N90-23061

DISTRIBUTED NEURAL CONTROL OF A HEXAPOD WALKING VEHICLE

R. D. Beer
L. S. Sterling
Computer Engineering and Science

R. D. Quinn
Mechanical and Aerospace Engineering

H. J. Chiel
R. Ritzmann
Biology

Case Western Reserve University
Cleveland, Ohio

ABSTRACT

There has been a long-standing interest in the design of controllers for multilegged vehicles. Our approach is to apply distributed control to this problem, rather than using parallel computing of a centralized algorithm. We describe a distributed neural network controller for hexapod locomotion which is based on the neural control of locomotion in insects. The model considers the simplified kinematics with two degrees of freedom per leg, but the model includes the static stability constraint. Through simulation we have demonstrated that this controller can generate a continuous range of statically stable gaits at different speeds by varying a single control parameter. In addition, the controller is extremely robust, and can continue to function even after several of its elements have been disabled. We are building a small hexapod robot whose locomotion will be controlled by this network. We intend to extend our model to the dynamic control of legs with more than two degrees of freedom by using data on the control of multisegmented insect legs. Another immediate application of this neural control approach is also exhibited in biology: the escape reflex. Advanced robots are being equipped with tactile sensing and machine vision so that the sensory inputs to the robot controller are vast and complex. Neural networks are ideal for a lower level safety reflex controller because of their extremely fast response time. Our combination of robotics, computer modelling, and neurobiology has been remarkably fruitful, and is likely to lead to deeper insights into the problems of real-time sensorimotor control.

1. INTRODUCTION

In rough terrain multi-legged walking machines promise much greater mobility than their wheeled counterparts. Walking vehicles are being researched and developed for hazardous rough environments such as battlefields, nuclear irradiated facilities and remote planetary exploration. Examples of these vehicles include some Mars Rover configurations (Ref. 1), the six-legged OSU-DARPA vehicle (Ref. 2), and various machines in research labs throughout the world (Ref. 3).

The major problems encountered in walking vehicle development are hardware (especially sensor) reliability and control. The controller must process all of the sensory data and coordinate the motions of the multiple legs with their multiple joints while maintaining stability. Most control approaches require position and rate feedback from all of the joints as well as tactile or force feedback from contact surfaces. The sensory data may be conflicting especially in the presence of sensor failure.

Centralized control, where all control decisions are made based on all sensory information and all performance requirements, has proven inefficient and cumbersome. Centralized control requires that the computational speed be extremely fast relative to the walking speed in order to process the large quantity of complex sensory data and choose an acceptable joint motion in real time. With centralized control, safety requires that the machine stop when sensory information conflicts or hardware failure occurs. Parallel processing can increase computational speed but in itself does not alleviate the basic flaws of centralized control.

Distributed control approaches, where some control decisions are made based on localized information, promise to speed the overall system. Mechanical subdivisions such as individual joints or legs are to be controlled by local dedicated processors. Some sensory and system information must be shared among these parallel processors and a central processor. The central processor is responsible for coordination of the subdivisions. A hierarchical approach to system control permits distributed control of basic (low-level) functions freeing the central processor for higher level control decisions. The parallelism of distributed control promotes robustness in the presence of malfunctions. The difficult questions encountered in applying this approach are: What control architecture is suitable, how are the subdivisions chosen, what information should be shared, and how much authority must the central processor have?

Artificial neural networks offer the possibility of highly distributed control. Each neuron can be viewed as a processor working in parallel with the other neurons. The synapses which connect the neurons permit the sharing of information. Most research in artificial neural nets has emphasized homogeneous architectures where all neurons are of the same design despite their function. Learning is the process where the synaptic weights are adjusted so that the nervous system exhibits the desired input/output characteristics. A synaptic weight of zero nullifies the synaptic connection between two neurons. Learning is generally required for even the most fundamental tasks.

Even relatively primitive animals such as insects have nervous systems which are orders of magnitude more complex than the most advanced artificial neural nets. Yet, biologists are now studying certain insect nervous systems in detail with the intent of understanding their architecture and input/output characteristics.

In nature insects solve the problem of coordination of six multi-segmented legs in real time in the presence of variations in terrain and developmental changes. Also, insects display robustness, that is, they continue to function, although less efficiently, after suffering mechanical and electrical damage (Ref. 4). Biologists have found that nervous systems are heterogeneous, that is, a neurons structure is closely tied to its function. As a consequence, insects display remarkable coordination at birth. Their neural architecture is such that they do not require learning to perform basic functions. However, learning permits the insects to adapt to their environment and become more efficient.

