Evolution of Central Pattern Generators for Bipedal Walking in a Real-Time Physics Environment

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***Abstract*—We describe an evolutionary approach to the control problem of bipedal walking. Using a full rigid-body simulation of a biped, it was possible to evolve recurrent neural networks that controlled stable straight-line walking on a planar surface. No proprioceptive information was necessary to achieve this task. Furthermore, simple sensory input to locate a sound source was integrated to achieve directional walking. To our knowledge, this is the first work that demonstrates the application of evolutionary optimization to three-dimensional physically simulated biped locomotion.**

***Index Terms*—Bipedal walking, evolutionary algorithms, evolutionary robotics, physics, recurrent neural networks.**

I. Introduction

Bipedal walking is a difficult task due to its intrinsic instability and developing successful controller architectures for this mode of locomotion has proved substantially more difficult than for other types of walking [1].

There is considerable interest in this matter from disciplines as diverse as robotics, computer graphics, virtual reality, and biology. However, previous approaches have been based on conventional control strategies. As will be discussed shortly, this brings about considerable complications and limitations. In addition, past work has been constrained by only limited available means to simulate the physics of the body to be controlled, thus, making it either necessary to build robots or resort to simplified models in simulation.

Given the inherent difficulties in designing stable controllers for natural-looking bipedal walking, it was decided to investigate the use of evolutionary robotics techniques [2] in developing recurrent dynamical neural-network-based controllers for the task. This paper describes successful experiments in evolving controllers for a realistically simulated biped.

The structure of the paper is as follows. We first review previous work on controller architectures for bipedal walking. These are subsequently contrasted with the approach taken here: evolutionary robotics. Section II describes the implementation of both the biped and the neural controller, as well as the evolutionary algorithm (EA) used in this research. As shown in the subsequent results section, this combination succeeded in producing natural-looking bipedal walking. Section IV addresses the integration of sensory input and describes a corresponding successful experiment. The paper closes with a discussion of the research.

A. Related Work

The major thrust of research on bipedal walking has come from computer graphics and robotics. In the case of the former, animation techniques such as motion capture [3] have come to dominate the area. Motion capture essentially implies filming the desired human behavior and using the obtained data to animate a computer generated equivalent. The advantage of this approach is clearly the ability to immediately generate realistic bipedal motion dynamics. However, Laszlo *et al.* [4] make it clear that motion capture does not provide us with sufficient understanding to create more general walking motions, especially when conditions are unpredictable, when new motions need to be generated, or when dealing with nonhuman characters.

These shortcomings can be overcome by a second approach, which is based on a semiphysical representation of the biped and a controller to create movement patterns. With techniques such as inverse kinematics and inverse dynamics, virtual limbs can be placed at the desired positions and the required forces are computed accordingly.

Several workers [4], [5] have followed this approach to create computer animations of humans. The equations of motion are either produced specifically for the model to be animated or are generated with available packages [5], [6]. Typically, a finite-state machine determines the control actions (with cyclic states such as heel contact, toe contact, unloading, or flight [4], [5], [7]) and special forms of limit cycle control may be applied to achieve the necessary stability [4]. The animated end results of these efforts closely resemble natural motion patterns, but may nevertheless fail to convince the human eye in specifically designed "motion Turing tests" [5] (these tests confront human subjects with computer generated and real-life animations and ask them to discern between the two). This lack of realism is a direct consequence of the controller architecture employed; a state machine does not readily produce the fluctuations typical of real locomotion. More significantly, it cannot easily be extended to integrate sensory input. Furthermore, the creation of state machines can be a cumbersome process, as states have to be identified, implemented and fine-tuned by hand for each type of gait to be modeled [5].

Bipedal locomotion in robots is subject to the physical laws of the natural world and hence short cuts like motion capture are not available. Bipedal robots with varying complexities have been produced and controlled by several researchers [8]–[16].

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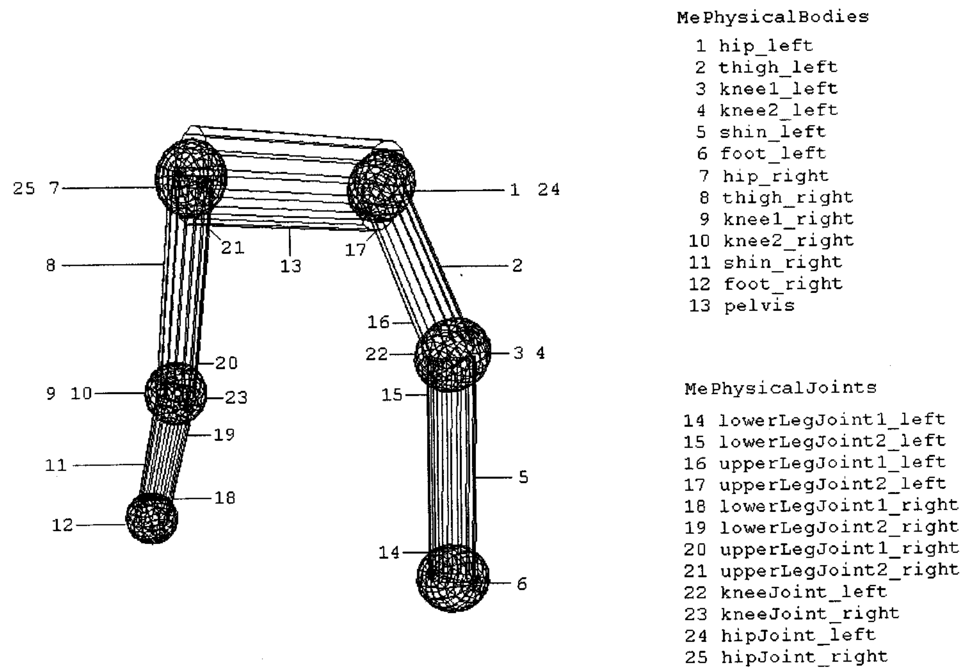

Fig. 1. MathEngine implementation of the biped. Note that although two bodies are used to implement the knee, only one body is necessary.

