From Affordances to Situated Affordances in Robotics - Why Context is Important

Marc Kammer*†‡, Thomas Schack*‡, Marko Tscherepanow*† and Yukie Nagai*§
*CITEC, Cognitive Interaction Technology - Center of Excellence
†Applied Informatics, Faculty of Technology,
‡Neurocognition and Action, Faculty of Psychology and Sport Sciences
Bielefeld University, Universitätsstraße 25, 33615 Bielefeld, Germany
§Graduate School of Engineering, Osaka University,
2-1 Yamadaoka, Suita Osaka, 565-0871 Japan

Abstract

We propose *situated affordances* as an extension to the well known concept of *affordances*. Situated affordances extend affordances by taking the environmental context, in which an object is embedded, into account. We argue that the extended concept allows the learning of qualitatively more complex tasks. In this paper we report the conceptual result of ongoing work in which a cognitive robotic architecture is developed that finally should be able to learn complex real world tasks. The purpose of this paper is to communicate the proposed conceptual idea to the scientific community, to get in touch with other researchers and to foster the interchange between roboticists, psychologists and associated researchers who are concerned with the learning of complex tasks in robots.

I. Introduction

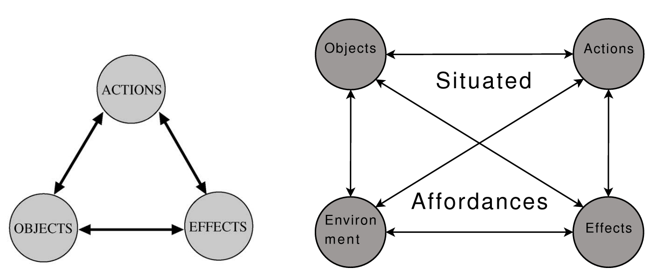
How humanoid robots can be enabled to learn complex tasks is still an open question. Recently the concept of affordances became a popular method in robotic research. The term affordances was defined by the psychologist Gibson [1]. It describes action opportunities an observer becomes aware of by looking at an environment or at an object. For example, a pen affords to write and a ball affords to kick. The adoption of the concept affordances in robotics research allowed the tackling of versatile and complex learning tasks.

Many researches have done a great effort in investigating how affordances can be learned by robots and by that how to teach complex tasks to robots. One of the first work was done in [2] and [3] in which a robot learns, by playing, to associate objects and their corresponding effects with its own action repertoire. Later works used a wide spectrum of methodologies to teach affordances, starting from basic feature association learning [4] up to an increasingly complex imitation architecture [5], [6]. Common to all affordances learning architectures we are aware of, is the fact they fit the formalized definition made in [6] stating that affordances “[...] encode relationships between actions, objects, and effects.”, visually depicted in Figure 1(a). A similar definition and an in depth discussion about affordances in the context of learning in robotics is done in [7]. Following, we present and formalize the idea of situated affordances, show an important difference between both concepts and motivate a discussion apart the common domain of robotic affordance experiments.

II. Situated Affordances

A. Background and Basic Concept

Based on the existing formalization we introduce the concept of situated affordances, which extends affordances by taking the *environment*, in which an object is embedded, into account. We define environment as all entities that directly or indirectly influences the effect, an action, executed on an object, will have. For example a ball affords to kick, this affordance changes if



(a) (b)

Fig. 1: In (a) affordances are represented as relationship between objects, actions and effects, taken from [6]. In (b) we describe situated affordances as an extended relationship constellation between environment, objects, actions and effects.

the ball is placed in a container full of water. Situated affordances allow the learning of more complex tasks than the original affordances does, which we will demonstrate. The extended relationship of situated affordances is depicted in Figure 1(b).

Many situations require to consider the environmental context in which an object is embedded. Humans do this easily, often unconsciously, by adapting their behavior or executed actions accordingly. A closer investigation of affordances reveal that each affordance experiment must also (implicitly) account the environment in which an object is embedded. For example in [6] the robot learns to imitate a demonstrator that pushes a ball that is laying on a table. In this case the table is the environment because it directly influences the effect an executed action on the ball has. Affordances therefore represent a special case of situated affordances, the case that the environmental context is constant and does not change. To our knowledge there is no affordance experiment in which the environmental context change.

