6 *Braitenberg Vehicles*

In this chapter we look at a famous kind of agent, the Braitenberg vehicles, named after their inventor, neuroscientist Valentino Braitenberg. Braitenberg vehicles are ideally suited for illustrating some fundamental theoretical points, such as the frame-of-reference problem. They also provide an interesting perspective on the problems of behavior segmentation and action selection. Moreover, the principles employed by Braitenberg vehicles have been extended to address the design of autonomous agents in general. Not surprisingly, this approach is called Extended Braitenberg Architecture (EBA). Braitenberg vehicles are instantiations of a synthetic methodology. Braitenberg proposed studying principles of intelligence by building successively more complex agents. The original Braitenberg vehicles were meant to be thought experiments. However, some of them can easily be implemented in physical robots, and we will discussed one such example, the ‘‘timid’’ vehicle, in this chapter. After a short discussion of Braitenberg’s motivation, his vehicles are introduced along with an additional example. We conclude with a note on segmentation of behavior and extensions of Braitenberg’s approach.

6.1 Motivation

Michael Arbib, one of the inventors of computational neuroethology—the discipline studying the neural systems underlying behavior—wrote in his preface to Valentino Braitenberg’s seminal book *Vehicles: Experiments in Synthetic Psychology* (1984): ‘‘[The book] is serious fun and will help many people, specialists and layman alike, gain broad insights into the ways in which intelligence evolved to guide interaction with a complex world’’ (p. x). Particularly relevant for our purposes is Arbib’s reference to interaction with a complex world. We have seen in chapter 5 that focusing on brain structures alone is insufficient for really understanding their operations—they must be looked at within a behavioral context. Although this is a very hard thing to do in real brains, it is both possible and important in artificial ones. Braitenberg vehicles demonstrate that often even extremely simple brains can show behaviors that look remarkably sophisticated to outside observers. The field of autonomous agents draws a lot of inspiration from the study of these vehicles: Everyone interested in intelligence, natural or artificial, should know about them. Braitenberg vehicles can teach us much about the interplay between brain and behavior, or in embodied cognitive science terms, between mechanism and behavior.

Braitenberg is a well-known brain researcher. Rather than explaining a lot of technical detail on neuroanatomy and neurophysiology, though, he discusses a series of thought experiments, conducted not on real brains but on toy brains. Many of the important ideas on autonomous agents have been discussed by Braitenberg in a highly entertaining way.

The design of Braitenberg vehicles has a strong biological motivation based on many years of in-depth brain research. It is interesting to see at what level a connection is made between neurobiology and vehicles or, in our terminology, autonomous agents. Clearly, no biological creatures have wheels. Nevertheless, even though equipped with wheels, Braitenberg vehicles have a definite biological appeal.

6.2 The Fourteen Vehicles

Braitenberg vehicles represent a series of agents of increasing complexity. Although some are purely reactive, others include learning mechanisms, and thus have their own history.

In the simplest vehicles, it is quite obvious what they do. As matters get slightly more involved, predicting their behavior turns out to be very difficult, even in purely reactive systems, because the mechanisms generating the vehicles' behavior interact in interesting ways. Even if we have complete knowledge of the vehicle's insides, it still proves difficult to control it. Its interaction with its environment adds complexity, which leads to some degree of unpredictability, even if the driving mechanisms are entirely deterministic—in physics, there are always fluctuations. Taking up on our discussion of autonomy in chapter 4, we can conclude that even the simplest vehicles have a certain degree of autonomy.

Let us examine the Braitenberg vehicles one by one. As always, we pay attention to the frame-of-reference problem. In examining

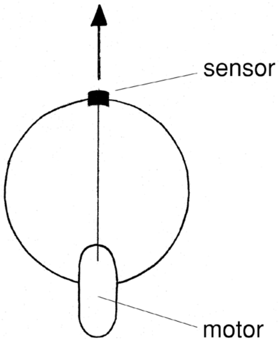


Figure 6.1 Braitenberg vehicle 1. A sensor controls the speed of the motor. Motion is always forward, in the direction of the arrow, except in the presence of perturbations, like friction.

this series of vehicles, it is always a good idea to imagine how they move around under various conditions. This process of imagination is best complemented with computer simulations or with experiments on real robots.

Vehicle 1: Getting Around

As shown in figure 6.1, the first Braitenberg vehicle has one sensor, for one particular quality, and one motor. The sensor and the motor are connected very simply: The more there is of the quality to which the sensor is tuned, the faster the motor goes. If this quality is temperature, it will move fast in hot regions and slow down in cold regions. An observer might get the impression that such a vehicle likes cold and tries to avoid heat. The precise nature of this quality does not matter; it can be concentration of chemicals, temperature, light, noise level, or any other of a number of qualities. The vehicle always moves in the direction in which it happens to be pointing.

