

## Improved neural net controller for a six-legged walking system

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### Abstract

A system that controls the leg movement of an animal or a robot walking over irregular ground has to ensure stable support for the body and at the same time propel it forward. To do so, it has to react adaptively to unpredictable features of the environment. As part of our study of the underlying mechanisms we present here a model which describes the control of the leg movement of a 6-legged walking system. The model is based on biological data obtained from the stick insect. It represents a combined treatment of realistic kinematics and biologically motivated, adaptive gait generation. The model extends a previous algorithmic model in substituting simple artificial neurons for the algorithms previously used to control leg state and interleg coordination. The model is able to walk at different speeds over irregular surfaces. The control system rapidly reestablishes a stable gait when the movement of the legs is disturbed or the model begins walking from an arbitrary starting configuration.

### 1 Introduction

Neural networks which initiate and control the behavior of animals embody several features. One feature concerns the role of sensory input. At one extreme are networks which mediate actions that are direct responses to sensory input, i.e., reactive or sensory-driven actions. At the other are networks which themselves generate the basic activation or movement parameters for the behavior, i.e. autonomous activity or actions controlled by central pattern generators. For a system to produce suitable actions in an unpredictable environment, however, the control system usually contains elements of both kinds. A second feature concerns the structure of the control network. In most complex biological networks, control functions, whether sensory-driven or autonomous, are dispersed among several subsystems which interact more or less strongly.

Both aspects are especially true for walking. Although it is sometimes regarded as quite a simple behavior, it involves a very strong and complex interaction with the physical environment. Typical control systems involve autonomous elements as well as simple reflexes and more complex sensory-driven modulations of central activity (Cruse Dean Heuer Schmidt 1990). The combination makes the walking system independent of particular stimulus inputs but at the same time enables the walking system to adapt to changes in the environment. The flexible control appears to arise from the cooperation of several autonomous control centers (in the terminology of Minski (1985) these may be called "agents") each of which controls the movement of one leg. Each center is responsible for two mutually exclusive microbehaviors ("states"), stance or power stroke and swing or return stroke. On a higher level the control systems for the individual leg have to cooperate to produce a suitable behavior of the overall system, propelling the body while maintaining postural stability.

From a biological point of view, walking is simple enough that one can hope to gain a complete

understanding of the basic mechanisms. In fact, a lot of information has been collected in recent years on how animals control the movement of the legs during walking (review Cruse 1990). A study of this system might therefore be of interest not only in itself but also as a model for the control of other, more complicated behaviors. From an applied control point of view, the next step is to incorporate the insights gained from the biological experiments into a model able to control a walking system.

To reach this goal, several problems have to be solved. One question concerns the way the movement of the individual leg is controlled. The second question refers to the coordination between legs. From biological experiments - most of the information comes from experiments using the stick insect - the following answers can be given. First, each leg has its own control system which generates rhythmic step movements (review Bässler 1983). The behavior of this control system corresponds to that of a relaxation oscillator in which the change of state, the transition between power and return strokes, is determined by thresholds based on leg position. Second, the coordination of the legs is not determined by a hierarchically superior control system. Instead, the gait pattern emerges from the cooperation of the separate control systems of the individual legs. This cooperation is based on different types of signals which convey information on the actual state of the sender to the control systems of the neighboring legs. The receiving system collects this information and, on this basis, decides on its own action. This distributed architecture results in a very stable gait but nevertheless allows the whole system to react flexibly to disturbances. At the present time no detailed information is available concerning the control of the individual leg joints of the walking animal and the control of the dynamics.

In an earlier paper (Müller-Wilm et al., 1992) a model was presented based on these biological results and, where necessary, several ad hoc assumptions. This model was constructed using the classical algorithmic approach. Because models using distributed networks show a number of advantages, such as error tolerance, generalisation etc., we plan to replace successively the algorithms of this earlier model by modules of artificial neural nets. In the present report we describe neural network modules for controlling the oscillatory movement of the individual leg and the coordination of legs. The movement of the individual joints of a leg is still controlled by the classical methods described in Müller-Wilm et al. (1992) and Pfeiffer, Weidemann, Danowski (1990).

The movement of the individual leg consists of two parts, the power stroke and the return stroke. During the power stroke, the leg is on the ground, supports the body and, in the forward walking animal, moves backwards with respect to the body. During the return stroke, the leg is lifted off the ground and moved in the direction of walking where it can begin a new power stroke. The anterior transition point, i.e. the transition from return stroke to power stroke in the forward walking animal, has been called the anterior extreme position (AEP) and the posterior transition point has been called the posterior extreme position (PEP). Either as a hypothesis or on the basis of experimental results several authors (Wendler 1968, Bässler 1977, Graham 1972, Cruse 1985b) proposed the idea that the transition from one mode to the other occurs when the leg reaches a given criterion position and that the step generator can thus be considered a relaxation oscillator. The role of load in modifying this criterion will be neglected here (see however Bässler 1977, Cruse 1983, Dean 1991a).

