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Affordances in AI

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Abstract
Affordances in AI refer to a design methodology for creating artificial intelligence systems that are designed to perceive their environment in terms of its affordances (Sahin et al. 2007). Affordances in AI are adapted from affordances introduced in The Ecological Approach to Visual Perception by James J. Gibson (1979). Design methodologies in the applied sciences use affordances to represent potential actions that exist as a relationship between an agent and its environment. This approach to artificial intelligence is designed for autonomous agents, making it suitable for robotics and simulation.

AFFORDANCES IN AI

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Synonyms

Affordance Based Agents, Affordance Based Design

Definition

Affordances in AI refer to a design methodology for creating artificial intelligence systems that are designed to perceive their environment in terms of its affordances (Sahin et al. 2007). Affordances in AI are adapted from affordances introduced in *The Ecological Approach to Visual Perception* by James J. Gibson (1979). Design methodologies in the applied sciences use affordances to represent potential actions that exist as a relationship between an agent and its environment. This approach to artificial intelligence is designed for autonomous agents, making it suitable for robotics and simulation.

Theoretical Background

Affordances are a concept rooted in the field of perceptual psychology, as part of Gibson's seminal work on ecological perception (J. Gibson 1979). An affordance is an action possibility formed by the relationship between an agent and its environment. For example, the affordance of "throwing" exists when the grasping and pushing capabilities of an agent are well matched to the size and weight of an object. This capacity for throwing is not a property of either the agent or the object but is instead a relationship between them. This relationship-oriented view of the potential for action has a growing following in the applied sciences, as it presents advantages for functionality and design over traditional AI techniques.

The first major usage of affordances within the applied sciences was in the human-computer interaction community as a result of the Norman (1988) book, *The Psychology of Everyday Things*. Design techniques emerged within the interface community, attempting to make the affordances of a user interface obvious to its intended users in the form of a tool indicating its function. The intent was that the look and feel of the application would help communicate information about its affordances. While affordances had made an inroad into the computer science community, Norman's usage of the concept was constrained compared to Gibson's definition and not well suited for artificial intelligence purposes.

Usage of affordances into the artificial intelligence community started with the intent to build better autonomous agents. Traditional AI approaches have had problems dealing with complex, dynamic environments (Maes 1993). There were two primary issues. Firstly, agents designed for one environment tended to be poorly designed for any other environment. This was the result of an agent being the sole focus of knowledge engineering. Since an agent's available actions were designed as intrinsic properties of an agent,

the agent itself would have to be designed around its environment. Affordances provide a pattern to decouple actions and agents by making actions available through affordances.

A second issue with traditional AI in complex and dynamic environments was that traditional approaches were processing information from the environment with little concern as to its ultimate purpose: action. Computer vision approaches exemplify this problem. Even if an agent has perfect segmentation and feature recognition capabilities, this new form of information may be hard to translate into appropriate actions. Simply put, knowing the objective properties of the environment still leaves the agent with the problem of figuring out what to do with that information. In a static environment with little data collection cost, this approach may work quite well. However, if the environment is constantly changing and there is a large amount of information, an agent could waste major resources collecting essentially useless and quickly outdated information without being any more informed about its relevant actions. By focusing agent perception around the detection of affordances, less importance is placed on processing sensory information simply for the sake of a well defined "mental image" of its environment that may have little utility for navigating that environment (J. Gibson 1979). In this way, the affordance-based paradigm can lead designers to a system that reacts quickly and effectively within its environment. This advantage primarily benefits AI developers for embedded applications. While robotics research has been most interested in this aspect, it is also relevant to web-agents such as automated shoppers or web-site interface testers.

As with most design decisions, each advantage comes at a cost. While affordances can be used to make agents reusable across multiple environments, the conditions that determine the existence of an affordance can become increasingly complex as a function of the environment. For example, the affordance "can throw" must be represented more elaborately if mass and an agent's strength are considered. While a more traditional representation allows agents to define their possible actions in their own terms, the affordance paradigm establishes global rules for the availability of an action. This could be a drawback in some systems. Similarly, for a fixed environment where detailed maps of all information are needed to perform an action then affordance-based AI will provide little advantage over traditional systems. For example, if an agent's "actions" consist of segmenting and labeling images then traditional machine vision techniques could be a better fit.