An artificial neural network was developed to control the *kinematic* problem of locomotion of a hexapod walking machine in the presence of the static stability constraint. The hexapods six legs each had two degrees of freedom: foot up/down and leg swing front/back. The controller architecture was inspired by neurobiology; The artificial neural net was heterogeneous and learning was not necessary.

A computer simulation was performed displaying locomotion of the hexapod.

Changing a single input caused the hexapod to change its gait. The gaits are very similar to those observed in nature. The robustness of the controller in the presence of malfunctions was investigated through "lesion studies". For this purpose particular synapses in the artificial neural network were severed rendering a particular neuron ineffective during simulations. These lesion studies demonstrated that the artificial neural controller is robust to damage to any neuron.

The neural controller described in this paper was developed by Beer, Chiel and Sterling and has been published in other forums (Refs. 5,6). We (the entire list of authors) have since been working together on the project. The pupose of this paper is to report what we believe are important findings to the Aerospace community and highlight direct applications of this type of neural control to the Aerospace field.

2. HEXAPOD MECHANICAL MODEL

The mechanical model is a six-legged walking vehicle with two degrees of freedom per leg. It is loosely based on Periplaneta americana, the American Cockroach and Fig. 1 is a top view of the model. The legs can swing back and forth and the foot can be raised and lowered. The small black squares in Fig. 1 denote the feet in the down position. The simulated locomotion of the hexapod takes place in a horizontal plane on a smooth surface. The dashed lines connecting the squares form what is known as the static stability polygon. When the center of mass of the hexapod lies inside this polygon, the system is statically stable. Other than satisfying the static stability constraint, the simulated model considers only simplified kinematics where the leg swing and foot up/down motions are considered to be independent.

The natural insect actually has what can considered to be four revolute degrees of freedom per leg for a total of 24 joint degrees of freedom. The "hip" joint where the leg attaches to the body has two revolute degrees of freedom permitting swing along the body axis and away from the body. The lower two joint degrees of freedom, the "knee" and "ankle", joint axes are aligned. The "foot" is long and relatively flexible. When a foot is down, consider that the foot translation is constrained to zero. Hence, ignoring flexibility, when all six feet are down, there are 18 constraints leaving 6 degrees of freedom. The insect can then move its body rigidly with all its feet down.

Our hexapod model, on the other hand, has only two degrees of freedom per leg. Furthermore, we make the simplification that the swing and foot up/down motions are independent. Actually, the joint motions must be coupled and the joints must move simultaneously to accomplish the desired walking motion. The desired walking motion involves only translation of the body forward or backward without unnecessary pitching or other body motions. With all feet down and constrained to zero translation, our model permits the body to translate forward or backward with appropriate coupled motion of all the joints.

3. NEURAL CONTROLLER MODEL

A schematic showing the electrical circuit of the most complex neuron used in the heterogeneous network is shown in Fig. 2. Weighted synaptic currents are input/output from/to connected neurons. The synapses are weighted to establish a hierarchy for the input information. Intrinsic currents are internal to the neuron and permit "self stimulation." The parallel RC circuit mimics biological cell membrane electrical characteristics. The output firing frequency of the cell is a nonlinear

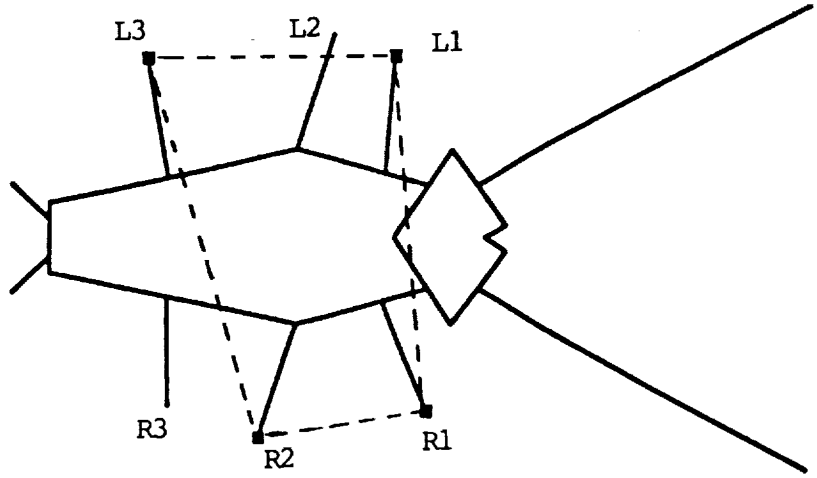

Fig. 1 Periplaneta computatrix (Simulated model)

