Horton, Thomas E. / Chakraborty, Arpan / St. Amant, Robert

Affordances for robots : a brief survey

Avant 3/2, 70-84

2012

AVANT, Vol. III, No. 2/2012
ISSN: 2082-6710 avant.edu.pl/en

Affordances for robots: a brief survey

Thomas E. Horton, Arpan Chakraborty, and Robert St. Amant*
Department of Computer Science, North Carolina State University, USA
* Corresponding author *stamant[]ncsu.edu*

Received 12 May 2012; accepted 20 November 2012; published online 24 December 2012.

Abstract

In this paper, we consider the influence of Gibson's affordance theory on the design of robotic agents. Affordance theory (and the ecological approach to agent design in general) has in many cases contributed to the development of successful robotic systems; we provide a brief survey of AI research in this area. However, there remain significant issues that complicate discussions on this topic, particularly in the exchange of ideas between researchers in artificial intelligence and ecological psychology. We identify some of these issues, specifically the lack of a generally accepted definition of "affordance" and fundamental differences in the current approaches taken in AI and ecological psychology. While we consider reconciliation between these fields to be possible and mutually beneficial, it will require some flexibility on the issue of direct perception.

Keywords: affordance; artificial intelligence; ecological psychology; Gibson; robotics.

1. Introduction

An ecological approach to the design of robotic agents can hold significant appeal for researchers in the area of artificial intelligence (AI). Embodied agents situated in a physical environment have access to a wealth of information, simply by perceiving the world around them. By exploiting the relationship between the agent and its environment, designers can reduce the need for an agent to construct and maintain complex internal representations; designers can instead focus on the details of how the agent interacts directly with the environment around it. The result is more flexible agents that are better able to respond to the dynamic, real world conditions. The ecological approach thus appears well suited to the design of embodied agents, such as mobile autonomous robots, where the agent may be required to operate in complex, unstable, and real-time environments.

First proposed by psychologist J.J. Gibson (1966), the concept of affordances serves as a basis for his theories of ecological psychology. Though "affordance" is often informally described as "an opportunity for action," there is as yet no commonly accepted formal definition of the term. In *The Ecological Approach to Visual Perception*, Gibson writes:

> *The affordances of the environment are what it offers the animal, what it provides or furnishes, either for good or ill. The verb to afford is found in the dictionary, but the noun affordance is not. I have made it up. I mean by it something that refers to both the environment and the animal in a way that no existing term does. It implies the complementarity of the animal and the environment. (Gibson 1979: 127)*

Despite a lack of agreement on what exactly an affordance is, a number of attempts have been made to apply ecological concepts to the design of artificial agents. In many cases, researchers in AI have drawn direct inspiration from ecological psychology, while in other cases, they have independently arrived at approaches that, though they may differ in some respects, are in many ways compatible with Gibson's proposals.

Often, however, it is apparent that psychologists and AI researchers have very different approaches to the problem of understanding what affordances are and how they are utilized by agents, whether organic or artificial. Thus, the purpose of this article is twofold. Our first goal is to provide a brief survey of existing work in the area of artificial intelligence, for the benefit of researchers in both fields. This survey is presented in section 2. Our second goal, addressed in section 3, is to identify some of the main issues that can complicate attempts to reconcile the approaches of ecological psychology and of AI, and that may inhibit communication across the two domains – in particular, the role of Gibson's theory of direct perception. In section 4, we conclude with some speculation as to the future of affordance-based approaches in AI.

2. The ecological approach in AI

In designing artificial agents, several successful patterns for control and coordination of perception and action have emerged. Some of these approaches share an important characteristic - a clear emphasis on utilizing the environment, and the agent's interaction with it, to reduce the complexity of representation and reasoning. This characteristic is founded on an ecological view of the agent - an entity embodied in a world rich with observable cues that can help guide the agent's behavior. As summarized by Brooks, "the world is its own best model" (Brooks 1990: 5).

We begin with a brief overview of the AI literature, focusing on agent design paradigms that incorporate elements of the ecological approach. While researchers in AI may not always make exactly the same choices Gibson might have, there is much here that will be familiar to a reader with a background in ecological psychology.

2.1. Agent design paradigms

Sensing, planning (or reasoning), and acting are three major processes that an agent needs to carry out. In traditional deliberative systems (Maes 1991), these are modeled as distinct components, typically activated in cycles with a linear sense-plan-act sequence (Gat 1998). This methodology has allowed for fairly independent development of the three components, especially domain-independent planners that have been able to exploit advances in general problem-solving and formal logical reasoning (Fikes et al. 1972; Newell & Simon 1963; Sacerdoti 1974).

