Parental scaffolding as a bootstrapping mechanism for learning grasp affordances and imitation skills

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Abstract.
Parental scaffolding is an important mechanism utilized by infants during their development. Infants, for example, pay stronger attention to the features of objects highlighted by parents and learn the way of manipulating an object while being supported by parents. Parents are known to make modifications in infant-directed actions, i.e. use "motionese". Motionese is characterized by higher range and simplicity of motion, more pauses between motion segments, higher repetitiveness of demonstration, and more frequent social signals to an infant.
In this paper, we extend our previously developed affordances framework to enable the robot to benefit from parental scaffolding and motionese. First, we present our results on how parental scaffolding can be used to guide the robot and modify robot's crude action execution to speed up learning of complex actions such as grasping. For this purpose, we realize the interactive nature of a human caregiver-infant skill transfer scenario on the robot. During reach and grasp attempts, the movement of the robot hand is modified by the human caregiver's physical interaction to enable successful grasping. Next, we discuss how parental scaffolding can be used in speeding up imitation learning. The system describes how our robot, by using previously learned affordance prediction mechanisms, can go beyond simple goal-level imitation and become a better imitator using infant-directed modifications of parents.

Keywords. Developmental robotics, affordance, imitation, parental scaffolding, motionese

1. Introduction

Scaffolding in developmental psychology refers to the support from an (adult) caregiver in order to speed up a child's skill and knowledge acquisition (Berk and Winsler (1995)). This support can take various forms, including the attraction and maintenance of the child's attention on relevant items, the shaping of the environment in order to ease the task (such as positioning and orienting the child so as to limit its degree of freedom), signalling the important features or subgoals of the task, or providing feedback and reinforcement (Wood et al. (1976)) (Fig. 1, left). When the task gets out of hand, puzzling the child, the caregivers step in as the "trouble-shooter" (Zukow-Goldring and Arbib (2007)). They interfere at different steps of the task, initially demonstrating the goal and drawing attention to task-relevant features, then "embodying" the child to co-achieve the goal. Throughout the process, they let the child have proprioceptive, force, tactile, visual, and auditory feedback, until the goal is achieved. Moreover, it is not only the adults who are interested in this kind of interaction. By acquiring the ability for joint attention, the children become aware of the caregiver as a "helper", and begin "asking" for help when faced a difficult task by displaying significant communicative gestures. From the age of 9-months, when the joint attention mechanisms begin to emerge, to 18-months, infants use more and more of these communicative signals (Goubeta et al. (2006)). These interactions have a purpose. Infants can exhibit certain skills in game-contexts together with their mothers far before they can perform them in isolated cognitive tests (Hodapp et al. (1984)).

The idea of parental scaffolding seems especially

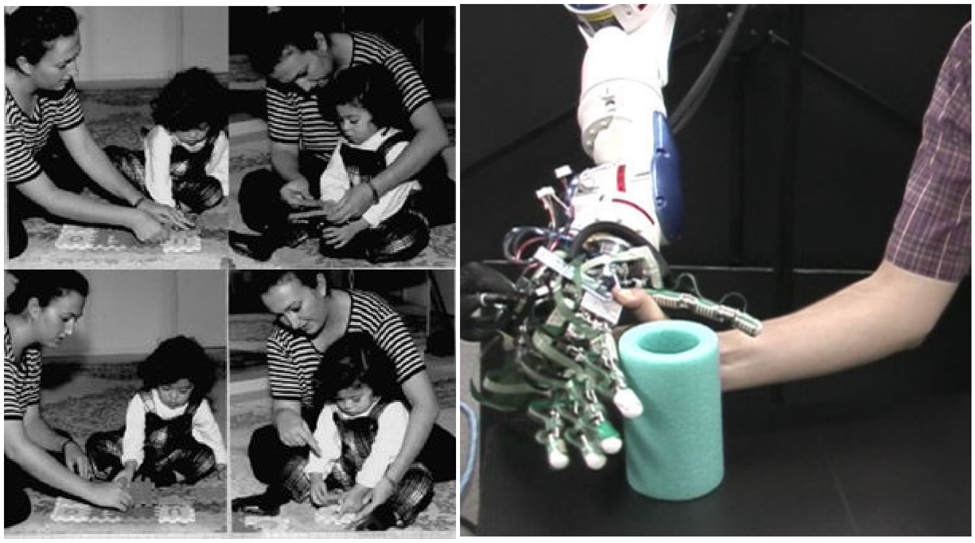

Fig. 1. Left: The caregivers step in when the task of the child gets out of hand. They teach infants different skills by highlighting important features of the task or marking the boundaries of action units. Right: 7 DoF robot arm, 16 DoF robot hand, table, and a sample object is shown. The range camera is placed on the top-right and not visible. The human teacher can change the default trajectory of the robot to enable grasping thanks to the force/torque sensor that is placed between robot arm and hand.

