 months of age by Spencer and Thelen [16] and von Hofsten [30] (see Fig. 1). The robot is suspended vertically over a stick attached to the pelvis. In each trial the ball is placed in a randomly selected point located within one of 9 sectors of the spherical surface centered on the iCub's neck (Fig. 2). The ball is attached to a pendulum. The robot is provided with a neural controller that is trained through an incremental trial and error process (see Learning Process).

A. The Robot

The iCub is a humanoid robot developed at IIT as part of the EU project RobotCub [38], [39]. It has 53 motors that move the head, arms and hands, waist, and legs. From

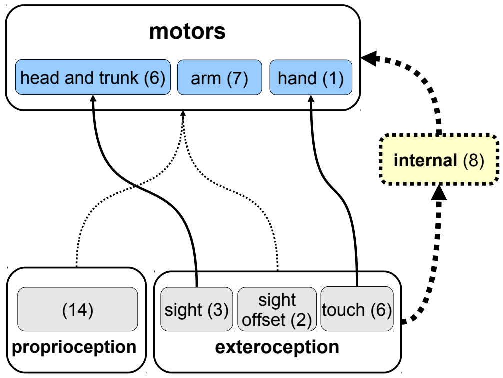

Fig. 3: The architecture of the robot's neural controller. Numbers between parentheses represent the number of neurons, arrows indicate connections. Full arrows indicate hand-designed connection weights used to implement motor reflexes. Dashed thin and thick arrows indicate connection subjected to variation during the first and the second training phases, respectively. The incoming and outgoing connections of the internal neurons are initially set to 0.0 and adapted from the second training phase only. Notice that dashed arrows pointing to the motor layer indicate connections toward all motor neurons.

the sensory point of view, the iCub is equipped with digital cameras, gyroscopes and accelerometers, microphones, force/torque sensors, tactile sensors. In the experiment reported in this paper, the sensors and actuators located on the left arm and on the legs have not been used. The experiments have been carried out through an open software tool available from *http://laral.istc.cnr.it/farsa*. The simulator included in this tool reproduces as accurately as possible the physics and the dynamics of the robot and robot/environment interaction, and is based on the Newton Game Dynamics open-source physics engine (*http://newtondynamics.com*).

B. The Robot's Neural Controller and Sensory-motor System

The robot's neural controller is constituted by a recurrent neural network that receives proprioceptive input from the right arm, torso, and head, exteroceptive input from the cameras located in the robot eyes and from the tactile sensors located on the right hand, and controls the motors of the torso, head, and of the right arm/hand (Fig. 3). As can be seen from the figure, the sensory layer is connected to the motor layer either directly, to take into account the fact that the initial pre-reaching behavior observed in children is highly reflexive and oriented to sensory-motor exploration [40], [22] and through 8 internal neurons, to allow the robot to develop more elaborated and effective motor strategies. Overall, the fact that the current sensory state can directly affect the current state of the actuators is in line with evidence collected on infants suggesting that they achieve reaching and grasping behavior through a sequence of corrective sub-movements and can correct their reaching trajectories online when the target is shifted [41].

Internal and motor neurons consist of integrator units (i.e. neurons whose current state also depends on their previous state) that are updated as follows:

$$x_i^{(t)} = \tau_i \cdot x_i^{(t-1)} + (1 - \tau_i) \cdot s_i^{(t)}$$

Where $x_i^{(t)}$ is the state of the i-th neuron at timestep t and $0 \leq \tau_i \leq 1$ is a time constant associated to each neuron [42], [43]. $s_i^{(t)}$ is computed as:

$$s_i^{(t)} = g_i \cdot \sigma \left(\sum_j^n (w_{ij} \cdot x_j^{(t)}) - \theta_i \right)$$

Where g_i is the neuron's gain, w_{ij} is the connection weight between the j-th and the i-th neuron, θ_i is the threshold and $\sigma(z)$ is the sigmoidal function $= 1/(1+e^{-z})$. Only the sight-offset and the internal neurons are provided with variable gain parameters. The gain of the other neurons is manually set to 1.0.

The state of the sensors, the network, and the motors is updated every timestep (0.1 seconds). The motor neurons set the desired angular position (scaled within the robot's joint limits) of 14 actuators controlling the following DOFs: head (3), torso (3), right arm (7), right hand (1). Each motor neuron controls a DOF of the robot with the exception of the hand, in which a single motor neuron controls the extension/flexion of all the fingers. The proprioceptors encode the current angular position of the corresponding joints (the average extension/flexion of the fingers' joints, in the case of the hand), scaled from -1 to 1.

A set of 6 tactile neurons binary encode (-1 or 1) whether the corresponding touch sensor located in the right hand palm and fingertips (Fig. 4, Top) detects an obstacle or not. The 5 sight sensors (indicated in the figure as sight and offset sensors), encode pre-elaborated information extracted from the robot's cameras (angle of view is 112° horizontally and 94° vertically) through a color blob identification software routine. More specifically the three sight sensors encode the relative position of the red color blob (ball) in the robot's visual field (Eq. 1 and 2) and the estimated ball distance up to 50cm (Eq. 3).

$$x_{\text{sight1}} = \text{sgn}(c_x) \cdot |c_x|^a \quad (1)$$

$$x_{\text{sight2}} = \text{sgn}(c_y) \cdot |c_y|^a \quad (2)$$

$$x_{\text{sight3}} = \begin{cases} 1 - 2l, & \text{if } l < 0.5 \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

Where c_x and c_y represent the coordinates of the detected color blob in the camera image and $\text{sgn}(x)$ is the sign of x.