If we introduce friction into the vehicle's environment, its behavior gets interesting, because friction is always a bit asymmetric. The vehicle eventually deviates from its straight course, and in the long run, is seen to move in a complicated trajectory, curving one way or another without apparent (to the observer!) good reason. Perturbations other than friction that will force the vehicle from its straight course are, for example in water, streams, waves, fish, and other obstacles.

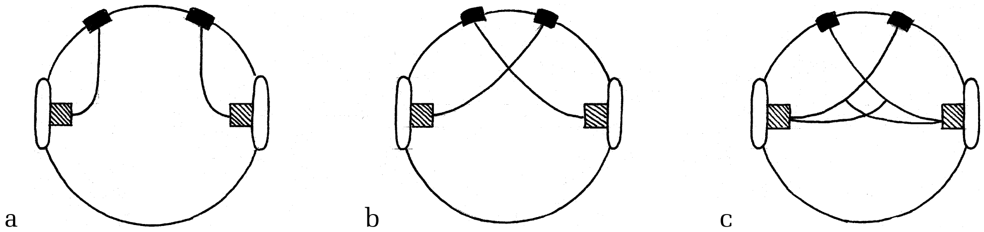


Figure 6.2 Vehicle 2. This vehicle has two motors and two sensors; otherwise it is like vehicle 1. Only the connections differ in (a), (b), and (c). 7.8

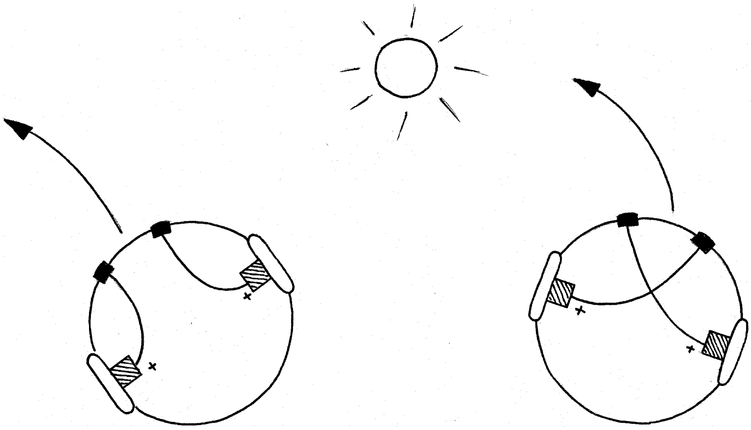


Figure 6.3 Vehicle 2a and 2b in the vicinity of a light source. Vehicle 2b orients itself toward the source, vehicle 2a away from it.

Vehicle 2: Approach and Avoidance

Vehicle 2 is very similar to vehicle 1, except that it has two sensors, one on each side, and two motors, right and left (figure 6.2). There are three possibilities for connecting the sensors to the motors, as the figure shows. Case (c) in which both sensors are connected in the same way to the motors, is essentially the same as vehicle 1, so we consider only (a) and (b). The resulting behaviors are shown in Figure 6.3, in which the sensors are tuned to a light source. Because the right sensor of vehicle 2a is closer to the light source than the left, it gets more stimulation and thus the right motor turns faster than the left. As outside observers, we might characterize the vehicles as follows: Vehicle (a) is a coward, whereas vehicle (b) is aggressive: Vehicle (a) avoids the source, whereas (b) moves towards it and will hit it, possibly even destroying it.

Focus 6.1: Helping Behavior

Let us look at an experiment involving a group of robots, each a Braitenberg vehicle 2b, which turns toward a light source. For this particular experiment, the generic robot scheme as introduced in chapter 4 was extended with a light mounted on top of the robot. The experiments have also been performed with the Didabot platform. Two Didabots are frequently observed to get stuck along a wall because they follow each other and because a white wall reflects the light very well. This following behavior is also generated by the Braitenberg architecture: One vehicle following another squeezes the one in front of it toward the wall (figure 6.4). A third robot comes from quite a distance and hits one of the robots in an effort to free it from being stuck. If it does not succeed in doing so, it turns back and hits the other agent again until all can get away from the wall. Of course, describing the robots' behavior in these terms attributes to them ''motivations'' they could not possibly possess. We can go to any level of anthropomorphization, actually, and there is nothing wrong with such descriptions, as long as we make no claims about the