inspiring from a robotics point of view. The idea has been exploited in various studies with different viewpoints, such as for better communication between humans and robots (Breazeal (1999)), or as a grounding principle for lifelong developing of robots "at home" (Saunders et al. (2006)). It has been shown that caregivers tend to modify their motions when teaching a task to a child. Analogous to "motherese", Brand et al. (2002) call these motions of higher interactiveness, enthusiasm, proximity, range of motion, repetitiveness and simplicity, as "motionese". In a similar line, Nagai and Rohlfing (2009a) reveals a significant amount of bottom-up saliency features in infant-directed interaction versus adult-directed interaction. Motivated by these findings, Nagai et al. (2008) develops a bottom-up architecture for robot-infants, who, like human-children, are equipped with minimal a-priori information, and therefore in need of depending mainly on bottom-up signals as much as possible. Interestingly, such infant-robots are also found to motivate humans to use motionese as if they were dealt like human children. Due to the robots' limited attention mechanisms, humans try to carefully teach a task for example by approaching to the robots and introducing the object closely to their attention, sometimes shaking it, amplifying their movements and making pauses. Evidently, these are also widely used tactics in parent-infant communication.

Another issue in robot imitation is the inability of the robot to understand "what" to imitate. In particular, there are goal-oriented tasks, where any means to achieve the goal are acceptable, versus means-oriented tasks, where the motion itself is equally important. This is also a problem faced by human infants. Here parents again come to rescue by signalling the important features (Nagai and Rohlfing (2008)). In a goal-oriented task, they emphasize initial and final states, as well as important sub-goals, by taking long pauses. Conversely, in a means-oriented task, they emphasize the movement itself by adding additional movements to the object, for instance by shaking it.

Scaffolding has also been used as a means of "correcting" the robot's experiences and letting it learn the "right" way: Saunders et al. (2006) demonstrates the scaffolding of the environment itself as one way of reducing complexity. The robot is expected to perform pre-taught behaviors, such as wall-following, by matching its current sensory values to previously memorized instances. The most "similar" previous instance is decided, however, by giving more weight to features with higher information gain for the specific task. Here comes in the human teacher, who modifies the environment in the learning phase, by reducing variations in irrelevant features. These features, having always constant values, will not affect the robot's behavior later on. Argall et al. (2010) takes a more direct approach, by correcting the very movement of the robot. The robot is allowed to learn a behavior from demonstrations by a teacher. Once it derives a policy, the human will help it correct its movement by online tactile feedback from sensors attached to its wrist.

Learning through self-exploration and imitation are crucial mechanisms in developing sensorimotor skills for developing robots. Our previous research (Ugur et al. (2011b)) contributed to this research program by showing that with self-exploration a robot can shape its initially crude motor patterns into well controlled, parameterized sensorimotor behaviors which it can use to understand the world around it. In this paper, we extend this framework by enabling the robot to use parental scaffolding in two major robot learning problems.

- Section 2 describes our first extension attempt (Ugur et al. (2011a)) where a human caregiver speeds up robot's affordance acquisition for grasp action through parental scaffolding. As the behavior parameter space is very large in grasping with dexterous robot hand and many different parts of complex objects provide graspability, learning through self-exploration is a slow and expensive process. A human caregiver can step in for help by physically modifying robot's built-in *reach-grasp-lift* behavior execution trajectory. While being guided by the human, the robot first detects the 'first-contact' points its finger made with the objects, and stores the collection of these points as graspable regions if the object is lifted successfully. Later, it builds up simple classifiers using these experienced contact regions and use these classifiers to detect graspable regions on novel objects. At the end, the robot hand was shown to lift an object in different orientations by selecting one of the experienced trajectories.
- In our previous work, we showed that after learning affordances, the robot can make plans to achieve desired goals and emulate end states of demonstrated actions. In Section 3, we extend this framework and discussed how our robot, by using the learned behaviors and affordance prediction mechanisms, can go beyond simple goal-level imitation and become a better imitator. For this, we develop mechanisms to enable the robot to recognize and segment, with the help of the demonstrator, an ongoing action in terms of its affordance based goal satisfaction. Once the subgoals are obtained, the robot imitates the observed action by chaining these sub-goals and satisfying them sequentially. In this study, the demonstrator is expected to modify his/her action executions for the robot to better understand and imitate these actions, similar to parents who make modifications in infant-directed actions.