B. Formalization and Challenges.

In order to proof that situated affordances describe qualitatively more complex learning tasks than affordances, we adopt the formalization from [6], enlarging it by the environment. Given (O, E_{nv}, A, E_f) represent Object, Environment, Action and Effect, consider two affordance setups 1 and 2 both using identical objects $O_1 = O_2$ and the same effect should be achieved $E_{f_1} = E_{f_2}$, by executing different actions $A_1 \neq A_2$. Although the robot can perfectly learn each individual affordance $\big(O_1, E_{f_1}\big) = A_1$ and $\big(O_2, E_{f_2}\big) = A_2$, it can not learn $\big(O_1, E_{f_1}\big) = A_1 \wedge \big(O_2, E_{f_2}\big) = A_2$ due to the fact that $(O_1 = O_2) \wedge (E_{f_1} = E_{f_2})$, which would lead to $A_1 = A_2$ which is wrong per definition. Wrong per definition could be interpreted as the fact that the robot is unable to distinguish setup 1 and setup 2.

By modelling the environment E_{nv_i} and by this representing the different environments, situated affordances allows to distinguish setup 1 and setup 2. For the given example it is true that $E_{nv_1} \neq E_{nv_2}$. Taking this into consideration leads to, $\big(O_1, E_{f_1}, E_{nv_1}\big) = A_1$ and $\big(O_2, E_{f_2}, E_{nv_2}\big) = A_2$. Now the robot can learn $\big(O_1, E_{f_1}, E_{nv_1}\big) = A_1 \wedge \big(O_2, E_{f_2}, E_{nv_2}\big) = A_2$ due to the fact that E_{nv_1} and E_{nv2} provide the necessary information to distinguish both setups and execute the appropriate action according to the situation. This basically is the learning of situated affordances.

III. Discussion

We mentioned and explained situated affordances in the context of complex task learning, as this is the domain in which robotic affordance experiments are normally conducted and it is the domain in which we are applying it. But we think by no means that it has to be restriced to this domain. Quite the contrary, we think that depending on the capabilities of the robot, situated affordances can be transferred to social situations as well. There are a many situations in which social conventions and cultural background define which behavior is appropriate and which not. We further think that the problems that have to be solved to enable a technical system to learn situated affordances are quite similar either in learning situated affordances for a complex task scenario or when learning situated affordances in a social context. In both situations complex time dependent associations between different features of necessarily distinguishable entities, have to be taken into account.

IV. Conclusion and Outlook

In this paper we introduced the concept of situated affordances, which enlarged the concept of affordances by taking the environment into account. We defined this conceptual term in an onging work of developing a cognitive robotic architecture which shall learn a complex real world task. We explained the basic concept, showed that learning situated affordances is a qualitatively different task from learning affordances and posed the idea that the concept of situated affordances could be transferred to social contexts as well. We hope that the presented idea of situated affordances could be beneficial for other researches in the robotic community who tackle the learning of difficult tasks and possibly inspire researches to use the concept beyond the usual domain.

Acknowledgment

This research was funded by the German Research Foundation (DFG), Excellence Cluster 277, “Cognitive Interaction Technology”.

References

[1] J. J. Gibson, “The Theory of Affordances,” *Perceiving, Acting, and Knowing*, pp. 67–82, 1977.

[2] G. Metta and P. Fitzpatrick, “Early Integration of Vision and Manipulation,” *Adaptive Behavior*, vol. 11, no. 2, pp. 109–128, 2003.

[3] P. Fitzpatrick, G. Metta, L. Natale, A. Rao, and G. Sandini, “Learning About Objects Through Action - Initial Steps Towards Artificial Cognition,” *In Proc. of ICRA*, vol. 3, pp. 3140–3145, 2003.

[4] B. Ridge, D. Skočaj, and A. Leonardis, “A System for Learning Basic Object Affordances using a Self-Organizing Map,” in *International Conference on Cognitive Systems CogSys 2008*, Karlsruhe, Germany, 2008. [Online]. Available: http://www.cognitivesystems.org/publications/ridgeCogSys08.pdf

[5] M. Lopes and J. Santos-Victor, “A Developmental Roadmap For Learning by Imitation in Robots,” *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, vol. 37, no. 2, pp. 308–321, 2007.

[6] L. Montesano, M. Lopes, A. Bernardino, and J. Santos-Victor, “Learning Object Affordances: From Sensory–Motor Coordination to Imitation,” *IEEE Transactions on Robotics*, vol. 24, no. 1, pp. 15–26, 2008.

[7] E. e. a. Sahin, “To Afford or Not to Afford: A New Formalization of Affordances Toward Affordance-Based Robot Control,” *Adaptive Behavior*, vol. 15, no. 4, pp. 447–472, December 2007.