Action Development and Integration in a Humanoid iCub Robot

How Language Exposure and Self-Talk Facilitate Action Development

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***Abstract*— One major challenge in evolutionary/developmental robotics is constituted by the need to identify design principles that allow robots to acquire progressively more complex action skills by integrating them into their existing behavioral repertoire. In this paper, we present a novel method that address this objective, the theoretical background behind the proposed methodology, and the results obtained in a series of experiments in which a simulated iCub robot develops lower-level and then integrated higher-level action skills. Moreover, we illustrate how the development of integrated action skill is facilitated by language exposure and self-talk.**

Keywords-developmental robotics; action integration; language and action; self-talk.

I. Introduction

The acquisition of new behavioral skills and the ability to progressively expand our behavioral repertoire represents one key aspect of human intelligence and a fundamental capacity for robots companion, i.e., robots that should cooperate with humans in everyday environments [1]. Unfortunately the issue of how robots can acquire new action skills by integrating them into their existing behavioral repertoire still represent an open challenge for evolutionary/developmental robotics [1-3].

In this paper we provide a model validated through a series of experiments that demonstrates how a simulated humanoid robot can be trained incrementally for the ability to develop lower-level and then higher-level goal directed action skills (i.e., action capabilities that enable the robot to achieve a given desired goal in varying environmental conditions).

The first assumption behind our approach is that behavioral and cognitive processes in embodied agents should be conceived as dynamical processes with a multi-level and multi-scale organization [4]. This means that behavior (and cognitive skills) are: (i) dynamical processes originating from the continuous interaction between the robot and the physical and social environment, and (ii) display a multi-level and multi-scale organization in which the combination and interaction between lower-level behaviors, lasting for limited time duration, give rise to higher-level behaviors, extending over longer time scale and in which higher-level behaviors later affect lower-level behaviors and the robot/environmental interaction from which they arise. This assumption implies that a behavioral unit does not necessarily correspond to a dedicated control unit or modules of the robot's neural controller. Moreover, it implies that the development of additional and higher-level behavior can occur through the recombination and re-use of pre-existing motor skills even when these skills do not correspond to separated physical entities but rather to processes that ultimately emerge from the robot/environmental interactions.

The second theoretical assumption behind our approach is that the concurrent development of cognitive and social skills (with particular reference to early language comprehension skills and language mediated interactions skills) might represent an important prerequisite for the development of action skills and vice versa [5]. Indeed, as originally hypothesized by Vygotsky [6-7], we believe that human language does not only play a communicative function but also constitutes a cognitive tool that facilitate/enable the development of other capabilities, including action capabilities. A comprehensive discussion of this hypothesis and of the implications of this idea for developmental robotics is provided by Mirolli and Parisi [8] that constitutes one of the main source of inspiration of the work described in this paper.

On the basis of these theoretical assumptions we studied how a robot provided with a non-modular neural controller can be trained for the ability to produce a series of lower-level elementary actions through a form of trial and error learning. Moreover we studied how such robot can later be trained for the ability to perform high-level integrated actions by re-using and re-combing previously learned skills. Such training process can potentially be extended to the acquisition of still higher-level action capabilities generated through the combination and re-use of previously acquired higher-level skills.

The acquisition of action skills at all level of organization is realized by enriching the robots' sensory state with symbolic linguistic inputs that allow the robot to more easily learn the affordance of different categorical contexts as well as to disambiguate between contexts affording multiple actions (for a related approach see [9]).

The acquisition of action skills at higher (non-elementary) level of organization is realized by also enriching the robot's sensory state with a linguistic description of the elementary actions that can be re-used to generate new integrated behavior capabilities (for a related approach see [10]). Moreover, the acquisition of higher-level skills is realized by providing the robot with a neural architecture that allows it to develop and exploit a form of self-talk. By talking to ourselves or self-talk we refer to the ability to self-generate the linguistic stimulation produced by other agents, as both children and adult human beings do both externally (as in private speech) and internally (as in inner speech [7,11]).

