A Survey of Tool Use and Analysis of its Implications for the Design of Robotic Tool Users

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The use of tools has long been pointed to as an indicator of intelligent behavior. One of the primary factors that lead homo sapiens from just another species to the position of dominance seen today is their ability to use tools to improve their capabilities(Sterelny 2003). Intelligent adaptation to novel situations is often indicative of intelligence guiding changes in behavior. The use of tools multiplies an organism's ability to adapt. By using tools an organism is no longer limited to just using corporeal resources in adaptation, but can bring in a huge range of external resources as well.

Human beings employ a wide range of tools. Just to clean a bathroom, you would likely use a rag, bucket, sponge, mop, toilet brush, and vacuum cleaner. Could you imagine cleaning the bathroom well without using any tools? The use of tools allows us to accomplish a wide range of tasks and indicates that we are intelligent agents with the wherewithal to understand the appropriate use of a tool. As we stand on the brink of what many have predicted to be nothing less than a fundamental revolution in robotics(Kurzweil 1999, Moravec 2000), it becomes interesting to consider tool use as it relates to robots.

From a strictly utilitarian point of view, it would be nice to have tool using robots. Most people would prefer to have a robot using all those bathroom cleaning tools in place of themselves. It is also interesting to consider tool use as an indicator of intelligence. If we create a robot which can use a range of tools well, the question arises, is that robot intelligent? So we will pursue two primary goals in this paper: to determine if it is possible to create a robot capable of using tools and to consider the question of whether or not such a robot would necessarily be intelligent.

To better understand this problem of creating a robotic tool user, this paper will consider a wide range of animals that make use of tools. The examples of animal tool use will then be used to create an overall taxonomy of tool use. The question of intelligence will then be considered based on the taxonomy. A general introduction to robotic technologies will then be provided followed by a specific analysis of technologies that could be employed to enable robots to use tools.

Ethological instances of tool use

Review of literature has shown that tool use is actually quite widespread within the animal kingdom. Perhaps the best know example is Jane Goodall's famous work with chimpanzee's use of reeds to remove termites(Goodall 1963), yet far from the only example of tool use, this is one of dozens. What actually constitutes tool use is also not entirely straightforward. The most widely accepted definition of tool use comes from Beck:

> Thus tool use is the external employment of an unattached environmental object to alter more efficiently the form, position or condition of another object, another organism, or the user itself when the user holds or carries the tool during or just prior to use and is responsible for the proper and effective orientation of the tool(Beck 1980).

Beyond the question of whether or not a behavior is tool use, lies the question of whether or not an instance of tool use is indicative of intelligence. To better understand tool use and to create a foundation for considering the intelligence inherent in instances of tool use, a survey of tool use throughout the natural world will be helpful. Beck(Beck 1980) in his book Animal Tool Behavior, along with his definition of tool use, provided a survey of animal tool use which is summarized and significantly extended here.

Invertebrates

Ant Lion: Neuropteran flies undergo a larval stage that may last for as long as two years. During this larval stage, they are known as ant lions. The ant lion has been observed constructing a funnel shaped depression in sand. The ant lion then waits in the bottom of the depression to catch and consume prey that fall in. The ant lion has also been observed to throw sand at prey which escapes its initial grasp. It is believed this serves the purpose of causing the escaping prey to fall back into the depression.

Myrmicine Ants: These ants have been observed using small bits of leaf, wood, mud and sand to transport soft foods, such as jelly, honey, fruit pulp, and body fluids of prey. The food is adhered to the tool and then the tool is used to transport the food back to the colony. The use of this type of tool allows the ants to carry ten times the amount of food they could carry in their crop alone.

Sphecine Wasps: The female sphecine wasp will lay her eggs within a hole. The top of this hole is then covered with small pebbles to help protect it. The pebbles are then pounded down to make the hole less conspicuous. The wasps have been observed to hold pebbles within their mandibles and then to use the pebble as a tool to hammer down dirt and other pebbles.

Marine Crab Melia Tessellata: This crab has been observed to remove small anemones from the substrate and then brandish them one in each cheliped(Duerden 1905) . The stinging properties of the anemones allows them to be used as both weapons and tools for the collection of food.

Fish

Toxotid and Anbantid Fish: These South American fish have been observed in the wild and captivity projecting spouts of water into to the air to disable prey and make it fall into the water for capture.

Birds

Bower birds: In Australia and New Guinea, the males of this species will collect all manner of flotsam and assorted colorful debris to decorate their elaborate nests, called bowers. One remarkable instance of this elaborate decoration is some birds which have been observed to use a piece of bark as a paintbrush in nest decoration. They will wet the "brush" with saliva and charcoal and proceed to use it to paint the nest.

American Robin: This bird has been observed using a twig to rummage through leaf little looking for ants(Potter 1970).

Black-breasted Buzzards: Circumstantial evidence has been provided that these birds will use stones to break open emu eggs for consumption.

Egyptian Vultures: Demonstrate similar use of rocks to break open ostrich eggs.

Raven: These birds have been observed in the wild using rocks to defend their nests(Janes 1976). The birds would fly into the air and drop rocks onto a human who was approaching their nest. One scientist reported being targeted by eight golf ball sized rocks in one encounter.

Crow New Caledonian crows have been observed in the wild creating two different types of hooked tools which aid them in capturing prey. This tool manufacture by birds has been observed by Hunt to have a high degree of standardization, distinctly discrete tool types with a deliberate and distinct imposition of form, and the use of hooks (Hunt 1996).

Geospizine Finches: These finches from the Galapagos Islands have been observed using a small twig to aid in the collection of insect prey(Gifford 1919).   The finches will obtain a small and narrow tool such as a twig or cactus spine. They then take this tool in their beaks and use it to probe for insects in narrow crevices. They have also been observed to use the tool to impale and remove insects from deep holes.

Nonprimate Mammals

Rodents

Pocket gopher: The female of the species uses stones and hard chucks of food to dig in the soil during burrow excavation. The tool is held in the forelimbs and aids in the loosening of the soil.

California Ground squirrels: Will throw sand into the face of predators such as gopher snakes and rattlesnakes. The throwing is accomplished by a shoving motion of the forearms.

Elephant Elephants are know for their intelligence and have been observed using a variety of tools. Elephants have been observed using a stick to scratch themselves(Douglas-Hamilton, Douglas-Hamilton 1975). They have also been observed constructing a tool from leafy branches to shoo flies(Hart, Hart 2001).

Dolphin Dolphins have been observed in the wild breaking sea sponges off the ocean floor and then using then to forage for food (Krutzen et al. 2005). This is not believed to instinctual behavior but behavior which is taught from mother to offspring as evidenced by mitochondrial DNA analyses.

Primates

Capuchin Monkeys Capuchin monkeys have been observed in the wild dropping sticks on intruders and using sticks as a weapon in aggressive encounters with conspecifics(Chevalier-Skolnikoff 1990), using environmental objects to open oysters (Fernandes 1991),and using a club to attack a snake(Boinski 1988).

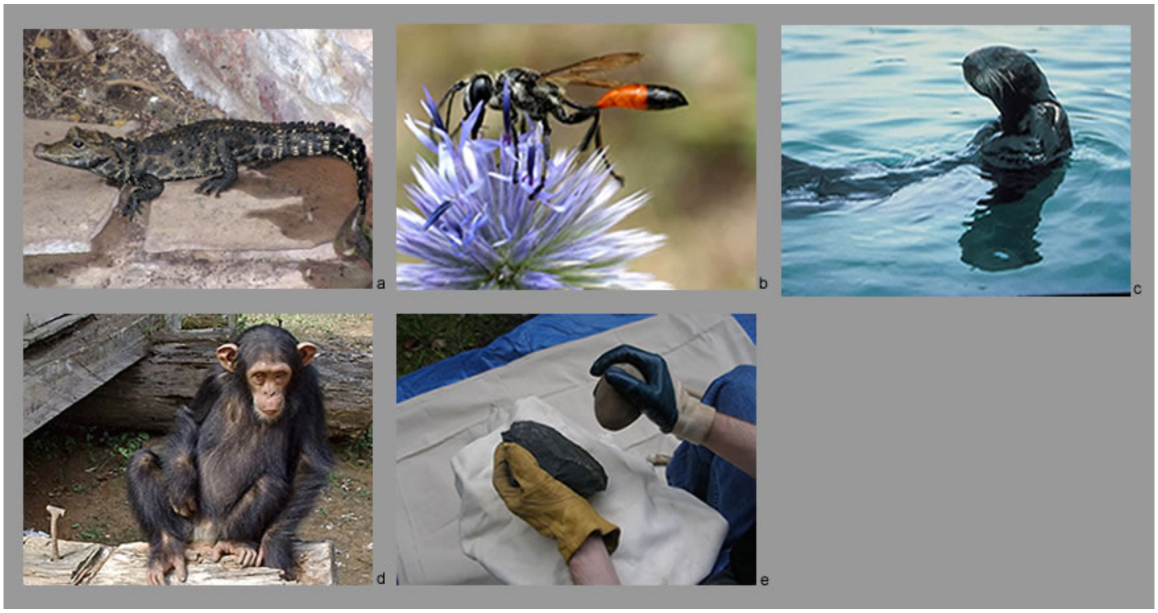
Gibbons Gibbons have been observed dropping sticks on intruders(Tomasello 1997).

