Structural Evolution of Central Pattern Generators for Bipedal Walking in 3D Simulation

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***Abstract*— Anthropomorphic walking for a simulated bipedal robot has been realized by means of artificial evolution of central pattern generator (CPG) networks. The approach has been investigated through full rigid-body dynamics simulations in 3D of a bipedal robot with 14 degrees of freedom. The half-center CPG model has been used as an oscillator unit, with interconnection paths between oscillators undergoing structural modifications using a genetic algorithm. In addition, the connection weights in a feedback network of predefined structure were evolved.**

Furthermore, a supporting structure was added to the robot in order to guide the evolutionary process towards natural, human-like gaits. Subsequently, this structure was removed, and the ability of the best evolved controller to generate a bipedal gait without the help of the supporting structure was verified. Stable, natural gait patterns were obtained, with a maximum walking speed of around 0.9 m/s.

I. INTRODUCTION AND MOTIVATION

The great interest in humanoid robots during the last decade is motivated by the many advantages of bipedal robots over wheeled robots. First of all, humanoid robots (and bipedal robots in general) are able to move in areas that are inaccessible to wheeled robots, such as staircases and rugged outdoor terrain. In addition, their human-like shape allows such robots to function in constructed environments, such as homes or industries which, naturally, are adapted to people. Furthermore, recent studies [1], [2], [3] have claimed that people are more comfortable interacting with a robot with an approximately human shape, rather than a tin can-like wheeled robot.

However, an obvious problem confronting humanoid robotics is the generation of stable gaits. Whereas wheeled robots normally are statically balanced and remain upright regardless of the torques applied to the wheels, a humanoid robot must be actively balanced, particularly if it is to execute a human-like, dynamic gait. Several methods for generating bipedal gaits have been proposed in the literature. An important example is the ZMP method [4], where control torques are generated in order to keep the zero-moment point within the convex hull of the support area defined by the feet.

However, the success of gait generation methods based on classical control theory, such as the ZMP method, relies on the calculation of reference trajectories for the robot to follow. That is, trajectories of joint angles, joint torques, or the centre-of-mass of the robot are calculated so as to satisfy the ZMP constraint [5], [6]. When the robot is acting in a well-known constructed environment, the ZMP method should work well. When acting in a dynamically changing real world environment, however, the robot will encounter unexpected situations which cannot all be accounted for beforehand. Hence, reference trajectories can rarely be specified under such circumstances. To address this problem, there has recently been a movement in the robotics community towards alternative, biologically inspired control methods. Such methods do not, in general, require any reference trajectory. Typically, robotics researchers employ bio-inspired control strategies based on artificial neural networks (ANNs) [7], [8] or central pattern generators (CPGs) [9]. Often some kind of evolutionary algorithm (EA) is utilized for the design of the controller [10], [11], [12], [13], and [14].

Clearly, walking is a rhythmic phenomenon, and many biological organisms are indeed equipped with CPGs, i.e. neural circuits capable of producing oscillatory output given tonic (non-oscillating) activation [15]. CPGs have been studied in several simple animals, such as the lamprey [16] for which mathematical models have been developed as well [17], [18]. CPGs have also been studied in more complex animals, such as cats and primates ([19], [20], [21]), and there are also observations that support the notion of CPGs in humans. For example, treadmill training of patients with spinal cord lesions is assumed to rely on the adequate activation of a CPG [21].

Developing artificial counterparts to biological CPGs, with the aim of generating robust gaits for bipedal robots, is an active field of research. In seminal works by Taga *et al.*, [9], [22], a gait controller based on the half-center CPG model (see below) has been investigated. It was demonstrated in a 2D simulation of a five-link biped that the controller made the robot robust against physical perturbations [9]. Furthermore, obstacle avoidance through regulation of the step length was realized [22].

Shan *et al.* [11] generated bipedal walking in a 2D simulation using CPGs. A multi-objective genetic algorithm was used to optimize the synaptic weights in a network composed of nine CPG units. Reil and Husbands [23] used genetic algorithms (GAs) to optimize fully connected recurrent neural networks (RNNs), which were used as CPGs to generate bipedal walking in 3D simulation. They used a GA, with a real-valued encoding scheme, to optimize weights, time constants, and biases in fixed architecture RNNs. Their biped model had six degrees-of-freedom (DOFs), and consisted of a pair of articulated legs connected with a link. The resulting CPGs were capable of generating bipedal, straight-line walking on a planar surface. Furthermore, simple sensory input to

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locate a sound source was integrated to achieve directional walking.