TABLE I
WALKER DIMENSIONS AND MASSES

Composite Body	Length	Mass
Pelvis	0.5 m	1 kg
Upper Leg	0.5 m	0.6 kg
Lower Leg	0.5 m	0.6 kg

MathEngine bodies are combined to composite bodies.

TABLE II
ANGLE LIMITS OF BIPED JOINTS

Joint Angle	Radians	Degrees
knee_front_back	-1.4 to 0.0	-89.1 to 0.0
hip_lateral	-0.8 to 0.8	-50.9 to 50.9
hip_front_back	-1.3 to 1.6	-84.7 to 101.7

Values were obtained heuristically.

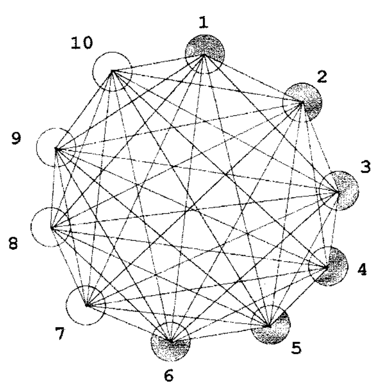

Fig. 2. Recurrent neural network used to control bipedal walking. Shaded nodes are motor neurons. Connections are bidirectional and asymmetric.

As with computer graphics models, the corresponding controller architectures are typically based on state machines with special algorithms added on top to provide the necessary stability. Most recently, Pratt *et al.* [14] have used Virtual Model Controllers for planar bipedal robots. Here, virtual mechanical components are attached to the robot and exert real actuator torques or forces. For example, a *virtual dog track bunny* is used to maintain a desired velocity in a planar biped robot. A state machine changes the virtual component connections or parameters at each state transition. Together with a set of simple rules for, e.g., height, pitch, and speed stabilization, this allows a more intuitive development of stable controller architectures and eases the problem of mathematical tractability encountered in previous attempts [13]. In addition to testing and optimising control strategies on the real robot, Pratt and Pratt [17] have used a rigid-body simulation [6] to create a realistic model of a biped. This allowed efficient experimentation with the robot's natural dynamics (such as passively swinging legs).

In summary, with few exceptions, such as Miller [18], who utilizes reinforcement learning for training a neural net, previous approaches to bipedal walking have been based on engineering techniques like state machines and conventional control theory. As remarked on earlier, this causes a number of problems: 1) mathematical tractability; 2) manual optimization; 3) limited extendability; and 4) limited biological plausibility. It is argued here that the evolutionary robotics approach presented below has the potential to overcome the first three constraints by improving on the last one, biological plausibility.

B. Evolutionary Robotics

Evolutionary robotics was introduced as an alternative to the hand design of robot controllers, especially for autonomous robots acting in uncertain and noisy domains [19], [20]. EAs are used to search spaces of controllers (and potentially body and sensor layouts too) described by a set of variables encoded on the artificial genotype. The fitness function is usually task-based, i.e., high scores are achieved by controllers that enable the robot to perform the desired task well. These con-

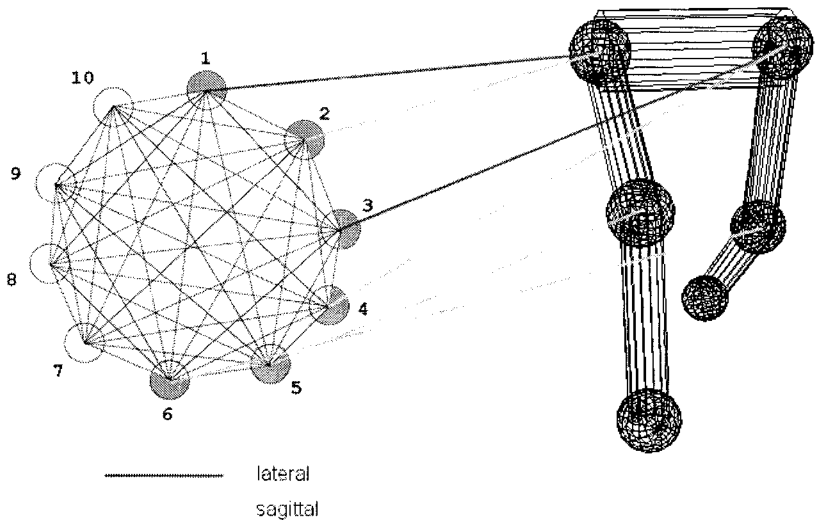

Fig. 3. Motor connections between controller and walker. Hips have two DOFs each (sagittal, i.e., front to back, and lateral); knees have one DOF each (sagittal).

