[Introduction of the book: DYNAMIC THINKING — A Primer on Dynamic Field Theory
GREGOR SCHÖNER, JOHN P. SPENCER, AND THE DFT RESEARCH GROUP,
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PART 1

Foundations of Dynamic Field Theory

Introduction

GREGOR SCHÖNER AND JOHN P. SPENCER

The goal of this book is to understand how perception, action, and cognition come together to produce behavior. Achieving this goal requires that we uncover the laws of behavior and understand the processes from which behavior emerges. There is no question that human behavior is generated by the nervous system, so a process understanding must be achieved in neural terms.

What does it mean to base an account of behavior on neural principles? Valentino Braitenberg introduced the metaphor of a "vehicle" that beautifully illustrates the challenges of creating a neural account of behavior (Figure I.1). His vehicles are simple organisms that have four elements, all of which are required to generate behavior:

1. They have sensors. Sensors transform physical variables, such as light intensity, the loudness of a sound, or the concentration of a chemical, into internal variables, such as the firing rate of a sensory neuron.
2. They have effectors. Effectors transform internal neural variables into physical variables, like the force or torque of a muscle, or, in the vehicle metaphor, the turning rate of a wheel.
3. They have nervous systems. The nervous system links the internal variables together. In the simplest case of a feed-forward nervous system, the internal variables that arise from the sensors are transmitted by the nervous system to the effectors.
4. They have bodies, a component that is, ironically, often overlooked. The body links the sensors to the effectors in the physical world. When the effectors drive the body around, the sensors move along with the body and sensory information changes. This, of course, has major consequences for subsequent behavior.

One way of thinking about how behavior emerges from nervous systems using this metaphor is to assume that sensors provide information about the environment, which is processed by the nervous system and then fed to the motor systems. This is a feed-forward view of the nervous system, and invites thinking in information-processing terms. In neuroscience and cognitive science, this perspective has been very helpful in characterizing the organization of the nervous system and in exploring how that organization is reflected in behavior. For instance, influential concepts like "neural coding" emerged from this way of thinking.

In Figure I.1, we have illustrated the feed-forward view. Here, the physical intensity of a stimulus is picked up by a sensor and transformed

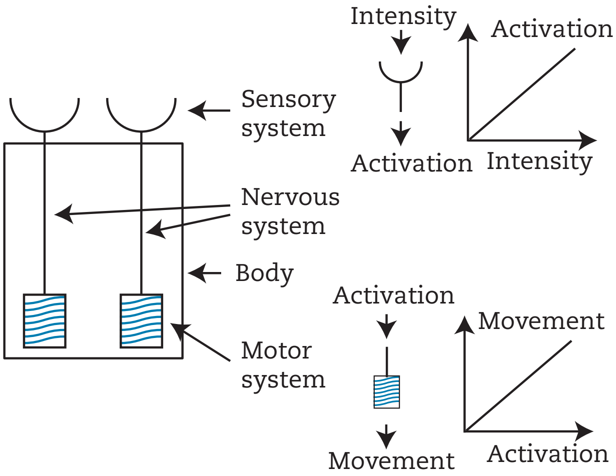

FIGURE I.1: A Braitenberg vehicle consists of sensory systems, motor systems, a nervous system, and a body. The sensory characteristic shown at the top right describes the activation output by a sensor system as a function of the physical intensity to which the sensor is sensitive. The motor characteristic shown at the bottom right describes the movement generated by a motor system as a function of the activation received as input.

into an activation value using a particular type of neural coding called "rate coding." The idea is that there is a one-to-one mapping from the physical intensity value in the world to the activation value in the nervous system, that is, to the firing rate induced by stimulation of the sensory cell. Similarly, motor systems can be characterized using a rate code picture where the activation value in the nervous system is mapped to the force generated by a motor.

Critically, Braitenberg took his metaphor one step farther by situating the vehicle in a structured environment. Figure I.2 shows one of his vehicles situated in an environment that has a stimulus off to the left such that stimulation hits the two sensors

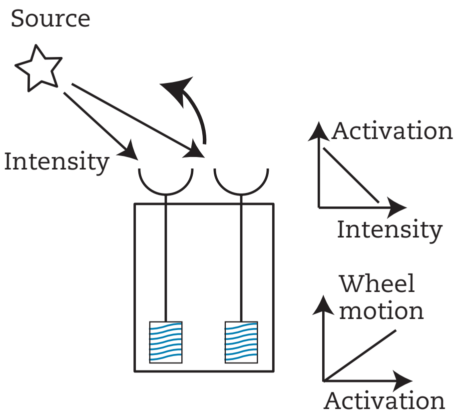

FIGURE I.2: The taxis vehicle of Braitenberg in an environment with a single source of intensity. The sensor characteristic is a monotonic negative function, the motor characteristic a monotonic positive function. This leads to taxis behavior in which the vehicle turns toward the source (curved arrow).