CPGs have desirable properties, such as intrinsic aptness for the formation of periodic output patterns and adaptation to the environment through entrainment, for the generation of gaits and other types of repetitive and stereotypic motions.

Manually tuning the parameters of the CPGs and defining the feedback and interconnection paths in an optimal way is a daunting task. In many cases reported in the literature, e.g. [22], [24], [25], [26], and [27], the design of CPG networks has commonly been carried out in an intuitive manner; a time-consuming and difficult process which may lead to sub-optimal performance. Even in cases where GAs have been applied, as in several of the references mentioned above, the approach has generally been restricted to parametric optimization in a network of fixed architecture.

In this paper, the problem of generating both the structure, i.e. the network feedback and interconnection paths, and the parameters of a CPG network controlling a fully three-dimensional, simulated bipedal robot with 14 DOFs will be considered, using a GA as the optimization method. The half-center CPG model, as originally proposed by Matsuoka [28], will be adopted as the oscillator unit. A challenging problem, which is seldom mentioned (the papers by Paul and Bongard [29] are an exception), is the fact that, while biological organisms have developed their walking patterns (and, indeed, other behaviors as well), over long periods of simultaneous evolutionary optimization of both body and brain, in robotics one attempts instead to provide an already fixed body structure with a brain capable of generating a bipedal gait. This poses many problems for a GA-based approach. For example, if only the distance covered is used as the fitness measure, a common result is to find individuals that simply throw themselves forward, rather than walking; Walking would certainly yield a higher fitness value, yet this solution may be very hard to find, given the readily accessible local optimum found by those individuals throwing their body forward. Thus, the evolutionary process grinds to a halt almost immediately. Of course, this type of solution can be avoided simply by adding constraints on body posture as part of the fitness measure. However, such constraints must often be added in an *ad hoc* manner, and they often lead to results (such as non-natural gaits) that are undesirable. Rather than changing the fitness measure, one may attempt to change the body of the robot. Evolving an upright, bipedal gait from, say, an initial population of crawling individuals would perhaps be infeasible. However, another option, which will be considered in this paper, is to add a supporting structure to the robot, helping it to balance as it starts to walk. Some different strategies for subsequently removing this support, while maintaining a dynamically stable gait, will then be investigated.

II. CENTRAL PATTERN GENERATORS

A. Models from biology

From biological studies, three main types of neural circuits for generating rhythmic motor output have been proposed, namely the *closed-loop model*, the *pacemaker model*, and the *half-center model*. The two former models are described in [30]. The half-center model, which will be considered in this paper, was proposed to account for the alternating activation of flexor and extensor muscles of the limbs of a cat during walking. The basis of this model is the classical experiments reported by Brown from 1911 [31] and 1912 [19]. Each pool of motor neurons for flexor or extensor muscles is activated by a corresponding half-center, or pool, of interneurons. Another set of neurons provides for a steady excitatory drive to these interneurons. Between each pool of interneurons are inhibitory connections which ensure that, when one pool is active, the other is suppressed. Matsuoka [28] analyzed the mutually inhibiting neurons and found the conditions under which the neurons generated oscillations.

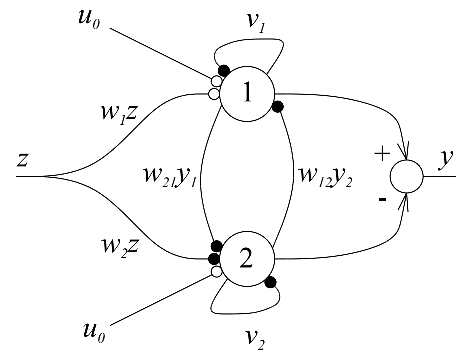

Fig. 1. A half-center model (Matsuoka) oscillator network. Excitatory connections are indicated by open circles, and excitatory connections are indicated by filled disks.