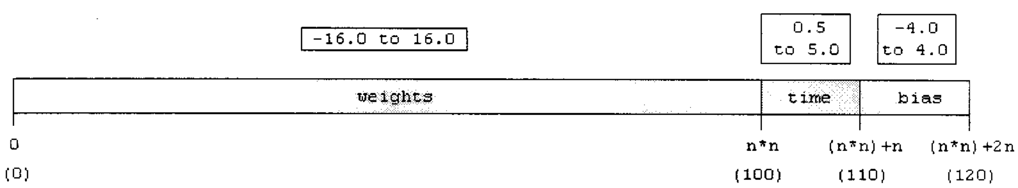

Fig. 4. Encoding scheme. Chromosome index is shown in general form (n is the number of nodes) and for special case of $n = 10$ (in brackets). Parameters are encoded as real values. Ranges in the boxes represent upper and lower bounds of the respective parameter types.

trollers are nearly always in the form of some kind of artificial neural network (ANN). The evolutionary search algorithm's job ranges from optimizing the parameters of a fixed-architecture ANN [21]–[23] to exploring complex network spaces where the architecture and many properties of the nodes and connections are under evolutionary control [24], [25].

There have been many successful applications of evolutionary robotics to date, ranging from simple reactive behaviors in wheeled robots with infrared proximity sensors [22], [26], through visually guided behaviors in simple wheeled robots [27], [28], to fairly complex nonreactive behaviors in simple wheeled robots [29] and a variety of locomotion controllers for six- and eight-legged robots [30]–[34]. For far more detailed reviews of the field, see [2] and [37].

To date, evolutionary robotics techniques have not been applied to a task as dynamically unstable as controlling bipedal locomotion.[1] It is this inherent instability (generally, two-legged walkers will fall over without continuous active control) that provides severe challenges to the hand design of such controllers, especially if smooth natural walking is required. However, given the success of evolved locomotion controllers for relatively stable hexapod and octopod robots [30]–[34], it was deemed appropriate to investigate the use of such techniques for developing bipedal locomotion controllers.

[1]While other researchers such as Rodrigues [35] and de Garis [36] did use evolutionary optimization in the context of bipedal walking, to the authors' knowledge, no research has so far demonstrated the applicability of evolved recurrent neurocontrollers for a real-time and physically realistic biped simulation.

As will be seen later in this paper, evolutionary robotics methods were indeed successful in finding stable controllers for bipedal walking.

II. Implementation

A. The Biped

1) MathEngine Bodies and Joints: Unlike previous, embodied approaches, the agent to be controlled here is modeled using the rigid body dynamics simulation software developer's kit (SDK) of MathEngine. This allows the evaluations to be run significantly faster than real time [36] and, thus, greatly increases the efficiency of the evolutionary approach.

MathEngine's Fast Dynamics Toolkit was developed to overcome the two most pressing problems in the simulation of physics: complexity and speed. Programmed in C, it supports bodies, joints, contacts, and forces, the attributes of which can be set by the user [39]. Once set up, a physical world is integrated by the engine over time in user-defined intervals. The SDK used here (1.0.5) is shipped with an OpenGL and Direct3D renderer to visualize the scene.

The implementation of the bodies for this research is characterized by the need to capture the fundamental features of a biped while limiting the body's complexity and degrees of freedom. Thus, the model used here consists of two articulated legs connected by a link. Thirteen MathEngine bodies and 11 joints are used to implement these structures, as illustrated in Fig. 1 (because each leg consist of two composite bodies with two spheres and one connecting link each, the present implementation uses two bodies for each knee).

TABLE III
INITIALIZATION (I) AND MUTATION (M) DISTRIBUTIONS FOR DIFFERENT PARAMETERS TYPES

Parameter	σ	μ_I	μ_M
weight	8	0	0
time constant	1.5	2.75	0
bias	3	0	0

Standard deviation and separate means of Gaussian distribution are shown.

The degrees of freedom (DOFs) of the joints are: 1) hip joint: two DOFs (pitch/roll) and 2) knee: one DOF (pitch), giving a total of six DOFs.

Although important for real walking (for example in birds or humans), feet and ankle joints are not implemented. They impose additional DOF and would, therefore, considerably increase the controller's search space. In addition, the capabilities of MathEngine SDK 1.0.5 make realistic foot-floor contact a computationally expensive endeavour (due to the need for multiple contact points). Sphere-plane contacts (sphere radius: 8 cm) provide an uncomplicated and fast alternative and are used instead. As will become clear later, this simplification does not come at a noticeable cost in terms of the overall body dynamics.

2) Actuators: Muscle action is modeled by proportional derivative (PD) controllers [5], [40], which are essentially equivalent to damped torsional springs. Their *modus operandi* is characterized by the following:

$$T = k_s(\theta_d - \theta) - k_d\dot{\theta} \tag{1}$$

where T is torque force, k_s is the spring constant, k_d is damping constant, θ_d is the desired angle, and θ is the current angle.

Rather than directly defining the strength of actuator forces, the controller updates the natural orientation of the PD controller (the desired angle of the limb). Equation (1) is then used to compute the force necessary to move the limb to that position. The spring constant and damping value determine the strength and the tendency to oscillate. Their values therefore significantly influence the realism of movements. By means of manual experimentation, values of $k_s = 5$ and $k_d = 4$ were found to be appropriate and are used for all actuators.

The PD approach largely eliminates the need to physically limit joint angles since the same effect is achieved by constraining the range of θ_d. Table I shows the constraints used for the biped introduced earlier. In addition, PDs provide control at the mechanical level as they automatically reduce any discrepancy between the current and desired angle; whether this discrepancy has come about by a controller-mediated updated value or by the dynamics of the physical world is irrelevant. As a consequence, the tendency of limbs, e.g., to buckle under the mass of the body is counteracted directly by the PDs, which otherwise would be accomplished by the neural controller.

B. Controller Architecture

Legged locomotion is characterized by cyclic activity of the limbs. In vertebrates and many invertebrates, the underlying rhythmic neural activation patterns are created by designated network structures called central pattern generators (CPGs) [41]. The defining feature of these is a high degree of recurrency, which greatly biases the dynamics of the system toward cyclic activation patterns.

