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Introduction

Research in the domain of biologically inspired walking machines has been ongoing for over 20 years [59, 166, 190, 199, 207]. Most of it has focused on the construction of such machines [34, 47, 216, 223], on a dynamic gait control [43, 117, 201] and on the generation of an advanced locomotion control [30, 56, 104, 120], for instance on rough terrain [5, 66, 102, 180, 192]. In general, these walking machines were solely designed for the purpose of motion without responding to environmental stimuli. However, from this research area, only a few works have presented physical walking machines reacting to an environmental stimulus using different approaches [6, 36, 72, 95]. On the one hand, this shows that less attention has been paid to walking machines performing reactive behaviors. On the other hand, such complex systems can serve as a methodology for the study of embodied systems consisting of sensors and actuators for explicit agent–environment interactions.

Thus, the work described in this book is focused on generating different reactive behaviors of physical walking machines. One is obstacle avoidance and escape behavior, comparable to scorpion and cockroach behavior (negative tropism), and the other mimics the prey capture behavior of spiders (positive tropism). In addition, the biological sensing systems used to trigger the described behaviors are also investigated so that they can be abstractly emulated in these reactive walking machines.

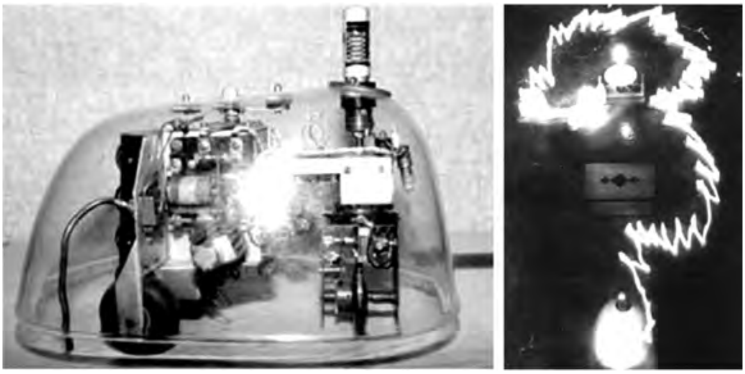
In the next section, the background of research in the area of agent–environment interactions is described, which is part of the motivation for this work, followed by the details of the approaches used in this work. The chapter concludes with an overview of the remainder of the book.

1.1 Survey of Agent–Environment Interactions

Attempts to create autonomous mobile robots that can interact with their environments or that can even adapt themselves into specific survival conditions have been ongoing for over 50 years [8, 41, 53, 75, 86, 136, 141, 143, 144, 157].

There are several reasons for this, which can be summarized as follows: first, such robotic systems can be used as models to test hypotheses regarding the information processing and control of the systems [69, 115, 146, 175]. Second, they can serve as a methodology for the study of embodied systems consisting of sensors and actuators for explicit agent–environment interactions [98, 99, 112, 135, 161]. Finally, they can simulate the interaction between biology and robotics through the fact that biologists can use robots as physical models of animals to address specific biological questions while roboticists can formulate intelligent behavior in robots by utilizing biological studies [63, 64, 173, 213, 214].

In 1953, W.G. Walter [208] presented an analog vehicle called "tortoise" (Fig. 1.1) consisting of two sensors, two actuators and two "nerve cells" realized as vacuum tubes. It was intended as a working model for the study of brain and behavior. As a result of his study, the tortoise vehicle could react to light stimulus (positive tropism), avoid obstacles (negative tropism) and even recharge its battery. The behavior was prioritized from lowest to highest order: seeking light, move to/from the light source, and avoid obstacles, respectively.



(a) (b)

Fig. 1.1. (**a**) Walter's tortoise (photograph courtesy of A. Winfield, UWE Bristol). (**b**) The tortoise *Elsie* successfully avoids a stool and approaches the light (copyright of the Burden Neurological Institute, with permission)

Three decades later, psychologist V. Braitenberg [32] extended the principle of the analog circuit behavior of Walter's tortoise to a series of "Gedanken" experiments involving the design of a collection of vehicles. These systems responded to environmental stimuli through inhibitory and excitatory influences directly coupling the sensors to the motors. Braitenberg created varieties of vehicles including those imagined to exhibit fear, aggression and even love

(Fig. 1.2) which are still used as the basic principles to create complex behavior in robots even now.

