

Learning Social Affordances and Using Them for Planning

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Abstract

This study extends the learning and use of affordances on robots on two fronts. First, we use the very same affordance learning framework that was used for learning the affordances of inanimate things to learn social affordances, that is affordances whose existence requires the presence of humans. Second, we use the learned affordances for making multi-step plans. Specifically, an iCub humanoid platform is equipped with a perceptual system to sense objects placed on a table, as well as the presence and state of humans in the environment, and a behavioral repertoire that consisted of simple object manipulations as well as voice behaviors that are uttered simple verbs. After interacting with objects and humans, the robot learns a set of affordances with which it can make multi-step plans towards achieving a demonstrated goal.

Introduction

Motor competences of robots operating in our environments, is likely to remain inferior to ours on most fronts in the near future. In order to complete tasks that require competences beyond their abilities, the robots will need to interact with humans in the environment towards compensating these deficiencies. The inspiration for our study comes from babies and small children who can compensate the lack of their physical competences through the use of adults via social interaction. For instance, for a child, the reachability of a candy on a high shelf becomes possible only in the presence of an adult, as long as he can “manipulate” him properly using his social behaviors.

In this paper, we extend an affordance framework proposed for robots towards learning interactions with inanimate objects, to learning interactions with humans. The notion of affordances, proposed by Gibson (Gibson, 1986), emphasized the interaction between the agent and the environment, as opposed to the agent or the environment only, and provided a unifying frameworks for the study.

Contribution

This study extends the learning and use of affordances on robots on two fronts. First, we use the very same affordance learning framework that was used for learning the affordances of inanimate things to learn *social affordances*¹ (viz. affordances whose existence requires the presence of humans). Second, we use learned affordances to make multi-step plans.

In our earlier studies, we had proposed a framework that allowed the robot to learn affordances such as traversability of an environment (Ugur & Şahin, 2010) or graspability

(Ugur, Şahin, & Oztop, 2009), liftability of objects (Dag, Atil, Kalkan, & Sahin, 2010) and showed how one can make multi-step plans using the learned affordances.

In this paper, we argue that robots can use the *very same framework* to learn what a human may afford. Moreover, we enhance our prior study on multi-step planning (Ugur et al., 2009) via a new form of prototypes for effect representation.

Specifically, we equipped the humanoid robot iCub with a perceptual system to sense tabletop objects, as well as the presence and state of humans in the environment, and a behavioral repertoire that consisted of simple object manipulations and voice behaviors that uttered simple verbs. After interacting with objects and humans, we show that the robot is able to learn a set of affordances with which it can make multi-step plans towards achieving a demonstrated goal.

Related Work

The notion of affordances provides a perspective that puts the focus on the interaction (rather than the agent or the environment) and was formalized as a relation a between an entity or environment e , a behavior b and the effect f of behavior b on e (Şahin, Çakmak, Doğar, Uğur, & Üçoluk, 2007; Montecano, Lopes, Bernardino, & Santos-Victor, 2008):

$$a = (e, b, f), \quad (1)$$

For example, a behavior b_{lift} that produces an effect f_{lifted} on an object e_{cup} forms an affordance relation $(e_{cup}, b_{lift}, f_{lifted})$. Note that an agent would require more of such relations on different objects and behaviors to learn more general affordance relations.

The studies on learning and use of affordances have mostly been confined to inanimate things, such as objects (Fitzpatrick, Metta, Natale, Rao, & Sandini, 2003; Detry, Kraft, Buch, Kruger, & Piater, 2010; Atil, Dag, Kalkan, & Şahin, 2010; Dag et al., 2010) and tools (Sinapov & Stoytchev, 2008; Stoytchev, 2008) that the robot can interact with. In these studies, the robot interacts with the environment through a set of actions, and learns to perceptually detect and actualize them. Moreover, with the exception of few studies (Ugur et al., 2009; Williams & Breazeal, 2012), the robots were only able to perceive the immediate affordances which can be actualized with a single-step action plan.