Chimpanzee In many ways the chimp is the holy grail of animal tool use. It was Jane Goodall's observation of chimps using narrow stalks to extract termites that exploded the myth that only humans use tools(Goodall 1963). This is surprising because as early as the 1600s there are written accounts by Portuguese explorers of chimps using stones to crack open nuts(Inoue-Nakamura 1997). Regardless of when knowledge of chimpanzee tool use became mainstream, it is not surprising that they come the closest to human-level tool use. Studies have shown chimpanzee and human DNA are 95-98% the same(Britten 2002). The chimpanzee is capable of remarkable feats of tool use. In captivity chimps have been taught to use tools ranging from hammers to complicated machinery(Hayes, Hayes 1951, Savage-Rumbaugh, S McDonald, K Sevcik, R A Hopkins, W D Rubert,E. 1986). Chimpanzees have even been taught in captivity to manufacture stone tools by knapping(Toth 1993).

Taxonomy of tool use

Looking at all these instances of tool use it is possible to draw some interesting conclusions about the nature of tool use. For a long time it was thought that tool use was only possible in highly intelligent beings. Tool use did not appear in hominids until their brains were very highly evolved relative to other animals(Mithen 1996). This lead many to conclude that a very complex cognitive architecture was a prerequisite to tool use. When Goodall first released her paper on chimpanzee use of tools(Goodall 1963) it was thought to have revolutionary implications as to the intelligence levels of chimps. This special status of tool use was quickly squashed as people provided counter-examples to the chimpanzee use of tools which were obviously directed by operant conditioning rather than intelligence(Hall 1963). The resistance to putting an ape on an equal footing with humans was one of the factors that lead to an extensive examination of tool use. This examination proved quite fruitful and, as the previous section shows, there are indeed a wide range of instances of animal tool use.

It is unlikely that all of the instances of tool use presented are representations of highly intelligent behavior. Examination shows the activities of the sphecine wasp and the chimpanzee differ greatly in the intelligence needed to be carried out effectively. To better understand how some instances of tool use may readily be classified as more intelligent than others it is helpful to create an overall taxonomy of tool use.

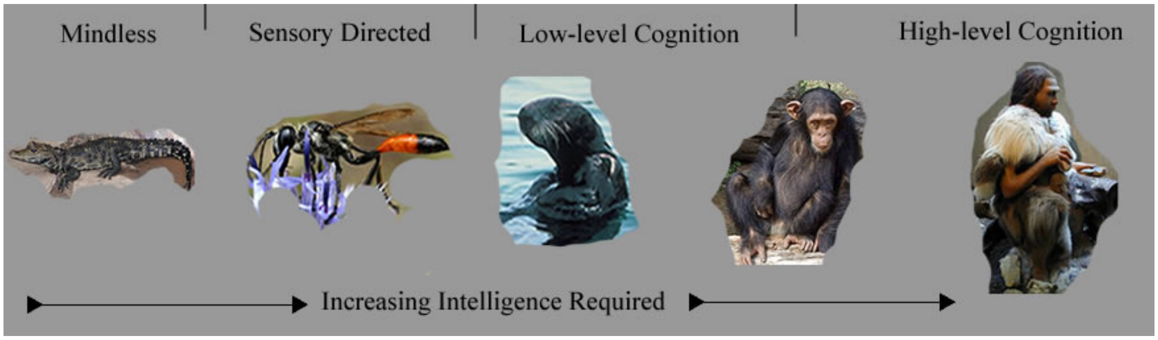


Five animals that use rocks in food processing. a)crocodile b) sphecine wasp c)chimpanzee d)human

Consider the five animals in the above figure, all of whom use stones to augment their capabilities. We see a crocodile which swallows rocks into its stomach (Taylor 1993). These rocks are utilized in the stomach to assist in crushing food. This is not an instance of tool use by Beck's definition, because the stones are not external to, nor oriented by the crocodile. The stones are aiding in the processing of food though and we will include the instance here, not as a good example of tool use, but to demonstrate that something which is considered a tool in other contexts may be effectively employed without knowledge, or comprehension of its use, being a requirement.

The sphecine wasp discussed earlier also uses rocks yet the behavior is far more directed. The wasp obtains a pebble and uses it to tap down dirt covering the nest containing eggs. The sea otter places rocks on its stomach and uses them as a surface against which shells may be broken open. The chimp uses a stone to break open nuts placed on a hard surface. In the final image we see a human knapping a stone tool.

In examining these five instances of the use of a stone, it is possible to place them within the following hierarchy.



At the far left of this continuum we see mindless use of a tool as evidenced by the crocodile. There is no conscious control of the stone. Stones may come and go from the animal's gut, without any awareness or control of their use. We will call this type of tool use, ***Mindless Tool Use***.

The next level of tool use is what we will call ***Sensory Directed Tool Use.*** This type of tool use is exhibited by the wasp. It uses a stone to tamp its burrow. It uses its vision and antennae to direct the application of the pebble onto the burrow, but it is following an instinctual sequence of instructions. The wasp lacks the comprehension that it using the tool towards the goal of protecting it's young. Insect behavior often appears intelligent while not bearing out that appearance on further examination. The lack of comprehension of a task being performed by insects is often demonstrated by the way the their ability to perform a task breaks down with slight intervention. This "apparent stupidity" of insects (Lubbock 1889) results from following a rule set in the absence of higher level comprehension. What is interesting is not that this type of control system eventually breaks down, but rather that it demonstrates such robustness as is seen.

The next level of tool use is ***Tool Use Directed by Low-level Cognition.*** At this level tool use may still be directed by the same real world feedback seen in the sensory directed level, but there is also a cognitive level that transcends it and allows low-level cognition to occur. This low level cognition allows for basic thoughts, such as the presence of goals. The sea otter demonstrates this level of tool use. It is likely that it understands that it is obtaining food through its use of the rock. A low level concept such as a goal which needs to be reached will allow for greater robustness in tool use. Since there is a goal the tool is being applied towards, there is a greater ability to adapt to change than in situations where a simple instruction set is blindly followed.

The forth and final level of tool-use which is seen is ***Tool Use Directed by high-level Cognition***. The best example of this type of tool use is humans' use of tools. At this level of tool use not only are there basic concepts, but there is an understanding of the tools itself as well as well as its substrates, that is deep enough to allow the tool to be used in novel ways. The tool is understood to such an extent that it may be employed differently or even modified to improve its effectiveness.

So we are left with the following taxonomy of tool use:

1 Mindless tool use
2 Sensory directed tool use
3 Tool use directed by low-level cognition
4 Tool use directed by high-level cognition

The level of intelligence is increasing from at each level of the taxonomy as we go from one to four. It is important to go into greater detail about what we mean when we say intelligence. Defining exactly what is meant by intelligent behavior can be difficult. Neisser has stated that "there are no definitive criteria of intelligence, just as there are none for chairness; it is a fuzzy-edged concept to which many features are relevant"(Neisser 1979). Pinker has described intelligence as "the ability to attain goals in the face of obstacles by means of decisions based on rational (truth-obeying) rules"(Pinker 1999).