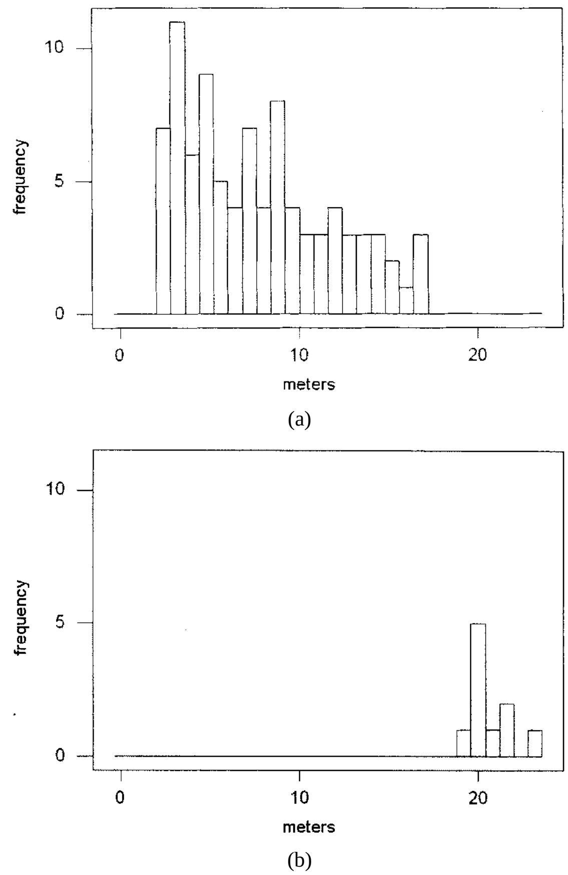

Fig. 5. Distributions of distances covered by (a) unstable and (b) stable individuals. Top individuals of a total of 100 different evolutionary runs are shown. Bin size: 1 m.

In order to capitalize on comparable inherent dynamics, the controller architecture used in this research is based on a recurrent neural net, the structure of which is depicted in Fig. 2. (Similar networks have been used successfully as CPGs by [42] and [32], in both cases for multilegged robots.)

Each network consists of ten fully interconnected neurons. Besides the weights, the behavior of a node is governed by two other parameters, a time constant τ_j, and a bias t_j. At each iteration (time step: 0.02 s), the activity of the jth neuron is computed according to

$$\tau_j \dot{A}_j = -A_j + \sum w_{ij} O_i \tag{2}$$

where τ_j is the time constant of the jth neuron, A_j is its activity, O_i is the output from the ith neuron, and w_{ij} is the weight from the ith to the jth neuron.

The corresponding output is calculated as follows:

$$O_j = \left(1 + e^{(\alpha_j - A_j)}\right)^{-1} \tag{3}$$

where α_j is the bias of the jth neuron.

Nodes 1 to 6 are special in that they control the biped's actuators and they can therefore be considered to be motor neurons. Their outputs (from 0.0 to 1.0) are scaled to map to the angle limits listed in Table II. Fig. 3 schematically depicts the motor connections.

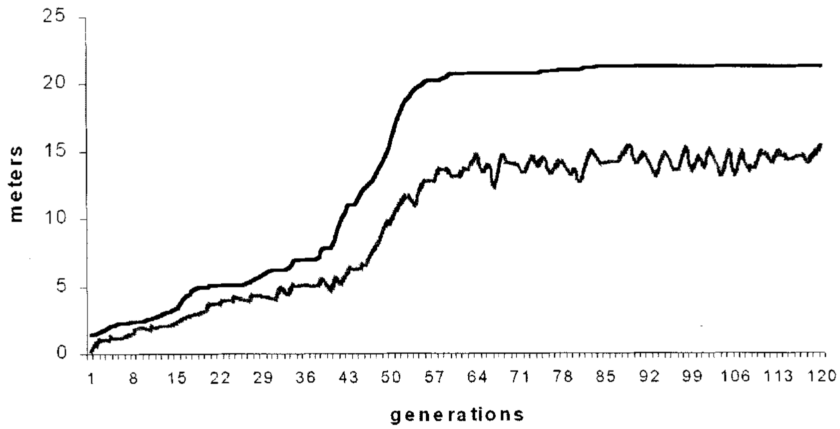

Fig. 6. Fitness graph of representative stable controller evolution. Top fitness (black) and average fitness (grey) are shown.