As in the model of Müller-Wilm et al. (1992), each leg is represented by three segments which are connected to each other and to the body by three simple hinge joints. Contact with the ground is assumed to occur at a non-slipping hemisphere at the end of the distal segment. This simplified leg omits the set of short segments forming the tarsus or foot of the insect. The structure of the leg and the definition of the angles are shown in Fig 1. The axes of rotation of the basal joints are arranged

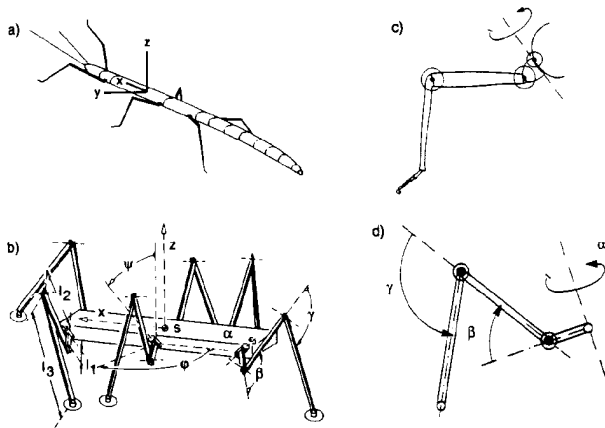


Fig 1. (a) Schematic drawing of a stick insect with the location of the body-centered coordinates, (b) mechanical model: arrangement of the joints and their axes of rotation, (c) single leg of a stick insect showing the axes of rotation, (d) the joints of the simplified leg of the model.

in the same way as in the stick insect and, therefore, are not orthogonal with respect to the body-fixed coordinate system shown in Fig 1. In the stick insect the basal joint actually is a ball and socket joint. However, the primary movement during walking involves only one axis of rotation (Cruse 1976). Therefore, for the present model we assume that the basal joint is used only to move the leg in the forward-backward direction and that all the up-down movement is performed at the coxa-trochanter joint.

## 2. Model

The movement of the individual leg is controlled in the following way. In order to simplify the model, we assume for the straight walking considered here that the tarsus always moves in a vertical plane parallel to the long axis of the body. The rhythmic movement in the direction of the x-axis (Fig 1), i.e. the axis parallel to the long axis of the body, is controlled by an oscillatory system. How can this be done using a neuronal system?

The oldest and simplest proposal for a network oscillator with neuronal elements is the Brown half center model (Brown 1911). Two neurones are connected by mutual inhibition (Fig 2a), forming a bistable system (flip-flop), in which either one neuron or the other is active. If the inhibitory channels are provided with high pass properties and tonic excitation is applied, the system oscillates. Alternative, two-neuron networks are discussed by Camhi (1984). For example, oscillation can also occur if the mutual inhibition is replaced by mutual excitation passed through a delay element. Some central pattern generators which have been characterized physiologically contain neurons with still more complex dynamical properties and connections (e.g. Getting and Dekin 1985).

As mentioned above, the step pattern generator of arthropods is better described as a relaxation oscillator which depends on sensory feedback. This means that the periphery has to be included in the system. In this case, as shown in Fig 2a, the signals from sensory feedback can provide appropriate feedback to produce a rhythmic movement (Land 1972, Bässler 1977, for a general discussion see Bässler 1986): the motor output of motor unit RS in Fig 2a, interpreted as a velocity signal moving the leg forward, is applied to the leg until a sense organ signals that the AEP has been reached. This sensory unit turns off the motor unit PS. This unit in turn inhibits RS and causes the leg to move to the rear until a sense organ signals that the PEP has been reached. This sense organ turns off the unit RS which in turn inhibits PS. As a result the system oscillates rhythmically moving the leg between AEP and PEP. The transformation from leg velocity to leg position is symbolized by the integrator in Fig 2a.