2. Scaffolding in learning affordances

In our parental scaffolding framework, the robot has a default *reach-grasp-lift* action where the object is detected by robot's perceptual system, a reach trajectory is computed based on robot's arm kinematics and object center, and the robot fingers are closed when they are nearby to the object. The robot has no initial knowledge about graspability of the objects. Different objects can be grasped from different parts with different hand orientations, so *reach to object center* execution should be modified by the human teacher during trajectory execution. Thus, the initial trajectory is modified by incorporating the force applied to the robot hand by the human during the course of the action. The points on the object where fingers make first contact are stored as potential grasp affording parts. After hand closure is completed, the robot lifts its hand and checks whether the object is lifted or not by searching table surface with its perceptual system again and through force sensor measurements. This online, human modified *reach-grasp-lift* action is repeated many times with different object configurations and graspable parts of the objects are discovered by the robot. Below, the tools and methods to realize this framework will be detailed.

2.1. Robot platform

An anthropomorphic robotic system equipped with a range camera is used as the experimental platform. This system uses a 7 DoF Motoman robot arm, that is placed on a vertical bar similar to human arm as shown in Figure 1. A five fingered 16 DoF Gifu robot hand is mounted on the arm to enable manipulation. 123 cm and 23 cm, respectively. For environment perception, a infrared time-of-flight range camera (SwissRanger SR-4000), with 176x144 pixel array, 0.23° angular resolution and 1 cm distance accuracy is used.

We aim to guide the robot similar to a caregiver guiding an infant's movement. It is natural for a human parent to hold the infant's hand, and position it in the space to help with a grasp. A similar intuitive effect is obtained by attaching a force sensor to right below the hand, at the wrist position. The desired effect is holding the wrist of the robot, and moving the 7-DoF arm in the 6-DoF Cartesian space freely. This is achieved by measuring the force applied to the robot and converting it into joint displacements.

2.2. Robot perception

The robot uses range camera to detect the object on the table. The detected object is represented as a 3D point cloud and from this point cloud various features such as local distance histograms as detailed in the next subsection are computed. Furthermore, the distance between any point on the object and hand fingers is computed by comparing the 3D position of that point measured by range camera and 3D position of the finger computed by forward kinematics based on arm and hand joint angles. As a result the robot can close its hand when the fingers are nearby to the object or can detect the object points that are in contact with fingers.

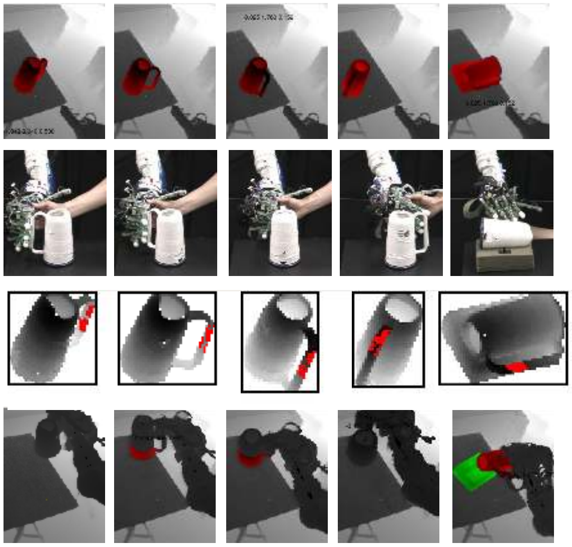

Fig. 2. Guided grasp experience. Rows from top to bottom show detected objects in the scene before action execution, how robot hand was controlled, detected 'first-contact' points, and scene after behavior execution.

2.3. Distance histogram based classifier

We used a feature that captures the relative property of the grasped-part with regards to the totality of the object. Inspired from shape and topological feature detectors in primate brain (Murata et al. (2000)), we proposed a metric that captures the distribution of three dimensional points (i.e. voxels) that make up a given object. We propose that each voxel is identified by the distribution of its distances from the neighboring voxels that make up the object. This distribution changes smoothly as one moves smoothly on the surface of the object, and is invariant of orientation changes. Our idea was to develop a classifier based on this metric, with the intuition that the handle voxels would have similar distance distributions that are significantly different from the body voxel distributions. For the handle, voxels found by interacting with the object are used to construct a distance distribution, p_H. Likewise the rest of the object points is used to construct a distribution representing the non-handle points, p_B. At a later time when the robot faces a novel object it computes a distance distribution for each point on the object and compares it with p_H and p_B, and decides what points can be used as handles.