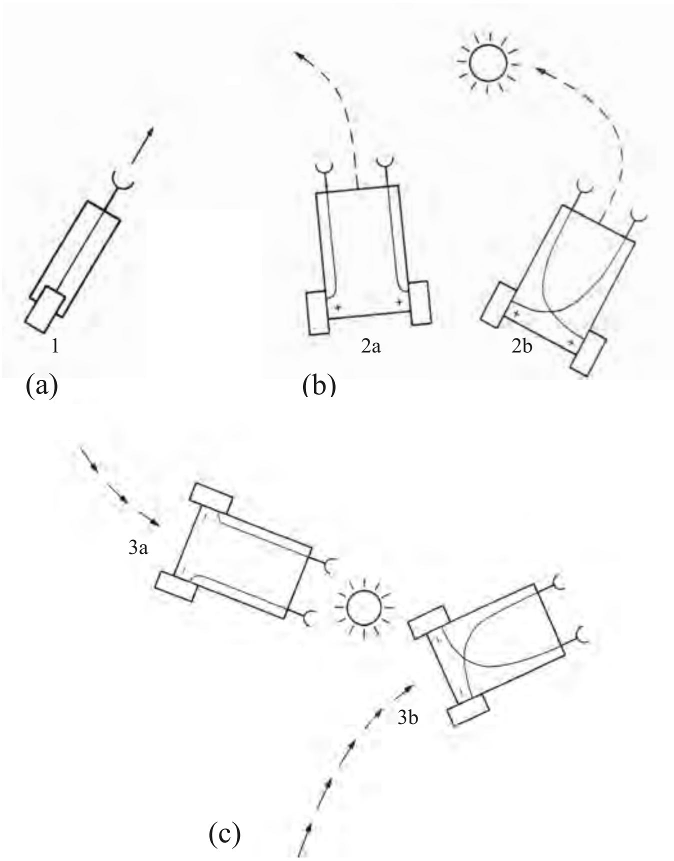
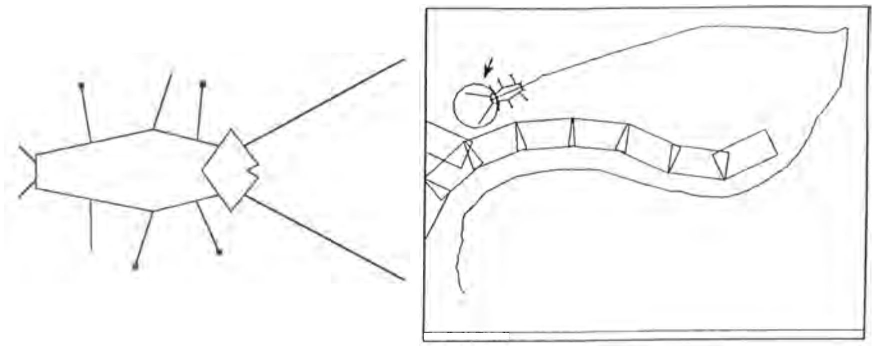


Fig. 1.2. Braitenberg vehicles. (**a**) Vehicle 1 consists of one sensor and one motor. Motion is always forward in the direction of the arrow and the speed is controlled by a sensor, except in the case of disturbances, e.g., slippage, rough terrain, friction. (**b**) Vehicle 2 consists of two sensors and two motors. Vehicle *2a* responds to light by turning away from a light source (exhibiting "fear"). Because the right sensor of the vehicle is closer to the source than the left one, it receives more stimulation, and thus the right motor turns faster than the left. On the other hand, vehicle *2b* turns toward the source (exhibits "aggression"). (**c**) Vehicle 3 is similar to vehicle 2 but now with inhibitory connections. Vehicle *3a* turns toward the light source and stops when it is close enough to the light source. It "loves" the light source, while vehicle *3b* turns away from the source, being an "explorer". (Reproduced with permission of V. Braitenberg [32])