Formalizations, such as 1, are proved to be practical with successful applications in navigation (Ugur & Şahin, 2010), and manipulation (Fitzpatrick et al., 2003; Detry et al., 2010; Ugur et al., 2009; Ugur, Oztop, & Şahin, 2011), conceptualization and language (Atil et al., 2010; Dag et al., 2010; Yürüten et al., 2012), and vision (Dag et al., 2010). However,

¹We would like to note that the term, social affordances has been used in different contexts, e.g., for the possibilities emerging from social networks (Wellman et al., 2003), or the affordances of an environment and properties of people that facilitate social interaction in a group of people (Kreijns & Kirschner, 2001).

in these studies, the environment is limited to objects only, excluding the possible diversities or use-cases that might arise due to the existence of humans in addition to the objects.

Human-assistance has been incorporated in (Montesano et al., 2008; Dag et al., 2010; Ugur, Oztop, & Şahin, 2011) using the same affordance formalization (1) to learn object affordances by imitation and emulation. However, the role of the human is limited to teaching affordances as part of the training phase, and he is out of the loop during execution of actions for possible assistance in creating a certain effect in the environment to extend robot’s motor capacities.

Robot’s motor capacities are extended by learning the affordances of tools in (Sinapov & Stoytchev, 2008; Stoytchev, 2008). However, these studies are focused on learning affordances of tools while the objects are kept fixed, hence the affordances of objects themselves couldn’t be captured.

In most of the HRI or social robotics studies, the robots are intended to collaborate with their human partners and they are “active learners” that learn from their partners the correct way to execute and sequence actions for achieving a goal (see, e.g., (Fong, Thorpe, & Baur, 2003; Breazeal, 2004; Weber, 2008; Cakmak, DePalma, Arriaga, & Thomaz, 2010) for a review). This way, one can teach a robot to learn complicated sequences of actions (e.g., dancing with a human partner (Kosuge & Hirata, 2004)) using several mechanisms like scaffolding (Ugur, Celikkanat, Sahin, Nagai, & Oztop, 2011; Saunders, Nehaniv, Dautenhahn, & Alissandrakis, 2007) or demonstration (Pastor, Hoffmann, Asfour, & Schaal, 2009; Argall, Chernova, Veloso, & Browning, 2009; Akgun, Cakmak, Jiang, & Thomaz, 2012). Similarly, affordances are also utilized in planning (Ugur, Oztop, & Şahin, 2011) over action possibilities, but human is not a part of the plan. However, in (Williams & Breazeal, 2012), humans are important part of the plan, yet their participation is limited with the experiment scenario, and participants are priorly acknowledged about the type of assistance they are going to provide to the robot.

For a similar goal, affordances (called “interpersonal affordances”) that emerge from coordinated joint actions of two robots are investigated (Richardson, Marsh, & Baron, 2007; Marsh, Richardson, & Schmidt, 2009); e.g., two robots learning the interpersonal affordance of lifting a table which, otherwise, is liftable by neither of them. Our approach differs from these studies in the sense that the human is seen as part of the environment (with no special status) and uses the very same framework to learn social affordances as the physical affordances of objects.

Research Platform

Perception and Environment Representation

iCub perceives its environment through two Kinect cameras (K1 and K2). K1 is used to extract table and tabletop objects. K2 –accompanied with a motion capture system (Visualizey II VZ4000)- is used to detect human’s body posture and gaze direction. For gaze direction detection, participants are provided with a hat with active LEDs on top. Overall interaction

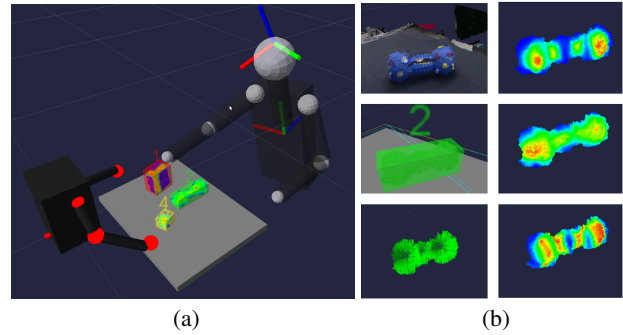


Figure 1: Visualization of the interaction environment. (a) Robot is on the left, and the human is on the right. (b) Object related features. From top left to bottom right: raw RGBD point cloud of an object on a table, table and extracted tabletop object with its oriented bounding box and id, surface normals, min curvatures, max curvatures, shape indices. [Figure best viewed in color]

environment is represented as a feature vector containing the following features:

Surface features are surface normals (azimuth and zenith), principal curvatures (min and max), and shape indices. They are represented as a 20-bin histogram in addition to the min, max, mean, standard deviation and variance information.