In section II, we describe the experimental scenario and in section III, the obtained results. Finally, in section IV, we draw our conclusions.

II. Experimental Scenario

A simulated humanoid iCub robot has been trained for the ability to display low-level (elementary) behaviors and higher-level behaviors by combining and integrating the previously acquired low-level behaviors.

A. *The robot and the environment*

The iCub is a humanoid robot developed at IIT as part of the EU project RobotCub [12]. 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 head, the right 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, Tomassino Ferrauto and others. 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.

The robot is located in front of a table containing a red object (Figure 1). The object is a sphere with a mass of 200 grams and a diameter of 7 cm with a flattened base to prevent it from rolling away. A green spot indicates the target location in which the object should be moved. At the beginning of each trial the target object is placed in one of four possible areas (10 cm to the front, back, left, and right respectively to a point 30 cm in front and 10 cm to the left of the robot). To increase robustness the position of the object is randomly moved between [-2, 2] cm from the four points indicated above. The target spot is randomly placed within two areas located 10cm left or right with respect to the front of the robot at a height of 25cm above the table and at a distance of 25 cm from the robot.

B. *The robot's neural controller*

The controller of the robot is constituted by an artificial neural network (Figure 2) that receives proprioceptive input from torso and from the left-arm/hand and exteroceptive input from the visual system, the tactile sensors, and from the linguistic input units that encode the labels provided by a caretaker (see below). The network produces as output the desired states of the joints of the torso and of the right arm/hand and an output that determines the focus of attention.

Figure 1. The simulated robot and the environment.

More specifically, the focus output unit binarily encodes whether the visual system of the robot is paying attention to the red object or to the green target, the 2 torso motor neurons encode the desired angular position of the rotation and extension/flexion Degree of Freedoms (DOFs) of the torso, the 7 arm motor neurons encode the desired angular position of the 7 DOFs of the left-arm and of the wrist, and the 3 fingers motor neurons indicate the extension/flexion of thumb, the opposition of the thumb with respect to the other fingers, and the extension/flexion of all other fingers (i.e. to simplify the model all fingers joints are actuated through only 3 motor neurons).

All the arm and hand joints are allowed to move in the full range of motion possible on the physical iCub. The yaw and pitch torso joints are both limited to a range of [-10,40] degrees to eliminate un-desirable postures.

The 3 position sensors indicate the relative position of the red ball or of the green target (depending on what the robot is paying attention to) with respect to the left-hand along the three orthogonal axis, the 12 propriosensors encode the current position of the torso, left-arm, and fingers joints, the 6 tactile sensors encode the activation state of the tactile sensors located on the left-hand palm and on the tips of the 5 fingers, finally the 4 linguistic inputs locally encode whether the caretaker produced the "reach", "grasp", "open", or "move" linguistic label.

The state of the robots' sensors, the state of the neural controller, the desired state of the robots actuators, and the state of the robot and of the environment are updated every step, i.e., every 50 milliseconds.

C. *The training algorithm*

The architecture of the neural controller is fixed. The connection weights, biases, and time constants are encoded as free parameters and trained thorough an evolutionary robotics method [13]. This method has been chosen since it is one of the most simple yet effective way to train a robot on the basis of a distal reward (i.e., for the ability to display behaviors producing a desired outcome without specifying how such behaviors should be realized) and since it does not put constraints on the architecture of the robots' controller and/or on the type of parameters that can be subjected to the training process.