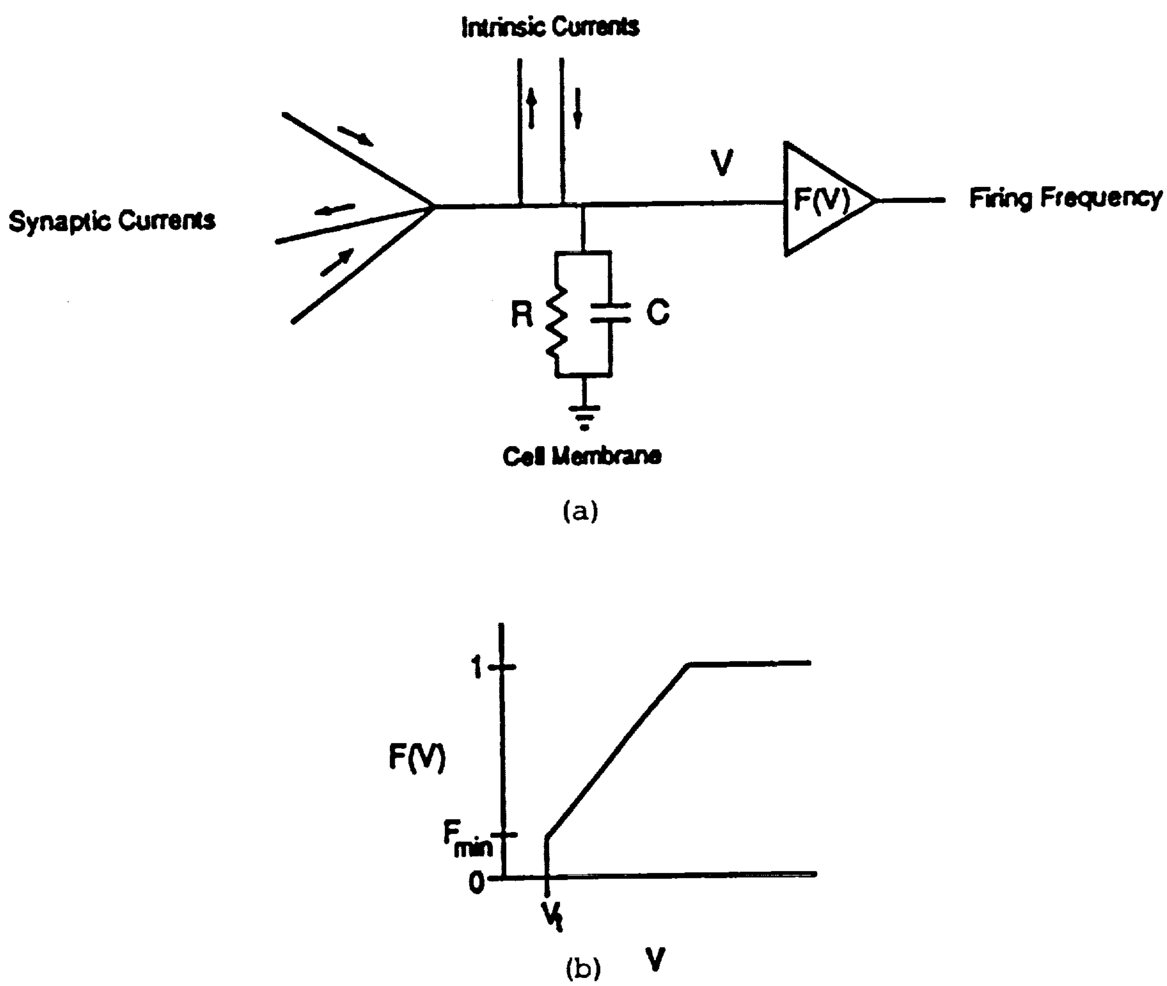

Fig. 2 Neural Model

function f(V) of the resulting neural potential V. Saturating linear threshold functions were used as shown in Fig. 2b.