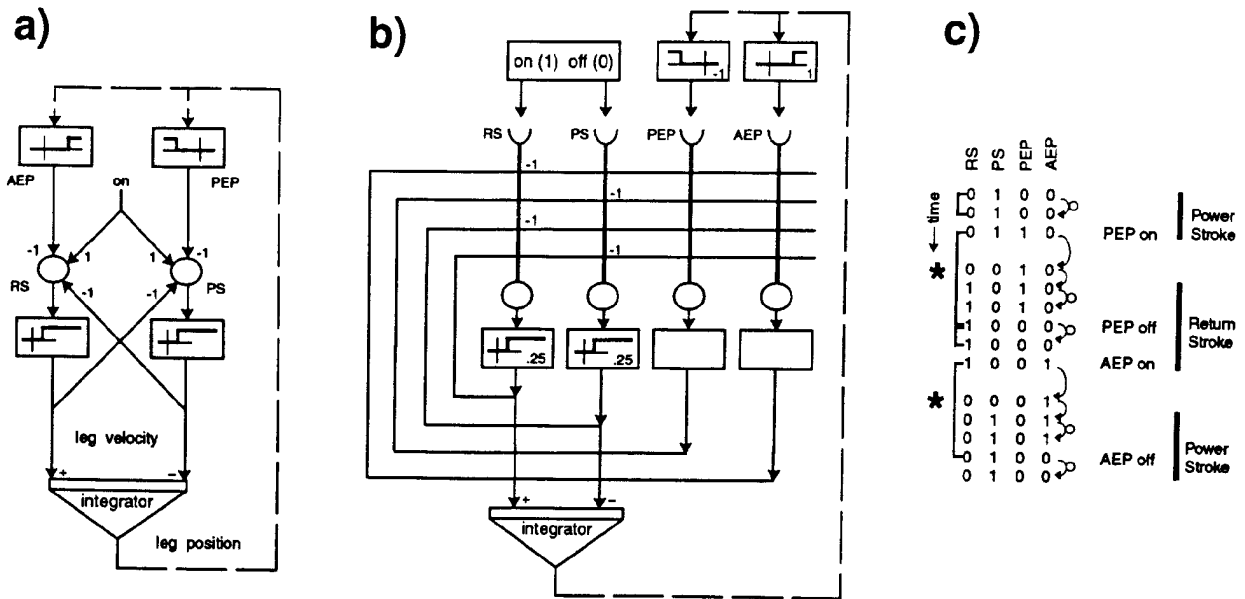


Fig 2. A model for the control of rhythmic leg movement using mutual inhibition between the motor units RS (return stroke) and PS (power stroke). Leg position is obtained by integration of the output of RS and PS. Once the leg has reached a given threshold (AEP, PEP), the system switches from one state to the other. (a) classical version. (b) the same system constructed as a fully recurrent network. (c) the output vector for consecutive iteration steps in one complete step. The square brackets on the left side indicate the input and output vectors used for training.

Fig 2b shows the same system in another, more general format. The four units are now part of a fully connected recurrent network. The weights of the synapses are given. If no number is given this means that the weight after training is zero. Again the integrator represents the mechanical periphery, the movement of the leg under the influence of RS and PS. The leg position oscillates as long as both motor units receive an input of 1 which can be interpreted as an "on" signal from higher centers. Fig 2c shows the output of the system for consecutive iteration steps.

An advantage of the artificial neural network approach is that training procedures can be used to find alternative and possibly better solutions. In order to test whether other versions of such oscillatory systems exist we started with a fully connected recurrent network with randomly distributed weights because, apart from the absence of hidden units, this is the most general form. We trained networks with this structure using a linear activation function and the Delta rule as proposed by Levin (1990) for the training. In a recurrent system the output vector is also the feedback vector and therefore the input vector for the next iteration. Therefore the Delta rule can be applied using the output vector of one time step as input for the next. In this way the net was trained on two autoassociative tasks: when the net is in power stroke (output vector: 0100), it should stay in that state, and the same should be the case for the return stroke (output vector: 1000). In addition, the net was trained on two heteroassociative tasks: the desired response to the feedback vector 1001, i.e. "return stroke on" and "AEP reached", was "power stroke on" (i.e. 0100) and the desired response to the feedback vector 0110, i.e. "power stroke on" and "PEP reached" was "return stroke on" (i.e. 1000). Using the Delta rule with an learning rate of 0.1 the error decreased to zero. The resulting weights are shown in Fig 3a. In this net the motor units receive a self-excitation instead of reciprocal inhibition. The sensory units have two different effects on the two motor units. One is excitatory, the other is inhibitory: Fig 3b shows the output of the system after training. This output lacks one cycle present in the results of Fig 2c.