One primitive and excellent example of a complex mobile robot (many degrees of freedom) that interacts with its environment appeared in Brooks' work [36, 38] in 1989. He designed a mechanism which controls a physical six-legged walking machine, *Ghengis* (Fig. 1.3), capable of walking over rough terrain and following a person passively sensed in the infrared spectrum. This mechanism was built from a completely distributed network with a total of 57 augmented finite state machines known as "subsumption architecture" [37, 39]. It is a method of decomposing one complex behavior into a set of *simple* behaviors, called layers, where more abstract behaviors are incrementally added on top of each other. This way, the lowest layers work as reflex mechanisms, e.g., avoid objects, while the higher layers control the main direction to be taken in order to achieve the overall tasks. Feedback is given mainly through the environment. This architecture is based on perception–action couplings with little internal processing. Having such relatively direct couplings from sensors to actuators in parallel leads to better real-time behavior because it makes time-consuming modeling operations and higher-level processes, e.g., task planning, unnecessary. This approach was the first concept toward so-called behavior-based robotics [10]. There are also other robots in the area of agent–environment interactions which have been built based on this architecture, e.g., *Herbert* [40], *Myrmix* [52], *Hannibal* and *Attila* [70, 71].

Fig. 1.3. The six-legged walking machine *Genghis*. It consists of pitch and roll inclinometers, two collision-sensitive antennas, six forward-looking passive pyroelectric infrared sensors and crude force measurement from the servo loop of each motor. (Photograph courtesy of R.A. Brooks)

In 1990, R.D. Beer et al. [22, 24] simulated the artificial insect (Fig. 1.4) inspired by a cockroach, and developed a neural model for behavior and locomotion controls observed in the natural insect. The simulation model was integrated with the antennas and mouth containing tactile and chemical sensors to perceive information from the environment; that is, it performs by wandering, edge following, seeking food and feeding food.



(a) (b)

Fig. 1.4. (**a**) *Periplaneta computatrix*, the computer cockroach where the *black squares* indicate feet which are currently supporting the body. (**b**) The path of a simulated insect. It shows periods of wandering, edge following and feeding (*arrow*). (Reproduced with permission of R.D. Beer [22])

In 1994, Australian researchers A. Russell et al. [179] emulated ant behavior by creating robotic systems (Fig. 1.5) that are capable of both laying down and detecting chemical trails. These systems represent chemotaxis: detecting and orienting themselves along a chemical trail.

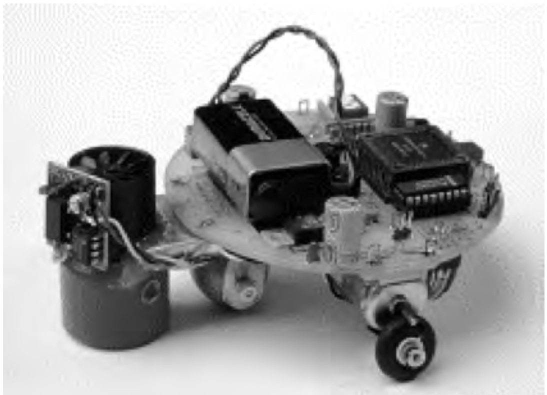


Fig. 1.5. Miniature robot equipped to follow chemical trails on the ground. (Photograph courtesy of A. Russell)

Around 2000, B. Webb et al. [212, 215] showed a wheeled robot that localizes sound based on close modeling of the auditory and neural system in the cricket (cricket phonotaxis). As a result, the robot can track a simulated male cricket song consisting of 20-ms bursts of 4.7-kHz sound. Continuously, such robot behavior was developed and transferred into an autonomous outdoor robot – $Whegs^{IM}$ ASP – three years afterwards [95]. The Whegs (Fig. 1.6) was able to localize and track the simulated cricket song in an outdoor environment. In fact, Webb and her colleagues intended to create these robotic systems in order to better understand biological systems and to test biologically relevant hypotheses.