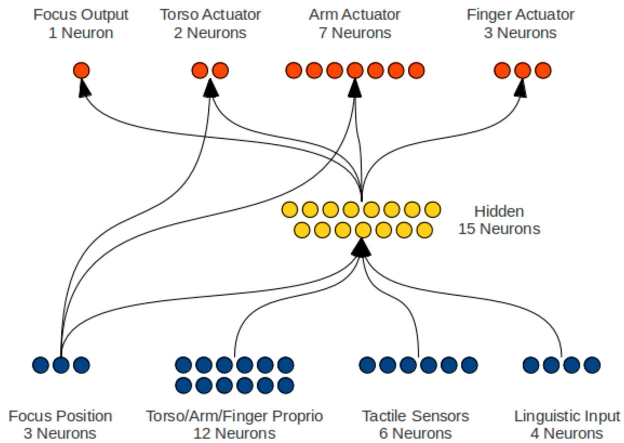

Figure 2. The architecture of the robot's neural controller during the first training phase. The neurons are grouped in clusters. Arrows between two clusters indicate full connectivity between the two corresponding groups of neurons.

The initial population consists of 100 randomly generated genotypes that encode the connection weights and the biases of 100 corresponding neural controllers. Each parameter is encoded by 16 bits, and normalized in the range [-1.0, 1.0] in the case of connection weights and biases, and in the range [0.0, 1.0] in the case of time constants. Each genotype is translated into a corresponding neural controller and evaluated as described below. The top 20 genotypes are allowed to reproduce by generating 5 offspring (1 unvaried and 4 varied copies). Variations are introduced by randomly flipping 0.005% and 0.04% of the bits, during the first and second training phase respectively. The selection of the top genotypes is realized on the overall performance of the robot, i.e., the sum of the rewards obtained by the robot during its entire lifetime.

The training is realized incrementally. During the first training phase, the robot is trained for the ability to display four lower-levels actions: REACH (i.e., bring the hand over an object), OPEN (i.e., open the fingers and align the palm to face downward), GRASP (i.e., close the fingers around the object), MOVE (i.e., move the object toward a target destination). The evaluation of candidate solutions is realized during 16 trials --- 4 trials for each of the four actions with the object placed in four different areas. At the beginning of each trial the posture of the robot is initialized in a position that enable the robot to potentially display the desired action also without possessing the other related skills (e.g., far from the object in the case of REACH, with the fingers closed in the case of OPEN, near and over the object in the case of GRASP, with the object in the hand in the case of MOVE). To force the robot to develop robust solutions the initial posture of the robot at the beginning of each trial is varied within 16 different alternatives. During each trial the robot is rewarded for the ability to achieve the goal of the current elementary action. The robot receives a small reward every time step on the basis of extent to which its current state approximate the desired state and a significant reward when the goal has been accomplished. In the case of REACH actions, the goal consists in bringing the palm of the left hand within 6cm from the top part of the object. The goal of the OPEN actions consists in stretching out all the fingers while aligning the palm downward and while keeping the palm within a distance of 6 cm from the top part of the object. In the case of GRASP actions, the goal consists in closing the fingers around the object (i.e., reducing the distance between the barycenter of the object and the centroid of the tip of the thumb, the tip of the pinky, and the center of the palm below a threshold). The goal of MOVE actions consists of moving the object within 6cm from the target location. The overall performance (fitness) of each individual robot is computed by calculating the harmonic mean of the scores obtained during trials involving the execution of different actions.

During the second training phase, the robot is trained for the ability to perform integrated actions, such as MOVE-TO-TARGET (i.e., moving a distant object from its location to a target location), by combining and integrating over time the previously acquired elementary action skills. During this second phase each robot is evaluated for 8 trials. At the beginning of each trial the object and the target spot are randomly initialized within the areas described above. The posture of the robot is initialized so that the position of the left-hand is far from the object and from the target location.

The goal of this integrated action is the same of the MOVE elementary action: moving the object to within 6cm of the target location. Due to the different initial conditions, however, the realization of this goal requires the execution of an integrated sequence of actions. The robot receives a significant reward when this goal is accomplished and smaller rewards when the object has been lifted and when the robot correctly focuses its attention on the object and on the target location before and after the object is lifted, respectively.