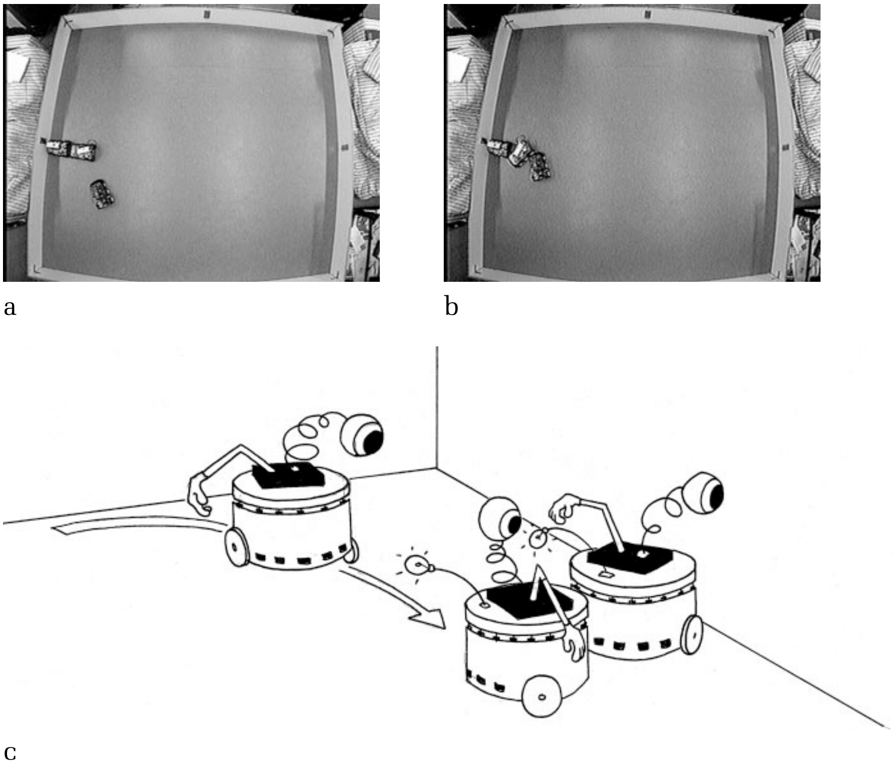


Figure 6.4 Helping behavior. (a) Two vehicles are stuck along the wall. A third vehicle is approaching. (b) The third vehicle hits the one pushing the other against the wall. Observers say ''it comes to the rescue'' of the two that are stuck. (c) Cartoon illustration of the same phenomenon.

Focus 6.1: (continued)

internal mechanisms based on such descriptions. In this case, we know that the internal mechanism is a simple Braitenberg architecture, in fact almost the simplest one. Nevertheless, the behavior looks surprisingly intelligent to an observer.

We have reproduced this phenomenon a number of times, so it is more than purely accidental. Why does it happen? One explanation is as follows: The robots are very sensitive to light. They move toward the brightest light source within their ‘‘visual’’ range. Two robots stuck along the wall have two lights relatively close together. Two lights are brighter than one. The ‘‘helper’’ is thus attracted to this double light source. Because it is simple Braitenberg, it runs into the other two vehicles. If it is ‘‘successful,’’ that is, if it breaks their deadlock, the two robots get away from the wall. If not, they stay there, and they continue to be the brightest light source in the ‘‘helper's’’ environment, so it returns and hit them again, repeating this pattern until they are freed. But nowhere is there any intention to ‘‘help’’ represented in the vehicle; it is simply acting as it has been programmed to do.

The ‘‘brains’’ of these vehicles are very simple. They consist merely of two neurons connecting the sensors to the motors. Note, however, that seemingly complex interactions among these vehicles can emerge. Focus 6.1 describes one example, ‘‘helping’’ behavior.

Vehicle 3: Attraction

The first two Braitenberg vehicles have only excitation: the more stimulation at the sensors, the more the motors are powered. Let us now introduce inhibition: the more stimulation, the less power is delivered to the motors. This principle is incorporated in Braitenberg vehicle 3 (figure 6.5).

The behaviors involved are fairly obvious. Vehicle 3a ends up facing, say, a light source, whereas vehicle 3b turns away from it but also remains near the source, unless there is a disturbance, like another source. Additional sensors can also be introduced, and each stimulus can be connected either to the motor on the same or the opposite side, and can be excitatory or inhibitory (see figure 6.6). Stimuli to which the sensors are attuned could be light, oxygen concentration, temperature, concentration of organic molecules (food), or similar things. The vehicle has a tendency to stay longer in certain areas than in others because when its sensors are

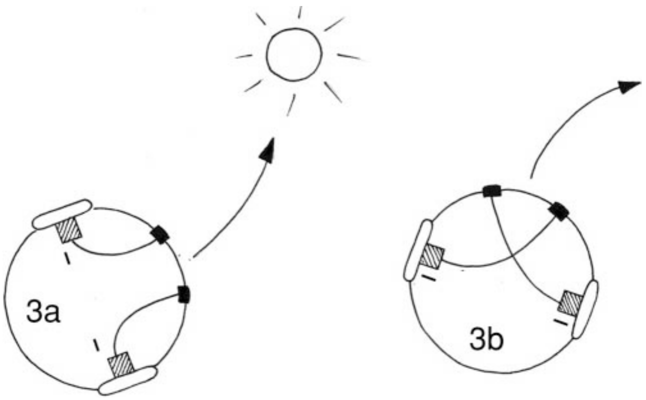


Figure 6.5 Vehicle 3. The vehicle's sensors exert an inhibitory influence on the motors. Vehicle 3a, turns toward the light source and stops, when it is close enough to the light source, i.e. as soon as the light stimulation is large enough to exert sufficient inhibitory activation. Vehicle 3b is similarly inhibited, but it moves away from the source.