On a certain level, each of the examples of stone tool use is demonstrative of a certain degree of intelligence. Even though the alligator is mindless in its employ of the stones, using a stone to break apart food is intelligent. The intelligence though is provided by evolution rather than the organism. Animals that had this quirk digested food more completely and therefore were more effective at breeding. Even in the case of the sensory directed tool use it is still very simple stimulus-response cycles directed by instinctual rules. These rules are often intelligent but the intelligence comes again from evolution rather that the organism itself.

When low level cognition comes into play the situation becomes more complicated. I would say that at this point there is the possibility to say that the intelligence is originating from the organism itself. The organism may have a simple goal in mind, such as obtaining food. Something as simple as a basic goal has remarkable power to make behavior more intelligent and adaptive. There is less of a tendency to blindly follow an instruction set that is not achieving results. Knowledge of a goal and then blindly attempting to achieve it can often result in learning effective strategies through trial and error. Success is reinforced and failure is not repeated and gradually through operant conditioning effective behaviors emerge (Skinner 1953).The organism is learning at a certain level yet the intelligence of this is severely limited.

These intelligent behaviors rapidly break down in the face of manipulation. Thorndike proposes that this breakdown is crucial to the apparent intelligence in many animal behaviors. He says of the works touting animal intelligence, "In the first place, most of the books do not give us a psychology, but rather a *eulogy* of animals. They have all been about animal *intelligence* never about animal *stupidity"*(Thorndike 2000). Thorndike's nod to animal stupidity is an important one. The apparent intelligence behaviors of many animals rapidly break down in the face of manipulation of a task. This is due to the fact that the behavior was learned through trial and error learning and not through a deeper understanding of the underlying task.

This deeper understanding is only seen when the tool use is directed by higher-level cognition. Cooper has called high-level cognitive process, "those central cognitive processes involved in thinking, reasoning, planning" which share representational and processing requirements(Cooper 2002). In this type of behavior there is a far deeper understanding of the task being performed. There is an ability to reason and plan as well as understand the nature and properties of the objects being manipulated, allowing for much more robust behavior. In the presence of a deep understanding of a task, it is far less likely that an animal's ability to perform that task will catastrophically fail in the face of manipulation.

To better illustrate this distinction between high and low levels of cognition, it is useful to examine some very interesting experiments done with capuchin monkeys(Visalberghi 1989). In these experiments there is a clear plastic tube securely attached to the floor. Peanuts are placed within this tube so that they are visible to the monkeys but cannot be reached by hand, because the tube is too small for the monkey's hands to fit inside it. To remove the peanut from the tube for consumption, the monkeys must employ a tool. In the most simple case, a long thin stick was provided as the tool. In this situation, the monkeys spontaneously picked up the tool and used it to remove the peanut.

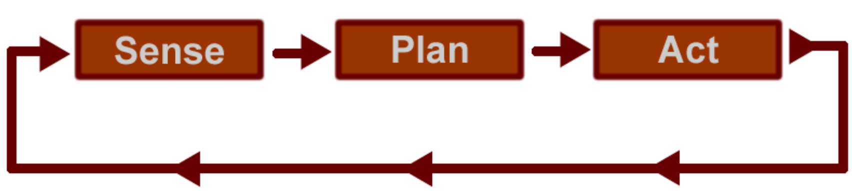
In other situations, a sufficient tool is not provided to the monkeys. Tools which are inappropriate are provided, such as a collection of reeds which have been joined together with a rubber tape. When bundled together, this collection of reed is too thick to be inserted into the tube. It is a simple matter though to remove the tape and then use one of the reeds to obtain the peanut. It was interesting to see that although the monkeys would succeed in this situation, the way in which they did so, demonstrated that they lacked any high level understanding of the task and the tools. The monkeys would first try to use the bundled stack and would eventually break it apart. At this point, one would expect the monkeys to simple use the small reed to remove the peanut. The monkeys were being asked to perform this task after they had successfully used a single reed to remove the peanut earlier. The monkeys did not go straight to a solution though. Some monkeys would have an appropriate single reed in their hands and put it down and pick up the flaccid rubber tape and unsuccessfully try to use that to reach the peanut.

So looking at the last example, the limits of the monkey's cognition are clear. Individuals who had previously solved the problem, lacked the wherewithal to understand the problem. They could not grasp the nature of their previous solution, nor could they understand the nature of the materials well enough to reason that a flaccid piece of tape was a poor choice. What they had was a clear understanding of their goal. They would strive to reach this goal though a fairly undirected search. They would keep trying new strategies without relying on reason to direct the behavior, until one of the strategies worked. Then they would stop. It is clear that it is the goal that is directing this behavior, not higher level cognition. So even though we see the monkeys using these tools, it is clear that they lack a deeper understanding of the nature of the tool and how it works such as that seen in the chimpanzee(Hayes, Hayes 1951, McGrew 1974). In the chimpanzee this kind of blind search where several options to reach a goal are tried, is not seen. The Chimpanzee will carefully select a reed that has the best properties for removing ants from a mound. It will also modify the tool before first use to further increase its effectiveness.

Survey of Robotics

Just as a hierarchy in the levels of tool use is seen, it is also possible to examine the design of intelligent robotics and see a similar hierarchy in robotic design with interesting parallels. There are three main design paradigms for the design of AI robotics, hierarchical, reactive and hybrid reactive/deliberative. Examining each of these paradigms in turn it is possible to see that interesting parallels exist between tool use and the design of intelligent robotics.

The hierarchical design paradigm dominated robotics from the late 60's through the early 80's when robots based on the reactive paradigm came to prominence. The Hierarchical paradigm is perhaps the most straightforward and intuitive of the three which have dominated robotics in the field's short lifespan.



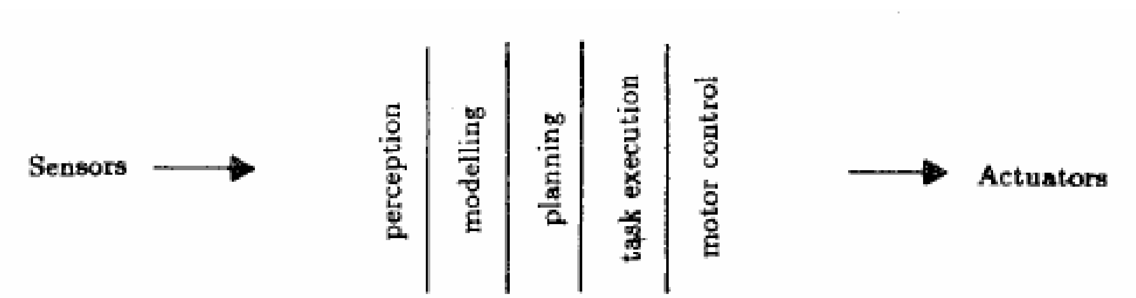
At its most basic level, the paradigm may be broken down into a cycle of sense, plan, act. The robot senses the world around it and gathers all the information relevant to planning the actions it will take. It then processes all relevant data in the planning stage of action. Often the external world will be simulated in some internal model which is examined and used to plan the action to be taken. Once planning is complete the time has come for the robot to act. The robot will then go through all of the actions which have been proscribed in the planning phase.

These phases of activity are discrete and sequential. Each stage follows the others in the order that was described and the stages are completely separate without any overlap. The sensing stage is carried out to completion then the planning stage begins. It is not possible to return to a previous stage once it has been completed. This leads to obvious problems. The world in which we wish to have our robots functioning is a dynamic one; it is not possible to sense the world and create a model of it and then expect that model to remain accurate. The world will undergo its own changes and the actions which the robot takes will also alter the environment as well. In dynamic worlds, completely separating sensing and action can lead to enormous problems with actions designed around a world model that is no longer accurate. Often times sensing is an integral parts of micro adjustments that need to be made to properly execute complicated acts. Imagine trying to thread a needle in a normal manner. Then imagine trying to thread a needle by looking at the needle and thread then closing your eyes and trying to complete the task based on memory alone.