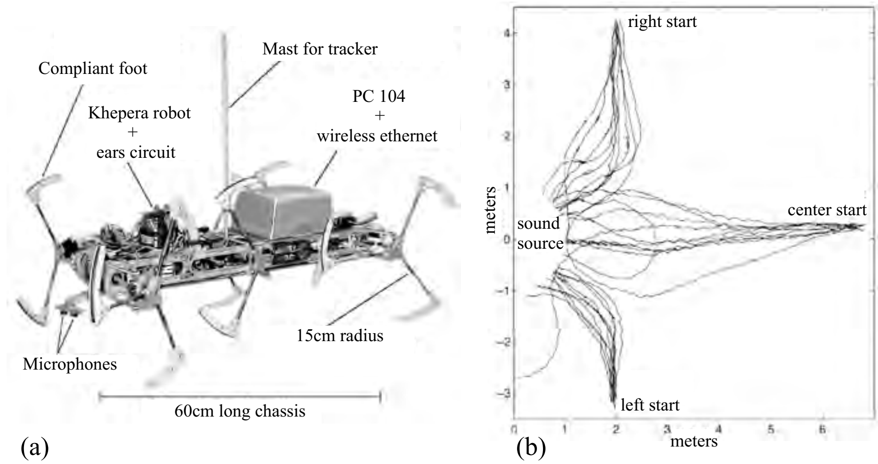
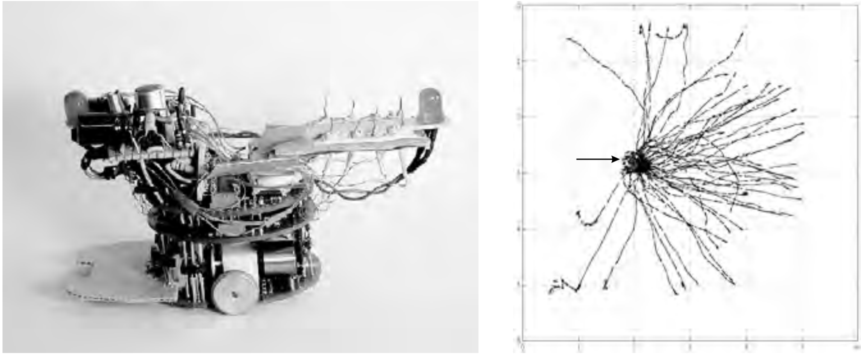


Fig. 1.6. (**a**) The Whegs. (**b**) Thirty sequential outdoor trials, recorded using the tracker, showing the robot approaching the sound source from different directions. (Reproduced with permission of A.D. Horchler [95])

The extension of the work of Webb was done by T. Chapman in 2001 [46]. He focused on the construction of a situated model of the orthopteran escape response (the escape response of crickets and cockroaches triggered by wind or touch stimulus). He demonstrated that a two-wheeled Khepera robot (Fig. 1.7) can respond to various environmental stimuli, e.g., air puff, touch, auditory and light, where the stimuli referred to a predatory strike. It performed antennal and wind-mediated escape behavior, where a sudden increase in the ambient sound or light was also taken into account.

In 2003, F. Pasemann et al. [155] presented the small recurrent neural network which was developed to control autonomous wheeled robots showing obstacle avoidance behavior and phototropism in different environments (Fig. 1.8). The robots were employed to test the controller and to learn about the recurrent neural structure of the controller.