Summing the currents in the network, the state equation for the ith neuron can be expressed as

$$C_i \frac{dV_i}{dt} = \sum_{j=1}^{n} S_{ij} F_j(V_j) + \sum_{k=1}^{m} \bar{I}_k(V_i,t) - \frac{V_i}{R_i}$$

where S_{ij} is the weight for the synapse carrying input current from the jth neuron to the ith neuron. If this weight is zero, there is no electrical connection between these neurons. In general the model includes n neurons in the network and m intrinsic currents for the ith neuron. $\bar{I}_k$ is the kth intrinsic current for the ith neuron and it is in general a function of the neuron potential and time.

Biological nervous systems display heterogeneous architectures. In particular, some natural neurons exhibit intrinsic stimulation characteristics and some do not. In fact, intrinsic currents have proven to be important neural components underlying many behaviors. A "pacemaker" cell is capable of intrinsically producing rhythmic bursting and can be externally inhibited or excited by other neurons. In this way the frequency and phase of the internal bursting rhythm can be changed by other neural inputs. As described by Kandel (Ref. 7), a pacemaker cell exhibits the following characteristics: 1) when it is inhibited below its threshold, it does not fire, 2) when it is excited beyond saturation, it fires continuously, 3) between these extremes, the firing frequency is a continuous function of the membrane potential, 4) transient excitation or inhibition can shift the phase of (reset) the intrinsic firing rhythm.

Pacemaker cells play a crucial role in our locomotion controller. In our model two intrinsic currents permitted a neuron to act as a pacemaker cell. One current I_H tended to raise the neural potential above firing threshold and the other intrinsic current I_L tended to lower the potential below threshold. The "control law" for these currents obeyed the following rules: 1) I_H is triggered or I_L is terminated when the cell potential goes above threshold, and remains active for a fixed time period, 2) I_L is triggered when I_H terminates, and then remains active for a variable time period which is a linear function of membrane potential.

4. NEURAL NETWORK CONTROLLER

The kinematic locomotion controller consists of a network of 6 neurons controlling each leg and 1 central command neuron for a total of 37 neurons. Figure 3 shows the controller for a single leg including the common command neuron. There are three motor neurons per leg: stance, foot, and swing. The stance neuron swings the leg backward and, if the foot is down, propels the body forward. When the foot motor neuron fires, the foot is lowered. The swing neuron swings the leg forward and, if the foot is down, propels the body backward. The level of the outputs of the motor neurons determines the speed of the motor actions.

The pacemaker P natural rythmic firing inhibits the foot and stance neurons and excites swing. The command neuron C excites the pacemaker and stance neurons. This excitation influences pacemaker burst rate and stance