In accordance with experimental findings on sight development [44], [45], we vary the visual acuity/peripherality of the robot between the first and the following training phases by setting the value of a to 3 and to 1, respectively (see Fig. 4, Bottom-Left). The offset sight sensors, that encode the offset of the target object with respect to the hand over the plane of the visual field [46], are updated on the basis of the following equation:

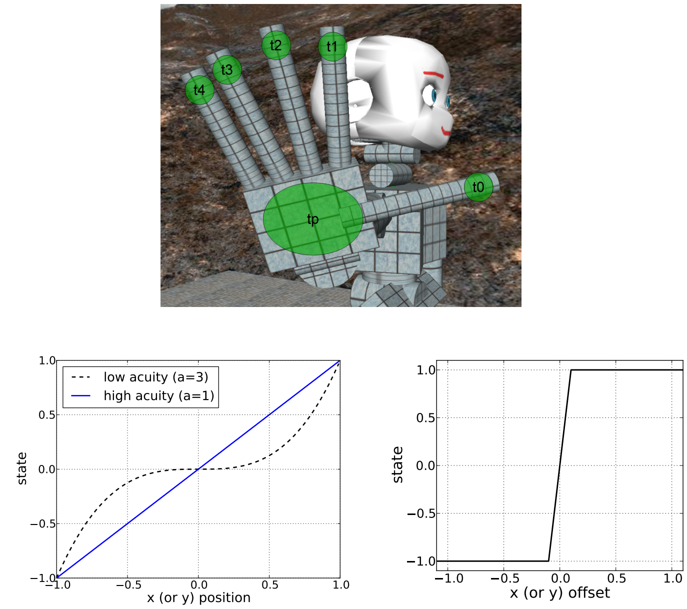

Fig. 4: Top: Location of the touch sensors in the robot's hand. Bottom Left: State assumed by the first two sight sensors for different positions of the colored blob field of view. The dashed and full lines indicate how the state varies with low and high acuity vision respectively. Bottom Right: State assumed by the two sight sensors on the basis of the offset between the position of the ball and the position of the hand in the robot's view field.

$$x_{\text{offset1}} = \begin{cases} z \cdot d_x & \text{if } -d_{\max} \leq d_x \leq d_{\max} \\ z \cdot -d_{\max}, & \text{if } d_x < -d_{\max} \\ z \cdot d_{\max}, & \text{if } d_x > d_{\max} \end{cases} \quad (4)$$

Where d_x is the hand-object offset in the camera along the x-axis. The value is clamped between $-d_{max}$ and d_{max}, then scaled by a factor z = 0.1. The state of the second neuron x_{offset2} is computed in the same way on the basis of the offset over the y-axis (see Fig. 4, Bottom-Right).

C. Learning Process

In accordance with empirical evidence indicating that early reaching and grasping skills in infants are acquired through self-learning mechanisms that do not rely on explicit forward and inverse model learning [33], [34] or imitation [32], the robot's training is realized through a form of trial and error learning during which the robot is rewarded for sensorial exploration and multimodal perception (seeing and touching [25]). More specifically, we evaluate the performance level of the robot at each time step by taking the smaller score between the perceptual modalities:

$$p_{\text{multimodal}} = \min\left(p_{\text{sight}}, p_{\text{touch}}\right) \quad (5)$$

The value is averaged over 18 trials each lasting 20 seconds. p_{sight} measures the proximity between the center of the robot's visual field and the object's projection in the visual field, p_{touch} measures the number of inner hand/fingers segments in contact with the object. Both factors are scaled between 0 and 1.

The agents are trained through a trial and error process in which the free parameters (connection weights, gains, biases and time constants) are varied randomly and variations are retained or discarded depending on their effect on the average $p_{\text{multimodal}}$ measure. This is realized by using an evolutionary method [47]. The initial population consists of 20 randomly generated genotypes encoding the connection weights, gains, biases and time constants of 20 corresponding neural controllers (each parameter is encoded by eight bits and mutated with probability 0.02). Every experimental condition is replicated 10 times, each time with a different seed for the random number generator.

The training process is intended to represent ontogenetic learning. The reason behind the choice of this algorithm is that it is one of the simplest yet most effective ways to train an embodied neural network through a trial and error process based on a distal reward [29].

D. Incremental Training

The robot is subjected to an incremental training process organized into the following three phases that model the three corresponding stages of the development of reaching/grasping capabilities in infants [12], [13], [14] (see Table I):

1) The pre-reaching phase, that in infants extends from birth to approximately 4 months of age, is characterized by the presence of simple head orientation [35] and grasping reflex behaviors [36], by a low involvement of cortical areas [48], and by a low visual acuity [44], [45]. During this phase infants develop a primitive orientation behavior of the arm [49] that is realized through a reduced usage (freezing) of the distal DOFs [24]), and through the exhibition of a form of motor babbling (i.e. a quasi-periodic behavior of the arm/hand leading to a form of exploration of the area in which the object is located) [7], [15]. To set similar conditions for this training phase we initially provided the robot with two simple motor reflexes: an orienting response that makes the robot turn its head toward the colored object [35] and a grasp reflex that makes the robot close its fingers when its right palm touch sensor is stimulated [36]. These reflexes are realized by manually setting the connection weights indicated with full lines in Fig. 3. The immature visual system is simulated by degrading visual acuity (see Fig. 4, Bottom-left). Sight of the hand is not included, because hand position is encoded indirectly by proprioceptive information. Experimental evidence showed indeed that infants can perform the first reaches without seeing their own hand [50]. Finally, the limited role of cortical areas during this phase is realized by freezing the connection weights to and from internal neurons to a null value (i.e. by subjecting to variations only direct sensory-motor areas).
2) A gross-reaching phase, that extends approximately from month 4 to the first year of age, is characterized by an improved visual acuity [44], [45] and by greater involvement of cortical areas [48]. At the end of the

pre-reaching phase infants experience a short period of motor suppression [30] followed by net improvement in their reaching and grasping ability. The main features of this developmental period are the reduced use of motor babbling [15] and the un-freezing of the distal DOFs [27], [36]. We modeled the maturational constraints characterizing this phase by increasing the visual acuity (see Fig. 4, Bottom-Left) and by also subjecting the internal neurons' incoming and outgoing connection weights to variation. This loosely simulates the intervention of cortical centers in the mediation of sensory-motor reflexive behavior [48].