The Hierarchical model, with all of its many limitations, has been implemented in successful robots. The first fully mobile robot, firmly grounded in AI, was Shakey, based on the hierarchical model and created at Stanford in 1967(Nilsson 1984, Wilber 1972). The National Institute of Standards and Technology (NIST) adopted a standard for hierarchically based Real-time Control (RCS) systems(Albus 1995). This standard known by its acronym NIST RCS has served as the basis for many industrial robots(Gazi, Moore & Passino 1998, Moore et al. 1999). The ability of a hierarchical model to accomplish relatively straightforward tasks in a fairly static environment has been demonstrated by these robots ability to accomplish the jobs for which they were designed.

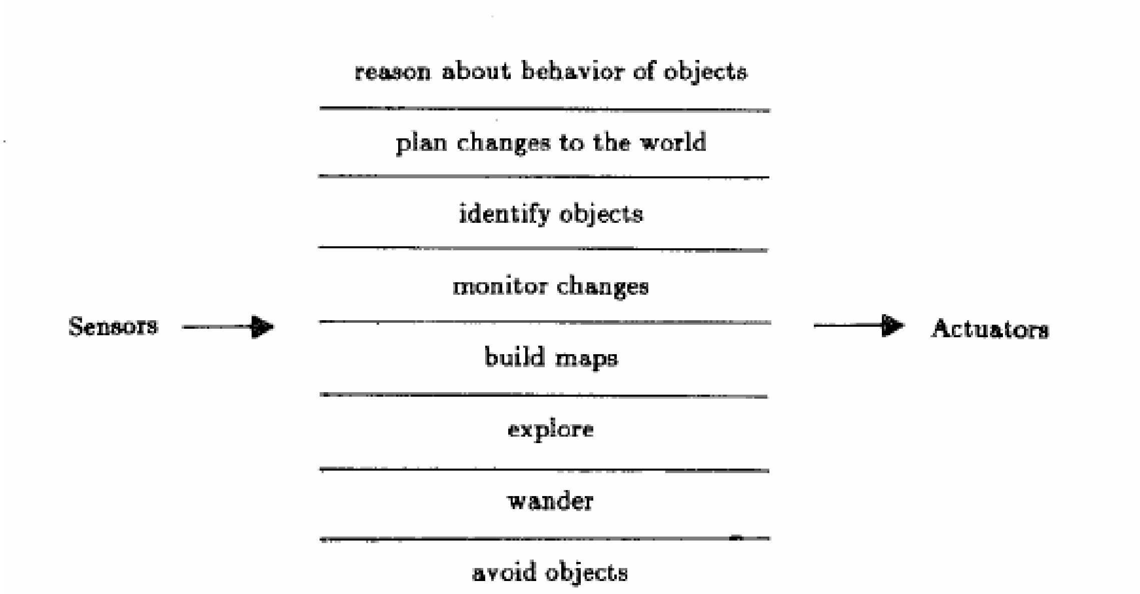
Although robots based on the hierarchical model did succeed at a few simple tasks, they were more notable for they could not accomplish than for what they could. The failure of these machines to accomplish of many seemingly simply tasks stood out in stark contrast when observers looked at the natural world. When in a natural setting, one need only look around to see a wide range of creatures effectively accomplishing all manner of complicated tasks. The earlier section on animal tool use gave many examples of very simple creatures successfully accomplishing complicated tasks. It became more and more clear that effectively modeling the types of behavior seen in nature was going to require an enhancement of the model to be successful.

A great leap forward in robot performance began to be seen in the late 80's as roboticists began to adopt a new paradigm. In a 1986 paper(Brooks 1986), Rodney Brooks first described the philosophies behind his concept of subsumption, a new approach to robot design which would come to be known as one of the most common examples of a reactive paradigm approach to robotics. In the paper Brooks attacked simplistic linear nature of the hierarchical model.



Brooks' image of traditional hierarchical model

If we look at the figure above we see Brooks' take on a traditional hierarchical model. This simple linear progression is not an accurate description of what we see in the real world. Far more accurate is a design that incorporates multiple tracks in parallel as we see in the following figure.



Brooks' new multiply parallel model

The above model, taken from Brooks' paper, is far more similar to what is seen in the real world. There is not one single path to action, but many parallel flows of control that allow for different sets of sensing and planning to occur simultaneously. This is far similar to what is seen in nature where many tasks could be active simultaneously. Imagine an individual walking to an apple tree. On a subconscious level they are doing things such as breathing. At a higher level they are walking towards the tree, navigating and avoiding obstacles, Then at the same time, they are also planning out how they will pick an apple once they reach the tree. This kind of description is far more comfortable than one where the individual stops, looks at the entire environment, then closes their eyes and plans every minute detail of getting the apple, then keeps their eyes closed and tries to pick the apple by following the plan they made, acting entirely from memory. The Reactive Paradigm differs in more ways than simple parallelism. Rather than elaborate internal planning, action in the paradigm is precipitated by behaviors.

A behavior is a direct mapping of a sensory input to a particular action to achieve some task. The plan aspect of the sense, plan, act cycle seen it the hierarchical model is thrown away entirely. The next section will give a detailed account of a formal language which may be used to implement behaviors.

The use of behaviors allows robots to behave intelligently without having to engage in any planning whatsoever. To better understand how this might be possible, consider work done by Micheal Arbib attempting to model frogs and toads(Arbib 1995). On the surface a frog seems to interact quite intelligently with the world around it. Obtaining food and avoiding predators. Arbib found that by creating a simple robot with two simple behaviors, much of frog behavior could be modeled. The first behavior is when a small object is seen, go towards it and grab it. This behavior would direct the frog in the use of its tongue to catch insects to eat. The second behavior is that if a large object is seen in motion, run away from it. This allows the frog to avoid predation. These are two extremely simple behaviors, but it is possible to imagine that just through these two behaviors a simple world could be effectively navigated, avoiding predation and obtaining food.

The adoption of reactive architecture lead to a mini revolution in the robotics field in the 1980's. Even with the limited processing power available at the time, robotics took a great leap forward in terms of their capabilities. The slow and awkward movements of Shakey, characterized more by long periods sitting still and planning than by motion(Wilber 1972), were replaced by exciting reactive robots that explored and interacted with the environment in real-time(Brooks, Flynn 1989, Morris 1997).

There are two main methods of design seen in reactive robots, subsumption and Potential Field Methodology. In subsumption a complex behavior is decomposed into many far simpler layers of more basic behaviors. To revisit the previous example of obtaining an apple from the tree, a higher level behavior of **get apple** would be built from lower level behaviors such as **go to apple** and **pick apple**. **Go to apple** could be further broken down into **travel towards apple** and avoid **collisions**. This process can continue to the most basic level with each behavior being said to subsume all of its constituent behaviors. In addition subsumtion, another method which has shown success is Potential Field

Methodology, where vectors are used to represent behaviors and vector summations are then employed to combine different behaviors and produce emergent behaviors. A much more detailed example of the implementation of the potential field methodology will be seen in the next section.

What makes the so called leap forward in robotics which was seen in the eighties so very intriguing is that in many ways it was in fact a leap backwards. To illustrate why, consider again the four types of tool use.

1 Mindless tool use
2 Sensory directed tool use
3 Tool use directed by low-level cognition
4 Tool use directed by high-level cognition

In terms of evolutionary development earth has seen these types of tool use emerge in the order they were presented. In fact the high level cognition is a very "recent" development as Brooks has pointed out:

> It is instructive to reflect on the way in which earth-based biological evolution spent its time. Single-cell entities arose out of the primordial soup roughly 3.5 billion years ago. A billion years passed before photosynthetic plants appeared. After almost another billion and a half years, around 550 million years ago, the first fish and vertebrates arrived, and then insects 450 million years ago. Then things started moving fast. Reptiles arrived 370 million years ago, followed by dinosaurs at 330 and mammals at 250 million years ago. The first primates appeared 120 million years ago and the immediate predecessors to the great apes a mere 18 million years ago. Man arrived in roughly his present form 2.5 million years ago. He invented agriculture a mere 19,000 years ago, writing less than 5000 years ago and "expert" knowledge only over the last few hundred years(Brooks 1991).

The decision to try to start with the highest level seen is any many ways a natural one. It made sense for robotics to try to mimic human level intelligence because that is the highest form of intelligent behavior which is seen in our world. This top-down approach was unrealistic in many ways and the immediate success seen from pursuing robotics based on the reactive paradigm bears this out.