differentially. In particular, the left sensor receives a higher intensity than the right sensor. If we assume that this critter is wired up such that strong stimulus intensity leads to low activation levels, this situation will generate an orienting behavior, what biologists have called "taxis"—the critter will turn toward the input. Why does this happen? In this vehicle, the nervous system is organized ipsilaterally, so the right motor receives input from activation associated with the right sensor. Because strong stimulation leads to a lower firing rate, the left motor will receive less activation than the right motor. Consequently, the left motor will turn more slowly than the right motor and the vehicle will turn toward the source. As it approaches the source, the intensities get stronger and the firing rates drop perhaps to zero—the critter approaches the stimulus and stops.

The lesson from this narrative is that meaningful behavior is not generated solely from a feed-forward view of the nervous system; rather, meaningful behavior emerges when an organism is situated in an appropriately structured environment. All four components of the vehicle are important. Indeed, we should really think of the structured environment as the fifth component of the vehicle—without it, no meaningful behavior will arise, as James J Gibson has forcefully argued.

When we put all five components together, the resultant "vehicle–environment system" forms something called a *dynamical system*. To see this, the graph on the top of Figure I.3 collapses the sensor and motor characteristics down into one direct

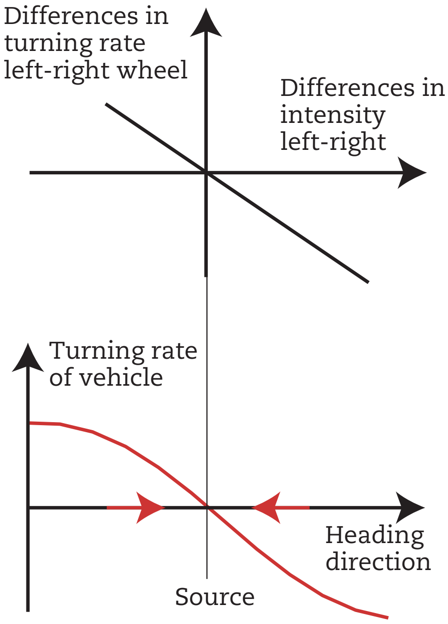

FIGURE I.3: Concatenating the two sensor and motor characteristics of the taxis vehicle of Figure I.2, and taking their difference, leads to the function shown on top. With a generic model of how intensity falls off as the heading direction deviates from the direction to the source (marked by the vertical line), this sensory-motor characteristics translates into the functional dependence of the vehicle's turning rate on its heading direction shown on bottom. This is a dynamical system of heading direction that has an attractor at the zero-crossing. Initial headings to the left or the right of this zero-crossing converge in time to the heading direction that points to the source (arrows).

mapping from physical intensity to a motor parameter. The difference in intensity sensed between the two sensors (the x-axis) determines the difference in movement generated by the two wheels (the y-axis). If there is a larger intensity on the left than on the right (i.e., a positive value along the x-axis), this will lead to a smaller motor command on the left than on the right. The vehicle will turn to the left. Conversely, if there is a larger intensity on the right than on the left (a negative value along the x-axis), this will cause the vehicle to turn to the right. These effects balance where the straight line crosses zero: Here, there is zero difference in intensity and no change in heading direction.

The differences in sensed intensity come from how the vehicle is oriented relative to the source: A positive difference left versus right corresponds to the vehicle heading to the right of the source, a negative difference corresponds to the vehicle heading to the left of the source. The difference in movement generated by the two wheels corresponds to different turning rates of the vehicle—positive for turning right, negative for turning left. Thus, the sensory-motor characteristic shown on top in Figure I.3 can be transformed into the functional dependence of the vehicle's turning rate on the vehicle's heading shown at the bottom of Figure I.3. Because the vehicle's turning rate is the rate of change of the vehicle's heading direction, this is a dynamical system that predicts the vehicle's future heading directions from its current heading direction. If you do not know yet what a dynamical system is and do not recognize this as a dynamical system, don't worry. We will provide a gentle introduction to these notions in the chapters that follow. In dynamical systems terms, the zero crossing of this dynamics has special meaning: This point is called an *attractor* because the vehicle's heading direction converges to this value over time from just about any initial heading. If the vehicle heads toward the right of that zero crossing, its turning rate is negative, so it will change heading toward the left. Analogously, if the vehicle heads toward the left of the zero crossing, its turning rate is positive, so it will change heading toward the right.