But such an organization has two significant implications. Firstly, decoupling of the processes creates the need for an abstracted internal representation of the environment (partial or complete) to pass information from the perceptual component to the planning system; this intermediate 'buffer' can potentially become a disconnect between the real state of the environment and the agent's beliefs. Secondly, plan failure is treated as an exception that is usually handled by explicit re-planning. With the uncertainty and unpredictability inherent in the real world, these aspects can limit the versatility of physical robots. These challenges have been addressed by researchers through refinements such as modeling uncertainty and nondeterminism (Bacchus et al. 1999), and dynamic planning (Stentz 1995; Zilberstein & Russell 1993).

The ecological view presents a fundamentally different approach to agent design, relying heavily on simple, efficient perceptual components (as opposed to complex mental constructs) and common underlying mechanisms for sensing, reasoning, and acting (Brooks 1986). Planning and execution in such systems is usually a tightly coupled process, with the agent constantly recomputing the best course of short-term action, simultaneous with the execution of the current task. This reduces dependence on a control state that keeps track of the agent's progress in a sequence of actions that might rely on potentially out-of-date information.

An ecologically-aware agent can demonstrate flexibility in the face of changing conditions, while still performing complex behaviors. Chapman (1991) demonstrates, using a simulated environment, how ecological principles can help an agent abort a routine that is no longer appropriate, re-attempt a failed action, temporarily suspend one task in favor of another, interleave tasks, and combine tasks to simultaneously achieve multiple goals. Similar characteristics have emerged in a number of physical robotic systems that follow different methodologies and design patterns, yet embody principles compatible with the ecological perspective.

Action-oriented or task-driven perception (Arkin 1990) is one approach roboticists have used to deal with inherent uncertainty in the real world. Knowledge of a robot's current situation, intended activity, and expected percepts can help introduce enough constraints to make perception tractable and accurate. Furthering this approach, Ballard (1991) argues with the Animate Vision paradigm that the ability to control visual input (specifically, gaze) enables the use of environmental context to simplify tasks such as object recognition and visual servoing. This has been reiterated by Brooks and Stein (1994) and validated by some later systems (Gould et al. 2007; Kuniyoshi et al. 1996; Scassellati, 1999).

The task-driven methodology can be generalized to include other aspects of the agent's current *situation*. Chapman (1991) and Agre (1987) illustrate how the affordances of an environment can be characterized within an overall theory of situated activity, which is one way of conceptualizing ecological elements. They also demonstrate how instructions given to artificial systems can refer to indexical functional entities, i.e. pointers to real-world objects specified directly in terms of their characteristics as relevant in the current situational context, instead of absolute identifiers. Properties of candidate objects, including their affordances, help disambiguate references present in such instructions, e.g. "it" in "pick it up" can only refer to objects that can be picked up.

Other ecological elements have also received attention in robotics. In their work on the humanoid robot Cog, Brooks et al. (1997) emphasize the need to consider bodily form when building representation and reasoning systems to control robots. In behavior-based robotics, Matarić (1994, 1997) emphasizes the learning aspect of behavior selection, and notes that this amounts to learning the preconditions for a behavior. In addition, reasoning about behaviors – especially in the context of planning – requires that behaviors be associated with properties or states of the environment. This kind of reasoning enables robots to "think the way they act" (Matarić 2002).

A number of researchers have even applied Gibson's concept of optic flow to autonomous robotic agents. For example, Duchon et al. (1998) describe the design of mobile robots that utilize optic flow techniques not only for obstacle avoidance, but to also implement predator-prey behaviors that allow one agent to chase after another as it attempts to escape.

2.2. Affordance-based approaches

Most of the research cited up to this point does not make direct reference to Gibsonian affordances. In this section, however, we consider examples from the AI literature where the focus is specifically on agents designed to utilize affordances. While there may be some disagreement as to how compatible the results are with the Gibsonian approach, generally speaking, the goal has been to apply concepts from ecological psychology to develop better agents.

Recent work in AI has led to the development of robots capable of exploiting affordances in support of a range of behaviors, including traversal and object avoidance (Çakmak et al. 2007; Erdemir et al. 2008a, 2008b; Murphy 1999; Şahin et al. 2007; Sun et al. 2010; Ugur et al. 2009, 2010), grasping (Cos-Aguilera et al. 2003a, 2003b, 2004; Detry et al. 2009, 2010, 2011; Kraft et al. 2009; Yürüten et al. 2012), and object manipulation, such as poking, pushing, pulling, rotating, and lifting actions (Atil et al. 2010; Dag et al. 2010; Fitzpatrick et al. 2003; Fritz et al. 2006a, 2006b; Rome et al. 2008; Ugur et al. 2011, Sun et al. 2010; Yürüten et al. 2012).