(a) (b)

Fig. 1.7. (**a**) The robot model-mounted artificial hairs, antennas, ocelli and ear. (**b**) The combined set of wind-mediated escape run tracks, where the *arrow* indicates the stimulus. The robot was oriented in different directions relative to the stimulus. The *tracks* show the complete set of 48 escape run trials. (Reproduced with permission of T. Chapman [46])

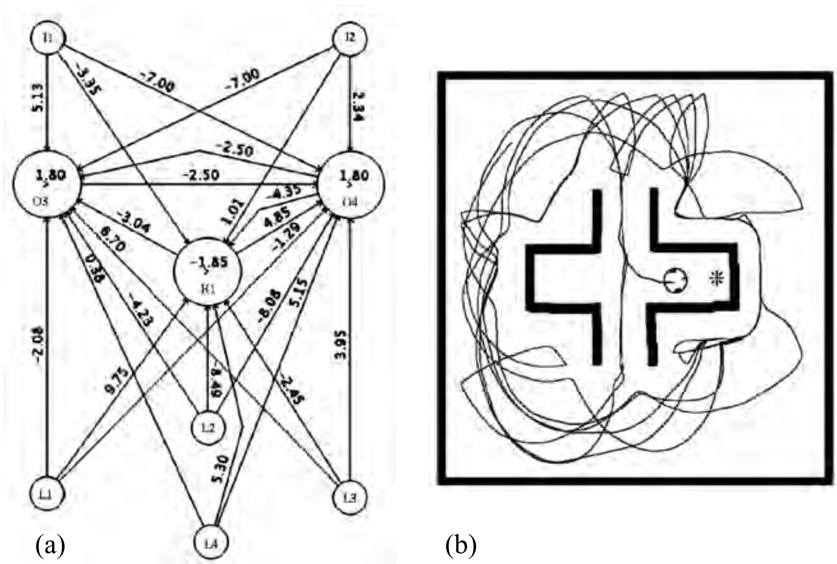


Fig. 1.8. (**a**) An evolved neural controller generating exploratory behavior with phototropism. (**b**) The simulated robot performing obstacle avoidance and phototropic behavior. (Reproduced with permission of F. Pasemann [155])

At the same time, H. Roth et al. [176, 177] introduced a new camera based on Photonic Mixer Device (PMD) technology with fuzzy logic control for obstacle avoidance detection of a robot called Mobile Experimental Robots for Locomotion and Intelligent Navigation (MERLIN, Fig. 1.9). The system was implemented and tested on a mobile robot, which resulted in the robot perceiving environmental information, e.g., obstacles, through its vision system. It can even recognize the detected object as a 3D image for precisely performing an obstacle avoidance behavior.

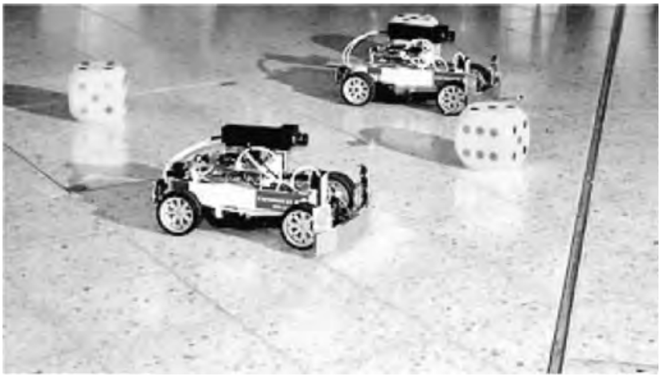


Fig. 1.9. MERLIN robots equipped with PMD cameras driving on a terrain with obstacles. (Reproduced with permission of H. Roth [177])

The above examples are robots in the domain of agent–environment interactions, a field which is growing rapidly. The most comprehensive discussion can be found in the following references: R.C. Arkin (1998) [10], J. Ayers et al. (2002) [11] and G.A. Bekey (2005) [26].

1.2 Aims and Objectives

The brief history of the research presented above shows that the principle of creating agent–environment interactions combines various fields of study, e.g., the investigation of the robotic behavior control and the understanding of how a biological system works. It is also the basis for the creation of a so-called Autonomous Intelligent System, which is an active area of research and a highly challenging field. Thus, the work described here continues in this tradition with the extension of the use of biologically inspired walking machines as agents. They are reasonably complex mechanical systems (many degrees of freedom) compared to wheeled robots, which have been used in most previous research. In addition, the creation of desired reactive behaviors has to be done using more advanced techniques.