3) A fine-reaching phase, that follows the first year of life, is characterized by the increasing role played by visual information concerning the hand-object relation [46] in later infancy [51], [52] and adulthood [53]. Due to limitation of attentional resources, this type of information plays a minor role in the pre-reaching phase [51], [50]. Furthermore experiments analyzing the role of hand and target visual information in 9-month-old infants during grasping show how visual monitoring of the hand and target is not yet fully exploited for online adjustment of the hand to match target object orientation [54]. During this phase children develop more reliable and smoother reaching [27], [14], [26] and grasping [54] behaviors. To model the maturation of the visual system, we provide the robot's neural controller with sight offset sensory information encoding the current hand/object spatial relation (that was missing during the previous phases). Note that these sensors encode only the relation between hand and object, so hand position is never explicitly given to the network [50]. Furthermore, we subject the gain parameters of the internal neurons to adaptive variations.

Each of the three adaptive phases is replicated 10 times. In the case of the fine-reaching phase, each replication randomly varies with respect to the initial value and to the variations of the free parameters. In the case of the gross-reaching and fine-reaching phases, each replication randomly varies with respect to the variation of the free parameters. The transition from the pre- to the gross-reaching phases and from the gross- to the fine-reaching phases is performed by merging the best 2 robots of each of the 10 replication of the previous phase into a single initial population made of 20 individuals and by introducing the maturational changes as described above. Each phase lasts 500 generations. The task, environment and performance evaluation are kept constant across the phases.

E. Relation to the state of the art

As we mentioned in the introduction, a few pioneering works addressed similar objectives. Schlesinger, Parisi and Langer [55] studied the development of reaching behavior in a simulated agent provided with a 2 dimensional arm with 2 actuated DOFs, a bi-dimensional vision system with 1 actuated DOF, and a tactile sensor located on the final portion of the arm. The agent's neural network controller received as input the angular state of the arm joints, the state of the tactile sensor, and the visual information extracted from the camera and controlled the 2 DOFs of the arm and 1 DOF of the visual system. The neural network controller was trained through an evolutionary algorithm on the basis of a performance criterion calculated by computing the average number of time-steps in which the agent touched the object.

Oztop et al [28] studied the development of grasping behavior in a simulated robot provided with an arm and hand with 19 actuated DOFs. A reaching behavior was preprogrammed in the robot on the basis of an inverse kinematics method. Learning was thus confined to the mapping of a series of object affordances (extracted from sensory information) into a series of grasping parameters able to shape the hand-coded reaching routine into an effective grasping behavior. The neural network controller was trained through a reinforcement learning algorithm and received positive reward for the trials producing successful or nearly successful grasps and negative reward for trials leading to unstable grasps or complete failures. A significant Gaussian noise superimposed on the network output state was introduced to generate exploratory behaviors that could enabled learning.

Berthier et al. [2] studied the development of reaching behavior in a simulated robot provided with an arm with 2 controlled DOFs on the shoulder (flexion-extension and adduction-abduction). The robot's neural network controller received as input the current state and velocity of the two joints and produced as output the intensity of the torque to be applied by two muscle-like actuators. The network was trained through a reinforcement learning algorithm by providing to the robot positive and negative rewards when the hand of the robot approached or moved away from the target, respectively. As in the case of Oztop et al. [28] noise was added to the actuator state to generate exploratory behaviors.

The model and experiments presented in this paper extend these pioneering works in several respects. We provide a model of reaching and grasping development rather than a model of reaching development only or grasping development only. We address the three primary developmental phases of reaching/grasping development rather than reaching or grasping onset only. We use a physically realistic model, that takes into account the gravity, inertia, and the physical consequences of robot/environmental interactions and that, as in the case of Oztop et al. [28], matches relatively well with human morphology in terms of the kinematic chain and DOFs. We demonstrate how the production of exploratory and motor babbling behavior and the freeze and de-freeze of distal DOFs can emerge spontaneously during the developmental process, as a result of the tendency of the adapting robots to self-structure their learning task to their current proficiency level. We demonstrate how the development of a new capacity can lead to the temporary regression of other pre-existing capacities. We will illustrate these aspects and the relation with previous studies in more details in the following sections.

IV. Results

In this section we describe the obtained results. First we describe the behavior displayed by the robots and the relation

TABLE I: Schematization of the developmental phases.