Our own interests relate primarily to the design of agents capable of utilizing the affordances of tools. Tool use is briefly considered by Gibson (1979) and by Michaels (2003), and has recently been studied by Jacquet et al. (2012), but it has received relatively little attention from ecological psychology. There is, however, a small but growing body of work on tool-related affordances in AI (e.g. Guerin et al. 2012), including studies of the affordances of tools used for remote manipulation of targets (Jain & Inamura 2011; Sinapov & Stoytchev 2007, 2008; Stoytchev 2005, 2008; Wood et al. 2005) and the use of external objects for containment (Griffith et al. 2012a, 2012b). Recent work in our own lab has focused on systems for identifying the low-level affordances that support more complex tool-using behaviors, such as the physical couplings between a screwdriver and the slot of a screw and between a wrench and the head of a bolt (Horton et al. 2008, 2011).

While most of these affordance-based systems utilize embodied agents in control of physical robots, others employ simulation environments or use simulation in addition to physical interaction (Cos-Aguilera et al. 2003a, 2003b, 2004; Erdemir et al. 2008a, 2008b; Fritz et al. 2006a, 2006b; Jain & Inamura 2011; Rome et al. 2008; Şahin et al. 2007; Sinapov & Stoytchev 2007, 2008; Ugur 2011).

As with much of the work in ecological psychology, the majority of these systems focus on visual perception, through either physical or simulated cameras. A few systems employ additional forms of input, however. For example, Atil et al. (2010), Griffith (2012a, 2012b), Murphy (1999), Şahin et al. (2007), and Ugur et al. (2009, 2010, 2011) utilize range finders for depth estimation, and the system described by Griffith (2012a, 2012b) also makes use of acoustic feedback. And in Atil et al. (2010) and Yürüten et al. (2012), the systems take labels assigned by humans to objects and actions as additional input.

Whether physical or simulated, many of these systems share a common approach in the utilization of exploratory behaviors, or "babbling" stages, in which the agent simply tests out an action without a specific goal, in order to observe the result (if any) on its environment. Through exploratory interactions, the agent is able learn the affordances of its environment largely independently. However, the affordances the agent can discover will be dependent not only on its physical and perceptual capabilities, but also on the types of exploratory behaviors with which it has been programmed (Stoytchev 2005).

Perhaps the feature most relevant in the context of this document is the almost universally shared view of affordances as internal relations between external objects and the agent’s own actions. This perspective conflicts with the approach advocated by Gibson. For example, Vera and Simon (1993) suggest an interpretation of affordances that is very different from the view commonly held in ecological psychology, based on an approach of the sort Chemero and Turvey (2007) classify as “representationalist” (as opposed to “Gibsonian”). Responding to proponents of situated action, an approach to cognition and artificial intelligence with similarities to ecological psychology, Vera and Simon argue that advocates of such approaches greatly underestimate the complexity of perception. Rather, they suggest that the apparent simplicity of perception is the result of complex mechanisms for encoding complicated patterns of stimuli in the environment. In this view, affordances are the internal functional representations that result from this encoding process; affordances are "in the head" (Vera & Simon 1993: 21).

A more recent formalization of this viewpoint is formulated by Şahin et al. (2007) and Ugur et al. (2009). They begin their formalization of affordances by observing that a specific interaction with the environment can be represented by a relation of the form (effect, (entity, behavior)), where the "entity" is the state of the environment, the "behavior" is some activity carried out by an agent in the environment, and the "effect" is the result. A single interaction leads to an instance of this relation. Multiple interactions can be generalized such that the agent becomes able to predict the effects of its behaviors on different environment entities. Thus, affordances can be considered to be generic relations with predictive abilities.

Additionally, we note that some of the systems we have mentioned are designed to explicitly assign objects and actions to categories (e.g. Sun et al. 2010). As the rejection of the need for categorization in the perception of affordances is a point emphasized by Gibson (1979), this, along with the view of affordances as internal relations, is another area that may cause conflict between the AI and ecological psychology communities.

As the research cited here illustrates, affordance-based approaches have been successfully applied to a number of problems in artificial intelligence. In doing so, however, AI researchers have often employed their own interpretations of ecological concepts like affordances – interpretations that sometimes differ significantly from those of ecological psychology.

Many possibilities remain for applying affordance-based approaches to the design of artificial agents. Thus far, many of the studied applications have been relatively basic, e.g. focusing on obstacle avoidance and pushing objects around on a surface. As more capable robotic agents are developed, able to employ tool use and other increasingly complex behaviors, we anticipate new opportunities for further exploring these approaches.

3. Open issues

In this section, we begin with a brief discussion of one of the first problems encountered by researchers in AI when studying the concept of affordances. Specifically, what do ecological psychologists mean by "affordance"? We then identify some of the additional issues that can arise when trying to reconcile the ecological approach with the demands of implementing an artificial agent.