2.4. Experiments

Touch region detection results: The robot initially has a rough grasping skill; it reaches for the center of the object and encloses its fingers upon contact. A human caregiver interferes with the execution of this basic skill in attempt to achieve successful grasping. The human provides only partial guidance, making this a true collaboration. In this setup, learning of

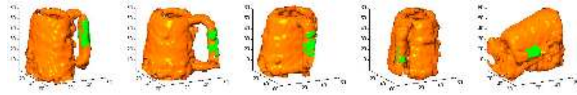

Fig. 3. Objects and their first contact voxels obtained during training (see Figure 2) are shown.

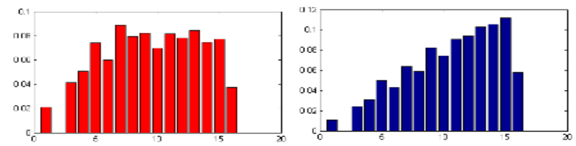

Fig. 4. The mean histograms of graspable and remaining voxel distances, respectively.

caregiver is also critical, as the ability of the robot control system and the properties of the robot hand for grasping must be learned by the caregiver. Once the human-robot collaborative system manages grasping, by using camera and proprioceptive information the robot can discern parts of the object that it grasps. In the current implementation, we show that this information can be used to develop 'handle detectors' so that the robot can perform general handle-grasps without human guidance. The successful grasping obtained by human guidance is detected by the robot and the positions of the fingers on the object are computed as illustrated in Fig. 2. Repeated application of this process, allows robust discrimination of object points that afford the current action (i.e. handle grasping).

Grasp region detection on novel objects: We tested this classifier using grasp executions mediated by the caregiver for a mug type object that is placed at five different orientation as shown in Figure 3. The final representative distributions for handle (p_H) and body (p_B) obtained by combining these individual histograms are shown in Figure 4.

We first, tested whether this simple classifier can identify the handle parts of the original object accurately or not. In particular, during an interaction not all parts of the handle are touched so they were initially marked as belonging to object body (Figure 3). With this density based classifier it can be seen that most of the handle voxels are indeed found as handle voxels (Figure 5 (a)) with little false positives. The more challenging task was to see whether this classifier could detect handle-like parts from unseen objects. For this, we used five different objects as seen in Figure 5 (b). Although there were false matches, most of the voxels identified as handles were indeed handles or could be considered handles (Figure 5 (c)).

Autonomous grasp executions: The focus was to learn and infer the graspable parts of the objects in our parental scaffolding framework. Although it is

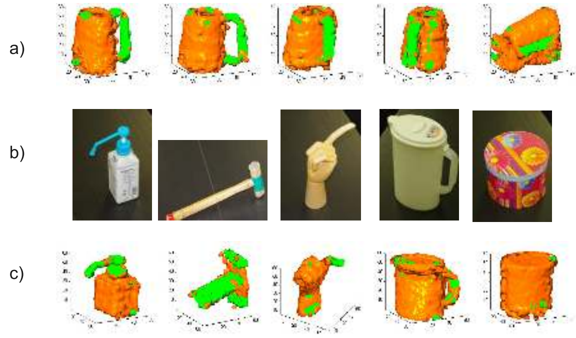

Fig. 5. (a) gives the results obtained from grasp classification of each voxel on training objects. See Fig. 3 for real touch regions of these objects. On the other hand, (c) gives the grasp classification results for novel objects whose pictures were shown in (b).

not the main focus, the learned knowledge can also be utilized to autonomously control robot arm and to lift the objects. For this purpose, we designed a simple lookup-table based mechanism to select a *reach-grasp-lift* execution trajectory to lift the object that had been used in training.

During training, the robot's guided lift experience was stored as a list of set of object voxels, set of touch voxels, and modified hand-arm angle trajectory. From this experience, the position of the largest touch region relative to the object center was computed. Then, a lookup table was constructed with relative position information in one column and hand-arm trajectory in the other column. When a new object is perceived, the robot first finds the grasp regions using the simple classification method, then computes the position of the largest grasp region relative to the object center. This relative position is searched in the lookup table, the closest experienced relative grasp region position is found, and the corresponding hand-arm trajectory is executed. Note that the use of this distance metric for trajectory selection is limited to the object that was experienced during training, i.e. this metric cannot handle multiple objects with different shapes and sizes.