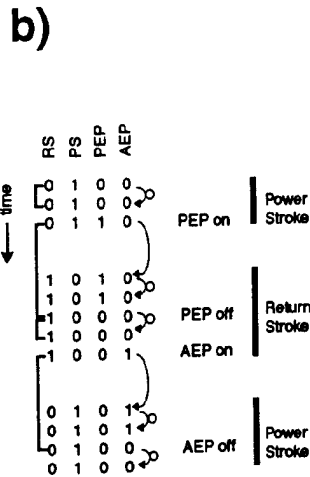
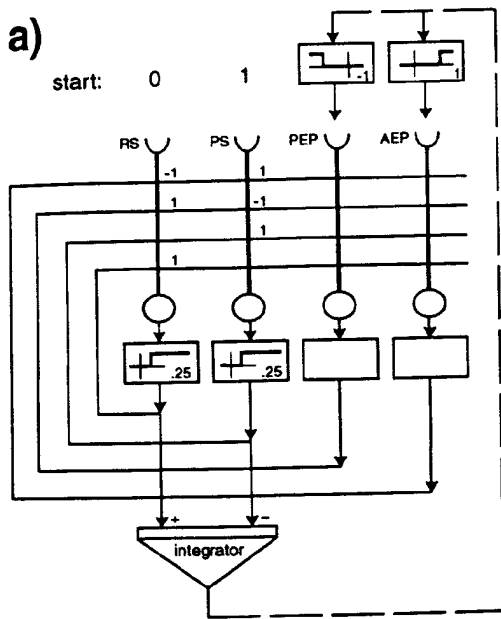


Fig 3. A model, obtained by training, for the control of the rhythmic leg movement. The oscillatory behavior of the system corresponds to that shown in Fig 2 except for the intermediate vectors marked by stars in Fig 2c.

sender	receiver			
	RS	PS	PEP	AEP
AEP	-0.5	0.5	0	0
PEP	0.5	-0.5	0	0
PS	-1.5	0.5	0	0
RS	0.5	-1.5	0	0

Table 1 The weight distribution of a network producing rhythmic oscillations. The format is the same as in Figs 2b and 3a.

For training vectors with values symmetrically distributed around zero, i.e. values of 0.5 or -0.5 instead of values of 0 and 1, another set of weights is obtained (Table 1). The network looks like a mixture of both the "inhibitory system" of Fig 2a and the "excitatory system" of Fig 3a. The behavior of the system corresponds to that shown in Fig 2b.

Although the unperturbed behavior of all three systems is nearly the same, they might still differ in stability when noise is present. To investigate this, the performance of all three oscillators was tested with noise of increasing amplitude range added to all four feedback lines. The stability was measured by observing the oscillatory behavior of the systems. When the noise amplitude exceeded a certain threshold, the oscillatory behavior suddenly vanished in all three systems. The inhibitory system (Fig 2) was most sensitive and the excitatory system (Fig 3) was least sensitive to noise. Quantitatively, a noise amplitude of +/- 0.25 is sufficient to disrupt the oscillatory behavior of the inhibitory system whereas amplitudes of about +/- 0.50 and +/- 0.76, respectively, are required to disturb the mixed system (Table 1) and the excitatory system (Fig 3) to the same extent. These differences in the stability correspond to the size of the mean error during the training procedure. For the excitatory system the sum of the total squared error was smaller than 0.01 after 180 epochs and approximated zero. For the mixed system this error could not be made smaller than 4.2. The inhibitory system was never obtained through training, even when the starting weights were chosen to correspond exactly to this solution.

It should be mentioned that the systems shown in Fig 3 and Table 1 can be switched on by a short impulse to one of the motor units. They do not require a continuous input as the inhibitory system does. As the excitatory system has proved to be the most stable we decided to use this module to control the state (power stroke, return stroke) of each leg. For the stick insect it has been shown that