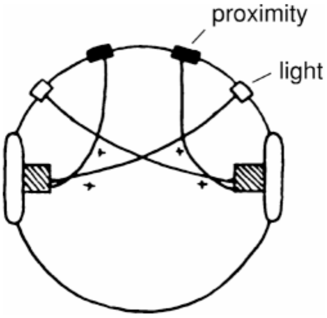


Figure 6.6 A multisensorial vehicle of type 3c. Sensors for various qualities have either positive or negative connections to the motors.

activated by the presence of a stimulus, its motors and thus its movement are inhibited. We cannot help admitting that the vehicle appears to have a set of ''values'' and that it incorporates them in some way that we would want to call ''knowledge.'' ''Knowledge'' in this context does not mean ''stored representations;'' that is, it is not—as in the classical AI view—stored in an explicit form to be manipulated by the agent (the vehicle) itself. Rather, it is attributed to the vehicle as a whole by an outside observer. Attributing ''knowledge'' to an agent is a way of describing its behavior—it has nothing to do with the agent's internal structure.

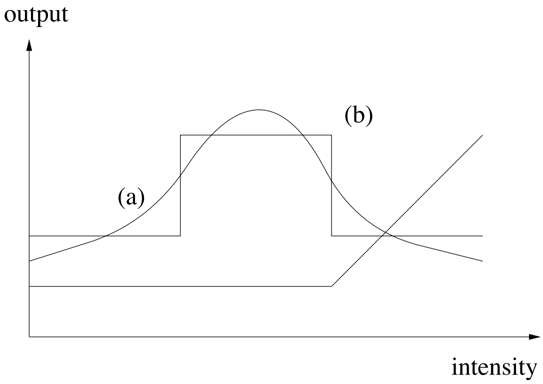


Figure 6.7 Nonlinear dependencies of motor output on intensity of sensory stimulation. Graph (a) shows a curve for a type 4a vehicle, graph (b) for a type 4b vehicle.

Vehicle 4: Values and Special Tastes

We can introduce a further complication by making the motors' dependency on the sensors nonlinear. Figure 6.7 depicts a few alternatives. Sensory stimulation may first increase, and then, at higher levels of stimulation, decrease the motor speed, for example. This would cause a vehicle to approach a distant source first slowly, then faster as it draws closer, and, as it gets still closer, it would slow down again. A vehicle of this sort is said to be of Braitenberg type 4a. If we allow thresholds, for example, a motor gets powered only if the stimulation of the corresponding sensor exceeds a certain threshold, we then have a vehicle of Braitenberg type 4b. The variety of such vehicles is enormous, and their behavior is very exciting. For example, a vehicle may sit still and, at some point, all of a sudden, start moving again. Or it may start describing patterns as shown in figure 6.8. As an observer, we might be tempted to say that these agents in fact ''ponder'' their decisions. Their behavior can be quite involved and difficult to understand.

Vehicle 4 is a purely reactive system: it does not have its own history; that is, it does not change over time. Nevertheless, it looks very much like an autonomous agent. If it has many sensors and they are connected in complex ways to the motors, it would in fact be very difficult to control the agent's behavior.

In chapter 4, we pointed out that neural networks are ideally suited to building agents capable of learning. We equated learning with changes of the weights in the connections within the neural network. As an aside, note that changes in the network are not

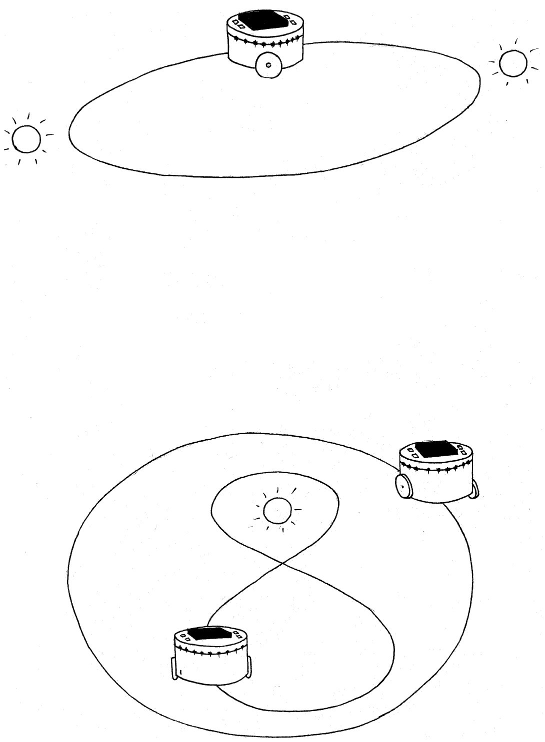


Figure 6.8 Trajectories of vehicles of type 4a around or between sources.

the only “experiences” a vehicle can have. It can also be damaged in some ways, receive a dent in the fender, suffer from a drained battery, or incur a broken sensor or motor. When experiencing these changes, the vehicle may behave quite differently, even if the internal control architecture remains the same. Thus, changes can occur without learning. This is another illustration of the implications of embodiment.