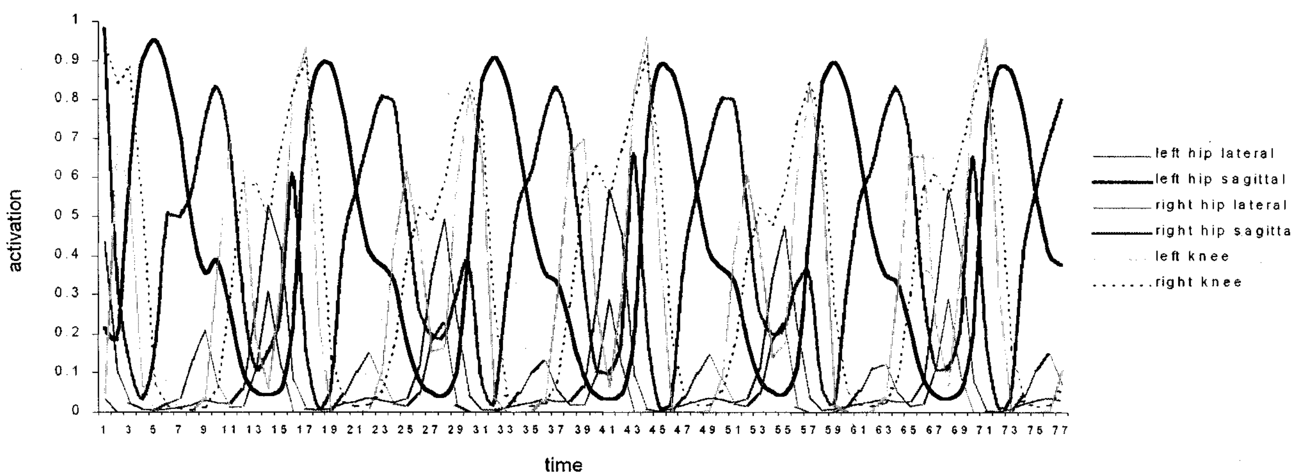

Fig. 7. Motor neuron activation levels of top individual of generation 120 (see Fig. 6).

C. Evolutionary Algorithm

1) Encoding Scheme and Population Parameters: The parameters to be optimized are weights, time constants and biases. The encoding scheme spatially separates the three types in the chromosome (see Fig. 4).

Parameter values are coded as real numbers, with different ranges for each data type. Following [42] and [32], these are $[-16.0, 16.0]$ for the weights, $[0.5, 5.0]$ for the time constants, and $[-4.0, 4.0]$ in the case of the biases. The assignment of these ranges is simplified by the spatial separation of the types; similarly, different mutation rates and sizes can be applied. While the former remains constant throughout the chromosome, the differential implementation of the latter is necessary due to the varying parameter value ranges. This is achieved by using Gaussian distributions. Table III shows the mutation sizes in form of standard deviations from mean zero. Values exceeding the allowed range are clipped to the maximally permitted level. (This is known to create disproportionate accumulations around the clipping points [43], which were, however, found to be negligible in this work.)

The mutation rate is calculated so as to cause on average one change per chromosome. Thus, for larger networks, an accordingly lower rate per locus is applied. Together with typically small mutation sizes (see Table III), this ensures that the evolutionary search is local and gradual. Each population consists of 50 individuals and its individual controllers are initialized with randomized values using the initialization distributions of Table III. Rank-based selection is used for reproduction with a fittest fraction of 0.5 (this essentially means culling the bottom half of the population and replacing it with a copy of the top half [44]). No crossover operations are applied both on theoretical (no identifiable functional units in the genotype and phenotype structure [45]) and empirical grounds (recent experimental evidence on lack of efficiency of crossover in this problem domain [25]).

2) Evaluation of Controllers: Despite the complexity of bipedal locomotion, it is possible to reduce the fitness function to the following two components:

1) maximize distance travelled from origin;
2) do not lower center of gravity below a certain height.

The first objective implicitly includes the locomotion component, while at the same time rewarding walking in a straight line rather than in circles (note that this would not be true for maximize overall distance travelled). The second goal combines two further factors: it penalizes falling down as well as grotesque movements. (Much of the second point is already prohibited by constraining the joint angles in the physical model.) To improve efficiency evaluations are terminated early

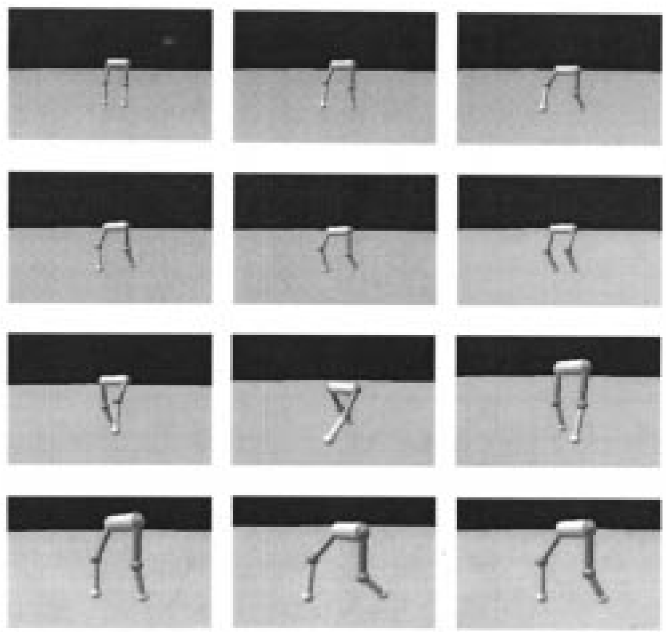

Fig. 8. Motion sequence of biped controlled by top individual of generation 120 (see Fig. 6). Frame order is from left to right and top to bottom.

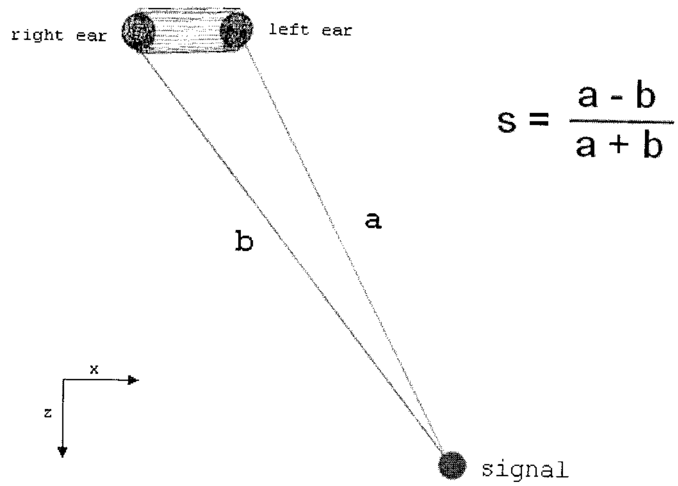

Fig. 9. Preprocessing of two signal values (a and b) resulting in final signal value s. Difference is divided by the sum of the two signal strengths to give a stronger directional signal close to the sound source. This also causes the signal to vanish with the biped facing the sound source.