There are a variety of ways of implementing affordances in artificial intelligence, which are based on different mathematical formalizations of the affordance concept. Sahin et al. (2007) gives an overview of the prevalent formalizations. Stoffregen's formalization will be presented as an example formulation in Figure 1, to help explain how affordances are implemented in a computational context (Stoffregen 2003). Figure 1 shows this formulation. In this formulation, W_{pq} is a system including an agent Z_q and part of the environment X_p. p are some traits of the environment and q are properties of the agent, respectively. h represents the potential affordance, which exists due to the relationship between the properties p and q (f represents that it is a relationship between these). Under this formalization, the affordance is said to exist if the system W_{pq} contains the affordance h but neither of the subsystems X_p or Z_q contain this affordance. This formulation ensures that the affordance emerges due to the relationship between agent and environment, rather than a property of either alone.

Figure 1: Stoffregen's Formalization (adapted from Stoffregen, 2003)

$$W_{pq} = (X_p, Z_q)$$
$$h = f(p, q)$$
$$h \in W_{pq}; \qquad h \notin X_p; \qquad h \notin Z_q$$

A common approach to implementing affordances is by defining affordances in terms of relationships between properties of an agent and properties of the environment. In other words, a programmer will define the relationship f in terms of the attributes of the agent (q) and the environment (p). For example, the affordance "can traverse" could exist if the agent had wheels and the ground was rigid and flat. Any combination of agent and landscape that fits the affordance's conditions would be able to take that action. Likewise, the "can traverse" affordance could be enabled for an agent with flippers and a watery environment. It can be readily seen that affordances provide a straightforward way for defining where different actions exist. Especially when allowing for nesting of affordances, affordances defined in terms of other affordances, this can be a powerful tool for abstracting the potential for action.

Affordances can then come full circle and be used for perception, in an artificial intelligence context. The simplest approach is to design an environment where an agent directly perceives affordances. For a person working in modeling and simulation, it is possible to design the affordance relationships in terms of the qualities of the agents and elements of the environment. This allows an agent to directly see the affordances available to them at any given time, if they are allowed to evaluate the existential conditions for the given action. Cognitive architectures such as PMFServ use affordances as fundamental elements of perception that can be observed within the environment (Silverman et al. 2007). For embedded autonomous agents, the situation is more complicated. The environment for an agent can be mapped into properties, emulating the affordance-only perception situation. Alternatively, an agent can be built to learn invariant properties through experience or imitation. These different techniques provide a basis for applied research in AI.

Important Scientific Research and Open Questions

The use of affordances within AI and adaptive agents has been growing over the decade. The increase in usage is evident in the development of new formalizations in order to accommodate new uses. An early formalization by Turvey (1992) presented a first pass at representing affordances. However, efforts to implement affordance-based adaptation did not truly catch on until almost ten years later. Three formalizations were presented by Steedman (2002), Stoffregen (2003), and Chemero (2003) in close succession. Additional representations have been developed since then, including Chemero and Turvey (2007) and Sahin et al. (2007). These formalizations suit different needs. The Steedman version, for example, is built for planning and computational logic. The Stoffregen and Chemero formalizations focus on issues of perception and existence rather than inference. Research developing formal representations helps drive the use of affordances in AI at the theoretical level.

Figure 2: Cog, A Robot Used to Learn Affordances. Source: Fitzpatrick and Metta, p. 2175 (2003)