Starting with a system that is in many ways an evolutionary precursor to what one hopes to eventually achieve makes sense logically. To return to our hierarchy of tool use, the parallels between reactive robotics and sensory directed tool use are strong. They both use sense input to direct behaviors which are based on a simple set of guidelines. They both generate remarkably adaptive and complex behaviors for the simplicity of their design. And finely, they both have profound limitations. To extend beyond simple behaviors, it is necessary to incorporate cognition into the system. This does not mean dropping the lower level paradigms, but rather incorporating them into a higher level overarching structure of cognition. The adaptively and quick reaction times of reactive systems are kept, while goals and situational awareness that can come from deliberation are also incorporated into the system. These new systems are not strictly reactive or hierarchical, but rather hybrids which attempt to incorporate the strengths of both approaches. There are many hybrid robots which have been created. Examples are TCA(Simmons 1994), Autonomous Robot Architecture (AuRA).(Arkin 1997), Sensor Fusion Effects (SFX)(Murphy 1996, Murphy, Arkin 1992), and Saphira(Guzzoni et al. "1997", Konolige 1997).

Implications for a robotic tool using agent

So at this point we have considered a range of instances of tool use and classified those examples within a hierarchical classification based on their inherent intelligence. We went on to consider the main methodologies of robotics. We have identified four levels of tool use:

1 Mindless tool use
2 Sensory directed tool use
3 Tool use directed by low-level cognition
4 Tool use directed by high-level cognition

We have described numerous examples in each category from the literature of animal and human cognition. We will now revisit each category in turn and consider what techniques are needed for a successful implementation in a robot.

Mindless tool use

Description: There is in interesting paradox in this level of robotic tool use. While prima facie it would seem to be the simplest and most severely limited of all the approaches to robotic use of tools, current industrial robotics perform a huge range of amazingly complicated manufacturing tasks with nothing more than mindless instruction sets(Nof 1999). Modern automobiles are made almost entirely by robots and many of our most complicated manufactured products such as microchips would not even be possible without the precision afforded by modern robotics(Van Zant 2004).

It is interesting to note that the behavior of a hypothetical smart robot performing a complicated task could then be replicated by a mindless robot programmed to imitate the behavior of the smart robot so long as the environment is held constant for both robot's task execution. On the surface the robots could appear identical. One would be figuring out its actions while the other is simply following a basic instruction set. The important distinction between these two robots would be the way in which they would respond to change. In our simple imagined scenario the intelligent robot would automatically adapt because it is intelligently directing its behavior in some way. The mindless robot would continue the same, no longer appropriate, instruction set in the face of change. Although the behavior will be unable to adapt to changes, a mindless robot can effectively use any tool, so long as it has been programmed correctly and task substrate remains constant.

Implementation: The mindless robots implementation details are fairly straightforward. There will simply be a set of motor and actuator control instructions which are recorded in some way. This instruction set may then be played back to perform the desired task.

Example of use: We could program a robotic arm to use a metal rod as a lever, say, to lift an object. To do this we would program an arm to grasp a rod, to insert the end of the rod under one of the bottom edges of the object, and to apply force upward so that one side of the object is raised. So long as the force is sufficient and the motion is programmed for a known object, surface position, and related geometrical constraints, which do not change, this should succeed in lifting the object.

Sensory directed Tool Use

Description: The addition of sensor information to a robot will change the dynamics of its operation. The sensors provide access to information about the environment and the actions being performed. This allows for far more adaptable behavior. Rather that needing an object to be in the same place every time an action is performed, a visual sensor can locate the object and direct the action towards that location. The tying of sensor data to a tool use task allows for a far greater degree of flexibility than that seen in mindless tool use. The location of the tool as well as the subject of the tools action do not have to remain in a fixed position. Sensor input can be used to direct performance so the proper location and orientation for task performance are maintained. There is also an enormous advantage in that sensors provide constant feedback. This means that if the robot is directed to do something and it is not accomplished as planned, the sensors can detect this. For example if the robot is directed to travel towards a wall, but does not reach the wall due to wheel slippage, sensors can detect this and direct the robot to continue to travel until the wall is reached.

Implementation:

Once an agent moves beyond pre-programmed mindless behavior, the question of behavior representation arises. Some work in AI can be applied to tool use scenarios, but only at a very abstract level. Some simple behaviors may simply be encoded as If Then rules, in the form:

IF *precondition* **THEN** *effect*

This approach is taken in a planning domain, init-flat-tire, due to Stewart Russell. The domain contains the following operators: cuss, open, close, fetch, put-away, loosen, tighten, jack-up, jack-down, undo, do-up, remove-wheel, put-on-wheel, and inflate. Objects in the domain include wheels, hubs, nuts, and a jack (the tool). The tool-using operators in this domain take the following typical form:

```
(:operator fetch
      :parameters (?x (container ?y))
      :precondition (:and (:neq ?x ?y) (in ?x ?y) (open ?y))
      :effect (:and (have ?x)
               (:not (in ?x ?y))))

(:operator jack-up
      :parameters ((hub ?y))
      :precondition (:and (on-ground ?y) (have jack))
      :effect (:and (:not (on-ground ?y))
               (:not (have jack))))
```

That is, a jack can be retrieved using the fetch operator and applied to the flat tire problem by using the jack-up operator. Any off-the-shelf planning algorithm can be used to sequence these operators appropriately for control. The limitations of such a representation should be obvious. It specifies what to do, but not how to do it; its level of abstraction is far above the sensory and motor level; it casts tool use simply as retrieving and using a labeled object appropriately.

Behavior mapping offers a more detailed approach better suited to sensory directed tool use. This method involves the creation of a functional mapping between sensor input and motor output. It is most commonly applied in robotics to navigation, such as the behavior implicit in the fetch operator above. Arkin has formalized these mappings in a language where all behaviors may be represented with a triple of the form $(\mathbf{S}, \mathbf{R}, \boldsymbol{\beta})$ where **S** denotes the range of all possible stimuli, **R** denotes the range of responses possible and $\boldsymbol{\beta}$ denotes a mapping:

$$\boldsymbol{\beta}:\mathbf{S}\rightarrow\mathbf{R}$$

This overall mapping is further broken down into instantaneous responses $\mathbf{r}$, where $\mathbf{r} \in \mathbf{R}$. Instantaneous responses are represented by vectors of up to six dimensions composed of sub vectors. The following vector would represent a response in a situation where an agent has two degrees of freedom.

$$\mathbf{r} = [\,\mathbf{x}\,,\,\mathbf{y}\,]$$

where

$\mathbf{x}$ represents the x plane

$\mathbf{y}$ represents the y plane

A flat-tire-fixing agent, for example, would represent relevant locations on and around the car in these terms.

Stimuli $\mathbf{S}$ is composed of a set of individual stimuli $\mathbf{s} \in \mathbf{S}$. $\mathbf{s}$ are represented by a binary tuple:

$$\mathbf{s} = (\,\boldsymbol{p}\,,\,\boldsymbol{\lambda}\,)$$

where

$\boldsymbol{p}$ represents perceptual class

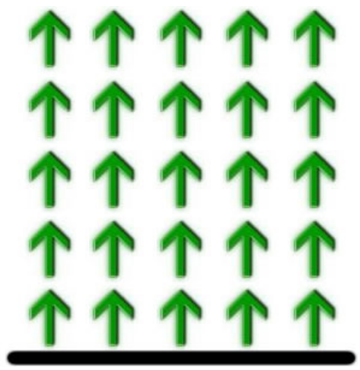
$\boldsymbol{\lambda}$ represents strength or intensity

With the addition of a threshold value $\boldsymbol{\tau}$, it becomes possible to then encode behaviors:

$$\begin{array}{lll} \boldsymbol{\beta}(\mathbf{s}) & \rightarrow & \mathbf{r} \\ \boldsymbol{\beta}(\,\boldsymbol{p}\,,\,\boldsymbol{\lambda}\,) & \rightarrow & \text{for all } \boldsymbol{\lambda} < \boldsymbol{\tau}\ \mathbf{r} = [0,0] \\ & & \text{otherwise } \mathbf{r} = [\,\mathbf{x}\,,\,\mathbf{y}\,] \end{array}$$

