Incremental Learning in a 14 DOF Simulated iCub Robot: Modeling Infant Reach/Grasp 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 maturations occurring during the relevant developmental period. The behavioral skills acquired by the robots closely match those displayed by children. Moreover, the comparison of the results obtained in a control non-incremental experiment demonstrates how the limitations characterizing the initial developmental phase channel the learning process toward better solutions.

1 Introduction

The control of arm and hand movements in humans represents a fascinating research area for researchers in psychology, neurosciences and robotics. The development of reaching and grasping behaviors in humans, in particular, constitutes one of the most deeply studied area of motor control. Despite of that, the attempt to replicate the development of reaching and grasping skills comparable to those acquired by humans still represents a challenging objective and an open issue [24]. We present a neurorobotic model that develops reaching and grasping skills analogous to those displayed by infants during their early developmental stages. The model is designed by using a holistic approach that aims to identify and model all the key characteristics of the natural phenomena, while abstracting and simplifying all the aspects that do not play a key causal role. In the context of infant reaching and grasping development, we hypothesize that the following aspects and modeling choices constitute essential prerequisites:

Embodiment. With the term embodiment we refer to the fact that the morphological and sensory-motor characteristics of the agent play an essential role in adaptive behavior [21]. 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 system of the robot by taking into account the empirical evidences about infants' development.

Situatedness. Behavior is not only the result of the agent's characteristics but also of the agent/ environmental interactions. 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. Moreover, we replicate as much as possible the characteristics of the experimental settings in which the behavior of infants was studied [27, 33], see Fig. 1. This allows us to generate data more easily comparable with experimental data, and to produce testable predications for infant motor learning.

Fig. 1: The simulated setting (Left) is derived from experiments on real children (Center and Right, adapted respectively from references [33] and [27]).

Nervous system and learning process. Here we refer to the formalism used to specify the agent's nervous system (or robot's controller) and its plasticity. 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 infants nervous system (at the level of the single neurons or at the level of the nervous system architecture), but to capture its essential features. The neural network formalism encodes and processes quantitative information, operates over time, displays generalization properties, and is a suitable and biologically plausible media for the learning process. A learning algorithm operating on the basis of distal somatosensory feedback complies with empirical evidences suggesting that young infants overcome problems associated with reaching and grasping by a self-learning trial and error process [28]. This form of learning allows the exploitation of sensory-motor coordination and overcomes the initial limited visual capabilities of young infants. Those perceptual limitations may prevent alternative form of learning, like imitation learning [17].

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, as it is strongly influenced by pre-existing behavioral skills and by concurrent maturational and developmental processes. To take this aspects into account we provide the robot, before learning takes place, with few simple reflexes homologous to some of the reflexes initially possessed by infants. Moreover, we model the developmental process in a series of cumulative phases subjected to physiological modifications originating from tissues maturation [31] and cognitive modifications (e.g. increased ability to process visual information [2]).

In the next Section we describe the robotic model and the experimental scenario in detail. In Section 3 we present the results. Finally, in Section 4 we discuss the implication of the results and plans for the future.

2 Robotic Model and Experimental Scenario

A simulated iCub robot [23] 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 carried on with children of about 4 months of age by Spencer and Thelen [27] and von Hofsten [33] (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 the 9 sectors of the spherical surface centered on the iCub neck (Fig. 2). The ball is attached to a pendulum. The robot is provided with a neural controller that is trained through a simple incremental trial and error process (Par. 2.4).

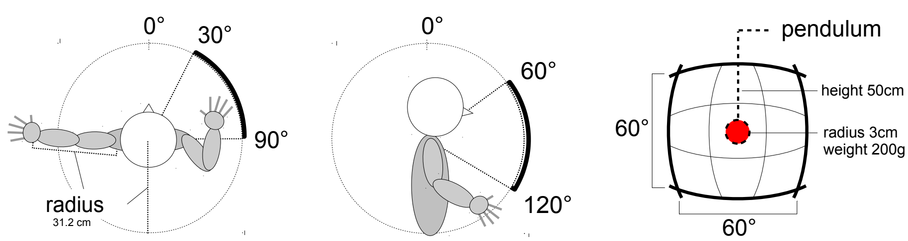

Fig. 2: The thick line in the three pictures shows the portion of the spherical surface in which the ball can be placed. To ensure a good distribution over space of the target objects, the surface is virtually divided into 9 sectors.

2.1 The Robot

The iCub is a humanoid robot developed at IIT as part of the EU project RobotCub [23, 30]. It has 53 motors that move the head, arms and hands, waist, and legs. From 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 by using the simulator developed at our lab by Gianluca Massera and collaborators (freely available from *http://laral.istc.cnr.it/laral++/farsa*). The simulator 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*).