However, there are many different techniques and approaches for robotic behavior control which can be classified into two main categories: one is deliberate control and the other is reactive control. According to R.C. Arkin (1998) [10], a robot employing deliberative reasoning requires relatively complete knowledge about the world and uses this knowledge to predict its actions, an ability that enables it to optimize its performance relative to its model of the world. This results in the possibility that the action may seriously err if the information that the reasoner uses is inaccurate or has changed since being first obtained. On the other hand, reactive control is a technique used for tightly coupling perception and action, and it requires no world model to perform the action of robots. In other words, this reactive system typically consists of a simple sensorimotor pair, where the sensory activity provides the information to satisfy the applicability of the motor response. Furthermore, it is suitable for generating robot behavior in the dynamic world. This means that robots can react to environmental stimuli as they perceive without concern for task planning algorithms or memory capacities.

In this book, we shall concentrate on the concept of reactive control to generate the behavior of four- and six-legged walking machines. In particular, we shall present a behavior controller based on a modular neural structure with an artificial neural network using discrete-time dynamics. It consists of two main modules: neural preprocessing and neural control[1] (Fig. 1.10).

The function of this kind of a neural controller is easier to analyze than many others which were developed for walking machines, for instance, by using evolutionary techniques [30, 72, 103, 119, 149, 168]. In general, they were too large to be mathematically analyzed in detail, in particular, if they used a massive recurrent connectivity structure. Furthermore, for most of these controllers, it is *hardly possible* to transfer them successfully onto walking machines of different types, or to generate different walking modes (e.g., forwards, backwards, turning left and right motions) *without modifying the network's internal parameters or structure* [22, 27, 56, 221].

In contrast, the controller developed here can be *successfully applied to a physical four-legged as well as to a six-legged walking machine*, and it is also able *to generate different walking modes without altering internal parameters or the structure of the controller*. Utilizing the modular neural structure, different reactive behavior controls can be created by coupling the neural control module with different neural preprocessing modules. Because the functionality of the modules is well understood, the reactive behavior controller of a less complex agent[2] (four-legged walking machine) can be applied also to a more complex agent (six-legged walking machine), and vice versa. A part of

[1] Here, *neural preprocessing* refers to the neural networks for sensory signal processing (or so-called neural signal processing). *Neural control* is defined as the neural networks that directly command motors of a robot (or so-called neural motor control). These definitions are used throughout this book.

[2] In this context, the complexity of an agent is determined by the number of degrees of freedom.

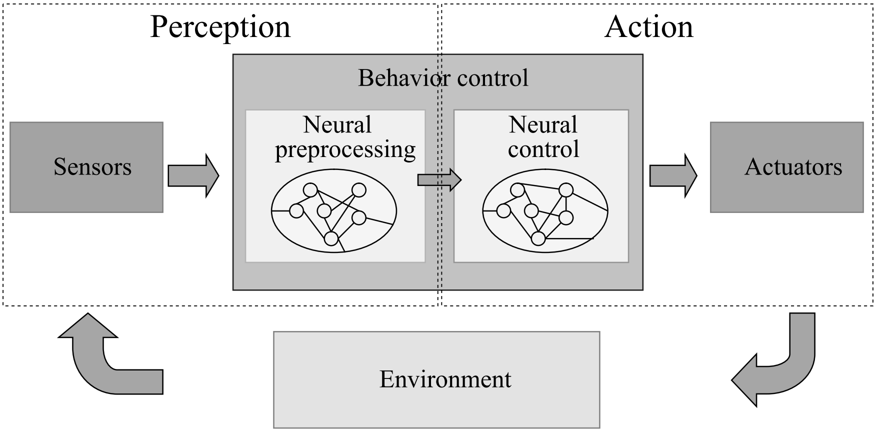


Fig. 1.10. The diagram of the modular reactive neural control (called behavior control). The controller acts as an artificial perception–action system, i.e., the sensor signals go through the neural preprocessing module into the neural control module which commands the actuators. As a result, the robot's behavior is generated by the interaction with its (dynamic) environment in the sensorimotor loop