Begin   *Find end-effector*   *Sweep*   *Contact!*   *Withdraw*
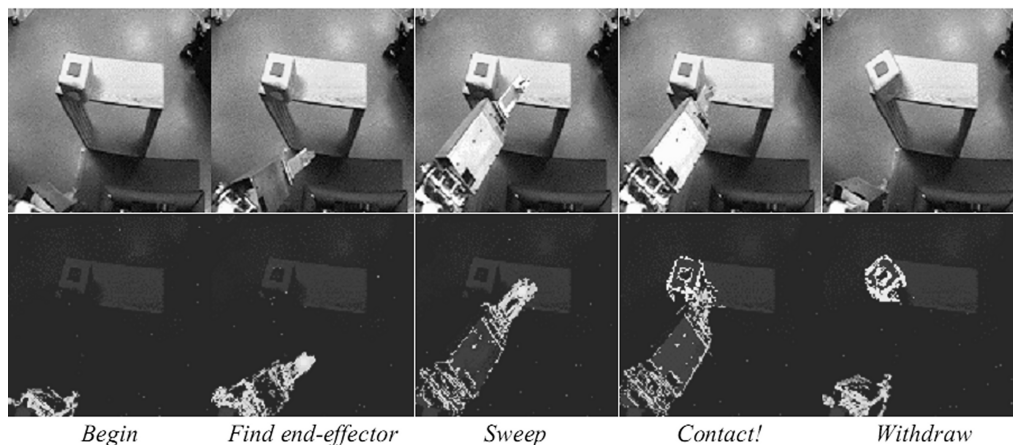
The formalizations of affordances enable applied uses of affordances. Robotics research currently uses affordances to help deal with the problem of autonomous robots in complex environments. One research topic is to have a situated agent learn about actions in its environment. This approach is based on the theoretical work by J. J. Gibson (1979) and also the later work on learning of affordances by Eleanor Gibson (Gibson & Pick 2000). One implementation of this is to have a goal-directed agent which gets feedback from outcomes in its environment through unsupervised or supervised learning, a design similar to empirical affordance learning research done with children. A common paradigm is that a stationary robot has certain available movements for interacting with objects within its environment such as Cog, shown in Figure 2 (Fitzpatrick and Metta 2003). The robot will be presented with different objects and allowed to manipulate the objects to learn invariant properties that help infer if an affordance is present. Research also has demonstrated the ability of robots to learn affordances from other robots, enabling basic imitation and social learning (Montesano et al. 2008).

Affordances have also gained a foothold in the agent based modeling and design community. Software-based agents are also autonomous, but they are embodied within a stylized environment, application, or even the internet. Affordance-based design has been applied to web agents, such as would be used within a semantic web. Economic applications, such as a comparative shopping or price bidding, are one of the goals of such research. Agents in virtual environments, such as games, can also be based on affordances in order to assist agent navigation or context-based adaptation.

Figure 3: PMFServ Affordance-Based Agent Applications

CountrySim Country Stability Simulation   Non-Kin Village Simulation
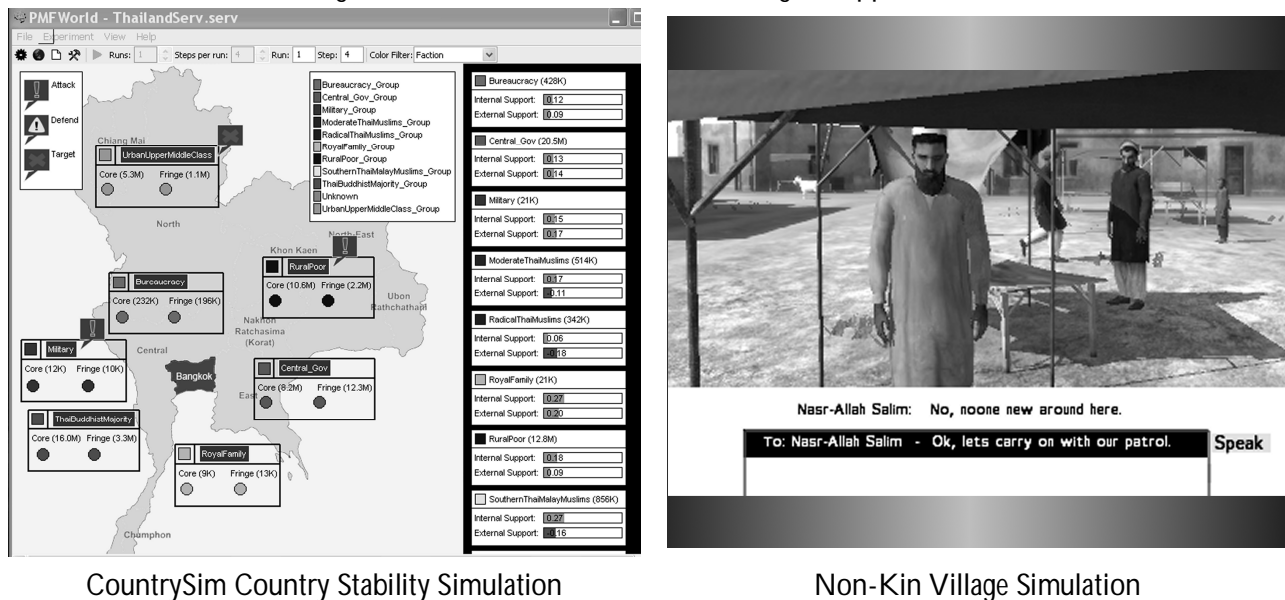
Agent based simulation has been using affordances to help build cognitive agents for some time. Affordance theory provides a plausible cognitive process for perception in humans, the ecological theory of perception. This makes affordance theory a desirable choice for cognitive modelers seeking a biologically plausible model for perception. PMFServ, a project started in 1998, is a cognitive architecture built up from descriptive models of cognition from the social sciences and an early adopter of affordance-based perception (Silverman et al. 2007). Affordance theory allows PMFServ agents' cognitive models to perceive actions within the environment, rather than endowing agents with a particular set of actions. This paradigm allows agents to learn and adapt to new contexts and also facilitates reuse of agents, actions, and environments. Simulations using PMFServ agents, shown in Figure 3, have modeled country stability, insurgent cells, and even an Iraqi