In the experiments, the object used in training was placed in 5 different orientations. Each row in Figure 6 corresponds to a grasp execution for a different orientation. The snapshots were taken for initial hand posture, while hand was reaching the object, during the first contact, during grasping and at the final stage of lifting, respectively. The first four executions were successful at the end since the object was placed in similar orientations with training instances. In the last execution, the handle was behind the object, so the robot selected an incorrect execution trajectory.

Fig. 6. Robot grasps objects using the trajectories learned during scaffolding. Each row corresponds to a different grasp execution.

3. Scaffolding in imitation learning

In this section, the next stage of developmental progression is discussed in the form of imitation learning where the affordance prediction capability can be used to emulate the end states but not to imitate the action trajectory. These tasks can be taught to a robot through imitation, where the robot observes the demonstration, extracts important steps from the movement trajectory, encodes those steps as sub-goals and find the behaviors to achieve these goals. Learning higher level skills based on previously learned simpler ones is more economical and usually easier for building a complex sensorimotor system (Kawato and Samejima (2007)). Therefore, here we propose to use learned affordances (in the form of (object, behavior, effect) relations) and affordance prediction capabilities as basic elements in understanding and achieving sub-goals.

Extracting sub-goals or important features from a demonstration is not straightforward as demonstrated action trajectory may not correspond to any robot behavior developed so far. For example when the robot is asked to imitate a demonstration shown in Fig. 7(a), as the observed trajectory is not represented in robot's sensorimotor space, executing the behavior that seemingly achieves the goal would not satisfy the imitation criteria (for example a right push of the ring would tip over the cylinder). Young infants also have similar difficulties in mapping observed actions within

(a) Without motionese (b) With motionese

Fig. 7. An example scenario where demonstration of enclosing a cylinder with a ring is continuous in (a) and exaggerated in (b). The goal configuration of the ring is indicated by the red colored ring enclosing the cylinder. (a) If the robot cannot capture the important features of the demonstration, it may attempt to bring the ring to the goal position by simply pushing it to the right, where the ring will push the cylinder away rather than enclosing it. On the other hand, when important steps are highlighted by for example pauses as in (b), the robot can extract sub-goals represented in its perceptual space and find a behavior sequence from its behavior repertoire to imitate the action correctly.

their own repertoire and in imitating these actions successfully.

As explained in the Introduction Section, to overcome this difficulty, parents are known to make modifications in infant-directed actions, i.e. use "motionese". Fine-grained analysis using a computational attention model reveals the role of motionese in action learning (Nagai and Rohlfing (2009b)). Longer pauses before and after the action demonstration underline the initial and final states of the action (i.e. the goal of the action) whereas shorter but more frequent pauses between movements highlight the sub-goals of the action.

Inspired from infant development, in this section we also use 'motionese' to enable the robot to identify the important steps and the boundaries in the otherwise complex stream of motion involving multi-objects. A human tutor can exaggerate the relevant features in his demonstration as in Fig. 7(b) and enable the robot to map the exaggerated sub-steps into its own behavior repertoire and imitate the action sequence successfully.

3.1. Affordances and Effect Prediction

In our previous work (Ugur et al. (2011b, 2012)), the affordances were defined as (object, behavior, effect) relations, and with this we have shown that affordance relations can be learned through interaction without any supervision. As learning the prediction ability is not focus of this paper, we skip the details and shortly present how prediction operator works. This prediction operator can predict the continuous change in features given object feature vector, behavior type and behavior parameters:

$$(f^{()}, b_j, \rho_f) \rightarrow f'[]^{b_j}_{\text{effect}} \tag{1}$$

where $f'[]^{b_j}_{\text{effect}}$ denotes the effect predicted ($'$) to be observed after execution of behavior b_j.

3.2. State Transition

The state corresponds to the list of feature vectors obtained from the objects in the environment:

$$\mathcal{S}_0 = [f^{()}_{o_0}, f^{()}_{o_1}, .., f^{()}_{o_m}]$$

where $()$ denotes the zero length behavior sequence executed on the objects, and m is the maximum number of objects. If the actual number of objects is less than m, the *visibility* features of non-existing objects are set to 0.

