Affordances, development and imitation

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***Abstract*— We present a developmental perspective of robot learning that uses affordances as the link between sensory-motor coordination and imitation. The key concept is a general model for affordances able to learn the statistical relations between actions, object properties and the effects of actions on objects. Based on the learned affordances, it is possible to perform simple imitation games providing both task interpretation and planning capabilities. To evaluate the approach, we provide results of affordance learning with a real robot and simple imitation games with people.**

***Index Terms*— robotic development, affordances, imitation**

I. INTRODUCTION

Humans have an unrivaled ability to solve many different tasks in a routine and very efficient way, by selecting the appropriate action or tool to obtain a desired effect. This capability is the result of a sophisticated ontogenetic development from conception to adulthood. Skills are acquired incrementally according to a genetic program conditioned to the surrounding environment, i.e. through the interaction with the world and other people. Once a set of basic initial capabilities is ready, many human skills are acquired through social interaction such as imitation or other humans observation [1].

In its different forms, learning has become a common approach to develop (humanoid) robots able to act in unconstrained environments, perform complex tasks and learn in an open-ended way. Inspired by biology [2], *Developmental Robotics* [3]–[5] appears as a natural framework to cope with this complexity.

Within this framework, the robot acquires new skills incrementally and uses them to learn more complex ones. In this paper we investigate which are the appropriate structures to represent knowledge about robot-object interaction. Many works have used learned sensory-motor representations of the robot motion as prior requirements to start body imitation [6], [7]. These maps have been extended to include object interactions [8]–[10]. Alternatively, it is possible to develop within a developmental perspective a new layer to represent knowledge about objects. The rationale behind this approach is that the robot develops its sensory-motor maps before being able to interact with the environment. Then, it uses them to explore the world around it, acquire more information and develop further its skills. What are the correct knowledge representations required at this developmental stage to obtain appropriate behaviors in real unpredictable environments? How can the robot re-use its own experience in new situations?

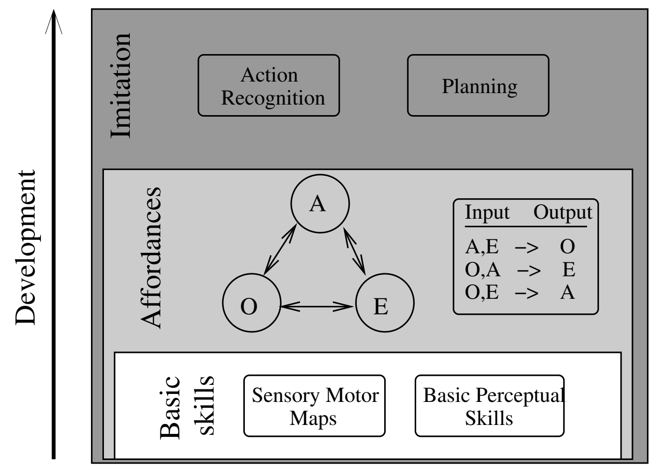

Fig. 1. Developmental architecture. The affordances are the link between basic motor and perception capabilities and higher level cognition tasks such as interaction and imitation.

To answer these questions, we resort again to a biological concept: affordances [11]. Affordances define the relation between an agent and its environment through its motor and sensing capabilities (e.g. graspable, movable or eatable). We propose affordances as the natural link between low level representations such as sensory-motor maps and higher cognitive skills like imitation, understanding the actions of others and social interaction (see Fig. 1).

Affordances are extremely powerful since they capture the essential world and object properties, in terms of the actions the agent is able to perform. They can be used to predict the effects of an action, to plan actions to achieve a specific goal or to select the appropriate object to produce a certain effect. Affordances describe the world and objects properties using the motor and perceptual capabilities of the agent. Therefore, the ability to learn an affordance model establishes maps between observed actions, objects, effects and the agent motor representations. It thus addresses important issues in imitation such as body correspondence [8], [10], imitation metrics [12], view-point correspondence [13] and task representation [14].

Several authors have already studied the problem of learning and using affordances in a robotic system [8], [9], [15]–[19]. However, in most cases the affordance model is task-specific, hindering its applicability to other contexts. In addition to this, affordances rarely appear integrated within a developmental approach.

The main contribution of this paper is to exploit a general affordance model within a developmental approach to: (i) learn affordances through self interaction with objects; and (ii) show how they provide the link between sensory-motor representations and imitation behaviors.