the controller is developed by realizing dynamic properties of recurrent neural networks, and the other is generated and optimized through an evolutionary algorithm. On the one hand, the small recurrent neural networks (e.g., one or two neurons with recurrent connections [150, 151, 153]) exhibit several interesting dynamic properties which are capable of being applied to create the neural preprocessing and control for the approach used in this book. On the other hand, the applied evolutionary algorithm Evolution of Neural Systems by Stochastic Synthesis (ENS^3) [97] tries to keep the network structure as small as possible with respect to the given fitness function. Additionally, every kind of connection in hidden and output layers, e.g., self-connections, excitatory and inhibitory connections, is also allowed during the evolutionary process. Consequently, the neural preprocessing and control can be formed using a small neural structure.

In order to physically build four- and six-legged walking machines for testing and demonstrating the capability of the behavior controllers, the morphologies of walking animals are used as inspiration for the design. The basic locomotion control of the walking machines is also created by determining the principle of animal locomotion. In addition, an animal's behavior as well as its sensing systems are also studied to obtain robot behavior together with its associated sensing systems. Inspired by the obstacle avoidance and escape behavior of scorpions and cockroaches, including their associated sensing systems, the behavior controller, called an "obstacle avoidance controller", and the sensing systems are built in a way that enables the walking machines to avoid obstacles or even escape from corners and deadlock situations. This behavior is represented as a negative tropism while a positive tropism is triggered by a sinusoidal sound at a low frequency—200 Hz. The sound induced behavior, in analogy to prey capture behavior of spiders, is called sound tropism. It is driven by a so-called sound tropism controller together with a corresponding sensory system. As a result, the walking machine reacts to a switched-on sound source (prey signal) by turning toward and finally making an approach (capturing a prey).

Eventually, all these different reactive behaviors are fused by using a sensor fusion technique[3] to obtain an effective behavior fusion controller, where different neural preprocessing modules have to cooperate. These reactive systems also aim to work as artificial perception–action systems in the sense that they perceive environmental stimuli (positive and negative tropism) and directly perform the corresponding actions. However, the created systems have no appropriate benchmarks for judging their success or failure. Thus, the ways to evaluate the systems are by empirical investigation and by actually observing their performance.

1.3 Organization of the Book

This chapter provided an overview of the research in the domain of agent–environment interactions, followed by the details of approaches to versatile artificial perception–action systems. The rest of this book is organized as follows:

Chapter 2 provides the biological background that served as an inspiration for the design of the reactive behaviors of walking machines, the physical sensing systems, the structures of walking machines and their locomotion control. It also shows how these biologically inspired systems are applied to the work done in this book.

Chapter 3 contains a short introduction to a biological neuron together with an artificial neuron model. Furthermore, it also describes, in detail, the discrete dynamical properties of a single neuron with a recurrent connection and an evolutionary algorithm. These are employed as the methods and tools used throughout this book.

Chapter 4 describes the biologically inspired sensory systems and walking machines which were originally built with physical components in this book. They serve as hardware platforms for experiments with the modular neural controllers or even as artificial perception–action systems.

[3] This fusion technique consists of two methods: a look-up table, which manages sensory input by referring to their predefined priorities, and a time scheduling method, which switches behavioral modes.

Chapter 5, which is the main contribution of this book, introduces the neural preprocessing of sensory signals and neural control for the locomotion of walking machines. It also presents different behavior controls which are the product of the combination between the different neural preprocessing units and the neural control unit. It ends up with the detail of behavior fusion control that combines all created reactive behaviors and leads to versatile artificial perception–action systems.

Chapter 6 shows the detailed results of the neural preprocessing tested with the simulated and real sensory signals. It also shows the capabilities of the controllers implemented on the physical walking machine(s) which generate different reactive behaviors.

Chapter 7 examines what has been achieved so far and suggests new avenues for further research.