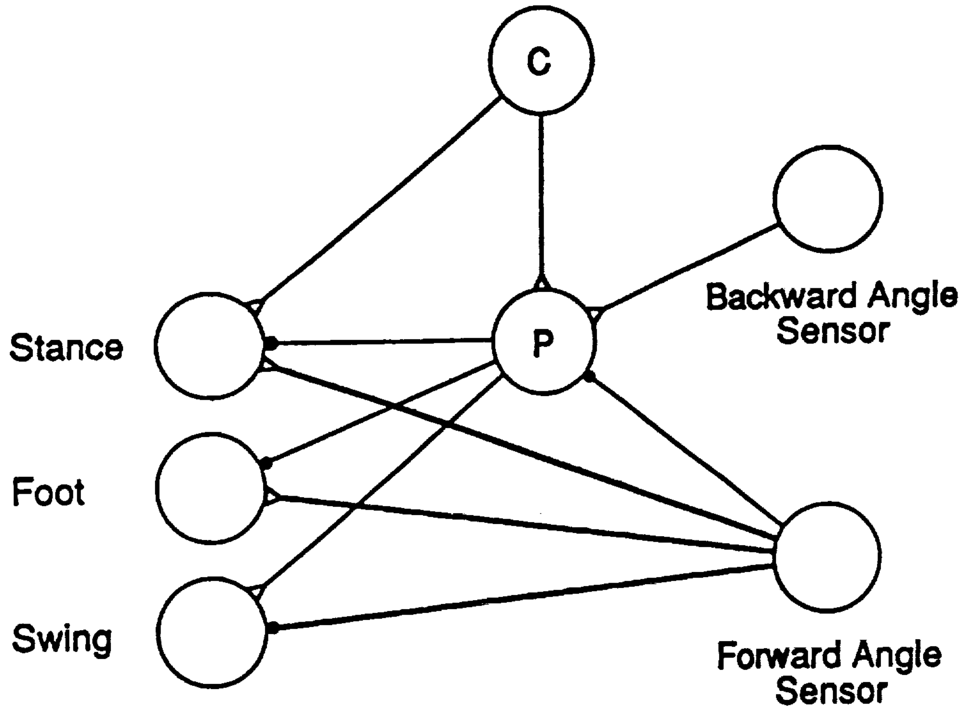

Fig. 3 Neural Network Controller for a Leg

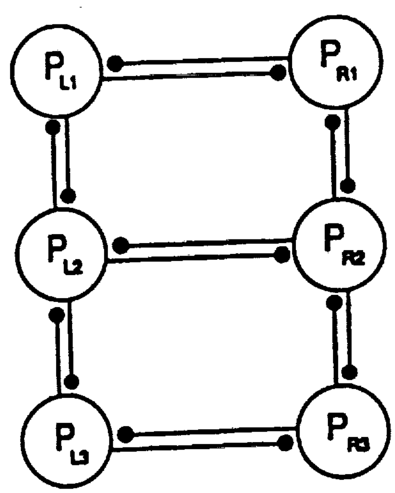

Fig. 4 Adjacent Leg Pacemaker Inhibition

speed so that the command neuron may be thought of in simple terms as the throttle.

The locomotion controller can function open-loop based on the "natural" pacemaker rhythm. However, in order to smooth and coordinate the swing/stance transitions, limit-switch sensor neurons were added to sense when the legs reached extreme backward and forward angle positions. This information is fedback to the pacemaker neuron. The forward angle sensor information is also fedback to the motor neurons which provides a biologically inspired "stance reflex" (Ref. 8). The stance reflex compensates for the delay at the end of each swing caused by the RC characteristics and smooths the jerky movements otherwise caused by the delay, and increases stability.

The backward angle sensor neuron excites the pacemaker which in turn excites the swing. The forward angle sensor inhibits the pacemaker and swing and excites the stance and foot (stance reflex). Hence, the sensors reinforce the controller strategy and coordinate the leg motors. These sensors were inspired by the hair plate receptors observed on the natural insect.

If we ended the controller development at this point, the legs would function independently except for the input of the common command neuron. The resulting walking gaits show arbitrary leg movements and are awkward, uncoordinated and often statically unstable. Again, inspired by observed natural insect walking gaits (Ref. 8), we observe that adjacent legs do not swing simultaneously which is clearly a good rule of thumb for maintaining static stability. This controller strategy was implemented through adjacent pacemaker inhibition shown in Fig. 4.

Stability remains a problem for the controller because there is no device to order the stepping sequence. The gaits were found to depend on the initial angles of the legs. Turning to biology for inspiration once more, we note that insects tend to walk with their legs in a particular sequence: the "metachronal wave" of stepping progresses from back to front (Ref. 9). This sequence was achieved by our controller by slightly increasing the leg angle ranges of the rear legs, lowering their stepping frequency for a given constant swing/stance angular rate.

The rear legs angle range increase along with the pacemaker coupling of Fig. 4 results in the rear legs entraining the middle legs as illustrated in Fig. 5. In this simplified example, R3 and R2 denote the right rear and right middle legs. The square impulses drawn with dashed lines show the coupling pacemaker inhibition by the other leg. The bold lines denote pacemaker firing. Note the longer stroke of R3. In this example the fourth R2 pacemaker firing is delayed through inhibition by R3. The entrainment is then complete, the middle leg swings immediately after the back leg.

5. SIMULATION RESULTS

When the neural controller was implemented on the simulated hexapod in a smooth environment, the hexapod walked successfully. The walking speeds and gaits changed when the firing frequency of the central command neuron was varied. A continuum of statically stable gaits was observed from the "wave gait" to the "tripod gait." Very similar gaits are observed in biological insects locomotion. Noteably, these gaits "naturally" occur in the simulation environment as a result of the interaction between the neural controller and the mechanical model.