To study the role of language exposure and self-talk four series of experiments have been carried out in four experimental conditions described in the following section. For more details see [14].

III. RESULTS

In this section, we describe the results obtained during the a training phase, in which the robot is trained for the ability to display the low-level (elementary) behaviors (Section A), and during a second training phase in which the robot is trained for the ability to display the higher-level integrated behavior (Section B-D). For the second phase we report the results obtained in: (i) a control experimental condition (C), (ii) a language exposure condition (LE) in which the robot receives from the caretaker the label that indicates the elementary action that is appropriate in the current context during part of the trials, (iii) a self-talk condition (ST) in which the robot is allowed to self-generate the labels of the elementary actions to be executed, and (iv) a learning to self-talk condition (LST) in which the robot is allowed to self-generate the labels during part of the trials and to anticipate the labels produced by the caretaker during the remaining trials. The first and second training phases have been replicated 10 times for each experimental condition.

A. Acquisition of elementary action skills

The training of the elementary behaviors reached optimal performance within 1500 generations in 9 out of 10 replications of the experiment. By optimal performance we mean robots displaying successful behavior in 16 out of 16 trials. The fastest and the slowest successful replications reached optimal performance at generation 246 and 711. The best individual of the worst replication (the only one that did not achieved optimal performance) was successful in 15 out of 16 trials.

B. Acquisition of integrated action skills

In the second phase, the robot was trained for the ability to display the MOVE-TO-TARGET high-level behavior that consists in moving a distant object from its current location to a target location indicated by a green spot. Since the initial posture of the robot's arm/hand is far from the object, the production of this higher-level behavior can be realized by re-using, combining, and integrating the REACH, OPEN, GRASP, and MOVE behaviors acquired previously.

To provide the robots with the computational resources necessary for combining and integrating the elementary action skills we provided their neural controller with four additional continuous time internal neurons receiving and projecting connections from and to the block of 15 internal neurons and from themselves (Figure 3). Moreover, the new block of internal neurons receives connections from high-level linguistic input neurons (only "move-to-target" in the case of the experiment reported in this paper).

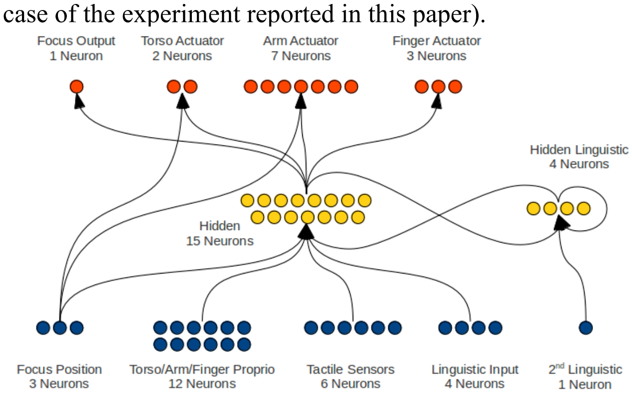

Figure 3. The architecture of the robot's neural controller during the second training phase (C and LE conditions).

The initial population of candidate solutions is generated by using the genome of the best 10 individuals of the 10 replications of the experiment described above in which the robot were trained for the ability to display the lower-level actions. The values corresponding to the newly added connection weights, biases, and time-constant were randomly generated and subjected to the training process. The values corresponding to the pre-existing connection weights were kept constant during the second training phase. The training process is continued for 100 generations.

The state of the high-level linguistic input is activated, the state of the four lower-level linguistic inputs is set to a null value.

By post-evaluating the best robots of each generation of each replication for 40 trials we observed that the average performance are rather low and no individual successfully produce the integrated behavior in all trials (see Figure 4, condition C). The best individual successfully displays the integrated behavior in 30 out of 40 trials.