2.2 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 camera and the tactile sensors located on the right hand, and controls the motors of the torso, head, and of the right arm/hand (Figure 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 [1, 20], or through 8 internal neurons to allow the robot to develop more elaborated and effective motor strategies.

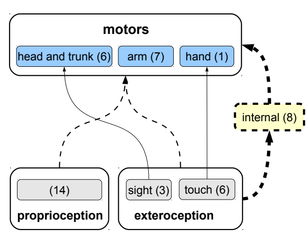

Fig. 3: The architecture of the robot's neural controller. Numbers between parenthesis represent the number of neurons, arrows indicate connections. Full arrows indicate hand-designed connection weights used to implement motor reflexes. Dashed thin and thick arrows indicate connection subjected to plasticity during the first and the second training phases, respectively. Internal neurons are added in the second phase. Notice that dashed arrows pointing to the motor layer indicate connections toward all motor neurons.

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:

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

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 [16, 18]. $s_i^{(t)}$ is computed as:

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

Where w_{ij} is the connection weight between the j-th and the i-th neuron, θ_i is the neuron threshold and $\sigma(z)$ is the sigmoidal function $= 1/(1+e^{-z})$.
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 binarily encode (-1 or 1) whether the corresponding touch sensor located in the right hand palm and fingertips (Fig. 4, Left) detects an obstacle or not. The 3 sight sensors encode pre-elaborated information extracted from the cameras through a simple color blob identification software routine. These sensors thus provide only a limited visual analysis of the object, its position (or approximate position, see below) and a crude assessment of grasp affordance. More precisely the first two encode the relative position of the color blob corresponding to the ball in the robot's visual field (Eq. 1 and 2) and the third encodes the estimated ball distance up to 50cm (Eq. 3).

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

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

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

Here 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 [7, 8], we vary the visual acuity/peripherality of the robot during the first and second training phases by setting the value of a to 3 and to 1, respectively (see Fig. 4, Right). The third sensor encodes l, the eye-object distance.

2.3 Learning Process

In accordance with empirical evidences indicating that early reaching and grasping skills in infants are acquired through self-learning mechanisms rather than by imitation [17], the robot's training is realized through a form of trial and

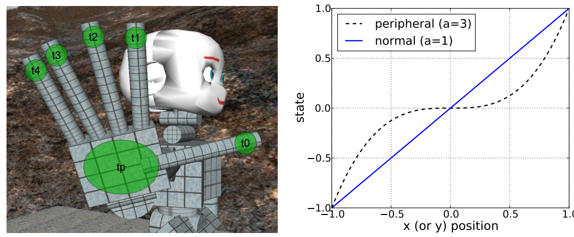

Fig. 4: Left: Location of the touch sensors in the robot's hand. Right: Dashed and filled lines indicate the state assumed by sight sensors for different positions of the colored blob in the camera image, for low and high acuity vision respectively.

error learning during which the robot is rewarded for sensorial exploration and multimodal perception (seeing and touching [22]). More specifically, we evaluate the performance level of the robot at each time step by taking the smaller score between the perceptual modalities:

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

The value is averaged over 18 trials each lasting 20 seconds. p_{sight} measures the distance between the barycenter of the object and the center of the robot's 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 are varied randomly and variations are retained or discarded depending on whether they lead to maximization of $p_{\text{multimodal}}$ at the end of the 18 trials. This is realized by using an evolutionary method [15]. The initial population consists of 20 randomly generated genotypes encoding the connection weights, the biases, and the time constants of 20 corresponding neural controllers (each parameter is encoded by eight bits and mutated with probability 0.02). The training process intends to represent ontogenetic learning. The reason behind the choice of this algorithm is that is one of the simpler yet effective ways to train an embodied neural network through a trial and error process based on a distal reward [25].

2.4 Incremental Training

The robot is subjected to an incremental training process organized into the following three phases, inpired to those used to describe the development of reaching/grasping in infants [10]:

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 [26] and grasping reflex behaviors [9], by a low involvement of cortical areas [13], and by a low visual acuity [7, 8]. From the behavioral point of view this