3.1. Defining "affordance"

Informally, affordances are often described as "opportunities for action." However, even within the ecological psychology community, there seems to be little consensus on how this concept can be understood more formally. Gibson's own ideas on the subject evolved over the course of decades. For example, Jones (2003) traces the origins of the concept back to the work Gibson did in the 1930's, and argues that Gibson's thinking on the subject was still evolving at the time of his death in 1979.

Gibson's most extensive writing on the topic of affordances comes from *The Ecological Approach to Visual Perception* (1979). Here, Gibson outlines the origins of the concept and proposes multiple examples, yet fails to provide a concrete definition; rather, his explanations are often quite vague. For example, in addition to the description included in the introduction at the start of this paper, Gibson also writes:

> *An important fact about the affordances of the environment is that they are in a sense objective, real, and physical, unlike values and meanings, which are often supposed to be subjective, phenomenal, and mental. But actually, an affordance is neither an objective property nor a subjective property; or it is both if you like. An affordance cuts across the dichotomy of subjective-objective and helps us to understand its inadequacy. It is equally a fact of the environment and a fact of behavior. It is both physical and psychical, yet neither. An affordance points both ways, to the environment and to the observer.* (Gibson 1979: 129).

Despite the lack of a single clear, unifying statement, however, Gibson does make certain points that help to reveal his thinking. As summarized by McGrenere and Ho (2000), Gibson specifies three fundamental properties of an affordance: an affordance exists relative to the capabilities of a particular actor; the existence of an affordance is independent of the actor's ability to perceive it; an affordance does not change as the needs and goals of the actor change. While this summary does help to clarify Gibson's position, it still leaves much open to interpretation.

Additionally, Gibson's descriptions of affordances tend to be very broad, including such examples as food affording nutrition and cliffs affording danger, as well as more concrete and familiar examples such as a hammer affording striking. While such a general approach may be desirable in some cases (Stoffregen 2004), it makes it difficult to evaluate the concept empirically. Gibson's descriptions lack predictive power; they say little about how affordances arise from physical properties, or about how an organism might recognize affordances in order to utilize them - key issues in the development of an artificial agent that is guided by affordances.

In the decades since Gibson's death, a debate within the field of ecological psychology has been held over how best to define the concept of affordance. This debate is often complex, with different authors proposing multiple interpretations and definitions, giving rise to several major points of disagreement, such as whether affordances are properties of the environment or aspects of a combined animal-environment system, whether affordances are dispositional properties or relations, and whether affordances relate to complementary "effectivities" of the organism or to its body scale. There is insufficient space here to go into detail, but see, for example, Chemero's (2003) analysis.

Additionally, Şahin et al. (2007) suggest that a further source of confusion has been the fact that affordances can be viewed from three different perspectives: the agent, the environment, or an outside observer, further complicating attempts to agree on a definition.

Unfortunately, a single, uniformly accepted formal definition of "affordance" is still missing. Attempts at a formal definition have been made (e.g. Chemero 2003; Heft 2003; Jones 2003; Michaels 2003; Stoffregen 2003), but these have only added to the debate, while consensus has remained elusive. And often, these attempts at definition suffer from the same problems as Gibson's original descriptions, being very broad and lacking in heuristic guidance (Kirlik 2004).

3.2. Are psychological and computational approaches compatible?

Perhaps in part due to the lack of a single accepted definition of affordance, when ecological psychologists and AI researchers talk about affordances, they may often be referring to very different things (Şahin et al. 2007). This disconnect may be the result of the differing goals between the two communities, with psychologists focusing on describing behavior and AI engineers focusing on implementing systems.[28]

There seems to be a general agreement that affordances are "relations," but here, too, psychologists and AI researchers may use the term very differently. In general, researchers in both fields seem comfortable with the notion that affordances are, in some way, relations between physical properties of the agent and the environment. Viewed this way, affordances are external relations, as opposed to internal mental constructs, and the key question is whether or not an affordance physically exists; i.e., does the environment allow the agent to act in a certain way?

In addition to the view of affordances as external relations, AI researchers also have a tendency to refer to affordances as internal mental representations (e.g. Vera & Simon 1993). This is where discussions between the two fields can become contentious. From this viewpoint, the key question is not whether or not an affordance exists in the environment, but the mechanism by which it is perceived by the agent. A physical affordance consists of a property or set of properties that can be sensed. From the common AI perspective, these percepts are associated by the agent with a particular course of action, possibly mediated by the agent's current state (e.g. its set of goals). Thus, AI researchers often refer to affordances as being the relation between the identification of a physical property and the associated response. Ecological psychologists, however, may object to the use of the word "affordance" to describe such internal representations, which were rejected by Gibson (e.g. Chemero & Turvey 2007, responding

[28] In addition, there are other usages of the term "affordance" in the areas of human factors and human computer interaction (Norman 1988, 1999), which differ significantly from the usage in both ecological psychology and AI, reflecting the priorities of practitioners in these fields.

to Şahin et al. 2007). We note that this viewpoint does not necessarily conflict with the view of affordances as physical relations; rather, it is an additional application of the term "affordance," where perhaps another choice of word might be less contentious.