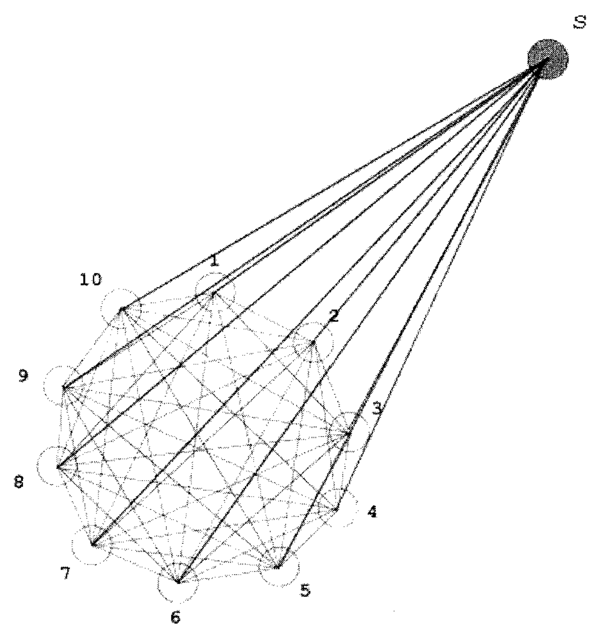

Fig. 10. Each node of RNN receives as input the preprocessed signal value s.

if they are unpromising, i.e., as soon as the second objective is not met. Hence, the fitness function for a biped on an x-z walking plane can be expressed as follows:

$$W = \sqrt{(x_t - x_0)^2 + (z_t - z_0)^2} \tag{4}$$

where W is the fitness, x and z are the planar components of the walker position, and t is the time of the evaluation termination. Evaluations are started with all neuron activations set to zero and with the biped set to an upright stance. One run is performed per evaluation, with a maximum possible length of 50 s each.

III. Results

Populations of randomly initialized individuals were evolved according to the fitness criteria outlined above. In order to yield meaningful statistics, 100 evolutionary runs were conducted, each consisting of 120 generations. Fig. 5 shows the distribution of the distances covered by the top individual of each run in the last generation. For reasons of clarity, the distributions for unsuccessful (unstable) and succesful (stable) controllers are shown separately.

Evaluations of individuals in Fig. 5(a) were terminated prematurely because their center of gravity fell below the specified height (see Section II-C2). Individuals of Fig. 5(b), on the other hand, did not fall over in the given amount of time (50 s). Additional trials with such controllers showed them to be capable of walking for an indefinitely long period. They can therefore be regarded as stable.

The fraction of evolutionary runs leading to stable walkers was 10%, of which the average walking distance was 20.577 m ($\sigma = 1.083$). This compares to an average walking distance of 7.878 m ($\sigma = 4.352$) for the unstable walkers. Fig. 6 shows the fitness graph of a run resulting in such a stable controller. The neural activation patterns of the top controller in generation 120 are depicted in Fig. 7. Fig. 8 contains a biped motion sequence of the evolved controller.

All controllers evolved in the course of the experiments walked in a straight line, a direct result of the fitness function (4). Backward walking controllers were also evolved, albeit at a lower frequency than their forward counterparts. The overall diversity of walkers was large; gaits differed markedly from each other both in terms of speed (as seen in Fig. 5) and use of limbs. Knee movements in particular showed considerable variation ranging from fully swinging to constantly extended. Moreover, several gaits displayed asymmetry, both in stride length and limb use.

A. Efficiency of Evolutionary Runs

The fact that only 10% of evolutionary runs led to stable walking appeared to indicate room for improvement. For the

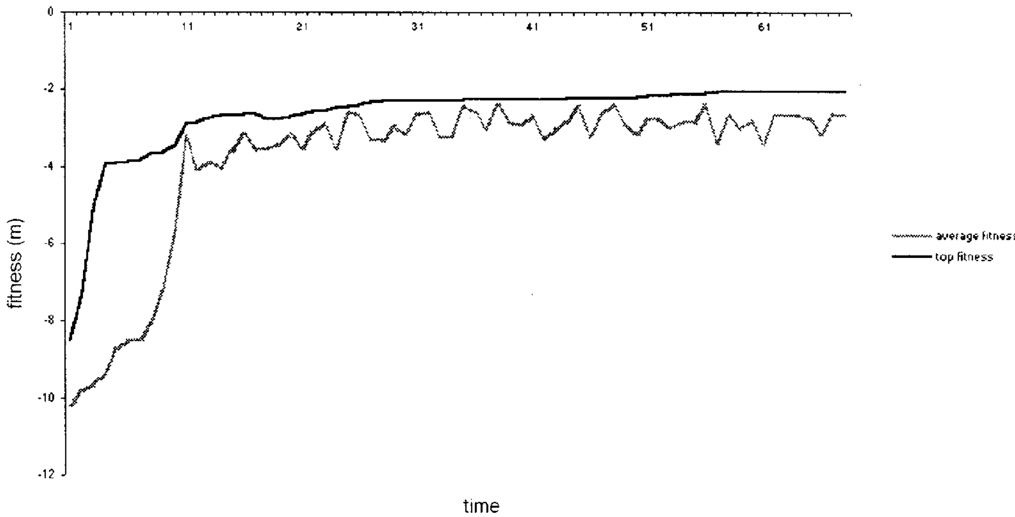

Fig. 11. Fitness graph of bipedal walking with sensory integration. Population was seeded with individuals from the run depicted in Fig. 7.

majority of unsuccessful controllers, analysis showed that the little distance they did cover was controlled by the settling phase of the recurrent net. We, therefore, added an additional fitness criterion that actively rewarded cyclic activity. This markedly increased the proportion of successful runs (to 80%), but was not reflected in a proportionate improvement of the overall time efficiciency (i.e., successful controllers per processor cycle). The reason for this lies in the fact that, even in the original configuration, unsuccessful controller evaluations are aborted early (see Section II-C2), thus, taking up only limited computational resources.