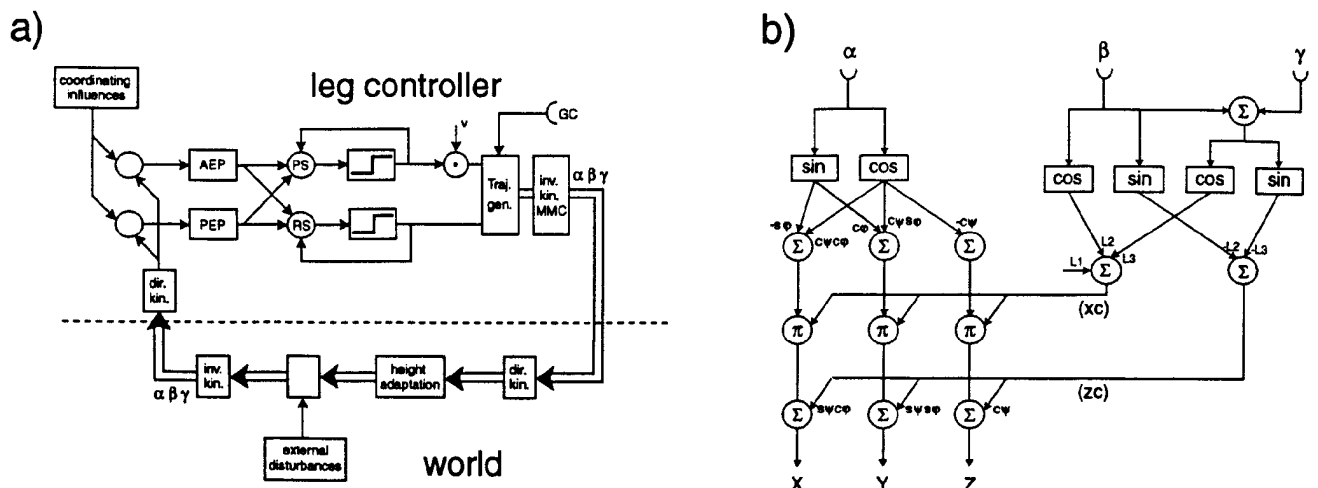


Fig 4. (a) The leg controller and the world model. (b) A simple network solving the direct kinematic problem.  $\phi$  and  $\psi$  are the angles describing the axis of rotation of the central leg joint (see Fig 1).

in both the power stroke and the return stroke the movement of the tarsus is controlled by a velocity controlling feedback system (Cruse 1985a, Dean 1984, Weiland and Koch 1987). Therefore, we use the output values of the state controller as reference signals for a velocity feedback controller. However, the state value is first put through a low pass filter. This causes the reversals in the direction of movement to be less abrupt and therefore more realistic.

This reference signal is used to control the movement of the leg tip (tarsus) in the horizontal and vertical directions, i.e. parallel to the x-axis and parallel to the z-axis, respectively (Fig 1). However, the movement along the x-axis is governed by a velocity controller, that along the z-axis by a position controller. When walking on irregular surfaces, the end of the downward movement during the final part of the return stroke has to be determined by an additional sensor which is assumed here to be a contact sensor ("ground contact" GC in Fig 4). The determination of the tarsus trajectory is described in detail by Müller-Wilm et al. (1992) and therefore not repeated here. Once the trajectory of the tarsus relative to the body is selected, the values of the joint angles can be calculated. This is done here using the inverse kinematic solution described by Pfeiffer et al. (1990). The calculation of the tarsus trajectory and the required joint movements is symbolized by the box marked (TT-JC) in Fig 5.

In the most recent version (Fig 4) the classical joint control system is replaced by a recurrent network designed to compute the complete set of state variables, in this case the three joint angles and the three workspace coordinates of the tarsus position. The system relaxes to a stable state and finds a geometrically correct solution even when the input does not fully constrain the solution. In this network the variable values are obtained by calculating the mean of multiple computation (MMC) and these values are fed back using a Hopfield-like, but asymmetric structure. The principal structure of this network is described in detail by Cruse and Steinkühler (1992). As applied to the stick insect, the network is able to calculate the direct and the inverse kinematics or the more general case of completing the set of position and angle variables based on any incomplete subset. Such a network has the advantage that it can be used for different tasks: during power stroke, for example, a mixed problem might arise when the desired height is given in tarsus coordinates (z) and the direction relative to the body is specified by an alpha (and perhaps a beta-) value. For different legs (e.g. the

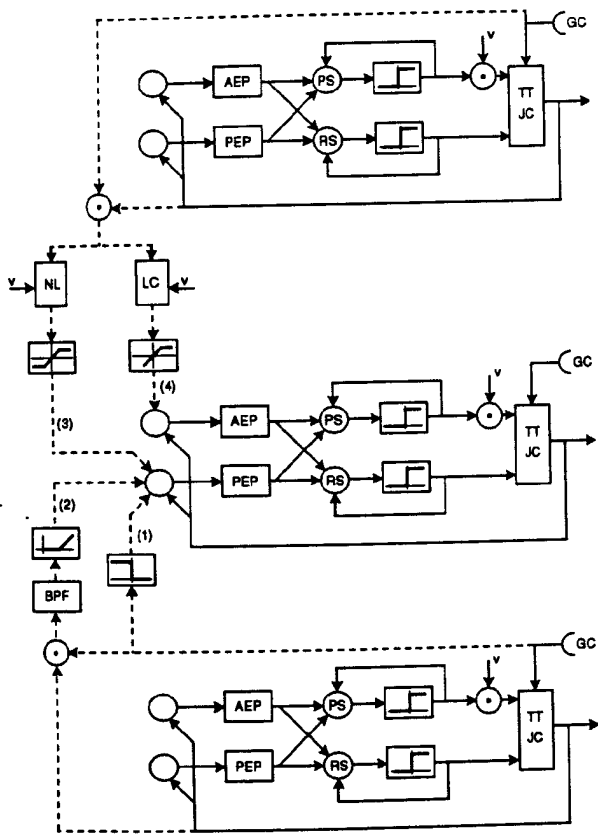


Fig 5. The four coordinating influences used in the model illustrated for a middle leg receiving the signals. Two influences occur from the front leg and two from the hind leg onto a centrally located middle leg. The oscillator, which corresponds to that of Fig 3, controls the state and forward-backward movement of the leg. The derivation of the corresponding tarsus trajectory and joint angles occurs in the box marked (TT-JC). The sensory input GC registers ground contact. See text for further explanations.

front leg) other subset of angles (e.g. beta and gamma) might be more relevant, or the appropriate variable to specify might change during the course of the power stroke. The same is true of return stroke.