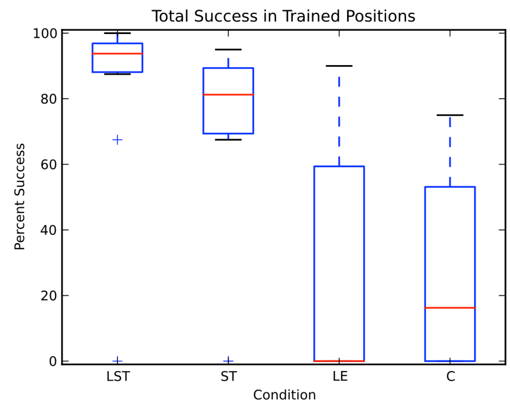

Figure 4. Percentage of successful trials for the best robots trained in the four experimental conditions (see text). Each robot has been post-evaluated for 40 trials during which it did not received any linguistic input from the caretaker. Each boxplot shows the percentage of successful trials displayed by the best 10 robots obtained in the 10 corresponding replications of the experiment. Whiskers expand to the minimum and maximum with outliers marked as +.

C. How language exposure facilitates action development

In a second experimental condition we studied whether the availability of linguistic inputs produced by a caretaker, that specify the label of the elementary behavior that is appropriate in any given circumstance, facilitates the acquisition of the integrated behavior. Given the nature of the integrated behavior, the following sequence of labels is provided: REACH, OPEN, GRASP, and MOVE. For practical reasons, the caretaker has been simulated through a software routine that analyzes the state of the robot and of the environment and determines the point over time in which the current label has to be substituted with the next label. More specifically, caretakers start to produce the "reach" label and switch to the next label as soon as the distance between the top part of the object and the left-palm of the robot decrease below 6 cm. Then, the "open" label is produced until all the fingers are extended sufficiently, the palm is horizontally oriented over the object, and the distance between the palm and the top-part of the object is below 6cm. Then, the "grasp" label is produced until 3 of the tactile sensors are in contact with the object. Finally, the "move" label is produced until the end of the trial.

To force the robot to develop an ability to produce the integrated behavior also autonomously, i.e., without the support of the caretaker, the artificial caretaker produced the linguistic input only during even trials (i.e., the state of the four linguistic inputs is always null during odd trials).

The linguistic inputs provided by the caretaker thus enrich the robots' sensory information during half of the trials. The way in which the performance of the robot is evaluated, as well as all other parameters, is the same of the experiments described in the previous sub-section.

The analysis of the trained robots indicates that optimal performance are obtained in 4 out of 10 replications of the experiment. The performance obtained by post-evaluating the best trained individuals for 40 trials without linguistic labels and the comparison with the performance obtained in the control (C) condition (Figure 4, condition LE) shows how the exposure to linguistic inputs enables the robot to achieve better performance, although only in few replications.

D. How self-talk facilitates action development

In the third and fourth experimental conditions, we investigated whether the possibility to self-talk, i.e. the possibility to self-generate over time the linguistic labels associated to the elementary actions, can facilitate the development of the integrated behavior.

To enable the robots to develop a form of inner-speech we extended the neural architecture used for the acquisition of the elementary actions in a different manner (Figure 5). More specifically, we added a layer of four neurons that receive and project connections from and to the layer of 15 internal neurons, and receive connections from themselves and from the higher-level linguistic input units (only the "move-to-target" unit in the case of the experiments reported in this paper). These four neurons are used to self-generate linguistic labels (i.e. vector of binary values encoding the labels "reach", "open", "grasp", and "move") that are then used to set the activation of the four lower-level linguistic inputs. This is realized by activating the linguistic input corresponding to the most activated linguistic output and by setting to a null value the activation states of the other linguistic inputs. All other parameters are kept the same as in previous experimental conditions.

As in the case of the experiments performed in the two conditions illustrated above, the value of the additional connection weights and biases are initialized to a random value and subjected to the training process. All other parameters are identical to those used in the experiments described in the other conditions.