Phase	Maturational Constraints	Constraints Implementation	Resulting Behaviors
Pre-reaching	- Reduced role of cortical areas [48] - Reflexes [35], [36] - Low visual acuity [44], [45]	- Adaptation of sensory-motor connections only - Handcoded weights - x_{sight1} and x_{sight2} with $a = 1$	- Motor babbling [22] - DOF freezing [24] - Arm orienting [49]
Gross-reaching	- Increased role of cortical areas [48] - High visual acuity [44], [45]	- Adaptation of both sensory-motor and internal connections - x_{sight1} and x_{sight2} with $a = 3$	- Initial motor suppression [30] - Reach onset [7]
Fine-reaching	- Hand/Object Perception [46]	- Availability of x_{offset1} and x_{offset2}	- Smoother and straighter reach [27], [12], [26] - Anticipatory grasp [54]

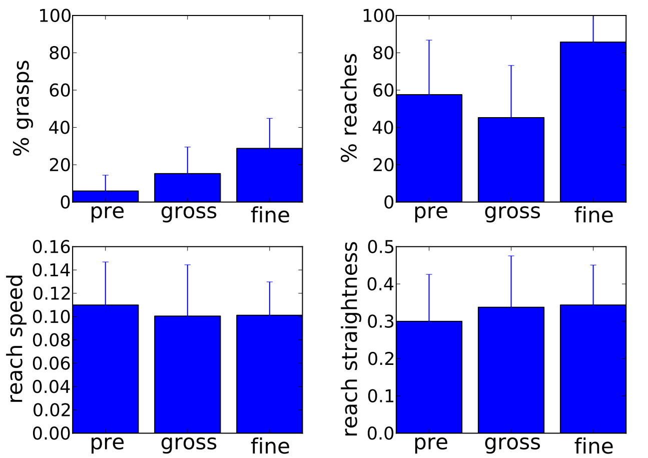

Fig. 5: Percentage of grasped objects, percentage of reached objects, reaching speed, and reaching straightness (i.e. the ratio between the hand/object initial distance and the length of the trajectory of the hand during successfully reaching actions [27], [26]). Each bar indicates the average results obtained by post-evaluating 50 robots (i.e. the best 5 robots of each of the 10 replications) for 45 trials at end of the pre-, gross- and fine-reaching phases.

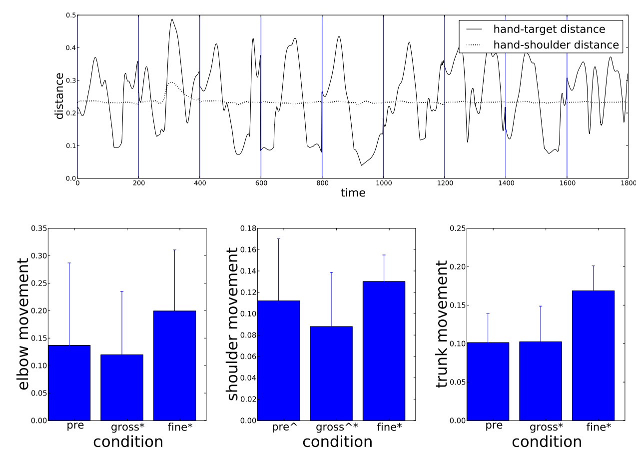

Fig. 6: Top: Hand-shoulder and hand-target distance (in meters). Data collected during a post-evaluation analysis conducted for 9 trials on the best agent of the best replication at the end of the pre-reaching phase. The vertical lines mark the beginning of each trial in which the posture of the robot is reset. Bottom: Movement variability (i.e. standard deviation of the joint encoders) for the elbow (Left), shoulder (Center) and trunk (Right) joints. Each bar indicates the average results obtained by post-evaluating 50 robots (i.e. the best 5 robots of each of the 10 replications) for 45 trials at end of the pre-, gross- and fine-reaching phases.

between the robots' and the infants' behaviors during the pre-, gross-, and fine-reaching developmental phases. Afterwards we describe the role of the different sensory modalities and the role of the maturational constraints. The implications of the results are discussed in the next section.

A. Relation between humans' and robots' behaviors

Overall, the analysis of the robots' performance (see Fig. 5 Top and Fig. 9 Top-Left) and the visual inspection of the robots' behavior (videos available from *http://laral.istc.cnr.it/esm/reach/*) show that the robots successfully develop quite good reaching and relatively good grasping capabilities. The analysis of the behavior displayed by the robots at the end of the three developmental phases (reported below) indicates that the robots' behavior and the course of the developmental process is analogous to that observed in humans from 2 to 18 months of age.

1) Pre-reaching: At the end of the pre-reaching phase the robots manage to reach (i.e. touch the object at least once with the hand) in about half of the trials (Fig. 5, Top-Right). The behavior of the robots at this stage consists in the exhibition of large quasi-periodic circular movements of the hand (Fig. 8, first column) produced with the arm extended. This is realized through a large use of the DOFs of the trunk and of the shoulder and a limited use (locking) of the DOF of the elbow, as demonstrated by the fact that the distance between the shoulder and the hand remains almost constant during reaching attempts (Fig. 6, Top). The exploratory nature of this behavior and the fact that at this stage the robots do not yet rely on visual information to bring their hand directly toward the ball is demonstrated by the fact that the behavior of the robot remains substantially the same during post-evaluation tests in which the target ball is absent and in tests in which the vision system is impaired (Fig. 8).
Therefore, as in the case of infants, the developmental process during the pre-reaching phase leads to the development of a preliminary reaching capacity [49] that is realized through the exhibition of periodic exploratory behaviors [15], [21], [22] characterized by the locking of the elbow [16], [24].