3.3. The role of direct perception

The issue of the perception of affordances leads to another, closely related, point of controversy, the role of direct perception. Chemero and Turvey (2007) refer to affordances and direct perception as the two components that define the ecological approach.

In direct perception, affordances are perceived via "invariants" picked up directly from the optic array. Proponents of direct perception argue that there is no need for internal mental representations to mediate the process of perception. Thus, examples from AI that refer to affordances as internal representations (as above), by being incompatible with notions of direct perception, can be contentious.

A frequently cited example of direct perception is the use of optic flow for navigation. Indeed, there is strong evidence to suggest that biological organisms make use of optic flow (e.g. Srinivasan & Zhang, 2004). Additionally, there have been successful applications of optic flow to the design of artificial agents (e.g. Duchon et al. 1998).

There is, however, a significant case made in the literature that direct perception is an oversimplification of the issue. For example, Marr (1982), while praising Gibson's overall approach, argues that there are two main shortcomings to Gibson's focus on the direct perception of invariants. First, that contrary to Gibson's assertions, the detection of physical invariants *is* an information-processing problem, and second, that Gibson significantly underestimated the difficulty of such detection (Marr 1982: 29-30).

Ullman (1980) provides a lengthy critique of the theory underlying direct perception from a cognitive science perspective, arguing that the processes Gibson considers to be direct can instead be further decomposed into simpler perceptual processes, and concluding that direct explanations should be considered a "last resort." Gyr (1972) summarizes a number of empirical studies that cast doubt on direct perception's claims, emphasizing that the state of the agent plays a key role in perception, by determining what part of the optic array is relevant at a given moment and how it will be interpreted. Fodor and Pylyshyn (1981) argue that the properties available in the optic array that could potentially be directly picked up are insufficient on their own to fully explain perception without mediation by memory, inference, or some other psychological processes depending on representations. The conclusion drawn from sources such as these is that the act of perception is highly dependent upon internal mental states, representations, and computations.

This does not mean that we should abandon the goal of simplifying agent design by attempting to *minimize* the need for complex representations, but suggests that attempts to *eliminate* them entirely are unlikely to succeed. Certainly, from a practical perspective, there seems to be no obvious way to implement more complex behaviors (e.g. tool use) that does not involve some sort of representation.

It is also important to note that our goal as AI researchers is often to reproduce *behavior*, which may or may not emphasize detailed modeling of the underlying mechanisms utilized by biological systems. That is, even if biological organisms employ a form of direct perception, it may not be practical or even desirable for artificial agents to duplicate those mechanisms (consider that the underlying "hardware" differs enormously between the neurons in a biological brain and the transistors on a microchip). Ease of implementation, speed of execution, and the final performance of the system must all be considered when deciding what models to apply to the design of an artificial agent. Thus, the fidelity of the model used will depend on several factors, including how well the biological mechanisms are understood, how easily they can be replicated with the available hardware and software, and the specific goals of the research.

Nevertheless, direct perception does remain a key element of the ecological psychology perspective. Thus, the issue of direct perception may be the single most contentious point in discussions between the two fields. For example, Chemero and Turvey (2007) assert in their response to Şahin et al. (2007) that despite debates about the nature of affordances, ecological psychologists all "insist on understanding affordances so that the other main component of Gibsonian ecological psychology [direct perception] is respected" (Chemero & Turvey 2007: 474). Michaels and Carello (1981) also seem to reject any reconciliation between direct and computational/representational approaches. Indeed, at times, the ecological psychology literature can appear almost hostile to any approach that questions the role of direct perception.

4. Conclusion

In principle, an ecological approach frees agents from the need to maintain complex representations of the world. The agent can instead interact with the world as it is, allowing for more flexible and timelier responses in a dynamic environment, with the agent able learn to the affordances of its surroundings through first-hand exploration.

A significant body of research now exists in which ecological and affordance-based approaches have been successfully applied to solve problems faced by robotic agents. While psychologists and AI researchers may not always agree on the details of the implementations, they share the goal of better understanding agent-environment systems.

Even so, there remain significant differences that we would like to see addressed. In particular, if the issue of direct perception cannot be resolved, we believe that it may be necessary to abandon attempts to reconcile strictly Gibsonian approaches with much of the current work in AI and robotics, which depends on internal representations. In such a case, either affordances would have to be defined so narrowly as to only permit behaviors that can be based on very simple mechanisms, such as optic flow, or defined so generally as to provide little practical guidance to researchers. Despite such issues, however, we remain hopeful that the ecological approach will continue to inform the design of artificial agents, and that increased dialog between psychologists and AI engineers may contribute to progress in both fields.