Spatial features are bounding box pose (x, y, z, θ), bounding box dimensions (x, y, z), and object presence.

Social features are human torso pose ($x, y, z, \text{roll, pitch, yaw}$), human gaze direction (roll, pitch, yaw), and human presence, all with respect to robot’s own coordinate system shown as coordinate axis in Fig. 1a.



Figure 2: The interaction objects. From left to right; balls, boxes, cylinders, mugs, and irregular objects.

Behaviors and Effect Representation

The robot is equipped with six behaviors (*push-left, push-right, push-forward, pull, top-grasp, side-grasp*) and some voice behaviors (“*pass me*”, “*hello*”, “*come*”, “*sit down*”, “*stand up*”, “*bye*”, “*push right*”, “*push left*”, “*take*”).

Effects –in their raw form- are computed as the difference between the final and the initial state of the environment (viz. difference between the feature vectors representing the environment before and after the behavior performance).

Effects are supervisedly matched to an effect category chosen from a set of effects such as *grasped, knocked, no-*

change², disappeared, moved right, moved left, moved forward, pulled, sat down, stood up, got attention, got closer.

Effect categories are compactly represented as a vector of “0”, “+”, “-”, and “*” to represent changes in certain feature value as *unchanged* (mean close to zero, small variance); *consistently increased* (positive mean, small variance), *consistently decreased* (negative mean, small variance); and *inconsistently changed* (large variance), respectively. This prototype-based effect representation is claimed to correspond to verb concepts in our earlier studies (Atil et al., 2010). For extracting the prototypes for each effect cluster, we analyze the mean and variance values for each element of the features in the cluster. Specifically, we apply unsupervised clustering (RGNG, (Qin & Suganthan, 2004)) on the mean-variance space. RGNG finds four clusters naturally formed. From the obtained effect consistencies, we determine the prototype of each effect cluster.

Methodology

Data Collection

We used 35 objects (Fig. 2) that are chosen to be in different colors, and shape complexities (from primitive cubes, spheres, cylinders to mugs, wine glasses, coke cans etc.), easily identified as “cylinder”, “ball”, “cup”, “box”, while some of them had irregular shapes to show generalization ability of the system.

We had iCub interact with objects and with humans by using all of the behaviors precoded in its behavior repertoire. In order to collect social interaction data, we have worked with 10 participants of different genders (4 female, 6 male), ages (20-40) and professions (4 undergrad, 2 grad students, 4 researchers with non-CS background). They were asked to respond naturally to a random sequence of voice behaviors enacted by iCub. Some of the voice behaviors were accompanied by simple movements (nodding head, waving arm, etc.).

Affordance Learning

We collected 413 triplets of (e, b, f) (Eqn. 1) for object interactions and 150 triplets for human interactions, and used them to train a Support Vector Machine (SVM) classifier for each behavior to predict the effect label given an entity. During training, we normalized the feature vectors with respect to the range of values each feature can take.

Planning with Forward Chaining

Since we trained SVMs for predicting the effect of each behavior on an object, iCub can do forward chaining to find the set of behaviors leading to a goal state. Since the effect labels are represented by effect prototypes, the similarity between the goal state (which is an effect instance) and the predicted

effect prototype is needed and we use the Mahalanobis distance, which is calculated by taking the mean μ_{E_i} of first effect cluster E_i (if the first E_i is an effect instance, we take the effect instance as μ_{E_i}) and using the second effect cluster’s E_j mean μ_{E_j} and variance σ_{E_j} :

$$d(E_i, E_j) = \sqrt{(\mu_{E_i} - f_{proto, E_j}^{+, -, 0})^T S_j^{-1} (\mu_{E_i} - f_{proto, E_j}^{+, -, 0})} \quad (2)$$

where S_j is the covariance matrix of the second effect cluster E_j . In computing the Mahalanobis distance, the features marked inconsistent in the prototype are disregarded (denoted by $f_{proto, E_i}^{+, -, 0}$ for the effect prototype f_{proto, E_i} of an effect cluster E_i), as those correspond to an unpredictable/inconsistent change in the feature elements.