More specifically, we studied two self-talk conditions. In the ST condition, the robots never received linguistic labels from the caretaker and always rely on the self-generated labels.

The analysis of the results obtained in this condition indicates that robots displaying successful behaviors in all trials are obtained in 8 out of 10 replications of the experiment. The performance obtained in the post-evaluation test (Figure 4, ST condition) are significantly better than the performance obtained in the language exposure (LE) and control condition (C). Overall the obtained results thus indicates that the possibility to self-talk strongly facilitates the development of the integrated behavior.

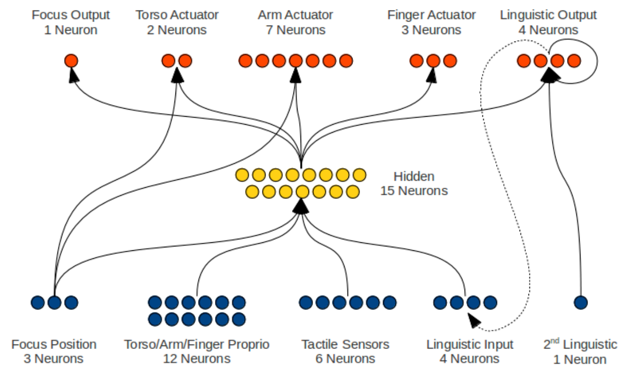

Figure 5. The architecture of the robot's neural controller during the second training phase (ST and LST conditions).

In the ST conditions the robots are not rewarded directly for the ability to self-talk but only for the ability to produce the integrated behavior. In the fourth and last condition (LST) we rewarded the robot for the ability to self-generate and to predict the linguistic labels produced by the caretaker during even trial and for the ability to produce the integrated behavior by self-generating the linguistic labels during odd trials. The aim of the experimental condition was that to verify whether an explicit training to self-talk, realized through the attempt to anticipate the caretaker linguistic behavior, can facilitate the acquisition of the integrated behavior.

To enable the development of an ability to anticipate the caretaker behavior we reward the robot with a big score every time it self-generates the new label 1-5 steps earlier than the caretaker and a smaller reward every time it self-generate the new label 6-20 steps earlier than the caretaker.

The analysis of the performance of individuals during the training process indicate that the best individuals achieve optimal performance in 9 out of 10 replications. Moreover, the analysis of the results obtained by post-evaluating the best individuals for 40 trials without linguistic inputs (see Figure 4, LST condition) indicates that the possibility to self-talk combined with an explicit training to self-talk produce better result with respect to the ST condition.

E. Generalization and integration strategies

To verify the generalization capabilities of trained robots and to compare generalization performance for agents trained in the four experimental conditions we post-evaluated the performance of trained robots by placing the object in 7x7 different positions uniformly distributed over a 35x35 cm^2 area and by varying the initial position of the arm for each object position within four different alternative postures. As can be seen in Figure 6, overall, the robots display rather good generalization capabilities. That is performance decrease only slightly with respect to the case in which the robots have been post-evaluated in the same condition experienced during the training process. A two-tailed Mann-Whitney U Test indicate that the LST condition is significantly better than the other three conditions and that the ST condition is significantly better than the C condition.

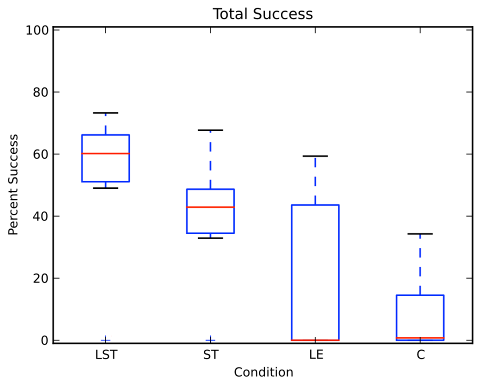

Figure 6. Percentage of successful trials for the best robots of the four experimental conditions post-evaluated for 49 different object positions.