In order to simulate walking over uneven surfaces, the physical properties of the environment are simulated using classical direct and inverse kinematics (Fig 4a). To close the loop, the leg controller requires the direct kinematics to determine tarsus position using information on the joint angle values. This is solved by a simple hard-wired network (Fig 4b).

How are the movements of these oscillators coordinated? In all, six different coupling mechanisms have been found for the stick insect (review Cruse 1990). Two of these will not be considered here. (One serves to correct errors in leg placement, the other has to do with distributing propulsive force among the legs). The other four mechanisms were successfully implemented in an earlier model (Dean 1991b,c 1992a,b) which formed the basis for the coordination module in the present model. The beginning of a return stroke, and therefore the end-point of a power stroke (PEP), is modulated by three mechanisms arising from ipsilateral legs: (1) a rostrally directed inhibition during the return stroke of the next caudal leg, (2) a rostrally directed excitation when the next caudal leg begins active retraction, and (3) a caudally directed influence depending upon the position of the next rostral leg.

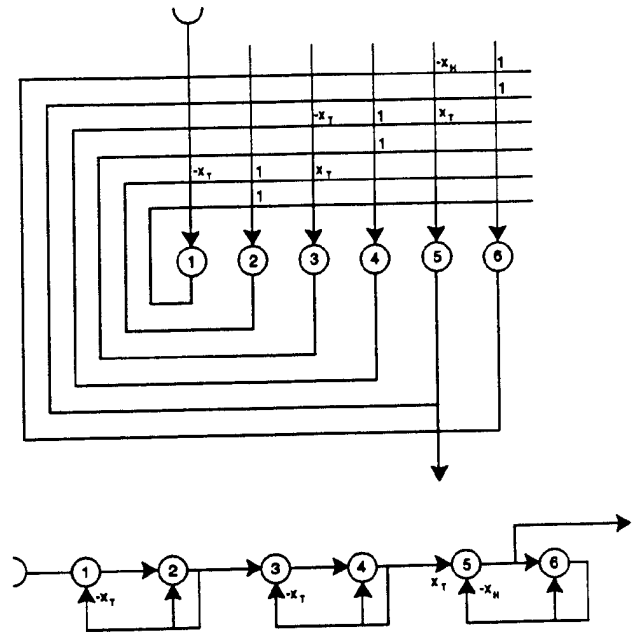


Fig 6. (a) A network model describing an asymmetric band pass filter which consists on two low pass filters (time constant  $1/x_L$ ) and a high pass filter (time constant  $1/x_H$ ). (b) shows the same net in a different way.

The beginning of the power stroke (AEP) is modulated by a single, caudally directed influence (4) depending on the position of the next rostral leg; this mechanism is responsible for the targeting behavior. Influences (2) and (3) are also active between contralateral legs.

Fig 5 shows, as an example, the influences from the front leg and the hind leg onto the ipsilateral middle leg. Influences (1), (2), and (3) act on the PEP unit, whereas influence (4) acts on the AEP unit. Influence (1) is only active, i.e. different from zero, when the caudal leg has no ground contact. Influence (2) is zero when the caudal leg has no ground contact. In neuronal terms these conditional effects (in Fig 5 shown by a multiplication symbol for convenience) are represented by inhibition subsequent rectification. If the caudal leg has ground contact, influence (2) corresponds to the band pass filtered value of the position signal of the caudal leg. The band pass filter (BPF in Fig 5) which is constructed of a small recurrent network consisting on six linear units (Fig 6) is followed by a rectifier. Influence (3) is zero when the rostral leg is lifted (again this is represented in Fig 5 by a multiplication symbol) and depends on the position of the rostral leg when the latter is in power stroke. This value passes through a non-linear characteristic (NL in Fig 5) the form of which depends logarithmically on a central command,  $v$ , corresponding to the general walking velocity. This command also serves as a gain factor in all power stroke units. The output of the NL - characteristic passes a non linear clipping function. Influence (4), which determines the AEP, is determined in a similar manner as influence (3). The main difference is that the position value depends on the parameter  $v$ , the retraction velocity, in a linear way (LC in Fig 5). The activation function is clipped only for values in the positive range. The contralateral influences correspond to the ipsilateral influences (2) and (3) and are not shown in Fig 4. In the contralateral form of influence (3), the dependence on the parameter  $v$  is linear.