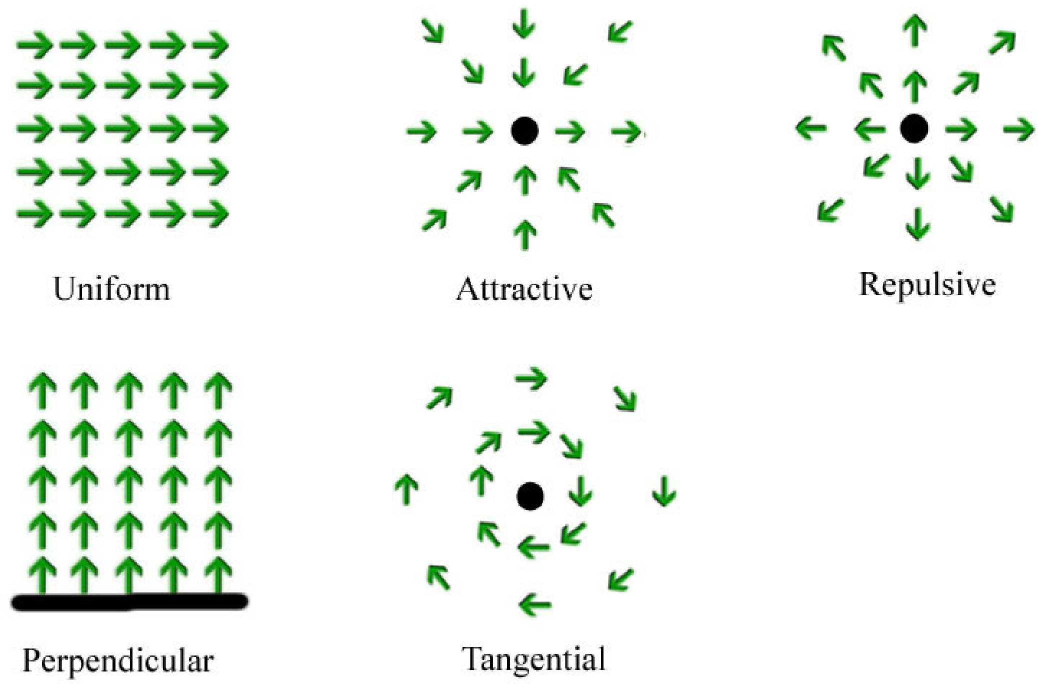
So for each stimulus $\mathbf{s}$ we encode thresholds and appropriate behaviors. While the mapping is far from a perfect match to the planning representation, we can imagine an agent stimulus corresponding, for example, to whether the agent is holding a jack. In the case that the jack is not being held, the behavior map could direct the agent's navigation to the location of the jack; if the jack is being held, the map could direct the agent to the location of the flat tire. This is clearly an artificial and incomplete solution, but it suggests a possible mechanism for dealing with spatial issues relevant to tool use (Kirsh 1995).

Descending to a lower level of detail, potential fields offer a useful approach to addressing other issues in sensory directed tool use. Potential fields use vectors to represent the motion of a robot; as with behavior maps, the most common application is in navigation for mobile robots. The sensor input is processed by the robot and then output as a vector for motion in the robot. The vector indicates both direction and intensity for the motion of the robot. For example in the following image we see a perpendicular field:



This field represents the motion the robot would take at each point. This type of field could be implemented in a robot by equipping it with a sonar sensor to detect walls. To return to our figure imagine that the black line represents a wall and the green arrows represent the motion away from the wall we wish our robot to exhibit. To implement this in a robot, whenever the sensor detects a wall, the software would trigger a vector for motion in the opposite direction. In the potential field methodology, the input from a sensor is correlated into a resultant vector for motion in the robot.

It is important to note that this method exhibits a major advantage over behavior mapping in that it is easy to combine the results of multiple sensors. The vectors resulting from each sensor are simply added together and the final vector summation is what the robot uses to direct motion. In the following image, we see five possible potential fields which could be tied to sensor input to direct behavior in various ways relative to a target.



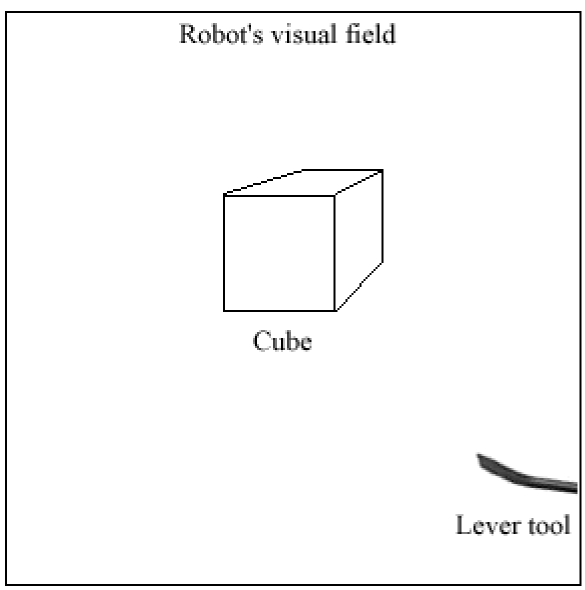
A robot might maintain a library of potential fields from which specific fields could be retrieved, based on sensory input, to guide its behavior in different situations.

Example of use: Consider our previous example of a robot using a very simple tool, a rod to apply leverage in lifting an object. Let us add a level of complication. Suppose we wish to create a robot to lift objects (imagine that someone has placed a $100 bill under one of several objects in a room), but we do not know in advance where the objects are located. The use of behavior mapping and potential field methodology could make such a robot possible. In this example we'll discuss one aspect of tool-using behavior to solve this problem.

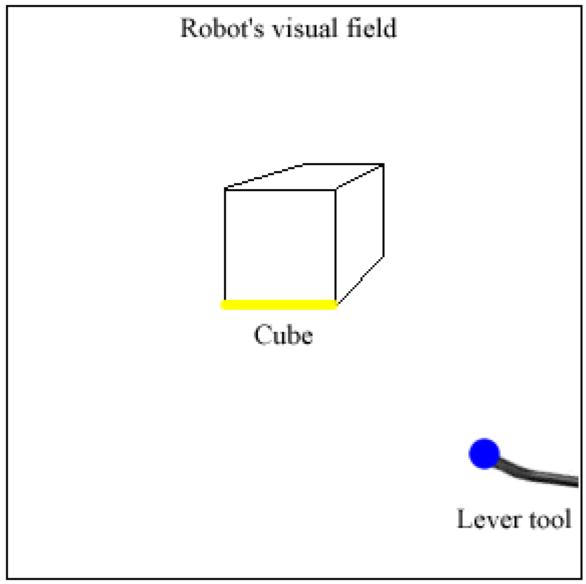
One of the behavioral components of tool use is the ability to identify opportunities for tool use, which have been characterized as "affordances" (Gibson 1987). In this example, an opportunity to use a lever is provided by a detectable edge, ideally a gap, between the bottom of an object and the surface on which it sits. (For example, we would not want a robot to attempt to lift interior building walls with a lever.) The geometrical match between appropriate edges and the end of the lever provides an opportunity for use of the lever. For the remainder of this example, we'll assume that the robot has a sensory system able to identify three-dimensional objects with edges nearly flush with the floor; this would require only the most straightforward application of machine vision techniques.

The robot could begin by surveying the room, its sensory system marking the locations of relevant objects, a lever in its gripper. Alternatively, it might wander through the room, encountering objects opportunistically. For each object so identified, the sensed data about the target object would trigger the application of a potential field that combines an attractive field and a tangential field, both centered on the object. The robot thus navigates closer to the object and circles around it. When the robot's sensors detects a bottom edge on the object (i.e., evaluation of edge detection information rises above a threshold value), the robot has identified an opportunity for use of its lever.