We are encouraged by the appearance of an increased interest in affordance-based robotics in the recent years. Further, many of the agents being developed are moving beyond the issues of basic navigation and obstacle avoidance, with ecological approaches being applied to the design of robots capable of modifying the environment with which they interact. We anticipate that the use of affordance-based design will continue to grow alongside the development of robotic agents capable of increasingly more complex behaviors.

References

Agre, P.E. & Chapman, D. 1987. Pengi: Implementation of a Theory of Activity. *Artificial Intelligence*.

Arkin, R.C. 1990. The Impact of Cybernetics on the Design of a Mobile Robot System: A Case Study. *IEEE Transactions on Systems, Man and Cybernetics*, 20 (6).

Atil, I., Dag, N., Kalkan, S., & Sahin, E. 2010. Affordances and emergence of concepts. *Proceedings of the Tenth International Conference on Epigenetic Robotics*: 11–18.

Bacchus, F., Halpern, J.Y. & Levesque, H.J. 1999. Reasoning about noisy sensors and effectors in the situation calculus. *Artificial Intelligence*, 111 (1): 171–208.

Ballard, D.H. 1991. Animate vision. *Artificial Intelligence*, 48 (1): 57–86.

Brooks, R.A. 1997. From earwigs to humans. *Robotics and Autonomous Systems*, 20: 291–304.

Brooks, R.A. & Stein, L.A. 1994. Building brains for bodies. *Autonomous Robots*.

Brooks, R.A. 1990. Elephants don't play chess. *Robotics and Autonomous Systems*, 6 (1-2): 3–15.

Brooks, R.A. 1986. A robust layered control system for a mobile robot. *Robotics and Automation*, 2 (1): 14–23.

Çakmak, M., Dogar, M., Ugur, E., & Sahin, E. 2007. Affordances as a framework for robot control. *Proceedings of The 7th International Conference on Epigenetic Robotics*.

Chapman, D. 1991. *Vision, instruction, and action*. Cambridge, MA, USA: MIT Press.

Chemero, A. & Turvey, M. 2007. Gibsonian Affordances for Roboticists. *Adaptive Behavior*, 15 (4): 473.

Chemero, A. 2003. An Outline of a Theory of Affordances. *Ecological Psychology*, 15 (2): 181–195.

Cos-Aguilera, I., Hayes, G., & Canamero, L. 2004. Using a SOFM to learn object affordances. *Proceedings of the 5th Workshop of Physical Agents*.

Cos-Aguilera, I., Canamero, L., & Hayes, G. 2003. Learning object functionalities in the context of behavior selection. *Proceedings of the 3rd Conference Towards Intelligent Mobile Robotics*: 9–14.

Cos-Aguilera, I., Canamero, L., & Hayes, G. M. 2003. Motivation-driven learning of object affordances: First experiments using a simulated khepera robot. *Proceedings of the 9th International Conference in Cognitive Modelling (ICCM'03),* 4.

Dag, N., Atıl, I., Kalkan, S., & Sahin, E. 2010. Learning affordances for categorizing objects and their properties. *International Conference on Pattern Recognition*.

Detry, R., Kraft, D., Kroemer, O., Bodenhagen, L., Peters, J., Krüger, N., & Piater, J. 2011. Learning grasp affordance densities. *Paladyn. Journal of Behavioral Robotics*, *2*(1): 1–17.

Detry, R., Başeski, E., Popović, M., Touati, Y., Krüger, N., Kroemer, O., Peters, J. & Piater, J. 2010. Learning continuous grasp affordances by sensorimotor exploration. *From Motor Learning to Interaction Learning in Robots*: 451–465.

Detry, R., Başeski, E., Popović, M., Touati, Y., Krüger, N., Kroemer, O., Peters, J. & Piater, J. 2009. Learning object-specific grasp affordance densities. *IEEE 8th International Conference on Development and Learning:* 1–7.

Duchon, A., Kaelbling, L. & Warren, W. 1998. Ecological robotics. *Adaptive Behavior*, 6 (3-4): 473–507.

Erdemir, E., Frankel, C. B., Kawamura, K., Gordon, S. M., Thornton, S., & Ulutas, B. 2008. Towards a cognitive robot that uses internal rehearsal to learn affordance relations. *Intelligent Robots and Systems*: 2016–2021.

Erdemir, E., Frankel, C. B., Thornton, S., Ulutas, B., & Kawamura, K. 2008. A robot rehearses internally and learns an affordance relation. *7th IEEE International Conference on Development and Learning:* 298–303.