Vehicle 5: Adding “Brain Power”

We can now add arbitrary complexity by introducing threshold devices. In chapter 5 we called these “devices” nodes or model neurons. The kinds of nodes suggested here are of the linear threshold variety, but they could also be of the sigmoid type. They can either be interposed between sensors and motors or connected to each other in various ways. A vehicle possessing these devices is of Braitenberg type 5.

Threshold units can also be used to implement some kind of memory by introducing recurrent connections or loops. Imagine a threshold node connected to a sensor for red light. When activated by a red light, the sensor activates the threshold node, which then activates another threshold node connected to the first. Thus, once one of the nodes is turned on by a red light, the two nodes will keep activating themselves forever through mutual feedback. If a wire is attached to one of the two nodes and connected to a bell, the ringing of the bell signals that at some point in the past, this particular vehicle encountered a red light.

Vehicle 6: Evolution

Suppose we put a number of vehicles that we have built on a table containing light sources, sounds, smells, and so forth and let them move around. We pick out one vehicle, the model, make a copy of it, and put both the model and the copy back on the table. We pick out another, and repeat the process indefinitely. Of course, we do not choose vehicles that have fallen on the floor, because they are obviously incapable of coping with this particular environment. We produce vehicles at a pace that roughly matches the rate at which vehicles fall off the table.

If we play this game in a hurry, we are likely to make mistakes now and then. A well-tested vehicle might still fall off the table. Particularly shrewd variations might also be introduced unwittingly into the pattern of connections with the result that our copy survives, whereas the original may turn out to be unfit for survival after all. If the imperfect copying results simply from sloppiness, the chances that something interesting will emerge because of the mistakes in copying are small. However, a ‘‘better’’ sort of error would involve creating new combinations of partial mechanisms, and structures such as IR sensors, cameras, motors, or wheels, each of which has not been disrupted in its own well-tested functionality. Such errors have a much greater chance of transcending the intelligence of the original plan. If these ‘‘lucky’’ incidents live forever, they will have many descendants, because they and their descendants will frequently be chosen for copying simply because they stay on the table all the time.

This is, of course, a model of Darwinian evolution. It reminds us of the metaphor of the blind watchmaker, created by Richard Dawkins (1988) to describe evolution. Vehicles created in such a scenario are said to be Braitenberg type 6. We may, by accident, create vehicles whose behavior is extraordinary without understanding why they behave as they do, because building something that works is typically much easier than analysis: Braitenberg called this the ‘‘law of uphill analysis and downhill invention.’’ Indeed in evolutionary approaches you can quite often get the agents to do what they should do, but it is usually hard to understand why they do what they do. (Evolutionary methods are discussed in detail in chapter 8.)

Other Vehicles

We discuss the remaining vehicles 7 to 14 only briefly, because for our purposes, the simple vehicles are more interesting: They illustrate the sensory-motor couplings and how they lead to remarkable behavior. The later ones, especially vehicles 7 and above, have a cognitivistic flavor and are therefore bound to run into the problems discussed in chapter 3.

For the sake of completeness, let us briefly summarize the remaining vehicles. The general idea is to augment existing vehicles by more sophisticated types of neural networks. For example, a vehicle of type 5 can be turned into one of type 7 by adding more network nodes, connecting them and using Hebbian learning to form associations between the nodes whenever they are simultaneously active. As we discussed in the previous chapter, associations can be formed in this way. In the Distributed Adaptive Control architecture, the presence of light has been associated with stimulation of IR sensors on the side of the robot. We could say, from our perspective of observers, that the robot has learned the concept ‘‘light along walls.’’ Such concepts can be used to guide the agents’ behavior: if light corresponds to food, then it is a good idea to follow walls to find food. These associations can become more complicated if more sensors and larger neural networks are involved.