A different potential field is activated that represents a linear attraction perpendicular to the edge, with a motor response specific to the application of the end of the lever. That is, suppose the robot can see the effecter end of the lever as well as the affordance in the target object upon which the lever should act. Let us say the robot has a bottom edge of the target object centered in view, as diagrammed below:

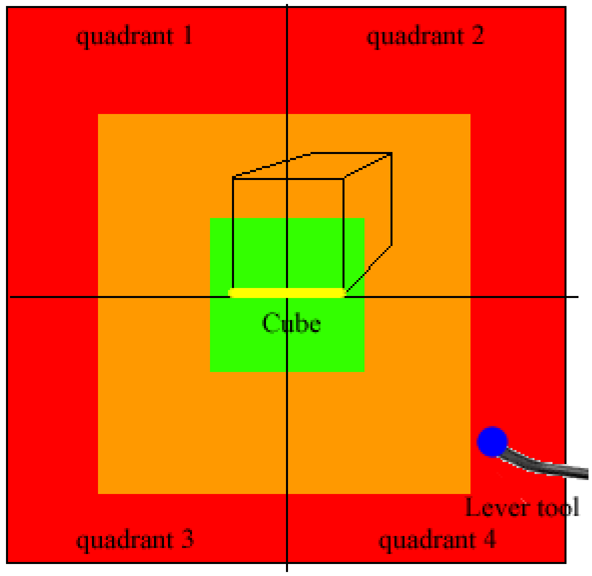


It would be a simple matter for the robot to take this image and process it to control motion with behavior mapping. To do so, image processing would be employed to identify the effecter of the tool and the affordance upon which the tool will act. In the image below the lower edge of the cube is the affordance and has been marked with yellow. The end of the lever is the effecter and has been marked with blue.



Once the affordance and the tool have been identified, it would be possible to use behavior mapping to bring the tool into position, so long as the robots position relative to the affordance being acted on is know. It would be possible for the robot to determine position relative to the cube by sonar, or the size of the cube in the view if the cube is a known size.

With the position of the affordance relative the robot know, it would be possible to use behavior mapping based on where the effecter is in the field of view to bring it into correct position. To illustrate how this might be accomplished consider the following figure:



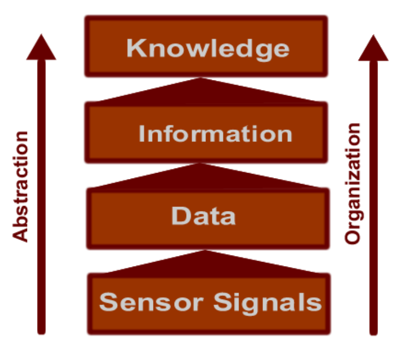
This is the same view as the previous picture, but the image has been divided into four quadrants by the addition of black lines. So long as the affordance is in the center of the quadrants, knowing which quadrant contains our effecter gives information about how to bring effecter and affordance together. In the image above, we see the effecter in quadrant four. Being in quadrant four signifies that our tool needs to move up and to the left. Looking at the figure it can be seen that if our effecter was in quadrant three, an up and right motion would be required, while if it was in quadrant two, a down and left movement would be needed.

In addition to four quadrants, there are three color bands. If the effecter is in the green region, it is close to the affordance, if it is in the orange region, it is at a mid-length distance, and if it is in the red, it is at the maximum distance that the field of view allows. So the intensity of motion would need to be small if the effecter is in the green segment, greater if it is in the orange and greater still if it is in the red. While this is a simple example it is possible to see how the use of this type of segmentation could be used to control direction and intensity of motion to bring an affordance and an effecter into alignment. It a real world implementation, it would be possible to divide the image into much more than four quadrants for more precise direction indications. A greater number of segments could also be used to give much more finely grained movement intensity recommendations.

Further discussion of the mechanics of lever manipulation is beyond the scope of this work, but we have described a plausible approach to solving one important aspect of sensory directed tool use. What is interesting about this example is the match to sensory directed tool use in animals such as the wasp, based on very simple computational mechanisms. Problem-solving capacity is limited—arguably nonexistent—and yet novel scenarios can be handled to a limited extent. As with examples in the animal kingdom, robustness is lacking. Imagine the robot we have described attempting to lift an object that is fastened to the floor; while with additional "rules" it could easily recognize failure, the robot has no ability to reason about why its actions are not successful.

Sensory directed tool use to tool use directed by low-level cognition

Description: The addition of low level cognition will further augment robotic tool using abilities. Low level cognition allows sensor data to be transformed to knowledge. For example again consider a robot designed to lift objects. A strictly sensory directed robot would simply gravitate towards an object driven by a basic conditional rule or potential field. The addition of some cognition allows this same data to be abstracted to the level of "This is where the object is, I want to go there." The addition of cognition will also allow for overall goals to be known and pursued. Knowledge of a goal allows for far more intelligent actions. The ability to have a goal greatly increases a tool using robot's ability to flexibly respond to change. The robot can make basic plans and then apply them until the goal is reached.



Implementation:

1) **Knowledge representation** Goals, tool affordances etc. must all be stored in some manner which is meaningful to the robot.

2) **AI planning algorithms** The robot will need the ability to formulate plans to try and reach its goal state.
3) **Behavior memory** If the robot is unsuccessful with a strategy, behavior memory will keep it from being repeated. This will also be helpful in avoiding endlessly looping behaviors.

Sensory directed tool use directed by high-level cognition

Description: With high level cognition, a robot would not just be able to use existing tools, but to actually create and modify new ones. By adding additional levels of understanding, the robot gains the wherewithal to better use tools. With sufficient understanding of a task and the nature of objects and their behaviors, it becomes possible to create novel tools from objects at hand and use existing tools in novel ways

Implementation:

Obviously the goal of achieving human level intelligence in a robot is beyond the scope of this research, but it is possible to incorporate some aspects of higher level cognition into robots. A more reachable goal might be to create a robot that could create a novel tool within a toy world. A few potential methods to help in realizing this goal will be listed with further examination left as a topic for future research.

Things needed for the creation of a novel tool in a toy world:
1) Extensible body schema
2) Understanding of object properties such as hardness, size, modifiability
3) Understanding of physics

Semantic grounding

To better understand the how apparently quite intelligent behavior is not necessarily intelligent, let us examine a thought experiment presented by John Searle. Searle feels that although we are capable of producing machines capable of very complicated calculations, it would be improper to say that they think. For example, in his book Minds, Brains, and Science(Searle 1984), he presents an example which he calls the Chinese room. The Chinese room is a closed room which contains a woman who has no knowledge whatsoever of Chinese. She can only understand English. The woman is fed Chinese symbols written on sheets of paper. She has a book which contains instructions on what symbols are the correct outputs for various symbol inputs. Although the symbols would appear to the woman as nothing more than squiggles, if the instruction book was well written, the woman could appear to respond quite intelligently to written questions presented to her in Chinese.

Searle sees his Chinese room example as analogous to a computer. He says that computers are like the woman in the Chinese room. They are capable of giving the appearance of responding intelligently to inputs but in reality they are simply following an elaborate instruction book, in the form of the program they are running.

Prima facie, there seems to be a lot of validity in what Searle is saying. I think that he is proper in dismissing a wide variety of so called artificial intelligence as not intelligent. The similarity between a computer program and the book in the Chinese room is often a valid one, but not always. There are some computers with outputs which represent more than a pre-programmed response to the input. This can be illustrated with an example.

Imagine two separate computers, both performing the process of adding together the real numbers from one to ten, but doing it in very different manners. One of the computers has a program which is ontologically very similar to the Chinese room instruction book. Every possible combination of two numbers for addition has been written into the program, as well as the product of their addition. So, if the numbers four and five are given to this computer for addition, it will run through its program until it comes to the entry for four plus five. It will them follow the instruction for that entry and output nine, much like the Chinese room. I think that we would all probably agree that we would not want to describe this computer as thinking, even though it will give us correct results, but let us imagine another computer.

This computer also performs the same task of single digit number addition, but it does it in a very different way. When it receives two numbers for addition it does not "look up" the answer like the other computer. It first converts the numbers in binary code. It then starts with the right most digits and moves from right to left combining same place digits with an AND gate, as well as carrying a digit when appropriate. This mechanism will output a third binary number which is the correct product of the addition. After the process is complete this third number is converted into decimal form and provided as the output of the program. This computer provides the same output as the other, but whether or not it thinks is much more problematic.