Figure 6 is a comparison of gaits of biological insects (Ref 10) with the simulated gaits of the model hexapod. The legs are labeled as in the top of Fig. 6. A black bar denotes the swing phase of each leg; during the space between the swings, the legs are in the stance phase. The simulated gaits

(Fig. 6b) were chosen from the continuum of possible gaits to most closely match the displayed natural gaits. These gaits were obtained by merely increasing the firing rate of the command neuron from the lowest (top figure) to the highest (bottom figure).

The bottom-figure (Fig. 6a) natural gate is statically unstable and so could not be obtained our model. In the wave gate, the metachronal waves on each side of the body are nearly separated (top comparative figures in Fig. 6a and 6b). In the tripod gate (bottom comparative figures in Fig. 6a and 6b) the front and back legs on one side of the body step with the middle leg on the other side.

Lesion studies were conducted to determine the robustness of the controller to particular neurons being disabled (Ref. 6). Because of its highly distributed architecture, the controller was found to be robust to damage to any individual element. For instance, when the command neuron was disabled during a stable gait, there was no effect. When the command neuron was disabled initially, a stable gait displaying the metachronal wave was slowly reached. This illustrates the value of the "self stimulating" pacemaker neurons. In another case, the rear sensors were disabled during the tripod gait with no effect. When the rear sensors were disabled during a slower gait, a stable gait ensued.

6. CONCLUSIONS AND ONGOING WORK

An artificial neural network was designed for the purpose of controlling a simulated hexapod walking vehicle. The neural model and network architecture were inspired by observed natural insect nervous systems. The simulation addressed the kinematic problems of locomotion of a six legged walking vehicle with two degrees of freedom per leg subject to the static stability constraint. The neural control "strategy" includes feedback from sensor neurons which fire when the legs reach their extremes angles. Pacemaker neurons which have an intrinsic firing rhythm play a crucial role in the controller.

The hexapod walked successfully exhibiting a continuum of statically stable gaits. The walking gait and speed depended on the central command neuron firing frequency so that the command neuron could be thought of as a throttle. The gaits appear "naturally" in simulation because of the interactions between the controller and the mechanical model. The gaits are very similar to those exhibited by natural insects.

The controller is highly distributed; The only coupling between the legs is through adjacent leg pacemaker inhibition and the command neuron is the only common central neuron. Furthermore, the pacemakers natural rhythm enables stable walking gaits even when the command neuron is silent. This high degree of control distribution (or parallelism) produces an extremely robust controller. In fact, the controller is robust to removal of any individual neuron.

The high degree of distribution also yields a controller with extremely quick reflex-like responses. A clear application of this type of system is for safety-reflex control of all types of robots and telerobots with advanced sensing capabilities. A great deal of complex sensing information can be provided by tactile and force sensors as well as machine vision. When a dangerous situation arises, the time delays associated with a centralized controller will not permit the robot to recognize the danger and react in the short amount of time that may be needed to avoid catastrophe. The danger could be for the robot itself, for humans, or for precious cargo. A lower level neural reflex controller can be preprogrammed to recognize dangerous situations and reside in the robot control hierarchy. When the situation arises, the reflex controller can then take command to move the robot to a predetermined safe configuration.

The reflex safety response is also biologically inspired. For instance, the American Cockroach senses wind from a suddenly approaching predator, turns away and begins to run in approximately 50 milliseconds. Biologists at CWRU are presently studying this phenomenon and the detailed nervous system of this insect.

We are also constructing a three dimensional simulated hexapod model including dynamics so that we can further validate and improve the controller. A small mechanical hexapod machine is being constructed with the intention of applying our controller to a working machine. The vehicle initially will have two degrees of freedom per leg , but a third degree of freedom is to be eventually added to permit smooth turning and climbing.