A. *Our Approach*

We follow the developmental roadmap proposed in [8] and extend it to include the learning and usage of a general affordance model in the world interaction phase. This framework considers three main stages in a possible developmental architecture for humanoid robots: (i) sensory-motor coordination; (ii) world interaction; and (iii) imitation, (Fig. 1).

In the sensory-motor coordination stage, the robot learns how to use its motor degrees of freedom and the coupling between motor actions and perception (kinematics, dynamics) [20], [21]. This level gives the robot perceptual skills such as recognizing object features and object motion. It also equips the system with basic actions to interact with the world. For instance, in our case the system developed grasp and tap action capabilities.

These skills enable a second level of development, the world interaction phase, where the robot interacts with surrounding objects. Based on its own action on different objects, the system learns a Bayesian network that represents affordances in terms of statistical dependencies between actions, object features and the resulting effects.

Affordances are used as the link between sensory-motor coordination and higher social skills. The learned affordance model allows to predict the effects of actions, to recognize actions performed by a human and to play simple imitation games. These imitation games are driven by the observed effects of the human action [8], [10], [17], and exploit knowledge contained in the affordance network to obtain the same effects. In this sense, imitation is not limited to mimicking the detailed human actions. Rather, it is used in a goal directed manner, as the robot may choose a very different action (when compared to that of the demonstrator) provided that its experience indicates that the desired effect can be met.

So as to validate our approach, we used the humanoid robot Baltazar [22]. We conducted several experiments to illustrate the capability of the system to discover affordances associated to manipulation actions (e.g. grasp and tap) applied to different types of objects with different shapes, colors and sizes. The effects of these actions were the changes perceived in the sensor measurements, e.g. object and hand velocities and hand-object distances in the image. Although simple, the playground is rich enough to illustrate how affordances capture the structural dependencies between actions, object features and action effects and discard irrelevant information. Later, this knowledge is used in simple imitation games where the robot performed different behaviors according to predefined reward functions.

B. *Structure of the paper*

The rest of the paper is organized as follows. Section II describes our approach for modeling and learning affordances. Section III shows how several imitation-like behaviors appear from the learned affordance model. Section IV presents the experimental results with a humanoid platform. Section V draws the conclusions.

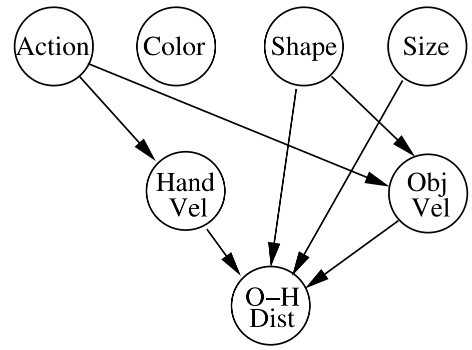

Fig. 2. Learned Bayesian network model to represent the affordances. The nodes represent the available actions, the object features (color, shape and size) and the perceived effects (hand velocity, object velocity and object hand distance). The arrows encode the dependencies among the nodes.

II. Affordance modeling and learning

This section describes how to learn affordances on top of a set of basic motor and perceptual skills. Before introducing our model, there are two important issues to take into account. First, affordances appear from the (ecological) interaction of the robot with the environment. Therefore, they should be learned through a set of experiences performed by the robot itself. Second, they require the existence of a certain number of elementary skills (developed during previous phases of our development framework). In particular, we assume the robot is equipped with a set of actions to interact with the world. It is also able to detect objects and extract information about them in the form of object characteristics (features) or their variations (effects). Affordance learning is placed at this level of abstraction where the main entities are actions, objects features and effects. Again, this abstraction is possible because the previous level processes the perceptual data and gives access to motor primitives, freeing the system from the need to process raw sensory data and to deal with all complexity of motor control.

More formally, let the discrete random variable $A = \{a_i\}$ represent the execution of a certain robot action. The object properties and effects are also modeled as discrete random variables. Each variable corresponds to the classification of a feature extractor done by the robot in an unsupervised manner. We denote $F = \{F_1, ..., F_{n_f}\}$ the object features and $E = \{E_1, ..., E_{n_e}\}$ the effects perceived after the action. The set of discrete variables A, F and E is $X = \{A, F, E\}$.