### 3. Results

The model shows a proper coordination of the legs when walking at different speeds on a horizontal plane. With increasing walking speed the typical change of coordination from the tetrapod to the tripod gait (Graham 1972) is found. As the movement of the legs is very similar to those found in the algorithmic model (Müller-Wilm et al., 1992) this is not shown here in detail.

The coordination pattern is very stable. For example, when the movement of the right middle leg is interrupted briefly during the power stroke, the normal coordination is regained immediately at the end of the perturbation (Fig 7a). A critical test of the stability of the coordination pattern is to consider the behavior of the model when starting to walk from arbitrary leg positions. The start is particularly difficult when contralaterally neighboring legs begin from the same  $x$ - position. In this case, contralaterally neighbouring legs reach their PEP thresholds at the same time, whereas they normally alternate. Fig 7b shows such a test: the normal coordination is regained after a very few steps. The 3-dimensional plot, which is not shown here, demonstrates that the model also maintains postural stability except for starts from some unnatural starting configurations.

The height control is illustrated in Fig 8. Here the model has to step over an obstacle. This figure represents two sections of a video film. Different frames are superimposed here to give an impression of the movement of the whole model. The figure also indicates that the leg glides over the ground for a short time after touch down. This gliding would correspond to a force decelerating the body if the tarsi were fixed to the substrate.



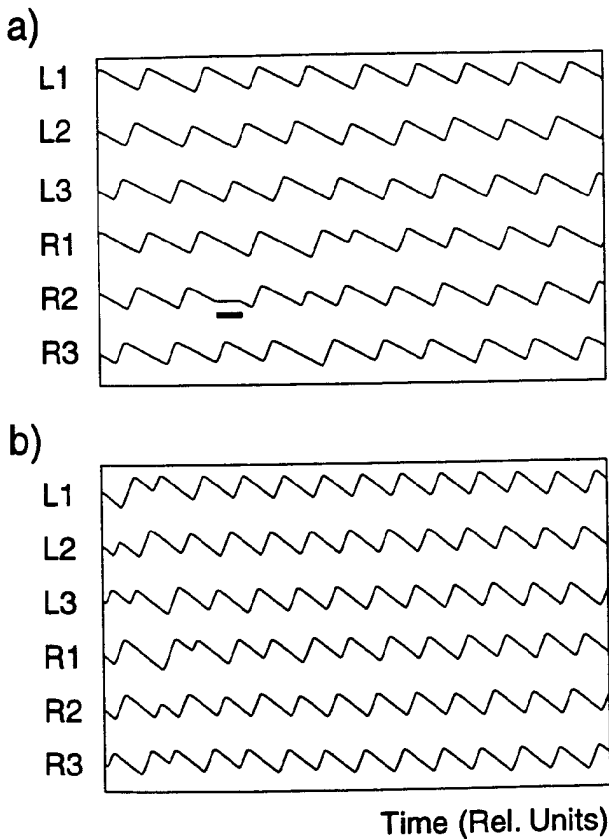


Fig 7. Stability of the coordination pattern. (a) movement of the legs when the power stroke of the right middle leg is interrupted for a short time. (b) Illustration of how the normal contralateral alternation is established when contralateral legs start from the same position.

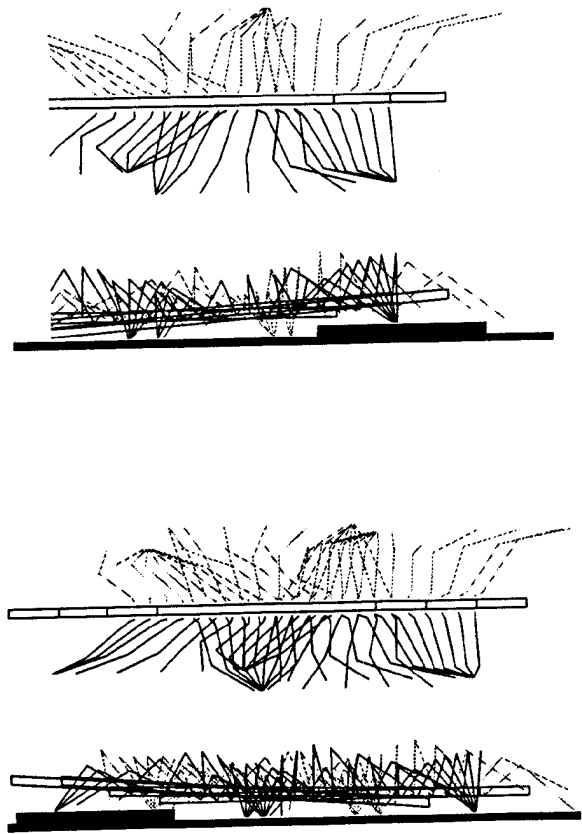


Fig 8. Two sections of superimposed frames from a video film showing the model walking over an obstacle. Upper part: top view, lower part side view. Leg position is shown only for every 5th frame, body position is shown only for every 15th frame. (a) The model approaches the obstacle and places the front legs onto it. (b) The model leaves the obstacle. The left hind leg steps onto the obstacle whereas the right hind leg touches the ground beyond the obstacle.