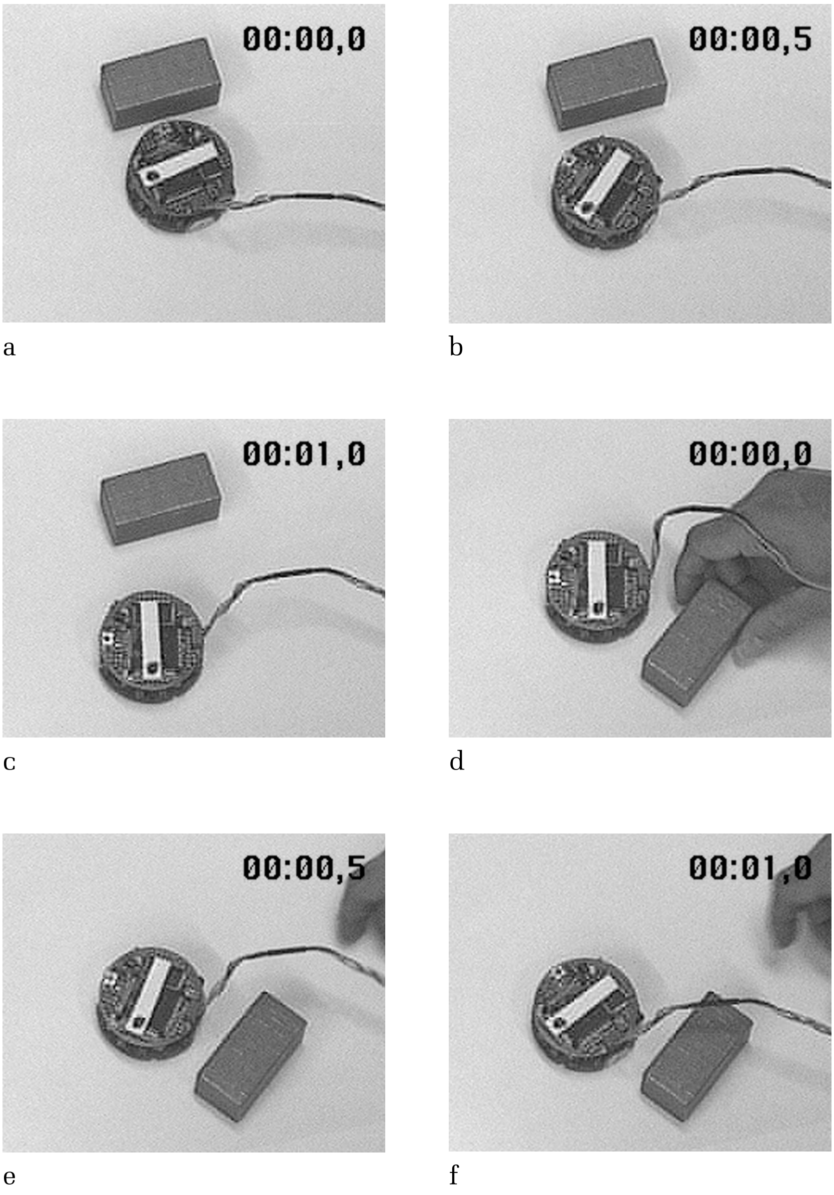
Further improvements of the vehicles include mechanisms for shape detection (e.g., for squares and circles), for detection of temporal order (strong stimulation in proximity sensor, activation of collision sensor), for prediction (strong sensory stimulation in the proximity sensors is a predictor for an impending impact), and for something like short-term memory (it is important to keep track of what has happened in the recent past in order to decide what to do next).

Let us now turn to a final example of a Braitenberg type vehicle: the timid vehicle.

The Timid Vehicle

The ‘‘timid’’ vehicle is one of a number of vehicles that Hogg, Martin, and Resnik (1991) have introduced. They describe 12 vehicles they have built with electronic bricks. Electronic bricks are specially modified LEGO bricks with simple electronic circuits inside. Braitenberg vehicles of various types can be constructed using these bricks. Among others, one can build ‘‘paranoid,’’ ‘‘dogged,’’ ‘‘insecure,’’ or ‘‘frantic’’ vehicles with these bricks. We focus on the ‘‘timid’’ vehicle, which is an instantiation of vehicle 2a discussed earlier: The more sensor stimulation it receives, the faster it moves. When it receives no stimulation, it does not move at all. We have implemented this vehicle in a Khepera robot. Figure 6.9 shows its basic behavior. The vehicle seems to be ‘‘timid’’: Whenever an object comes in its vicinity, it avoids contact with the object by powering its motors appropriately. In the implementation shown in the figure, all IR sensors of the Khepera robot were connected to the motors, so the vehicle avoids obstacles coming from any direction.

More interesting is an experiment that shows how even such simple vehicles can show rather complex behavior. Let us add a bias toward moving forward to the ‘‘timid’’ vehicle just described. By adding, at each time step, a small constant to both motors. Now in addition to turning away from objects it approaches, the vehicle also moves forward a specified, constant distance for each unit of time (say, a second). Figure 6.10 shows the resulting behavior: The ‘‘timid’’ vehicle can drive through mazes without hitting the walls! This occurs because the vehicle is ‘‘timid’’—it avoids all walls—and because it also has a bias to move forward. As a result, it avoids the walls, but still drives through the maze. If a biologist showed us such a trajectory that he recorded from, say, a rat, we might be inclined to postulate some kind of sequence generator in the animal. We therefore have to be careful with such speculations about internal mechanisms that generate a given trajectory. The maze-following behavior of the ‘‘timid’’ vehicle illustrates beautifully that coherent, sequential behavior can emerge out of a number



a b c d e f

Figure 6.9 Basic behavior of the timid vehicle. When an object approaches the vehicle from the right (panels a, b, c) or left (panels d, e, f), it moves away.