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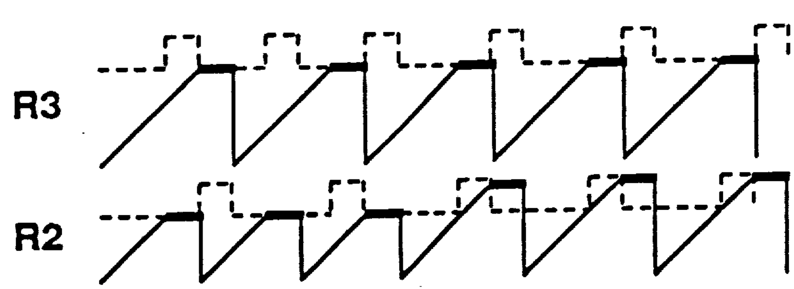
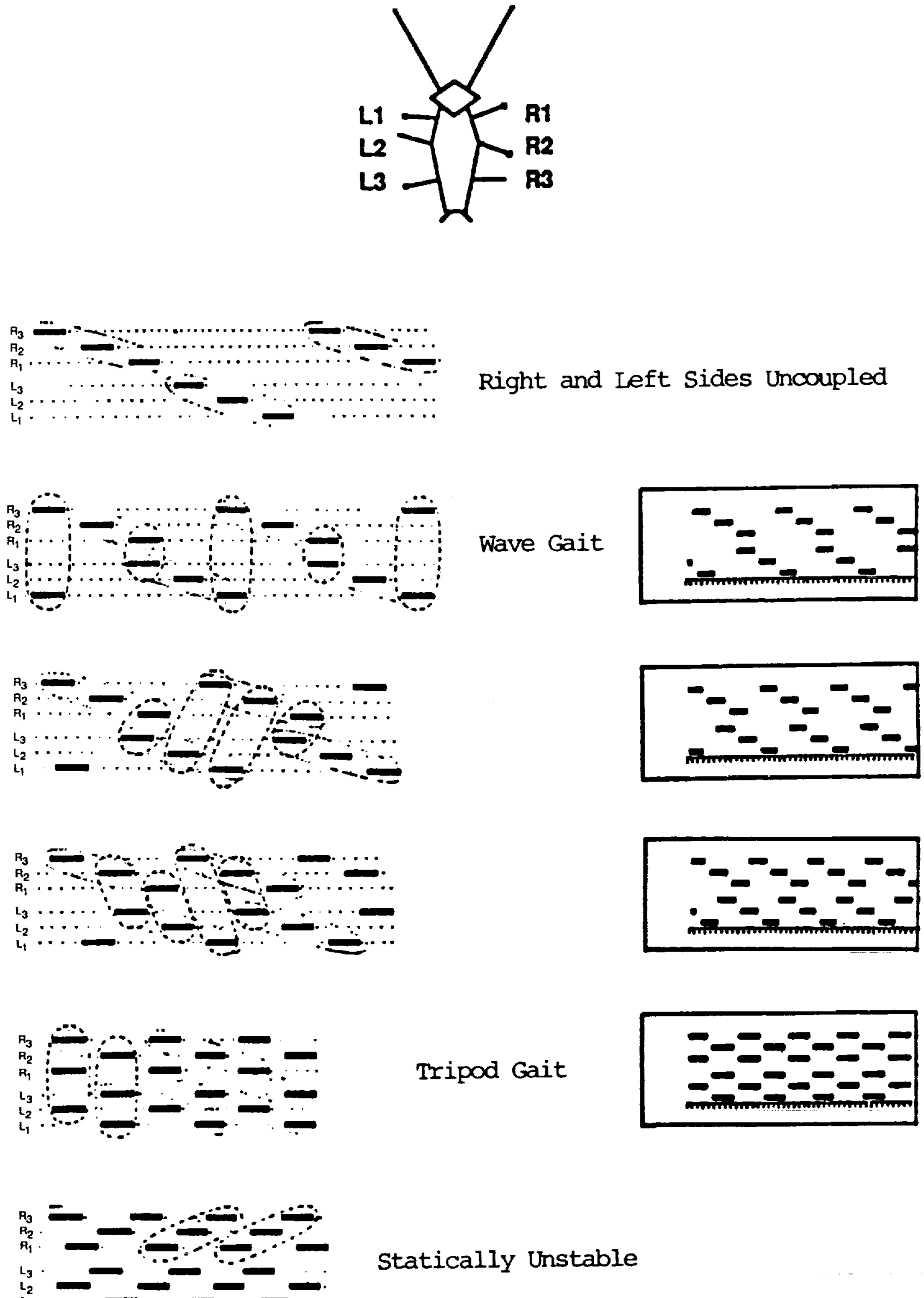


Fig. 5 Entrainment of Middle Leg by Rear Leg



(a) Natural Gaits (Ref. 10) (b) Simulated Gaits

Fig. 6 Comparison of Natural Gaits with Simulated Gaits