B. Mathematical formulation of the CPG model

Commonly, a CPG is computationally modeled as a network of identical systems of differential equations, which are characterized by the presence of attractors[1] in the phase space [32]. Usually, a periodic gait of a legged robot is a limit cycle attractor, since the robot periodically returns to (almost) the same configuration in phase space.

Each node in the network is referred to as a neuron, or cell. The half-center model mentioned above is commonly adopted as the biological foundation for a rhythm generator, see e.g. [9], [11], [22], [24]. The neurons in the half-center model are described by the following equations [9]:

$$\tau_u \dot{u}_i = -u_i - \beta v_i + \sum_{j=1}^{n} w_{ij} y_j + u_0, \tag{1}$$

$$\tau_v \dot{v}_i = -v_i + y_i, \tag{2}$$

$$y_i = \max(0, u_i), \tag{3}$$

where u_i is the inner state of neuron i, v_i is an auxiliary variable measuring the degree of self-inhibition (modulated by the parameter β) of neuron i, τ_u and τ_v are time constants, u_0 is an external tonic (non-oscillating) input, w_{ij} are the weights connecting neuron j to neuron i, and, finally, y_i

[1] Attractors are bounded subsets of the phase space, to which regions of initial conditions converge as time evolves.

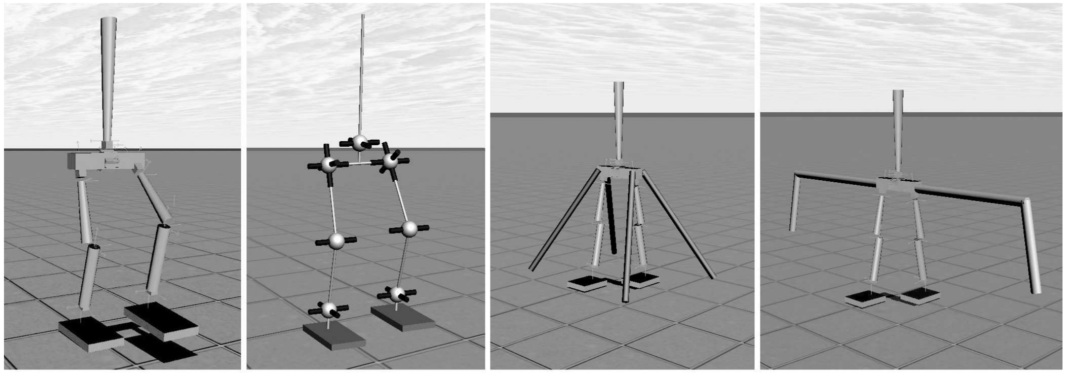

Fig. 2. The leftmost panel shows the simulated robot, and the second panel from the left shows its kinematics structure with 14 DOF. The two right panels show the robot with its supporting structure, the left one having four contact points, while the right one has two contact points.

is the output of neuron i. Two such neurons arranged in a network of mutual inhibition (a half-center model), as shown in Fig. 1, form an oscillator, in which the amplitude of the oscillation is proportional to the tonic input u_0. In addition, if an external oscillatory input is applied, the oscillator will lock to the frequency of the input. If the input is removed, the oscillator smoothly returns to the original frequency.

III. METHOD

In this section the physical simulation environment, the CPG network structure, the feedback paths, and the evolutionary algorithm will be described.

A. Dynamical simulation

A fully three-dimensional bipedal robot with 14 degrees of freedom, shown in the leftmost panel of Fig. 2, was used in the simulation experiments. The simulated robot weighs 7 kg and is 0.75 m tall. The distance between the ground and the hips is 0.45 m. As shown in the second panel from the left in Fig. 2, the waist has 2 DOFs, each hip joint has 3 DOFs, the knee joints have 1 DOF each, and the ankle joints have 2 DOFs each. The hip$_3$ joint, however, responsible for rotating the leg around its vertical axis, has not been active here. The CPG network generates torques, which are applied to their respective joints in order to control the robot. To guide the evolution towards a natural biped gait, the robot has been fitted with two different mass-less posture-support structures, as depicted in the two right panels of Fig. 2.