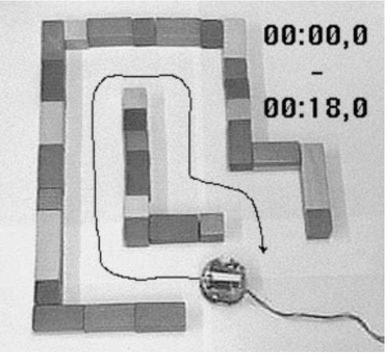


Figure 6.10 Maze-following behavior of the ''timid'' vehicle. When a simple default speed is added to the motors, the ''timid'' vehicle can be made to drive through mazes.

of simple processes that operate in parallel. Similar to Simon's ant on the beach, the complexity arises from the interaction with the environment (beach, maze) and not from the agent alone.

Conclusions

Braitenberg vehicles are great fun to work with. They also provide deep insights into the nature of intelligence. For example, they beautifully illustrate the ''frame-of-reference'' problem: Even very simple designs can lead to surprisingly interesting kinds of behavior, especially if several vehicles are involved. They also demonstrate nicely that the neural substrate is by no means the only thing that governs the vehicles' behavior. It is just as important what sorts of sensors are on the vehicle, how they function, and where they are positioned.

An interesting point relates to the vehicles' autonomy. Braitenberg vehicles are hard to control. Although fairly accurate predictions can be made about the general quality of the behavior of certain vehicles, it is next to impossible to make more precise forecasts. In other words, Braitenberg vehicles have a certain degree of autonomy: Getting them to do exactly what you want is difficult. This is true even for vehicles with no learning.

For our purposes in this book, the simple Braitenberg vehicles are the most interesting, because they illustrate sensory-motor couplings and how they lead to remarkable behavior. In vehicles 7 through 14, in essence, the sophistication of the ''brain'' is progressively increased with each subsequent vehicle built. Although this is useful to some extent, it cannot be continued indefinitely, unless the sensory-motor complexity is also increased. Take, for example, vehicle 1. If we increase the complexity of the vehicle's brain, not much will change in the behavior of the agent, because its sensory-motor system is so simple: Increasing its brain power doesn't have any real effect on the simple behaviors it is set up to perform, because the original brain power was already more than sufficient for the simple tasks. However, if we add additional sensors and motor capabilities, we get more interesting behaviors very easily.

These vehicles illustrate an additional fundamental point: the segmentation of behavior. From these considerations, we can derive important principles for control architectures. This requires some elaboration.

6.3 Segmentation of Behavior and the Extended Braitenberg Architecture

Assume that you have a Braitenberg vehicle of type 3. It has no internal ‘‘actions,’’ in the sense of separate internal modules, only internal processes connecting sensors, via some intermediate mechanisms, to effectors. So it is not possible to list the actions in which the agent is involved. It is obvious that in this case any segmentation of behavior is purely observer based, and it is very difficult to come up with a consistent rating between different observers. Consider now a vehicle of type 3c, as shown in figure 6.11. There is a light process with a positive connection, meaning that the vehicle is attracted to the light. There is a proximity process (high proximity means high activation) that makes the vehicle turn away from close objects. If we consider the potential trajectory, the vehicle will initially turn toward the light source (because of the light process), then slowly begin to turn away as it approaches it (because of the proximity process). What action is it involved in, ‘‘turning toward the light’’ or ‘‘turning away from the obstacle’’? We cannot say, because there are no internal actions, only processes feeding onto the two state variables, namely the speeds of the motors.

How could we then sensibly segment the agent's behavior? What the agent really does is engage in behavior that is emergent from the dynamics of its internal variables (the intensity of the sensor stimulation and the motor speeds) in the interaction with the environment. We can extend this architecture to any number of internal variables, some of which, like the speed variables, will directly

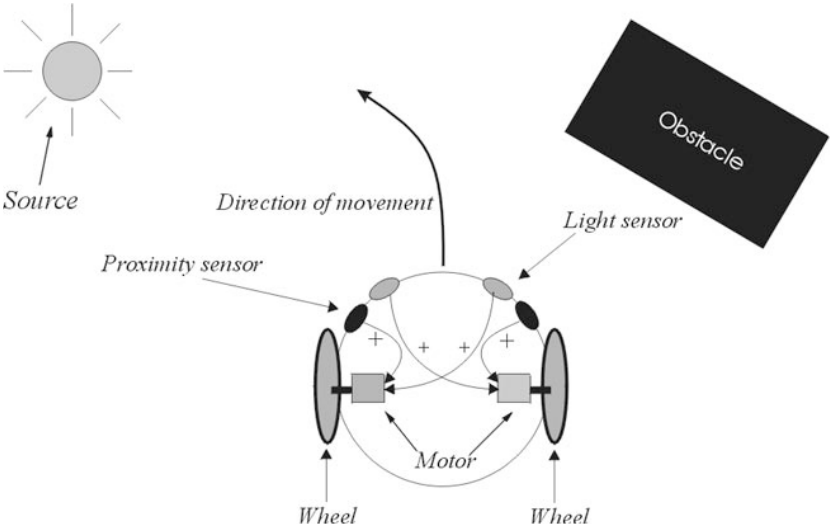


Figure 6.11 A vehicle of type 3c. The vehicle has two light sensors and two proximity sensors. The closer to an object the agent comes, the higher its activation. Because of its wiring, this vehicle turns towards a light source, but if the weights are chosen appropriately, it will turn away from the light source, when it is close enough.