phase is characterized by a primitive orientation behavior of the arm [32], by the freezing of certain DoFs (i.e. by the reduced use of the distal DoFs [3]), and by the emergence 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) [28, 34]. To subject the robot to a similar process we initially provide it with two simple motor reflexes: an orienting response that makes the robot turn its head toward the colored object [26] and a grasp reflex that makes the robot close its fingers when its right palm touch sensor becomes activated [9]. 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 Section 2.2). 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 plasticity 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 [7, 8] and by an higher involvement of cortical areas [13]. This phase, that leads to an improved reaching and grasping ability, is characterized by a initial motor suppression [33], by a reduced use of motor babbling [34] and by de-freezing of the distal DoFs [4, 9]. The variations occurring during this phase have been modeled in the robotic experiment by increasing the visual acuity (see Section 2.2) and by subjecting to plasticity also the internal neurons' incoming and outgoing connection weights. This loosely simulates the intervention of cortical centers to mediate the sensori-motor reflexive behavior [13].
3. A fine-reaching phase not yet modeled in the experiment reported in this paper, that follows the first year of life. From the behavioral point of view this phase is characterized by a more reliable, faster and smoother reaching and grasping behavior [4, 12, 14, 29]. In future experiments the variations occurring during this phase will be modeled providing the robot's neural controller with additional sensory neurons encoding the current hand/object spatial relation [6]. For more details and for videos of the trained robots see *http://laral.istc.cnr.it/esm/reach/*.

3 Results and Discussion

The first objective of the work is to verify whether the robotic model proposed could effectively lead to the acquisition of reaching and grasping skills analogous to those developed by infants. The analysis of the performance (Fig. 5) shows indeed that at the end of the pre-reaching phase robots manage to reach (i.e. touch the object) through the exhibition of an exploratory behaviour (more details below) in about half of the trials.

During the gross-reaching phase the robots develop an ability to orient their arm toward the area in which the object is located and improve their ability to grasp the object (i.e. touch the object with the palm and at least one of the fingers). The comparison of the robots' performance at the end of the pre-reaching

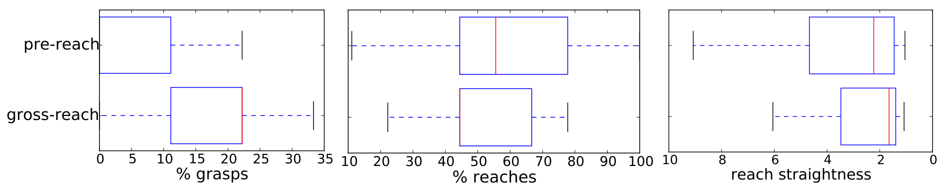

Fig. 5: Boxplot of the performances observed at the end of the pre-reaching and gross-reaching phases. Data computed by post-evaluating the best 5 robots of each replication of the experiment for 45 trials. The straightness indicates the ratio between the length of the trajectory of the hand during successfully reaching actions and the hand/object initial distance (lower values correspond to more efficient reaches).

and gross-reaching phase reveals a significant improvement in the frequency of successful grasps and reach straightness (both with $p < 0.001$, two-tailed Mann-Whitney U test). Surprisingly, the frequency of successful reaches is lower in the gross-reaching phase ($p < 0.001$). This indicates that the robots specialize on certain regions of their peripersonal space in which they can robustly grasp an object, instead of trying to reach it in each position. For videos of robots behavior see *http://laral.istc.cnr.it/esm/reach/*.
The robots' behavior at the end of the pre-reaching phase (Fig. 6, Top and Bottom respectively) is characterized by an exploratory motor babbling behavior that is realized by extending the arm and by producing circular movements [19, 20, 28, 34] around the area in which the object can be located (Fig. 6, Top). We compared this behavior (Fig. 6, Top Left) with a control condition in which tactile stimulation is impaired (Fig. 6, Top Right). The confrontation indicates that tactile stimulation plays almost no role in this phase. In the gross-reaching phase instead, the robots keep producing an exploratory motor babbling behavior which is now restricted in the area in which the object is located and regulate their movement on the basis of tactile information so to keep touching and to grasp the object (Fig. 6, Bottom Left and Right pictures).
Moreover, the behavior displayed by the robots at the end of the pre-reaching phase is characterized by a large use of the DoFs of the trunk and of the shoulder and by a reduced use (locking) of the elbow DoF. This is demonstrated by the fact that, as in the case of real infants [3, 27], the distance between the shoulder and the hand remains almost constant during reaching attempts (Fig. 7). Note that after touching the ball (distance$<$ 0.1 meters in Fig. 7) the robot is not yet able to remain near the ball at the end of the pre-reaching phase. This skill starts to be developed during the gross-reaching phase.

The second objective of the experiments is to verify whether the realization of an incremental process analogous to those occurring in humans facilitates the development of the required skills and/or channels the developmental process toward specific solutions (Fig. 8). To study this aspect we ran a non-incremental