IV. Integrating Sensory Input

The controllers described in Section III are purely rhythm-generating structures. Although sufficient to produce stable walking behavior in a nonfluctuating environment, they are not capable of dealing with rough terrain or responding to external stimuli. In order to achieve this, sensory input must be integrated and the CPG activity modified accordingly. A simple set of experiments was carried out to explore the potential to integrate basic sensory input and will be described now.

The biped is to walk toward the equivalent of a sound source. It is equipped with two "ears," the inputs of which are preprocessed to give a single signal which becomes stronger with decreasing distance from the source.[2] In addition, the signal vanishes when the biped is directly facing the source (see Fig. 9). The signal is fed into the CPG as depicted in Fig. 10. The population is initialized uniformly with clones of the top individual from the run depicted in Fig. 6. The CPG weights are clamped, but the weights of the ten connections between the sensory node and the RNN nodes are under the control of the EA. At each evaluation, the biped starts from its default position and is presented successively with two sound source locations. Because the task is to approach the signal as closely as possible, the fitness function is the negative distance of the walker to the sound source at the time of termination (as caused by the conditions outlined in Section II-C2) or the natural end of the evaluation (after 50 s).

[2]This approximation does not hold true when the biped is very close to the sound source (i.e., when the distance to the source is comparable with the distance between the agent's ears).

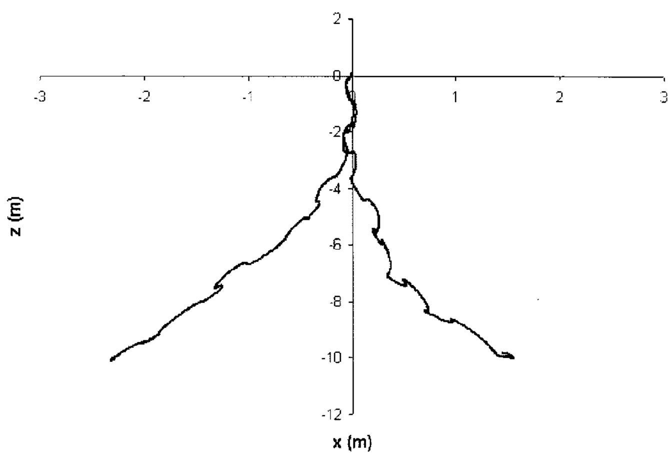

Fig. 12. Trajectories of biped with sensory integration (two runs are shown). Signals are located at $[-3, -10]$ and $[3, -10]$. Run one: left. Run two: right.

A. Results

Fig. 11 depicts an evolutionary run with the population seeded with individuals from the run depicted in Fig. 6. The graph is characterized by an initially strong increase in fitness, but it fails to reach the maximum fitness value of zero.

As illustrated in Fig. 12, the controller succeeded in walking toward the respective signal positions in the two runs. However, visual analysis of the walkers made clear that the gait becomes unstable close to the respective signal sources. This is particularly true for the second (right) run.

To further investigate the ability of the sensors to modulate the net's activity pattern as well as to examine the reasons for the eventual instability, the neuronal activation patterns of the two runs were recorded and are represented in Fig. 13.

The activation graphs indicate that the turning behavior is at least partly achieved by modulating the amplitude of the right hip sagittal motor neuron (which controls the front to back movement), with a decrease resulting in right (top