State transition occurs when the robot executes one of its behaviors on an object. Only one object is assumed to be affected at a time during the execution of a single behavior, i.e. only the features of the corresponding object is changed during a state transition. Thus, the next state can be predicted for any behavior using the prediction scheme given in Eq. (1) as follows:

$$\mathcal{S}'_{t+1} = \mathcal{S}_t + [...0, f'_o[]^{b_j}_{\text{effect}}, 0, ..] \tag{2}$$

where b_j behavior is executed on object o and features of this object change by the summation operator.

Using an iterative search in behavior parameter space, the robot can also find the best behavior and its parameters that is predicted to generate a desired (des) effect given any object:

$$bb(f^{()}, f[]^{\text{des}}_{\text{effect}}) = \underset{b_j, \rho_f}{\arg\min}(f[]^{\text{des}}_{\text{effect}} - f'[]^{b_j}_{\text{effect}}) \tag{3}$$

where *bb* denotes "best behavior" operator.

3.3. Goal-emulation and plan generation

In the previous section, how the robot can (1) predict the effect given object-behavior pair and (2) find the best behavior to acquire a desired effect were explained. Because prediction is based on vector summation, the robot can estimate the total effect that a sequence of behaviors will create by simply summing up all effect vectors, and thus can use this for multi-step prediction.

Goal-emulation is achieved by generating a plan, i.e. finding the behavior sequence required to transform the given state into the goal state. Forward chaining can be used to search the state space and find a sequence. Forward chaining uses a tree structure with nodes holding the perceptual states and edges corresponding to (behavior-object) pairs. The execution of each behavior on each different object can transfer the state to a different state based on Eq. (2). Starting from the initial state encoded in the root node, the next states for different behavior-object pairs are predicted for each state.

The goals are represented as desired world states:

$$G = [f_{o_1}, f_{o_2}]..$$

3.4. Imitation through scaffolding

Imitation and goal emulation are achieved by finding behavior sequences that will bring the initial state ($\mathcal{S}_{\text{init}}$) to the goal state ($\mathcal{S}_{\text{goal}}$) depending on or independent of demonstration, respectively. For this purpose, the robot should have the ability to predict the effects of its behaviors on the objects, i.e. it should be able to predict the next state ($\mathcal{S}_t$) for any behavior executed in a given state ($\mathcal{S}_t$). In this rest of this section, we present the structures and methods that enable imitation and goal emulation.

The robot observes the demonstration and extracts the initial and goal states, as well as the intermediate states (encoded as sub-goals) by detecting pauses which may be introduced by a motionese engaged tutor. If no pause can be detected, then a random intermediate state would be picked up as the sub-goal state.

Imitation module finds the behavior sequence that brings the initial state to the goal state following the detected state sequence. Finding the behavior that transfers one observed state to the next observed state corresponds to one-step goal-emulation, which the robot can perform as described in Section 3.3. Thus, imitating the behavior sequence practically corresponds to applying goal-emulation for each successive sub-goal extracted from the observed demonstration.

Selecting behaviors based on Imitation Module results in following the exact trajectory of the demonstrator, to the extent that as decimated by the pauses inserted by the tutor. On the other hand, when Goal Emulation Module, right panel) is selected, then it finds a behavior sequence that brings the current state to the goal state using forward chaining independent of the intermediate states. In the Introduction Section, we discussed that understanding "what to imitate" is a nontrivial problem both in infants and robots; and an active line of research in robotics. An autonomous mechanism that is guided by caregiver/demonstrator signals should be formalized and implemented based on insights obtained from developmental psychology.

4. Conclusion

In this paper, we discussed how we can extend our previously developed unsupervised affordance learning framework so that the robot can benefit from parental scaffolding and motionese in learning of complex affordances and in replicating observed actions. For this purpose, we realized the interactive nature of a human caregiver-infant skill transfer scenario on the robot. First we utilized parental scaffolding to speed up learning of complex grasp action through human caregiver's physical interaction. Next, we discussed how parental scaffolding can be used in enabling or speeding up imitation learning. We proposed an extension to our framework where the robot, by using previously learned affordance prediction mechanisms, can go beyond simple goal-level imitation and become a better imitator using motionese, i.e. infant-directed modifications of parents.

In the future, the motionese based imitation extension should be tested and verified in the real robot with human caregivers who demonstrate particular tasks for imitation. These human subjects should be observing robot's imitation attempts (which probably initially fail) but should not be informed about the working mechanisms of the system. We expect to observe that even naïve subjects will modify their movements so as to make the robot understand their actions as the motionese theory predicts; similar to human parents who unconsciously modify their demonstrations for the infants. Such modifications should be elicited by the responses of an action learner as in (Nagai et al. (2010)).

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