Searle would dismiss the first computer we mentioned as being incapable of any thought because it lacks any semantic understanding of the numbers it is evaluating. It merely recognizes them and then "looks up" the correct answer. The second computer though does not simply look up the answers, but in fact figures them out, in a very real way. It could also be said that the numbers in the second computer do have a semantic value. They are not just symbols, but eight bit electronic entities that are stable, entities that can be manipulated and combined to yield predictable new eight bit electronic entities. By converting the numbers into something that could be said to have real semantic meaning for the computer (binary code), does the computer gain a semantic understanding of the numbers themselves? Daniel Dennett would say yes.

For Dennett computers are capable of holding semantic meaning for symbolic entities. With the second computer we considered we tried to give the numbers semantic meaning by giving them symbolic grounding in binary code. Dennett has been involved in a project by Rodney Brooks that takes this endeavor to the next level. This project is called COG, and it is an attempt to give a computer the ability to attach semantic meaning to entities more complicated than simple numbers(Dennett 1997, Dennett et al. 1994). COG is not a simple computer program but an entire robot. He has foveal vision, hearing and even touch. COG is being designed not just to run prewritten software, but to in fact to write his own software. COG is being programmed so that he will be able to learn things by receiving input and altering his own programming.

It is hoped that COG is going to be a huge leap in artificial intelligence. In many ways, COG is an attempt to avoid (and answer) the problems brought up by Searle. By giving COG sensations, his creators hope that they are giving semantic meaning to his programs. They will no longer be meaningless symbols, but things grounded in sensations he has experienced, much as our own thoughts are grounded in sensations we have experienced. Just as our own thoughts represent things which we have experienced through sensation, COG's "thoughts" will also represent things he has experienced through his own sensations.

Searle would be wary of this line of reasoning which we have been following. He does not believe that a computer brain running a program such as COG's is capable of any beliefs whatsoever, but I feel he is wrong. To see this let us examine more fully exactly what it is to have a belief that means something. F. Dretske examines this very question in his book, Explaining Behavior(Dretske 1988). Let us now consider some of the arguments presented on beliefs in chapter four of the book.

Dretske presents the following example. Consider sitting in your home and becoming thirsty. Eventually your thirst builds to the point where we say it causes you to get up and go to the refrigerator to get a beer. If you were asked, "Why did you go get the beer?", you would answer, "Because I was thirsty." Dretske feels this relationship can be diagrammed in the following manner:

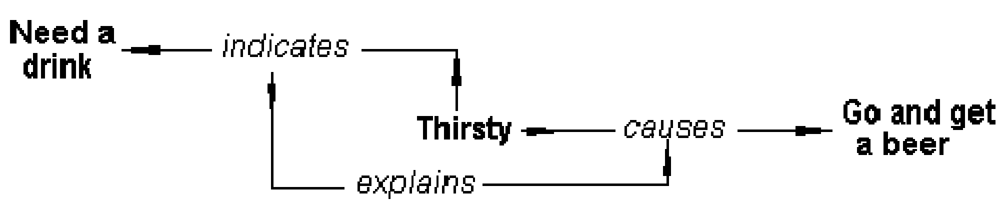


Figure 1

I am thirsty. This indicates that I need a drink and causes me to go and get a beer. The fact that thirst indicates a need for a drink explains why it causes me to go and get a beer. Earlier I talked about how Searle recognizes the importance of semantic meaning for something to be a true thought. This diagram clearly shows and example of a belief with semantic meaning. Being thirsty, has the meaning behind it of needing a drink. Searle feels machines, such as COG, are incapable of this type of semantic meaning. This is questionable. Let us again consider COG. Let us imagine that COG sometimes runs on a battery. This battery eventually runs out of power. If COG does not save his data before his battery runs out he will lose all of it. Imagine that COG has a low battery alarm, and let us again construct a diagram of the same form as Figure 1:

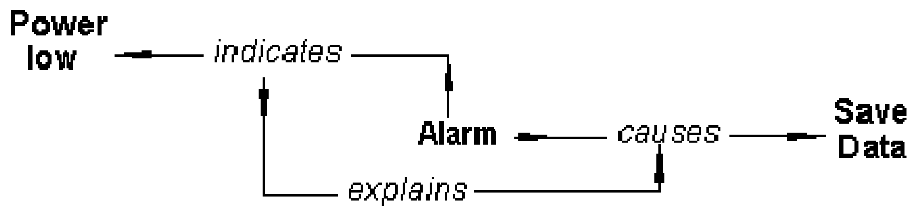


Figure 2

We agreed that the thirst had semantic value. Does not this low battery alarm also have semantic value. The alarm is not merely a computer state. It has semantic grounding in the fact that it represents the charge status of the battery. Some people might say that this alarm is just too simple a mechanism for us to describe COG as thinking. It would be like saying that a thermostat thinks, so let us examine a third example where COG actually learns.

COG will have arms which are moved around by electric motors. These motors are delicate so it is important that COG does not hit them against things. Rather than simply putting a protective case around the motors, COG's designers plan to make him capable of learning how to protect them. This will be accomplished by placing pressure sensitive film on COG's motors. This will send pressure data to COG when his motors are being hit. COG can then take evasive action and record what motion ends the pressure data the most effectively. The next time COG experiences a similar system state and pressure data he can repeat the evasive action that he previously learned was the most effective. Again this can be diagrammed in the same manner:

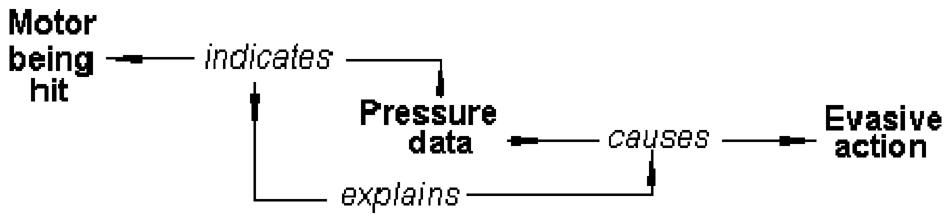


Figure 3

With this learning mechanism, COG could be expected to begin to demonstrate behavior that went beyond anything he was programmed to do. Let us consider an example. COG will be able to recognize faces. Suppose that there is one particular person who for whatever reason particularly enjoys being cruel to COG, and hitting his sensitive motors. COG takes various evasive actions until he finds an arm position were his motors are not exposed to being hit. If this person is consistent in her abuse of COG, eventually he would learn that when he recognizes this person's face, he should place his arms in the safe position.

Can we really dismiss this behavior as unintelligent? Is it really that different from the child who learns to cover his head whenever he meets the uncle who loves to give noogies? Searle is correct when he recognizes that we are unable to distinguish intelligent action by behavior alone. We would be able to simply program COG to protect his arms when he saw the certain face, and behaviorally COG's actions would be identical to if he had learned the action himself. Searle's point is valid, but to make the leap of logic that computers can not think, because "intelligent" action would be indistinguishable externally from programmed action, is wrong. Even though COG is only following a program he has taught himself, when he protects his motors, there is a certain degree of intelligence and semantic meaning behind the action.

At this point it is simply too soon to say what level of consciousness artificial intelligence may one day reach. Although to this point it appears that scientist have been unable to create a computer which is rationally self aware, I think the question of whether they have created computers that can think, or believe, is not so clear. After we have considered our second adding machine and some of COG's operations I think that we can make a defensible claim that, computers can think, albeit at the most abecedarian level.

We may never succeed in making a computer which is capable of a human's level of consciousness, but the move towards making a computer's "thoughts" about something is one of the paths we need to take in that direction.

So after all of our analysis, let us return to questions we asked initially, can we make a robot that uses tools and is such a robot intelligent? We have firmly established that we could create a robotic tool user. Current technology allows robotic arms to employ screwdrivers and welders. The question of creating a tool using robot becomes more interesting the higher up we ascend the taxonomy we created. As we are able to succeed at each higher level we will be able to make a more plausible argument that we have created an intelligent robot. Our survey of animal tool use and current robotics control methodologies has identified several appropriate Computer Science technologies to guide our creation of tool using robots. Using these methods our task now is to write the software to control our robot in the use of tools and then again revisit these questions. We will create a robot that can dynamically use tools and is firmly semantically grounded in its world and then again ask the question “Is this robot intelligent?”

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