2) Gross-reaching: During the gross-reaching phase the robots improve their ability to grasp, i.e. touch the object with the palm and at least one of the fingers (Fig. 5, $p < 0.001$). Moreover, they reach objects through more direct trajectories as indicated by the significant increase of straightness ($p < 0.01$) and decrease of movement speed ($p < 0.05$), see Fig. 5, Bottom. This phase also leads to a reduction in the shoulder DOFs usage ($p < 0.001$, see Fig. 6). The visual inspection of the best robots at the end of this phase reveals that they bring their arm on the lower part of the target area while orienting their palm up and then produce long swipes up. When they don't grasp the ball they try again with similar swipes. On the other hand, the frequency of successful reaches decreases ($p < 0.001$, see Fig. 5) with respect to the pre-reaching phase. As indicated by Fig. 7, that shows the spatial distribution of successful reaches, this is due to the fact that during the gross-reaching phase the robots specialize on certain regions of their peripersonal space in which they succeed in reaching and grasping objects.

Many of the behavioral variations reported above are analogous to those observed in infants during this phase. In particular, the onset of the grasping skill [56], the emergence of more direct reaching movements [7], the reduced mobility of the shoulder [16], [30] and the (temporary) regression on reaching capabilities [16] have been documented in the cited developmental studies. However, the un-freezing of the elbow joint displayed by infants during this phase [24] is observed later in our robots (i.e. during the fine-reaching phase).

3) Fine-reaching: During the fine-reaching phase, the robots improve their ability to reach and grasp the objects ($p < 0.001$) and acquire a capacity to successfully accomplish these actions in all areas (Fig. 7). The analysis of speed and straightness in reaching, instead, does not indicate any significant improvement during this phase (Fig. 5, Bottom). The analysis of the DOFs (Fig. 6) indicates a significant increase in the mobility of the elbow, shoulder, and trunk joints with respect to the gross-reaching phase ($p < 0.001$).

Overall, the improvement in reaching and grasping performance observed in this phase [26], [54] and the increase in mobility for the elbow, shoulder and trunk joints [13], [24] are in line with what has been observed in infants, who however also show a significant improvement in smoothness and straightness [12], [27] during this phase. Notice also how the robots do not reach an optimal performance level in grasping. This might be the result of some of the simplifications introduced in the robotic model, i.e. the fact that the robot is made of completely rigid material, the limitation in the resolution of the robots' sensory system, the fact the five fingers are controlled by the same actuator.

B. On the role of the different sensory modalities

To better analyze the role of proprio, tactile and visual sensory information during the developmental process we compared the performance of the robots at the end of the three training phases in a normal condition and in three control conditions in which: tactile sensory information was not provided (no touch), visual information was not provided (no sight), neither tactile nor visual sensory information were provided (nothing). As shown in Fig. 9, performance significantly varies within the four experimental conditions (normal vs. no touch vs. no sight vs. no exteroceptive, $p < 0.01$, Kruskal-Wallis test).

The most notable effect is the strong impairment caused by the absence of visual information in the fine-reaching phase. In normal conditions and in absence of tactile information the fine-reachers outperform the gross-reachers ($p < 0.05$ and the gross-reachers outperform the pre-reachers ($p < 0.05$, two-tailed Mann-Whitney U test). Thus the absence of tactile information does not reverse the performance relation between the three phases. On the contrary, in the control conditions in which visual information is not provided or neither visual nor tactile information are provided, on the contrary, the gross-reachers outperform the fine-reachers ($p < 0.05$). This indicates that the development of an improved capacity to reach and grasp objects based on the exploitation of visual information during the fine-reaching phase leads to a temporal regression in the capacity to reach and grasp objects on the basis of proprio and tactile information only.

C. On the role of maturational constraints

In this section we describe the results obtained in a series of control experiments carried out to verify whether the maturational constraint have an adaptive or bias role, i.e. channel the adaptive process toward better solutions or toward specific types of solutions. For this purpose we took advantage of the possibility offered by our artificial model to freely modify any possible parameter or combination of parameters to carry out experiments that could not be performed on real children.

Fig. 10 shows a graphical summary of the experimental conditions and their relations. The pre-reaching (*pre*), gross-reaching (*gross*), and fine-reaching (*fine*) labels indicate the standard experiments reported above. We used *-h* to indicate a pre-reaching phase in which the robots were provided with full visual acuity (*pre-h*) or a gross-reaching phase following a *pre-h* phase (*gross-h*). The asterisk indicates the absence of reflexes, the symbol ˆ indicates non-incremental experiments. So *grossˆ* indicates experiments in which the robots are allowed to modify or the connection weights of the internal neurons from the beginning without first undergoing a pre-reaching phase. To allow fair comparison, in this control condition the training lasts the sum of the pre- and gross-reaching phases. *grossˆ** is an experimental condition analogous to *grossˆ* in which however the robots do not have the reflexes. Finally, *fineˆ* indicates an experimental condition in which the robots are trained from the beginning in the maturational state that characterize the fine-reaching phase. Training length in this case equals the sum of the pre-, gross- and fine-reaching training length.