influence the vehicle's behavior. Such an architecture is called an *Extended Braitenberg Architecture*. For natural systems, this kind of architecture has high explanatory power, and it demonstrates nicely why the segmentation of behavior is notoriously difficult. The Extended Braitenberg Architecture is illustrated with a number of examples in chapter 11.

Issues to Think About

Issue 6.1: Sensory-Motor Coupling and Brains

Braitenberg vehicles 1 through 6 capitalize on system-environment interaction. Their behavior control is based largely on direct sensory-motor couplings with relatively little internal processing. In this sense, they represent the epitome of embodied cognitive science. As we mentioned above, vehicles 7 through 14 have a strongly cognitivistic flavor. Remember the thought experiment we suggested with vehicle 1: We simply increased its brain power. Now, what on earth is this more powerful brain going to do? What functions could it have? As it turns out, it is hard to think of any sensible task for this brain. Thus, it becomes obvious that increasing brain power alone does not make sense: The sensory and the motor systems have to be improved as well. This is an important design principle that we will discuss more later. As we said in chapter 1, we feel that AI and psychology have focused too much on the brain itself (see figure 1.4: the brain as the ''seat of intelligence''). From this perspective, vehicles 7 to 14 are less attractive. In vehicle 10, for example, the idea of a coin with two faces should evolve through the observation of someone repeatedly turning a coin. However, from the mechanisms described, it is not clear how that could come about. Just think of the awesome complexity a perceptual system would have to have to make sense of a coin-flipping situation. Neglecting the coupling to the real world in this way is typical of approaches focusing on so-called higher-level processes and on brains. A better approach is to start from the working hypothesis that we have simple sensory-motor processes with little intermediate processing that form the substrate of intelligence. How far we can get with this assumption is an open question. Because of the fundamental importance, this issue is discussed in a number of places throughout the book. Think of other examples of tasks that look very simple in the abstract but get enormously complex as you add the interaction with the environment.

Issue 6.2: Uphill Analysis and Downhill Invention

Intuitively, we would think that it is easier to analyze something that already exists than to build something new. The law of uphill analysis and downhill invention suggests the exact opposite. Indeed, experience shows that it is surprisingly simple to build Braitenberg-style vehicles and to increase their complexity step by step. Even for relatively simple vehicles, however, it is very hard to understand what precisely is going on as they exhibit various behaviors. Their interaction with the environment is largely unpredictable in detail. This is somewhat counterintuitive, because we built the systems ourselves—but we still have a hard time understanding their behavior. This holds in particular for neural networks, and Braitenberg architectures are specific instances of neural networks. In spite of these difficulties, they are highly productive tools. We consider the synthetic approach to cognitive science to be the most successful one currently.

Points to Remember

- Braitenberg vehicles are a set of fourteen types of vehicles designed to explore, in a bottom-up fashion, principles of intelligence. They are ideally suited to studying the relationship between behavior and mechanism.
- Often, even very simple Braitenberg vehicles display, because of their interaction with the environment, surprisingly sophisticated kinds of behavior. This is especially true if other vehicles are present in their environment.
- Braitenberg vehicles consist of parallel processes connecting sensory stimulation to actuators via some intermediate mechanisms. The values of the motor variables determine what the agent does. There are no internal actions.
- The Braitenberg approach can be extended to agent design in general. This is called the Extended Braitenberg Architecture.
- Braitenberg vehicles explain why the problem of segmentation of behavior is notoriously hard to solve. The vehicles have no internal actions corresponding to specific observer-based behavioral categories.
- The mechanisms implemented in Braitenberg vehicles are entirely deterministic. Nevertheless, it is virtually impossible to predict the vehicles' behavior.
- The Braitenberg approach is appealing, since it is biologically motivated and has high explanatory power.

Further Reading

Braitenberg, V. (1984). *Vehicles: Experiments in synthetic psychology*. Cambridge, MA: MIT Press. (A must for anyone interested in cognitive science and autonomous agents. Beautifully written, simply a seminal book.)

Hogg, D. W., Martin, F. M., and Resnick, M. (1991). *Braitenberg creatures*. MIT Media Laboratory, Cambridge, MA. (Available online at http://les.www.media.mit.edu/people/fredm/papers/vehicles/). (Describes how various Braitenberg vehicles can be constructed using simple electronic bricks. Strongly suggested for those interested in actually building Braitenberg vehicles.)

Understanding Intelligence.
Rolf Pfeifer and Christian Scheier.