Finding the effects Planning toward achieving the goal is found using a breadth-first tree search. Starting with the initial state, we construct a tree such that it contains all the possible effect sequences with length n (empirically chosen as 3). The plan is made as the goal is matched with the predicted states after applying a sequence of behaviors.

In the first step of future state calculation (Fig. 3), the current state of the object is fed to the trained SVM for each behavior. Then, the predicted effect’s prototype is determined. The mean value of this effect is added to the initial features, with the exception of the inconsistent features, and the predicted future state is found. After this application, the predicted future state can be compared with other states; but the inconsistent features of the applied effect (denoted as black columns in predicted after-state) is excluded from the comparison calculations.

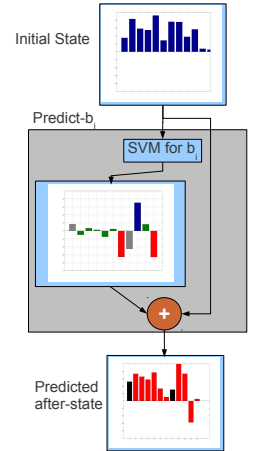


Figure 3: Future state prediction.

Application of effects Given the object, we can obtain from the trained SVMs the behavior that can achieve a desired effect with the highest probability. Thus, we obtain the behaviors required for each step in the planned effect sequence, forming a sequence of behaviors. If the obtained effect at any step in the behavior sequence does not match with the expectation, then the planning restarts. Fig. 3 and 4 respectively exemplify how a sequence of effect prototypes for reaching a desired effect is sought and how a behavior that produces an effect on an object is found. The system executes the planned behavior sequence. If, at any step, the predicted effect is not achieved (including overshoots or undershoots), the planning restarts from the current object state.

²The no-change label denotes that the applied behavior did not produce any notable change on the object. For example, when iCub asks a participant to stand up who was already standing, the participant would not change his position. This yields negligibly small changes in the feature vector.

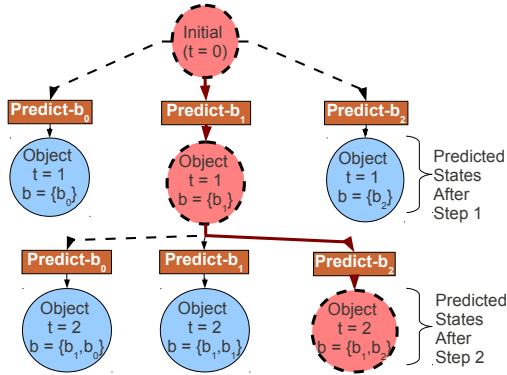


Figure 4: A simple depiction of how the planning is performed using the combinations of effects in the repertoire. At each step, the prediction block described in Fig. 3 is applied for each behavior. Once a future state close enough to goal state is obtained, the search is terminated.

Results

Social Affordance Learning

Fig. 5 shows some of the effect prototypes that lead us to interesting observations. In the first place, some effects can apparently be produced both by social and non-social behaviors. An obvious example is “say push to your left” and push-right (causing the *moved right* effect most of the time). Furthermore, we observe that in some cases, social behaviors can be a better option for goal emulation. For instance, when the object is far enough from the robot, the predicted effect for *pull* behavior is *no change*; whose effect prototype has only *’s and 0’s (features with inconsistent change and negligible change), whereas the predicted effect for “pass me” behavior is *pulled*, the effect whose prototype denotes consistent decrease in object’s distance to the robot (x-position). In emulating a goal to pull this object towards itself, Eq. 2 yields that *pulled* effect brings the object closer to the goal, hence iCub chooses to ask a human to pass the object.