Why do we care about this dynamical system? Because it fully describes the laws of behavior for this simple vehicle—behavior emerges from this dynamical system as the vehicle moves around in a given environment. In a different environment, a different dynamical system arises. For instance, the environment of Figure I.4 with two sources leads to the dynamical system with two attractors shown on the left that enables the vehicle to make a selection decision, orienting to one source, ignoring the other. The dynamical system captures the closed loop in which the vehicle's sensation drives its action that, in turn, determines the vehicle's sensation. If we know the dynamical system, we can fully characterize—and predict—how the vehicle will behave. We build on this sense of understanding behavior throughout the book.

Concretely, our goal is to create a theoretical language that allows us to characterize the dynamical system that underlies human cognition and behavior. This dynamical system will specify the processes from which behavior emerges. And this dynamical system will be specified using neural dynamics that can be coupled to sensory and motor systems on a body that acts within a structured environment.

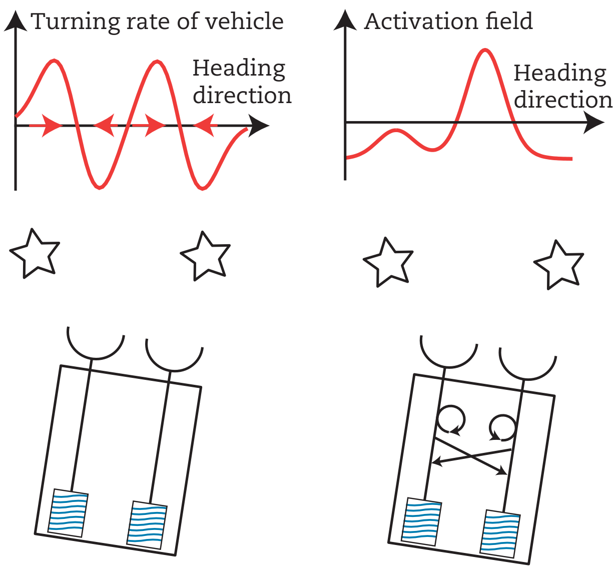

FIGURE I.4: *Left:* With two sources of intensity in the environment, the dynamical system from which orientation behavior emerges has two attractors (two zero-crossings toward which heading direction converges as indicated by the arrows). The vehicle selects one of the two sources depending on its initial heading. *Right:* Nervous systems with internal loops have neural dynamics in which activation evolves toward neural attractors. The activation field shown on top is in a neural attractor in which a peak of activation is positioned over the heading direction of one source, while input from the other source is suppressed. The first three chapters of the book provide the concepts to understand this form of internal neural processing.

Chapter 1 begins building this dynamical systems view with an overview of neural dynamics. We will see that to describe real nervous systems, we must move beyond the simple feed-forward picture captured by Braitenberg's vehicle. Instead, we will use closed loops that take place entirely within the nervous system to create internal attractor states—neural patterns that make decisions, select one input over another, and keep those decisions active even when the input is removed (see right side of Figure I.4).

In Chapter 2, we ask how such neural activation variables come about. The Braitenberg picture suggests that "neurons" must be intricately connected to the sensory surface and the motor surface. In simple vehicles, those surfaces are sampled by a small number of sensor or motor cells, but in real organisms, the sampling is so dense that we can describe these "surfaces" in terms of continuous spaces that are continuously coupled to the nervous system. Dynamic fields are the result—dynamical systems that reflect distributions of activation over appropriate feature spaces, including physical space. This enables the nervous system to know where a stimulus is located in space and to identify its particular features (e.g., color, shape, and so on).

In Chapter 3, we review the neural foundations of dynamic fields. We show that populations of neurons in cortex and many subcortical structures can be thought of using the concept of neural activation fields. In fact, it will turn out that real neurons in the brain operate as if they are smeared out over activation fields.

Finally, in Chapter 4, we come back to behavioral dynamics. We show how behavioral and neural dynamics can be combined within dynamic field theory, linking perception, action, and cognition. We demonstrate how this link enables embodied cognition by implementing a behavioral and neural dynamics on a robotic vehicle that orients toward targets, which it detects, selects, and keeps in working memory.