We use a probabilistic graphical model known as Bayesian Networks [23] to encode the dependencies between the actions, object features and the effects of those actions (see Fig. 2). A BN is a probabilistic directed graphical model where nodes represent random variables $X = \{X_1, ..., X_n\}$ and (the lack of) arcs represent conditional independence assumptions.

The network also has a set of parameters Θ to describe the conditional probabilities among the variables in X. This representation has several advantages. First, BNs are able to represent causal models since an arc from $X_i \rightarrow X_j$ can be interpreted as X_i *causes* X_j (see [24]). Second, they take into account the uncertainty of the real world and provide a unified framework for learning and using affordances.

Given a set of actions, object features and effects, affordances are represented by the dependencies of the graph and the parameters Θ of the conditional probability distributions. As mentioned before, the learning is accomplished from a set of experiences $D = X^{1:N}$ where the robot acts on an object and observes the resulting effects.

In a Bayesian framework, this can be formalized as estimating the distribution (or the maximum a posteriori) over the possible network structures $G \in \mathcal{G}$ given the data. Using the Bayes rule, we can express this distribution as the product of the marginal likelihood and the prior over graphs,

$$p(G \mid D) \quad = \quad \eta p(D \mid G) p(G) \tag{1}$$

where $\eta = p(D)^{-1}$ is a normalization constant. The term $p(D \mid G)$ is the likelihood of the experiences given structure G. The prior term $p(G)$ allows to incorporate prior knowledge on possible structures[1].

The number of BNs is super exponential with the number of nodes [26]. Thus, it is unfeasible to explore all the possible graphs and one has to approximate the full solution. We use Markov Chain Monte Carlo (MCMC) to approximate the distribution $p(G \mid D)$ [27]. Once the structure of the network has been established, the parameters Θ are estimated using [28]. The estimated parameters can still be sequentially updated online allowing to incorporate the information provided by new experiences.

Once the network has been learned, one can compute the distribution of a group of variables given the values of some others. The most common way to do this is to apply the junction tree algorithm [29]. Based on these probabilistic queries, we are now able to use the affordance knowledge to answer the relations between actions, objects and effects depicted in Fig. 1 simply by computing the appropriate distributions. For instance, the prediction of the effects when observing an action a_i, given the observed object features f_j, is just $p(E \mid A = a_i, F = f_j)$. It is important to note that the query can combine features, actions and effects both as observed information or as the desired output.

III. IMITATION GAMES

In this section, we show how to use affordances for imitation. When an agent imitates another it can copy the exact behavior or try to infer the important parts of the task. The former is not usually considered true imitation [1], [30] and only the latter is accepted as the most complex cognitive skill.

[1]Due to space constraints we cannot provide a full description of the learning algorithm and related issues such as interventional data or equivalent classes. We refer the reader to [25] for further details.

Inferring the important parts of the task is an ambiguous concept, but the resulting behavior must abstract among different viewpoints, different body kinematics and action repertoires.

We use affordances to abstract the particular action performed by the human by mapping the observed effects to the agent's internal representation. As a result, different kinematics and body capabilities do not restrict the replication of actions. We describe next a set of imitation games between a human and a robot. In an imitation game, the robot observes a human acting upon objects. Then the robot is presented with another object or objects and replies with a compatible action. This behavior is a fundamental capability that lies at the core of any general framework for imitation.

More formally, let a^d be the action performed by the demonstrator; f^d the features of the object and e^d the resulting action effect. The robot is then presented with a set of objects $\mathcal{O}$ and must select an action $a \in A$ and an object $o \in \mathcal{O}$ that matches a given criteria. We pose the imitation problem as a one step Bayesian decision problem [31] where a reward function $\mathcal{R}$ defining the imitation metric sets the objective of the imitation task. The function to optimize is

$$< a^*, o^* >= \underbrace{\arg max}_{a \in A, o \in \mathcal{O}} \mathtt{E}\left[\mathcal{R}(a^d, f^d, e^d, a, f^o, e^o)\right] \tag{2}$$

where f^o and e^o represent the object features for object o and the resulting effects of action a. The maximization is over the set of available robot actions A and the possible objects $\mathcal{O}$ the robot can select as an answer to the demonstration. Since the knowledge about the action, objects and effects is not deterministic we need to take the expectation $\mathtt{E}[]$ over the reward function. In particular, the probability of the effects of a particular action-object pair, $p(E \mid A, O)$, is encoded by the affordance network presented in Section II. For the sake of simplicity, in the remainder of the section f^d of e^d are deterministic values corresponding to the maximum likely object features and action effects perceived by the robot during the demonstration.