Fikes, R.E., Hart, P.E. & Nilsson, N.J. 1972. Learning and executing generalized robot plans. *Artificial intelligence*, 3: 251–288.

Fitzpatrick, P., Metta, G., Natale, L., Rao, S., & Sandini, G. 2003. Learning about objects through action-initial steps towards artificial cognition. *IEEE International Conference on Robotics and Automation*, 3: 3140-3145.

Fodor, J. & Pylyshyn, Z. 1981. How direct is visual perception? Some reflections on Gibson's ecological approach. *Cognition, 9(2)*: 139-196.

Fritz, G., Paletta, L., Breithaupt, R., Rome, E., & Dorffner, G. 2006. Learning predictive features in affordance based robotic perception systems. *IEEE/RSJ International Conference on Intelligent Robots and Systems*.

Fritz, G., Paletta, L., Kumar, M., Dorffner, G., Breithaupt, R., & Rome, E. 2006. Visual learning of affordance based cues. *From Animals to Animats 9*: 52-64.

Gat, E. 1998. On three-layer architectures. *Artificial intelligence and mobile robots: case studies of successful robot systems*: 195–210.

Gibson, J.J. 1979. *The Ecological Approach to Visual Perception*. Houghton Mifflin.

Gibson, J.J. 1966. *The Senses Considered as Perceptual Systems*. Boston, MA: Houghton Mifflin.

Gould, S. et al. 2007. Peripheral-foveal vision for real-time object recognition and tracking in video. *Proceedings of the Twentieth International Joint Conference on Artificial Intelligence (IJCAI-07)*.

Griffith, S., Sukhoy, V., Wegter, T., and Stoytchev, A. 2012. Object Categorization in the Sink: Learning Behavior–Grounded Object Categories with Water. Proceedings of the 2012 ICRA Workshop on Semantic Perception, Mapping and Exploration.

Griffith, S., Sinapov, J., Sukhoy, V., & Stoytchev, A. 2012. A Behavior-Grounded Approach to Forming Object Categories: Separating Containers From Noncontainers. *IEEE Transactions on Autonomous Mental Development*, *4*(1): 54-69.

Guerin, F., Kruger, N., Kraft, D. 2012. A Survey of the Ontogeny of Tool Use: from Sensorimotor Experience to Planning. *IEEE Transactions on Autonomous Mental Development*.

Gyr, J. 1972. Is a theory of direct visual perception adequate? *Psychological Bulletin*, 77 (4): 246–61.

Heft, H. 2003. Affordances, Dynamic Experience, and the Challenge of Reification. *Ecological Psychology*, 15 (2): 149–180.

Horton, T. 2011. A partial contour similarity-based approach to visual affordances in habile agents. Ph.D. thesis, North Carolina State University.

Horton, T., Williams, L., Mu, W. & St. Amant, R. 2008. Visual affordances and symmetries in canis habilis: A progress report. *AAAI Fall Symposium Technical Report*.

Jacquet, P. O., Chambon, V., Borghi, A. M., & Tessari, A. 2012. Object Affordances Tune Observers' Prior Expectations about Tool-Use Behaviors. *PloS one*, *7*(6): e39629.

Jain, R., & Inamura, T. 2011. Learning of Tool Affordances for autonomous tool manipulation. *IEEE/SICE International Symposium on System Integration*: 814-819.

Jones, K. 2003. What Is an Affordance? *Ecological Psychology*, 15 (2): 107–114.

Kemp, C. C., & Edsinger, A. 2006. Robot manipulation of human tools: Autonomous detection and control of task relevant features. *Proceedings of the Fifth International Conference on Development and Learning*.

Kirlik, A. 2004. On Stoffregen's Definition of Affordances. *Ecological Psychology*, 16 (1): 73–77.

Kraft, D., Detry, R., Pugeault, N., Başeski, E., Piater, J., & Krüger, N. 2009. Learning objects and grasp affordances through autonomous exploration.*Computer Vision Systems*: 235-244.

Kuniyoshi, Y., Kita, N., Suehiro, T. & Rougeaux, S. 1996. Active stereo vision system with foveated wide angle lenses. *Recent developments in computer vision*, 191–200.

Marr, D. 1982. *Vision: A Computational Investigation into the Human Representation and Processing of Visual Information*. New York, NY, USA: Henry Holt and Co., Inc.

Matarić, M.J. 2002. Situated Robotics. Ed. L. Nadel. *Encyclopedia of Cognitive Science*: Nature Publishing Group.

Matarić, M.J. 1997. Behavior-Based Control: Examples from Navigation, Learning and Group Behavior. *Journal of Experimental and Theoretical Artificial Intelligence*, 9 (2-3): 323–336.

Matarić, M.J. 1994. Interaction and Intelligent Behavior. Ph.D. thesis, Massachusetts Institute of Technology.