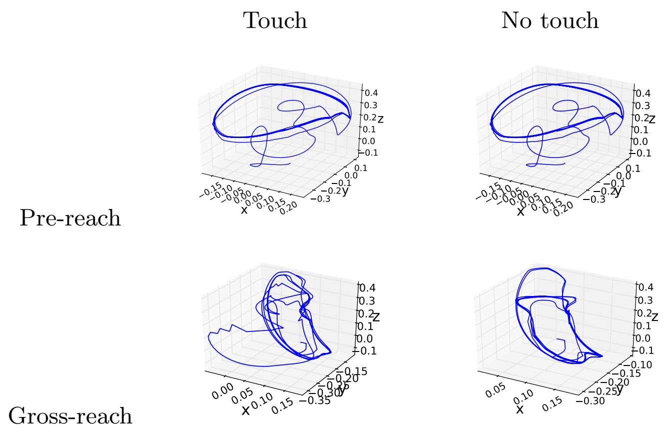

Fig. 6: Typical trajectories of the hand in 3D during a trial produced by a robot at the end of the pre-reaching (Top) and gross-reaching (Bottom) phase. Tests performed by placing the target object in the central position. Results produced in a normal (Left) and control (Right) condition in which robots are deprived from tactile stimulation.

control experiment involving a single developmental phase (lasting the sum of the pre-reaching and gross-reaching phases) in which the robots are not provided with reflexes and are have from the beginning both high visual acuity and internal processing resources (i.e. plastic internal neurons). The performance in this control condition is significantly lower than the performance of the gross-reaching condition ($p < 0.001$, two-tailed Mann-Whitney U test), indicating that indeed the incremental process enables the development of more effective solutions. The fact that robots trained in the non-incremental condition do not display motor babbling suggests that the development of motor babbling plays an important functional role. An additional control experiment performed in a pre-reaching condition with high visual acuity did not lead to significantly different performance respect the low-acuity pre-reaching condition ($p = 0.14$), indicating that the main factor channeling the developmental process toward effective human-like behavior is constituted by the addition of the internal neurons.

4 Conclusions

We illustrated how the design of humanoid robots able to develop relatively complex action capabilities can be successfully approached by using robotic models that incorporate the following fundamental aspects: embodiment, situatedness, brain-like control/learning, incremental development. The use of an experimental setting similar to those employed by experimental psychologists to study children's behavior allowed us to closely compare human and robot data.

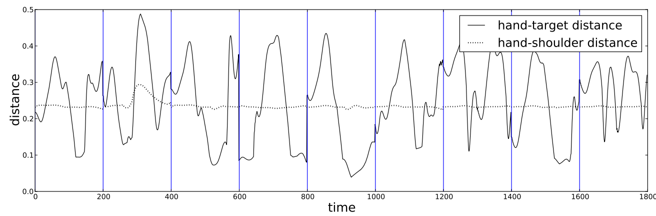

Fig. 7: Hand-shoulder and hand-target distance (in meters) during 9 trials. At the beginning of each trial the posture of the robot is reset and the target object is placed in a different position.

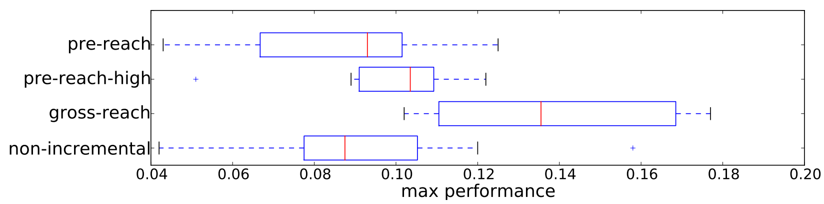

Fig. 8: Performance of the different developmental phases and experimental conditions. Each bar represents the best performances obtained in each condition over ten different replications. Pre-reaching-high inidicates the pre-reaching control condition with high visual acuity.

The analysis of the behavioral skills acquired by the robots indicate they closely match those displayed by infants. More specifically, during the pre-reaching phase robots develop a motor babbling strategy similar to that observed in infants [20, 28, 34]. The development of such strategy is channelled primarily by the availability of limited internal processing capabilities. This maturational constraint [31], possibly coupled with the presence of reflexes, constitutes a prerequisite for the development of better capability later on since allows robots initially provided with limited internal resources to later outperform (when internal resources become available) robots not affected by this initial limitation. As in the case of infants, the developmental process in robots leads to a form of proximo-distal maturation of the DoFs [3]. Indeed, during the first developmental phase, the robots immediately extend the arm and try to reach and grasp the object by exploiting the DoFs of the trunk and of the shoulder while locking the DoF of the elbow. The spontaneous freezing of the elbow joint in our experiments suggests that proximo-distal maturation might result as a side effect of the need to start from simple control policies rather than a maturational constraint [5]. Finally, the results indicating that the incremental version of the model leads to better performing robots than the non-incremental control experiment demonstrates that the incremental process might represent a key factor not only from a modeling but also from an engineering point of view.
In future works we will extend the simulations to the fine-reaching phase, by

providing the robot with sensors encoding information about the hand/object offset. Finally we will test the trained neural controller in hardware. The long term challenge we propose is to identify the scalability of this approach and its applications to different domains in robotics and control.

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