The imitation metric can be defined to achieve different behaviors in the imitation game:

a) Effect imitation: The goal of this behavior is to achieve the same effect as the observed one, by acting on a particular object. Since there is no object selection, the reward function depends only on the observed and expected effects e^d and e^o. Since effects classes result from a discretization of continuous values, we use the continuous distance between classes descriptors to define a generic similarity measure h. The reward function for the imitation behaviors becomes:

$$\mathcal{R}(e^o, e^d) \quad = \quad h(d(e^o, e^d)) \tag{3}$$

where e^d and e^o are the most likely effect detected by the robot and the resulting effect on object o respectively. In the simplest case where one is just interested in obtaining exactly the same effect, the reward reduces to:

$$\mathcal{R}(e^d, e^o) = \begin{cases} 1, & \textit{if } e^o = e^d \\ 0, & \textit{otherwise} \end{cases} \tag{4}$$

Since the reward does not depend on the object or the features and is zero for effects not equal to the observed ones, the general expression simplifies to

$$a^* = \arg max_a \mathcal{R}(e^d, e^o) p(E^o = e^d | a, f^o) \quad (5)$$

where f^o are the object features and e^o the resulting action effects.

A more complex situation arises when the robot has to select among a set of available objects $\mathcal{O}$. Since the goal is still to replicate the action effects of the demonstrator, the choice of the specific object to manipulate plays the role of an extra parameter for the optimization:

$$< a^*, o^* >= \underbrace{\arg max}_{a, o \in \mathcal{O}} \mathcal{R}(e^d, e^o) p(E^o = e^d | a, f^o) \quad (6)$$

b) Effect and object imitation: The last behavior adds information about the object features in the cost function. This allows to favor those objects similar to the one used by the demonstrator, while trying to obtain similar action effects. For instance, the following cost function requires to have the same object features as in the demonstration

$$\mathcal{R}(e^d, f^d, e^o, f^o) = \begin{cases} 1, & \textit{if } e^o = e^d \wedge f^o = f^d \\ 0, & \textit{otherwise} \end{cases} \quad (7)$$

Notice that one could weigh the features with different rewards according to different object features as in Eq. 3. For instance, if the desired object is a big sphere, we could weigh the object sizes as a function of their distance to the class model, expressed in the measurements space. Since the current observations of the robot are not deterministic, the expectation of Eq. 2 is now also taken over the possible classes of each of the available objects. Using the reward function of Eq. 7, the expression to optimize simplifies to

$$\begin{aligned} < a^*, o^* > \; &= \; \underbrace{\arg max}_{a, o \in \mathcal{O}} \mathcal{R}(e^d, f^d, e^o, f^o) \\ & \qquad p(E^o = e^d | a, f^o) p(F^o = f^d) \end{aligned} \quad (8)$$

where $p(F^o = f^d)$ represents the likelihood of the features of o being equal to the features f^d. Again this probability is computed based on the distance to clusters in the metric space of each feature.

IV. Experiments

In this section we present a set of experimental results obtained with a real robot that implements the proposed methodology. First, we briefly describe the robot platform, the experimental setup and the acquisition of the skills required to learn the affordances. Then, we illustrate the acquisition of the affordance model and its use for basic imitation games.

We used Baltazar, a 14 degrees of freedom humanoid torso equipped with a binocular head and an arm. Table I shows the current implementation of the developmental roadmap of Fig. 1.

As mentioned before, the sensory-motor maps are learned following [20], [21]. Using these maps, Baltazar is able to perform two different actions $A = \{a_1 = grasp, \ a_2 = tap\}$. The robot applies its actions to a set of different objects with two shapes (box and ball), four colors and three sizes.

TABLE I

Implementation of the developmental approach.

Sensory-Motor	Step 1: Learn sensory-motor maps
World Interaction	Step 2: Cluster object features Step 3: Cluster effects Step 4: Learn object affordances Step 5: Prediction and planning skills
Imitation	Step 6: Perform imitation games

We recorded a set of 300 experiences. At each experience, the robot was presented with an object. Then, Baltazar randomly selected an action and approximated its hand toward the object. When the reaching phase was completed, it performed the selected action (tap or $grasp$) before returning the hand to the initial location.