The effects *got attention* and *got closer* turned out to be ambiguous effect labels - their corresponding clusters did not have any consistently increasing or decreasing features. This might also be related with our feature set. Similar results were observed for the effects clustered as *sat down* and *stood up*, although they were unambiguously interpreted by the participants. The amount of standing and sitting of our experiment participants has had a high variance. The participants had two major interpretations for the “pass me” behavior: they either (i) pushed the object towards the robot (causing *pulled* effect) or (ii) tried to pass it to robot’s hand (Fig. 6). Similar response was also observed when the voice behavior “take this” was applied: while most of the participants took the object and removed it from the scene (causing the *disappeared* effect), some of the participants just dragged the object towards themselves (causing *moved forward* effect). We were expecting that when iCub enacted the voice behavior “bye”,

the participants would leave the scene. However, participants mostly kept their positions and responded by waving back.

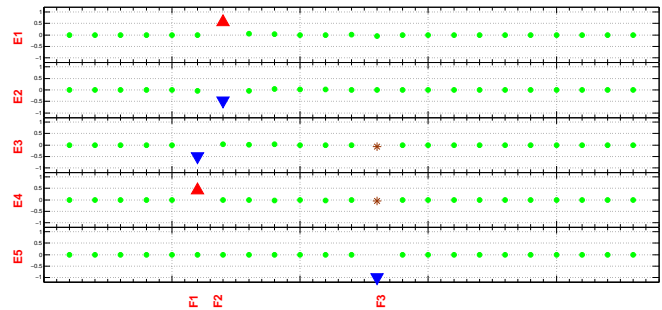


Figure 5: Some of the results obtained from unsupervised clustering of feature mean and variances. Vertical axis represents some of the effects (E1: *moved-right*, E2: *moved-left*, E3: *moved-forward*, E4: *pulled* and E5: *disappeared*) and the horizontal axis represents some of the features detected as consistently increasing (red upwards arrow) or decreasing (blue downwards arrow) in the given effects (F1: *position-x*, F2: *position-y*, F3: *human presence*)



Figure 6: Some different reactions by experiment participants when the robot uses the “pass me” voice behavior.

Both social and non-social behaviors contribute to these results. For example, *pulled* can be produced both from *pull* and “pass me” behaviors. Note that some of the features, which were inconsistently changed (marked with star) or negligibly changed (marked with circle), grouped into one column for brevity.

Social Affordances and Multi-step Planning

We demonstrate social affordances in three scenarios:

1- Multi-step planning without human presence In this scenario, the object is placed in front of iCub as the initial position, and the target position is shown with red circles (Fig. 7a). After initial and final positions are shown to iCub, it plans without a human present in the environment; i.e., it cannot make use of “social affordances”. According to the plan, the effect sequence is determined as *moved forward*, *moved left*, *moved forward*. After a successful *push-forward* behavior, the object is *moved-forward* (Fig. 7b), then with a *push-left* behavior, the object reaches close to the target position (Fig. 7c). Appropriate behaviors to end up with the last *moved-forward* effect may have been *push-forward* behavior or “pass me” voice behavior. Since there is no human across

the table and because the object is too far to be moved forward to its target position, iCub figures out that it is impossible for the object to reach its final position (Fig. 7d) and stops at this stage.

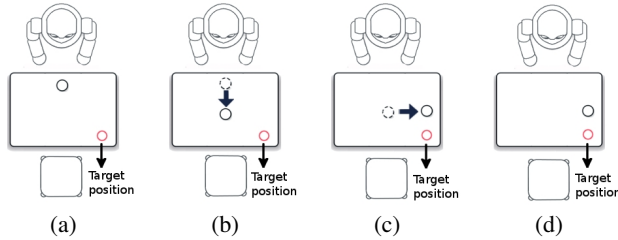


Figure 7: Scenario #1: The robot cannot reach the target position and cannot fulfill the goal due to absence of a human.