From the statistical comparison between each performed experimental condition reported in Fig. 10 we can observe that the maturational constraint constituted by the lack of internal resources (i.e. internal neurons) during the pre-reaching phase plays an adaptive role since the *gross* condition significantly outperforms the non-incremental *grossˆ* condition ($p < 0.05$, two tailed Mann-Whitney U test). On the other hand, the reduced visual acuity during the pre-reaching phases, the

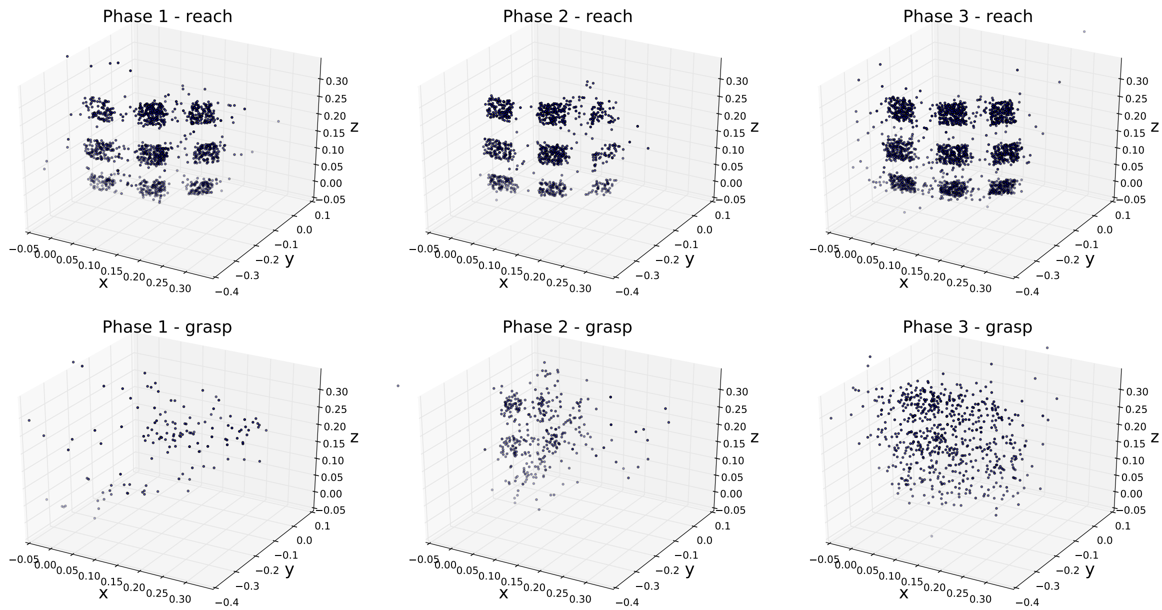

Fig. 7: Spatial distribution of successful reaches (upper row) and grasps (lower row) at the end of the pre-, gross-, and fine-reaching phases. Data obtained during a post-evaluation analysis in which the 5 best robots of each of the 10 replications of each phase has been tested for 45 trials, during which the position of the target objects has been systematically varied so to cover all possible target positions.

availability of reflexes, and the inability to perceive the offset between the hand and the object during the pre- and gross-reaching phase do not constitute adaptive constraints. Indeed the standard experimental conditions do not lead to significantly better performance with respect to the control experiments in which the visual acuity is not reduced during the pre-reaching phase (*pre* versus *pre-h* and *gross* versus *gross-h*), the reflexes are not provided (*pre* versus *pre**, *gross*ˆ versus *gross*ˆ*, *fine*ˆ versus *fine*ˆ*) and the offset between the hand and the object is perceived from the beginning of the developmental process (*fine* versus *fine*ˆ).

For what concerns the qualitative effects of maturational constraints on the strategies developed by the robots, the reduced visual acuity during the pre-reaching phase does not lead to an appreciable effect on the observed behavior with respect to the control condition. Similarly, the lack of reflexes does not alter significantly the type of behavior exhibited by the robot with respect to the control condition. On the contrary, the lack of visual perception of the hand/object offset and the lack of internal processing resources constitute two pre-requisites for the development of the exploratory (motor babbling) behavior. Indeed, the robots trained in the *fine*ˆ* and *fine*ˆ experimental conditions never display such behavior during the course of their developmental process.

V. Discussion

Our model and results demonstrate how reaching and grasping skills, analogous to those displayed by infants from 2 to 18 months of age, can be acquired through a trial and error learning process driven by simple visual and tactile feedback. We extend the evidences provided by previous related works [2], [19], [28], [55] modeling three subsequent developmental phases and using an experimental scenario that matches rather closely the complexity of the problem domain.

The model proposed account for a large set of the empirical observations reported in the literature and for the factors that can be at the basis of the emergence of the observed phenomena. A first aspect that characterizes both infants' [16], [24] and robots' development consists in the reduced use (freeze) followed by a re-extended use (un-freeze) of the distal DOFs of the robot arm. The observation that these variations emerge spontaneously in our experiments indicates that the presence of maturational constraints that control directly the freezing and de-freezing of selected joints, postulated by [19], might be unnecessary. Our results thus indicate that, as hypothesized by [20], this process might rather result as a side effect of the attempt to acquire the required skills. In other words it might results first by the tendency to simplify the learning task and then by the tendency to relax the restrictions once a good level of proficiency is attained.

A second phenomenon that characterize the developmental process of our robots and that matches experimental evidences [7], [15], [21], [22] is constituted by the emergence of the exploratory (motor babbling) behavior during the pre-reaching phase. This transient behavior is later replaced by more effective movements directed toward the target objects during the gross- and fine-reaching phases. The fact that in our experiments the motor babbling behavior occurs spontaneously without the need of dedicated mechanisms (e.g. white noise affecting the output of motor neurons, as proposed by Berthier et al [2], and Oztop et al. [28]) demonstrates that it might be the result of a self-structuring process. In this case, the initial simplification of the task is achieved