The objects measured features and effects are clustered from the sequence of images in an unsupervised manner using the *X-means* algorithm [32]. Table II summarizes the clustering results for the different variables and provides the notation used in the remainder of this section[2].

TABLE II

Summary of variables and values.

Symbol	Description	Values
A	Action	*grasp, tap*
C	Color	clustered in *green*$_1$,*green*$_2$, *yellow, blue*
Sh	Shape	clustered in *ball, box*
S	Size	clustered in *small, medium, big*
OV	Object velocity	clustered in *small, medium, big*
HV	Hand velocity	clustered in *big, small*
OHD	Object Hand Distance	clustered in *small, medium, big*

It is important to note that the final objective is to learn the affordance model, that is, create a plausible model of the interactions with the world using the robot current perceptual and motor capabilities; and use it for imitation. The focus is not on making perfect object classification or selecting better descriptors. Indeed, clustering errors occurred, for instance, due to different illumination conditions. As a result, some features were misclassified and the affordance learning process had to cope with these errors.

A. *Affordances*

We now present the affordance model learned by the robot using the MCMC algorithm and the experimental dataset. We used 5000 samples with a burn-in period of 500, BDeu priors for the graphs [33] and random initialization. Although, one can use conditional independence tests to provide a rough initialization for both algorithms, in our case we got similar results using randomly generated networks.

Figure 2 shows the resulting most likely network. Although there is not a ground truth network, we can check that it

[2]Note that big, small at different features/effects do not have any common scale.

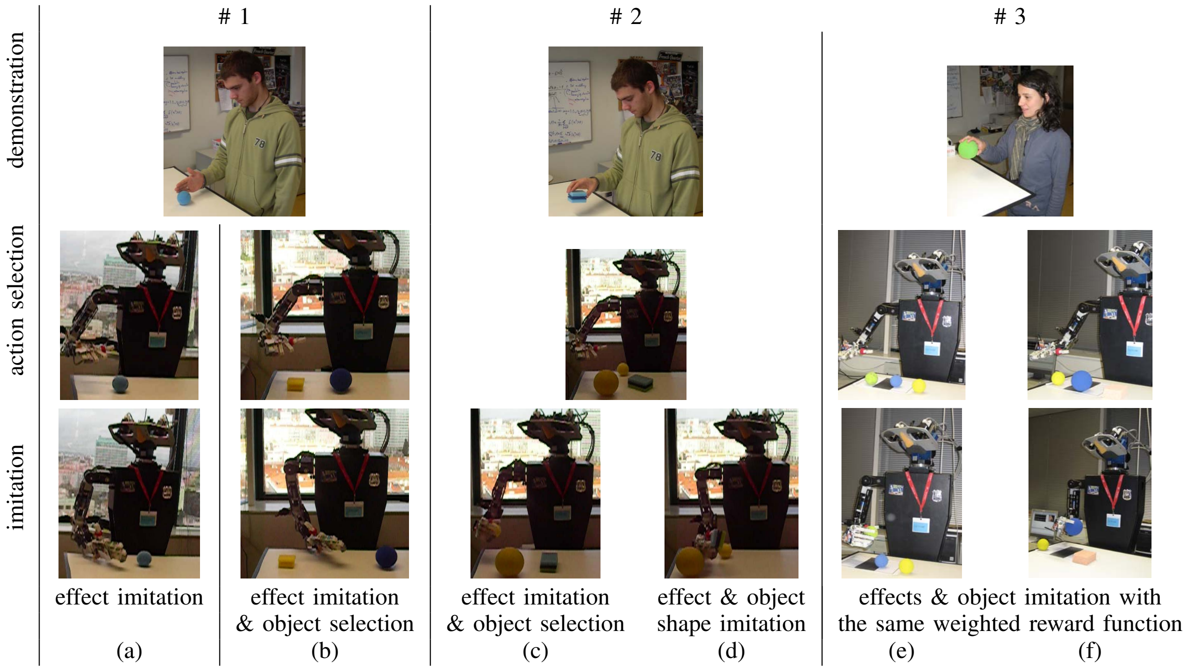

Fig. 3. Different imitation behaviors. Top: demonstration, Middle: set of potential objects, Bottom: imitation. Situation a-d represent imitation of action (a), effect (b), effect (c), effect with object shape (d) and effect with weighted features combination (e-f).