2- Multi-step planning with a human - using “pass me” voice behavior This scenario demonstrates a case for successful planning. As the initial position, the object is placed closer to the human and the target position is shown with a red circle (Fig. 8a). After planning, the effect sequence *pulled, pulled, moved left* is determined to reach the target position. For the first *pulled* effect, since the object is placed far from iCub and with the contribution of human presence, “*pass me*” voice behavior has the highest probability and is executed (Fig. 8b). For the remaining *pulled* and *moved-left* effects, *pull* (Fig. 8c) and *push-left* (Fig. 8d) behaviors are executed respectively. As a result, each planned effect is achieved and the object reaches its target position (Fig. 8e).

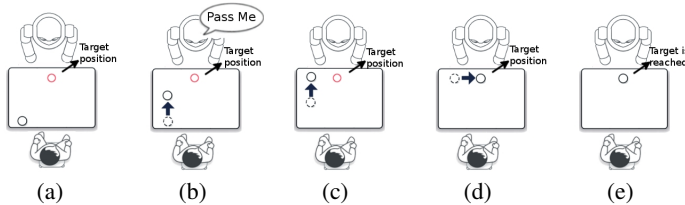


Figure 8: Scenario #2: The robot can use human’s affordances when stuck, by using the “*pass me*” voice behavior.

3- Multi-step planning with a human - using “take” voice behavior This scenario shows a demonstration in which iCub finds a valid plan but because of a behavior which results with an unexpected effect, iCub re-plans. For this scenario, the object is placed close to iCub and the target position is shown with a red circle (Fig. 9a). The planner finds out the required effect sequence as *moved forward, moved right, moved forward*. The first two effects are achieved using the *push-forward* (Fig. 9b) and then *push-right* behavior (Fig. 9c). For the last effect, *push-forward* behavior is executed. However, instead of a *moved-forward* effect, *moved-right* effect occurs (Fig. 9d). Because of this unexpected effect, iCub needs a re-planning (Fig. 9e). This re-planning results with

a new effect sequence of *moved left, moved forward*. This re-planned effect sequence is achieved by using *push-left* behavior (Fig. 9f) and “*take*” voice behavior (Fig. 9g) and object reaches its target position (Fig. 9h).

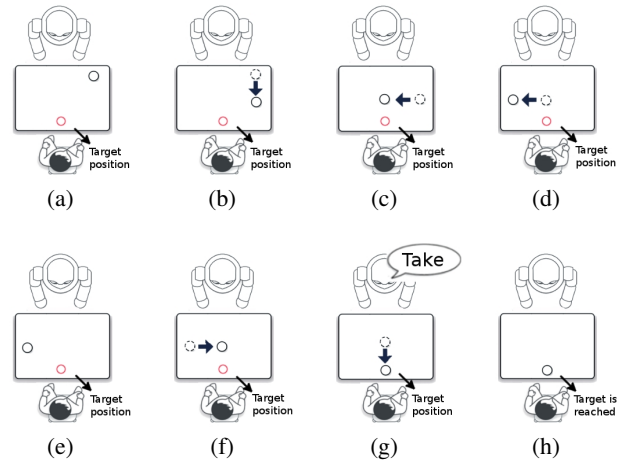


Figure 9: Scenario #3: The robot can use human’s affordances when stuck, by using the with “*take*” voice behavior.

From these 3 different scenarios, we conclude as follows: (i) After iCub executes a behavior, if it observes an unexpected effect, it re-plans. (ii) iCub executes its behaviors by planning (and re-planning if necessary) until the object reaches the target position or iCub decides that it is impossible for the object to reach the target position. (iii) If there is a human, iCub may benefit from the affordances offered by the human to get a desired effect. (iv) If there is no human and the desired effect requires a human, iCub can realize that it is impossible for the object to reach the target.

Conclusion

In this paper, we used the very same affordance learning framework developed for discovering the affordances of inanimate things to learn social affordances, that is affordances whose existence require the presence of humans. We demonstrated that our humanoid robot can interact with objects and with humans (using simple verbal communication) and from these interactions, it can learn what the objects as well as the humans afford. Moreover, we showed that the robot can ask for human assistance whenever it is required while executing multi-step plans to satisfy demonstrated/given goals.

Our approach towards learning the social affordances is in line with the findings that affordances at different levels (intra-level and inter-level) share the same intrinsic constraints and organizations (e.g., (Richardson et al., 2007)).

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