#### 4. Discussion

The model proposed here represents a combined treatment of realistic kinematics and of biologically motivated, adaptive gait generation. In contrast to earlier biologically motivated models it contains the joint geometry and, with some simplifying assumptions, describes the movement of the joints and the tarsi. The movement of the tarsus is also more realistic in the sense that the velocity profile is rounded at the transition points. The results show that the information obtained from biological experiments can be incorporated into a 6-legged model which is able to walk at different speeds at different speeds over irregular surfaces. The model shows a stable gait even when the movement of the legs is disturbed. The system can control walks beginning from arbitrary leg positions. Thus, the control system described here can be used to control a real walking machine. To increase the stability for difficult starting positions, the introduction of load feedback might be helpful.

The system is based on extremely simple connections. Unlike the model proposed by Müller-Wilm et al. (1992), the model consists of simple artificial neurons, except for that part which controls the movement of the individual joints of the leg. The connections of the state controller were learned.

The connections which provide the coordination between legs were hard-wired based on biological experiments. Current work with various, biologically based optimization methods (reinforcement learning, genetic algorithms, etc.) is testing whether these mechanisms can be further improved. (In our modelling of a six-legged walker, we relied heavily on results with stick insects, but it should be noted that other animals walking under different conditions use different coordinating mechanisms (crayfish: Cruse Müller 1986, Müller Cruse 1991, cat: Cruse Warnecke 1992).

Other approaches to modelling walking have incorporated biological features to different degrees. Knowledge of the neural control of walking in any animal is still quite rudimentary. Brown's (1911) half-center hypothesis, that alternating activity for stepping arises from two subsystems coupled by reciprocal inhibition, is still the most applicable model. Vertebrate walkers have proved quite intractable neurophysiologically. However, work on a simple model system, lamprey swimming (Grillner et al. 1991), has shown that even simple systems embodying this reciprocal inhibition depend upon complex neuron properties and interconnections. Pearson (1972), working with an insect, proposed a model of alternation in which activity of one center is periodically interrupted by activity in a second center initiated either by peripheral sensory signals or by intrinsic neural properties.

This organization has parallels in the subsumption architecture created by Brooks to step control in a successful hexapod robot (1986, 1989). For interleg coordination this robot used a typical insect gait, the alternating tripod gait, but this gait was generated by a single timing center. Hence, interleg coordination in this robot did not emerge out of interactions among semi-autonomous centers in the way that is more typical of animals. This property was exhibited by a later version in which the subsumption architecture was extended to control interactions among independent leg controllers (Maes Brooks 1990). These interactions were not based on biological models. Nevertheless, they were able to learn the tripod coordination.

Such decentralized mechanisms have been considered by several researchers. Based on physiological results from an insect preparation, Pearson and Iles (1973), studying a non walking insect preparation, described intersegmental activation which could mediate reciprocal inhibition serving for interleg coordination, an idea proposed by Wilson (1966) on the basis of behavioral studies. This inhibition resembles mechanism 1 in the present model. As discussed elsewhere (Cruse 1980, Dean 1991c, 1992b), this mechanism alone provides incomplete control of step phase. Moreover, it can easily produce tripod gait but requires a gradient of natural step frequencies in different legs if metachronal rhythms are to occur. Nevertheless, this type of inhibition has been incorporated into several robot control systems (Donner 1984, Beer, Chiel and coworkers 1989, 1992). Beer and Gallagher (1992) have also used genetic algorithms to successfully train intra- and interleg coordination under conditions where tripod gait is the gait of choice. Our results show that a combination of mechanisms provides a better control of phase, which is necessary for example in controlling starts from unfavorable leg configurations.

Our future studies are directed toward removing three restrictions in the present model. First, the movement of the tarsus is restricted to a vertical plane parallel to the long axis of the body. Besides being somewhat artificial, this does not permit turns to be simulated. Second, our model does not take into account the dynamics of the system, i.e. the forces needed to perform the described movements. Third, we did not consider the mechanical coupling of the legs in power stroke through the substrate and the resulting effects when the legs attempt to move with different velocities. The reader is referred to Müller-Wilm et al. (1992) for a more detailed discussion of these restrictions. Fourth, all robots mentioned above use relatively simple legs, possessing two degrees of freedom and

fixed to the body in an orthogonal and bilaterally symmetrical manner. We hope that a leg geometry more similar to that evolved in animals will provide greater flexibility.

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