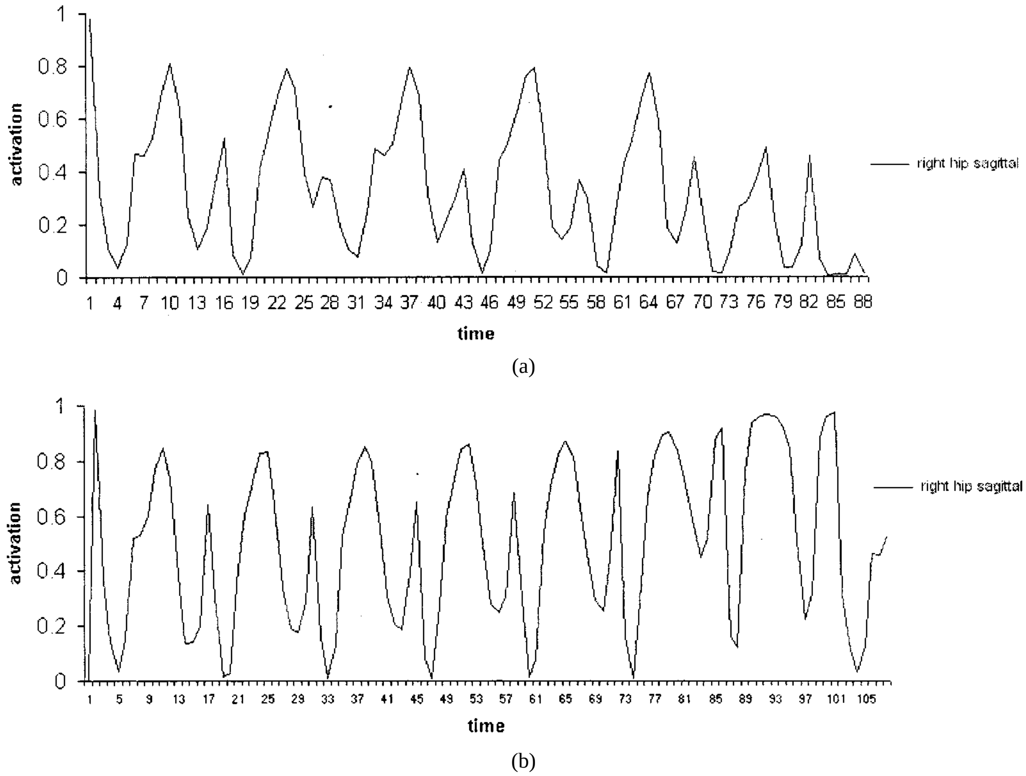

Fig. 13. Neural activation graph of bipedal walking toward (a) right and (b) left signal. Only activation of right hip sagittal (i.e., front to back) neuron is shown. (Other neural activations did not differ markedly from those of Fig. 7).

graph) and an increase resulting in left (bottom graph) turning. Additional experiments were carried out, including evolution of the behavior from scratch (i.e., unseeded populations) and evolution with seeded populations but with evolvable CPG weights. However, neither of these additional experimental series produced results superior to those documented above.

V. Discussion

Despite an extremely simple fitness function, the EA employed in this research was capable of producing stable straight-line walkers without the use of proprioceptive sensory input. EAs rely on evolvable systems and the gradual nature of the fitness graphs (e.g., Fig. 6) indicates that the recurrent networks used here can indeed be optimized in a continuous gradual manner. This notion has recently been corroborated by Rendel [47], who has shown that the fitness landscape underlying the current controller architectures is very smooth. For example, it was possible to gradually modify the amplitude and period of specific motor neuron cycles without affecting those of others.

A further characteristic of the current setup is the ability to create a large diversity of gaits, both in terms of speed and the use of limbs. Several gaits showed considerable similarity to human walking, although this was not specifically selected for. A potential way to further increase the realism of the motion is to select for minimum energy expenditure (a simple measure for this would be the average actuator activity). It is expected that this fitness component will particularly reward the use of knees. In the current implementation, several controllers walked with extended legs because this is concomitant with a large stride length. Humans, however, use the momentum of a forward-swinging lower leg, which is energetically more favorable [17].

The evolved controllers were further characterized by nonrepetitive activity cycles; instead, small fluctuations were observed (see Fig. 7). Similar fluctuations have elsewhere been found to contribute to the perceived realism of simulated locomotive behavior [48]. Real bipedal walking contains fluctuations in successive cycles and it is the lack of these that the human eye picks upon in other artificial walking bipeds.

The preliminary experiments on the integration of sensory input indicate that CPG activity can indeed be modified by external stimuli in a meaningful way (Fig. 13). However, it is clear that the current sensory architecture is insufficient to modulate the biped's behavior and retain stability. For example, the simple preprocessing function causes large destabilizing fluctuations if the biped is close to the signal source. This problem is further intensified by the lack of active balancing mechanisms. The integration of proprioceptive (e.g., limb positions and velocities) and vestibular (balance) input is, therefore, a necessary next step to achieve more interactive and robust behavior.

A question that was not systematically explored is in how far the network size affects the efficiency of the approach, both in terms of search space as well as internal dynamics of the net. With the current architecture, a linear increase in the number of nodes leads to an quadratic increase of the corresponding search space. A possible way to circumvent this problem is to employ identical subnetworks for each leg. Such a constellation seems to reflect the natural arrangement of coupled oscillators more accurately [49], [50] and has been successfully used elsewhere in the context of multilegged locomotion [42], [51].

We would like to reiterate that the stable walkers arrived at did not require proprioceptive input to achieve stable walking in a straight line. This corroborates results obtained elsewhere [52] that show that mechanical walkers can attain stable straight-line walking on a planar surface without active balance control. While those bipeds were mechanically fine tuned to exploit gravity as an energy source, the implementation presented here relies on evolutionary optimization to fine tune active actuation.

We believe that the neuroevolutionary approach described here brings about several major benefits: 1) it is fully automated; hence, changes in morphology or actuator implementations can be easily accommodated by reevolving the controllers; 2) the diversity of locomotive behaviors is large because the system does not require *a priori* knowledge as to how to solve the control problem; and 3) the evolved controllers are computationally very cheap (typically taking up 0.5% of the processing power required by graphics and physics).

VI. Conclusion

We have demonstrated the suitability of an evolutionary robotics approach to the problem of stable three-dimensional bipedal walking in simulation. The current implementation is capable of walking in a straight line on a planar surface without the use of proprioceptive input. However, the use of the latter will become necessary to stabilize the biped on uneven terrain or in response to directional changes. The neural controller employed in this research lends itself to the incorporation of such additional input.

The quality of the results is expected to further improve by a refined fitness function, as well as a shift toward coupled neural oscillators instead of a single network. Furthermore, it is desirable to incorporate biomechanical knowledge about human walking in order to make maximum use of the passive dynamics of the bodies. These aspects are currently being implemented.

In theory, the results obtained here are directly transferable to embodied robots. In practice, however, there are likely to be complications due to a possible lack of accuracy of the physics engine. It remains to be seen whether this "reality gap" can be crossed with appropriate techniques such as noise envelopes [26].

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