village known as the Non-Kinetic Village, upon which a cultural training game runs. These agents are designed for adaptation, decision-making, and emotional concerns. Alternatively, affordances have also been used by finer-grained agents that simulate spatial problems such as path-finding (Raubal 2001). Each of these areas has significant opportunities for further exploration, as affordance-based AI is still maturing as a field- drawing off of formalizations developed within the last decade.

Cross-References

→ Affordances

→ Artificial Intelligence

→ Cognitive modeling with simulated agents and robots

→ Modeling and Simulation

→ Robot learning

References

Fitzpatrick, P. and Metta, G. (2003). Grounding vision through experimental manipulation. *Phil. Trans. R. Soc. A: Mathematical, Physical and Engineering Sciences.* 2165-2185. The Royal Society.

Gibson, E. J. and Pick, A. D. (2000). *An Ecological Approach to Perceptual Learning and Development.* Oxford University Press, USA.

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

Maes, P. (1993). Behavior-based artificial intelligence. In *Proceedings of the fifteenth annual conference of the Cognitive Science Society.* Institute of Cognitive Science, University of Colorado, Boulder. 74-83. Lawrence Erlbaum.

Montesano, L., Lopes, M., Bernardino, A., & Santos-Victor, J. (2008). Learning Object Affordances: From Sensory Motor Maps to Imitation. *IEEE Transactions on Robotics,* 24(1).

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

Raubal, M. (2001). Ontology and epistemology for agent-based wayfinding simulation. *International Journal of Geographical Information Science.* 15(7), 653-665.

Sahin, E., Çakmak, M., Dogar, M. R., Ugur, E., and Üçoluk, G. (2007). To afford or not to afford: A new formalization of affordances toward affordance-based robot control. *Adaptive Behavior,* 15(4), 447-472. ISAB.

Silverman, B. G., Bharathy, G., Nye, B. D., and Eidelson, R. J. (2007). Modeling factions for "Effects based operations": Part I- Leaders and followers. *Computational & Mathematical Organization Theory,* 13(4), 379-406. Springer.

Stoffregen, T.A. (2003). Affordances as properties of the animal-environment system. *Ecological Psychology,* 15(2), 115-134. Lawrence Earlbaum.

Steedman, M. (2002). Formalizing affordance. In *Proceedings of the 24th Annual Meeting of the Cognitive Science Society.* 834-839.

Turvey, M. T. (1992). Affordances and prospective control: an outline of the ontology. *Ecological Psychology,* 4, 173–187.