The comparison of the behavior produced during even and odd trials in the LST conditions (in which the robot receives and does not receive the linguistic labels from the caretaker, respectively) indicates that 6 of the 10 robots of the LST condition that have a better generalized performance when they operate autonomously than when they receive the linguistic inputs from the caretaker. Moreover, during self-talk all the 6 robots are also faster in performing the integrated behavior. The significance of the difference has been evaluated on the basis of a two-tailed Mann-Whitney U Test. This result indicates that robots are capable of developing better strategies than those conveyed by the caretaker.

IV. DISCUSSION AND CONCLUSION

In this paper, we demonstrated how a simulated iCub robot can acquire multiple goal-oriented action skills through an incremental training process in which it first develop lower-level (elementary) actions and then higher-level integrated behaviors by combining and integrating previously acquired lower-level action skills. Overall, the obtained results represent one of the first demonstrations of how a relatively complex robot can acquire and display multiple behavioral skills and can expand its behavioral repertoire (for a related work see [15]).

The behavioral skills developed by our robots are not simply elements or objects but rather dynamical processes that originate from the robot/environmental interaction (and in some cases also from the interaction with the social environment constituted by the caretaker). They are flexible entities that are able to achieve the appropriate goal in varying robot/environmental circumstances. Similarly, the way in which these processes are combined to generate higher-level action skill is realized in a manner that is fluid and flexible enough to achieve the appropriate goal in varying environmental circumstances.

One important aspect that characterizes the model presented is that it relies on a non-modular controller, i.e., it does not require a control system divided into modules (as for example in [16]) and does not assume a one-to-one correspondence between modules and behaviors. This aspect is particularly important from a developmental point of view, since it allows the development of behaviors that emerge from the interaction between the robot and the environment and from the interaction between previously developed control mechanisms that are responsible for the generation of other action skills. Moreover, this aspect facilitates the development of behavioral capabilities that are more suitable to be recombined and integrated. To appreciate this point we should consider that the development of low-level action capabilities (such as “REACH” and “GRASP”) through the use of different control modules will likely end up with the exhibition of behaviors based on different equivalent postures that are hard to combine to produce integrated behavior. The realization of the lower-level behaviors through the same neural controller, instead, leads to the production of more similar behaviors that are more ready to be integrated.

A second important aspect that characterizes the model proposed is constituted by the key role played by language mediated social interactions with particular reference to language exposure and self-talk.

For what concern language exposure, the availability of linguistic labels such as “grasp” and “move” during the acquisition of low-level actions facilitate the acquisition of an ability to discriminate the categorical contexts affording specific actions. Moreover, as previously demonstrated by [17] in a study conducted on a similar experimental scenario, the availability of linguistic inputs indicating the current appropriate action allows the robot to overcome the problem caused by the need to handle robot/environmental contexts affording multiple actions. Finally, the availability of linguistic inputs indicating the sequence and the timing with which lower-level actions should be concatenated to generate new high-level behaviors facilitates the acquisition of an ability to produce integrated actions also autonomously, i.e. without linguistic inputs.

For what concerns self-talk, the possibility to self-generate internal states analogous to the linguistic inputs produced by the caretaker strongly facilitates the development of integrated behaviors and leads to robust solutions that generalize well also in new environmental circumstances. This can be explained by considering that the combination of language exposure and self-talk facilitates the re-use of previously developed action skills. An additional facilitation effect can be gathered by explicitly training the robot to anticipate the linguistic inputs provided by the caretaker.

The model proposed also allows the robot to develop more effective strategies with respect to those demonstrated by the caretaker. Indeed, the training method proposed constitutes a form of socially assisted individual learning that on one hand allows the robot to exploit the social feedback to facilitate the discovery of effective solutions, but that on the other hand, leaves the robot free to improve its current solution also with respect to the strategy illustrated by the caretaker.

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