captures the type of knowledge one expects. First, color has been detected as irrelevant when performing any action. Second, shape and size influence the successful execution of tap and grasp actions (squares do not roll and too big objects cannot be grasped). Thus, these object features have an impact on observed object velocity, and distance between the hand and the object. Finally, the hand velocity only depends on the action since our robot does not change its trajectory after the action. Recall that the actual dependencies are encoded in the multinomial conditional distributions of each variable. In the next section, the robot uses these distributions to perform basic imitation what, at the same time, validates the learned model.

B. *Affordances and imitation*

We next describe the imitation behaviors obtained resulting from the formulation of Section III and the most probable affordance model learned using the MCMC algorithm.

The experimental procedure was as follows. The robot observed a person performing an action on a given object. Then, the robot selected an action and an object to act upon reacted according to one of the functions described in Section III. We present the results for different reward functions using three demonstrations (see Fig. 3). Table III shows for each experiment the action performed by the human, the features and the objects detected by the robot.

TABLE III

DEMONSTRATION

		Object features (f^d)			Effects (e^d)		
# Dem	Action	Color	Size	Shape	OV	HV	OHD
1	Tap	blue	small	ball	big	small	big
2	Grasp	blue	small	square	small	big	small
3	Grasp	green_1	med	ball	med	big	small

The objective of the robot is to obtain the same observed effects (see Eqs. 5 and 6). In the first case, (Fig. 3(a)), there is only one object and, therefore, the robot simply selects the appropriate action. Given the affordance model, this is trivial as a *tap* is the action that maximizes velocity. In Fig. 3(b), the robot has to choose between a square and a box. Table IV shows the probabilities for the desired effects given the four possible combinations of actions and objects. The robot selected the action with highest probability and taps the ball.

TABLE IV

PROBABILITY OF ACHIEVING THE DESIRED EFFECTS FOR TWO ACTIONS AND TWO OBJECTS.

obj \ action	grasp	tap
Blue, big, ball	0.00	0.20
Yellow, small box	0.00	0.06

Figures 3(c) and (d) illustrate how including the object features in the reward function produce different behaviors. In this case, we used the reward function of Eq. 8. The robot had to select among three objects: big yellow ball, small yellow ball, small blue box. In the first case, the objective was just to obtain the same effects. The probability for each of the objects is 0.88, 0.92 and 0.52 respectively and the robot grasped the small yellow ball even if the same object is also on the table (Fig. 3). This is because, according to the robot experience, it is easier to grasp a small ball than a box. As described in Section III, we can include object information within the reward function of the robot. When the reward was modified to include a similar shape, the robot selected the blue box instead.

In the last experience, we illustrate how to combine feature descriptors in the reward function,

$$R(\cdot) \quad = \quad \begin{cases} \sum_i \alpha_i exp(-d(f_i^d, f_i^o)), & \text{if } (E^o = e^d) \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

where $d(f_i^d, f_i^o)$ is a distance between the observed feature f_i^d during the demonstration and the feature f_i^o of object o. The parameters α_i balance the importance of each feature descriptor in the imitation. Figures 3 (e-f) show the results of this imitation metric in two situations where there is not a perfect match between the features of the object used in the demonstration and the options presented to the robot. In the first case, the robot selects the objects with the most similar color, since the size and shape are equal for the three objects. In the second case, the robot grasps a blue yellow ball instead of the small yellow one or the pink big square. These behaviors come out from the combination of the α_i weights of each feature and the conditional probabilities of achieving the same effects given the object features. Notice that action selection is still done based on the observed effects and the robot action repertoire.

V. Conclusions

In this paper we have proposed a developmental architecture where affordances act as the link between sensory-motor representations and imitation. The proposed affordance model allows to encode the dependencies between the robot actions, the object features and the resulting effects. This information plays a crucial role in imitation learning since it provides much of the knowledge required to imitate. The experimental results suggest that this approach leads to goal directed imitation behaviors. As future work, we are exploring how to use the affordance knowledge to learn the reward functions and the corresponding optimal policies from a set of demonstrations.

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