Maes, P. (Ed.). 1991. *Designing autonomous agents: Theory and practice from biology to engineering and back*. MIT press.

Michaels, C. 2003. Affordances: Four Points of Debate. *Ecological Psychology*, 15 (2): 135–148.

Michaels, C. & Carello, C. 1981. *Direct perception*. Englewood Cliffs, NJ: Prentice-Hall.

Murphy, R.R. 1999. Case Studies of Applying Gibson's Ecological Approach to Mobile Robots. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, 29 (1): 105–111.

Newell, A. & Simon, H. 1963. GPS: A program that simulates human thought. Feigenbaum & Feldman, eds. *Computers and Thought*. New York: McGraw-Hill.

Norman, D. 1999. Affordance, conventions, and design. *Interactions*, 6 (3): 38–41.

Norman, D. 1988. *The psychology of everyday things*. New York: Basic Books.

Rome, E., Paletta, L., Şahin, E., Dorffner, G., Hertzberg, J., Breithaupt, R., Fritz, G., Irran, J., Kintzler, F., Lörken, C., May, S. & Uğur, E. 2008. The MACS project: an approach to affordance-inspired robot control. *Towards affordance-based robot control*: 173-210.

Sacerdoti, E.D. 1974. Planning in a hierarchy of abstraction spaces. *Artificial intelligence*, 5 (2): 115–135.

Şahin, E., Çakmak, M., Doğar, M., Uğur, E. & Üçoluk, G. 2007. To Afford or Not to Afford: A New Formalization of Affordances Toward Affordance-Based Robot Control. *Adaptive Behavior*, 15 (4): 447.

Scassellati, B. 1999. A binocular, foveated active vision system. Technical report, DTIC Document.

Sinapov, J., & Stoytchev, A. 2008. Detecting the functional similarities between tools using a hierarchical representation of outcomes. *7th IEEE International Conference on Development and Learning, 2008:* 91-96.

Sinapov, J., & Stoytchev, A. 2007. Learning and generalization of behavior-grounded tool affordances. *IEEE 6th International Conference on Development and Learning:* 19-24.

Srinivasan, M. & Zhang, S. 2004. Visual motor computations in insects. *Annual Review of Neuroscience*, 27: 679–696.

Stentz, A. 1995. The focussed D* algorithm for real-time replanning. *Proceedings of International Joint Conference on Artificial Intelligence*, 14: 1652–1659.

Stoffregen, T. 2004. Breadth and Limits of the Affordance Concept. *Ecological Psychology*, 16 (1): 79–85.

Stoffregen, T. 2003. Affordances as Properties of the Animal-Environment System. *Ecological Psychology*, 15 (2): 115–134.

Stoytchev, A. 2008. Learning the Affordances of Tools using a Behavior-Grounded Approach. E. Rome et al., eds. *Affordance-Based Robot Control*, Springer Lecture Notes in Artificial Intelligence: 140-158.

Stoytchev, A. 2005. Behavior-grounded representation of tool affordances. *Proceedings of IEEE International Conference on Robotics and Automation*.

Sun, J., Moore, J., Bobick, A. & Rehg, J. 2010. Learning visual object categories for robot affordance prediction. *The International Journal of Robotics Research*, 29 (2-3): 174–197.

Ugur, E., Oztop, E., & Sahin, E. 2011. Goal emulation and planning in perceptual space using learned affordances. *Robotics and Autonomous Systems*, *59*(7), 580-595.

Ugur, E. & Şahin, E. 2010. Traversability: A case study for learning and perceiving affordances in robots. *Adaptive Behavior*, 18 (3-4): 258–284.

Ugur, E., Şahin, E. & Oztop, E. 2009. Predicting future object states using learned affordances. In *Computer and Information Sciences, 2009. ISCIS 2009. 24th International Symposium on*, 415–419. IEEE.

Ullman, S. 1980. Against direct perception. *Behavioral and Brain Sciences*, 3 (373-415): 200.

Vera, A. & Simon, H. 1993. Situated action: A symbolic interpretation. *Cognitive Science*, 17 (1): 7–48.

Wood, A., Horton, T. & St. Amant, R. 2005. Effective tool use in a habile agent. *Systems and Information Engineering Design Symposium*, 2005 IEEE, 75–81.

Yürüten, O., Uyanık, K., Çalışkan, Y., Bozcuoğlu, A., Şahin, E., & Kalkan, S. 2012. Learning Adjectives and Nouns from Affordances on the iCub Humanoid Robot. *From Animals to Animats 12*: 330-340.

Zilberstein, S. & Russell, S.J. 1993. Anytime sensing, planning and action: A practical model for robot control. In *Proceedings of International Joint Conference on Artificial Intelligence*, 13: 1402–1402.