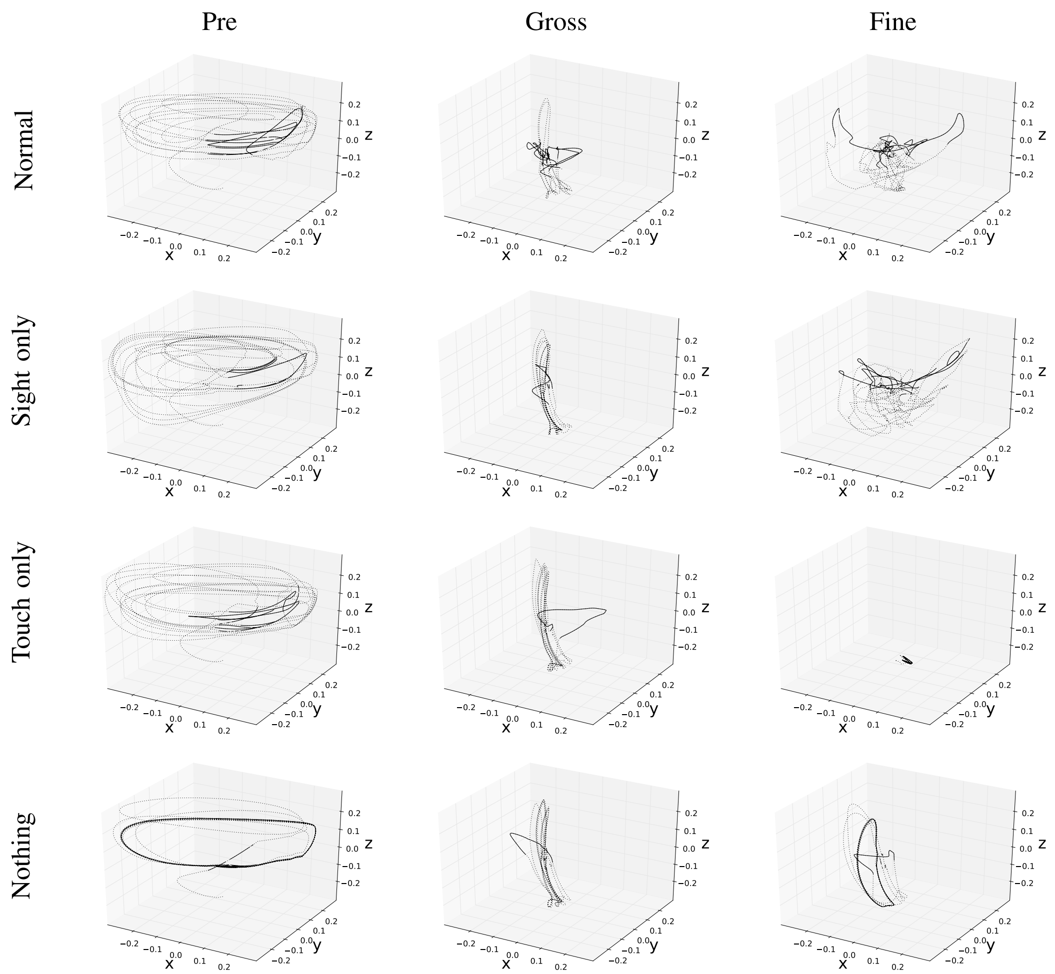

Fig. 8: Trajectories of the robot's hand observed during post-evaluation analysis in which the robots have been deprived of tactile and/or visual sensory information. Data collected for one trial on the best robot of the best replication at the end of the pre-, gross-, and fine-reaching phases.

through a reduction of the processed sensory information (i.e. which is achieved by ignoring tactile information). Such simplification is then abandoned after the robots achieve a given competence level. At this point, in fact, the utilization of tactile information becomes a necessary prerequisite for further improvements.

A third phenomenon consistent with the experimental literature [16] consists in the temporal regression of the reaching capabilities occurring during the gross-reaching phase at the onset of a reliable grasping capability. The fact that the regression involves a reduction of the peri-personal space in which the robot operates suggests that also this phenomenon can be interpreted as a side effect of the robots' tendency to temporarily simplify their learning task until they reach a proficiency level that creates the adaptive conditions for the elimination of the self-imposed simplification.

The three phenomena described above can thus be considered as manifestations of a general self-structuring process that operates by reducing temporarily the complexity of the motor space, of the sensory space, and of the relevant task space, respectively.

Finally, another contribution of this work concerns the identification of the role of the maturational constraints. The obtained results indicate that the lack of internal neural resources during the pre-reaching phase has an adaptive role (i.e. channels the developmental process toward better solutions during the gross-reaching phase) and a bias role (i.e. represent a necessary condition for the development of the exploratory motor-babbling behavior). This result suggests that the later involvement of cortical areas [48] can play an adaptive role in humans and might have evolved to accomplish this function. On the other hand, the fact that the other considered maturational constraints do not play an adaptive role suggests that they are simply a manifestation of parallel maturational processes. This result might serve as a general warning against the attempt to overestimate the functional role of the incremental nature of the developmental process.

VI. Conclusions

We presented a neurorobotic model of early reaching and grasping development. The characteristics of the model, of the training scenario, and of the maturational factors that

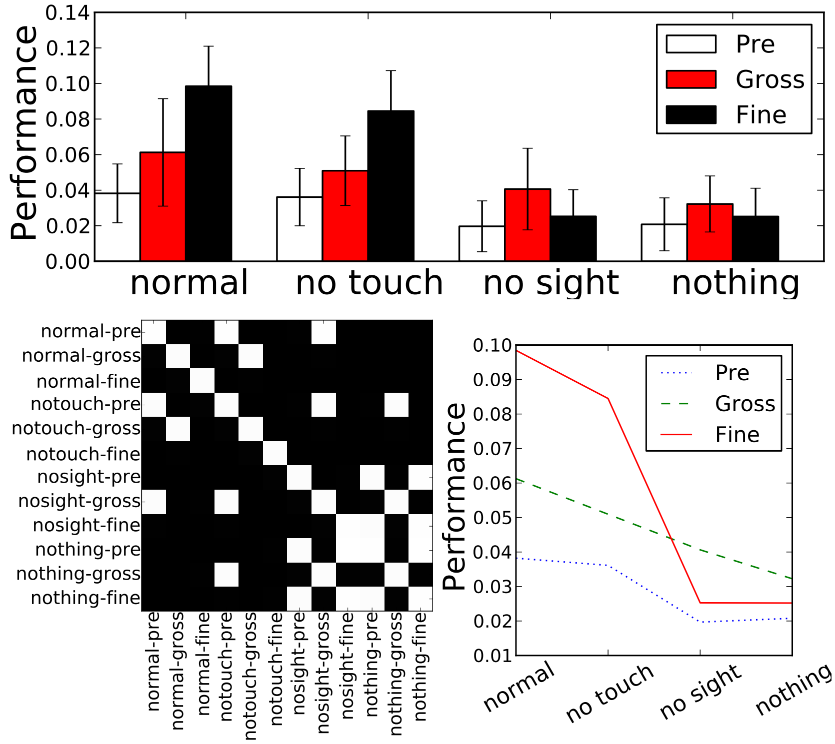

Fig. 9: Top: Performance level (calculated on the basis of Equation 5) in normal condition and in control conditions in which the robots have been deprived of tactile and/or visual information. Data obtained during a post-evaluation analysis conducted by testing 50 robots (5 robot for each of the 10 replications) for 45 trials. Bottom left: table of comparisons between groups (see text), where black squares represent a statistically significant difference ($p < 0,05$, two tailed Mann-Whitney U test). Bottom right: Different layout for the data displayed in the top graph. Note how fine-reachers strongly rely on visual information.

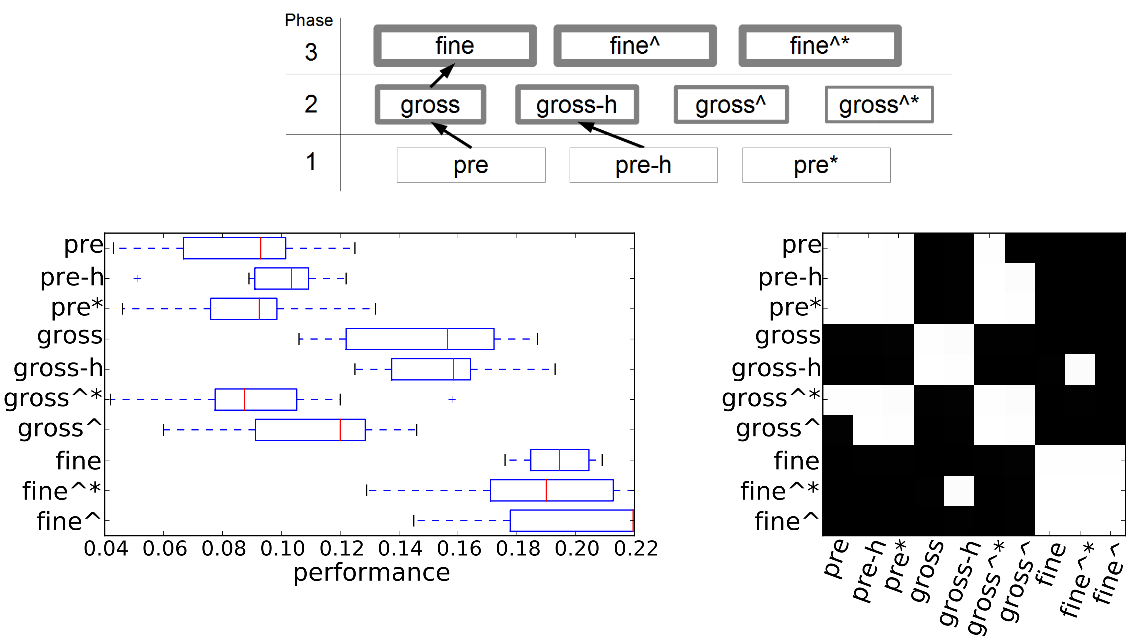

Fig. 10: Top: Overview of the comparison between the standard and control experimental conditions. Arrows indicates the time dependency between the developmental phases. The thickness of each rectangle represents the median performance over the ten replications. h = high visual acuity, * = no reflexes, ˆ= non-incremental condition (see also the text). Bottom Left: Box plot of the performance obtained in all experimental phases and conditions. Each bar displays the distribution of $p_{\mathrm{multimodal}}$ performances obtained in ten replications of the corresponding condition. Bottom Right: pairwise comparison of the conditions. A black square indicates a significant difference ($p < 0.05$, two-tailed Mann-Whitney U test).

constraint the successive phases of the developmental process have been designed on the basis of the relevant knowledge reported in the child development literature. The obtained results demonstrate how the robots acquire reaching and grasping capabilities analogous to those displayed by infants. The analysis of the behavior exhibited by the robots during successive developmental phases demonstrates how the model is able to account for and to integrate into a single framework a large set of the empirical observations reported in the literature. Overall, the analyses performed highlight the importance of multiple self-structuring processes characterized by the retention of variations that temporarily reduce the complexity of the adaptive task followed by the retention of variations that re-expand the adaptive challenge as soon as a given competence level is acquired.
The realization of comparative experiments (that could not be performed on humans) in which the maturational constraints have been manipulated systematically allowed us to disentangle the constraints that play an adaptive role and/or that bias the adaptive process toward the development of specific strategies from those that do not play any significant role.

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