The simulations were carried out using the EvoDyn simulation library [33], which was developed at Chalmers University of Technology. Implemented in object-oriented Pascal, EvoDyn is capable of simulating tree-structured rigid-body systems and runs on both Windows and Linux platforms. Its dynamics engine is based on a recursively formulated algorithm that scales linearly with the number of rigid bodies in the system [34]. For numerical integration of the state derivatives of the simulated system, a fourth order Runge-Kutta method is used. Visualization is achieved using the OpenGL library.

B. CPG network

In the CPG network, which is responsible for the generation of motions, each joint is assigned a specific half-center oscillator consisting of two neurons; a flexor neuron and an extensor neuron. The overall structure of the CPG network is depicted in Fig. 3.

In order to reduce the size of the search space for the GA, symmetry constraints were added, motivated by the fact that, modulo a phase difference, the movements of the left and right parts of the robot are symmetrical. Hence, the structure of the CPGs on the right side of the robot mirrors that of the left side. For example, the connection weight between the left hip and the left knee is equal in value to the weight connecting the right hip to the right knee. In the network the hip CPG on a given side responsible for rotation in the sagittal plane, can be connected to all the other ipsilateral[2] joint CPGs, the corresponding contralateral hip CPG, and the waist CPGs as well. Note, however, that this hip joint CPG can only receive connections from the corresponding contralateral hip joint CPG. Thus, the total number of connections to be determined sums up to 32, see also Fig. 3 for the details of inter-CPG connectivity.

For reasons that will be discussed in Sect. IV, the internal parameters of the individual two-neuron CPGs were set to fixed values, generating a frequency approximating that of a normal walking pattern. The CPG parameters were set to the following values for all CPGs, except for the knee joint CPGs and the waist joint (rotation in the sagittal plane) CPG: $\tau_u = 0.025, \tau_v = 0.3, \beta = 2.5, u_0 = 1.0, w_{12} = w_{21} = -2.0$. In analogy with human gait, the knee joint CPGs and the waist joint CPG oscillate with double frequency, compared to the other CPGs. Thus, for these joints' CPGs the $\tau_{u,v}$ values were set to half of the value for the other CPGs.

C. Genetic algorithm

A GA has been used for optimizing the structure of the CPG network controlling the movements of the robot. The total number of evolvable connections equals 32. In the

[2]The term *ipsilateral* refers to the same side of the body, and is thus the opposite of *contralateral*.

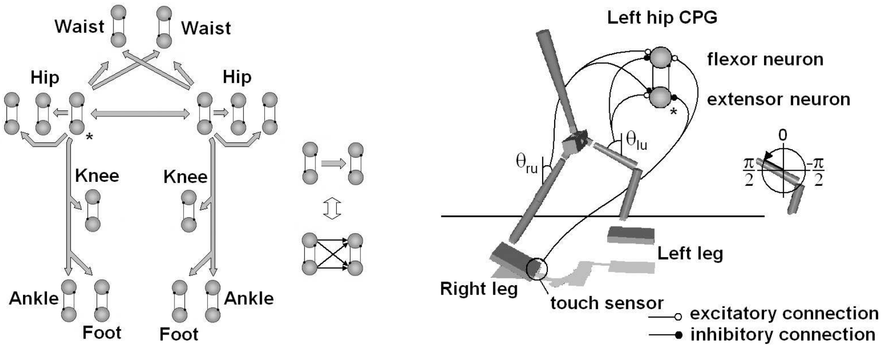

Fig. 3. Left panel: The structure of the CPG network used in the simulations. The connections are represented, in a slightly simplified way, by the arrows in the figure. Note that an arrow indicates the *possibility* of full connection, as shown in the rightmost part of the panel. Right panel: The robot depicted with a single hip joint CPG with feedback paths, and a possible choice of connection types. In the situation shown in the figure, the flexor neuron is responsible for rotating the hip joint in the counterclockwise direction.

GA, two chromosomes were used for the CPG network: one binary-valued chromosome determining the presence or absence of each of the 32 connections, and one real-valued chromosome determining the parameter values for those connections which are actually used in a given individual. Along with the CPG network structure, the feedback network can also be evolved using a third (real-valued) chromosome, which includes 20 parameters determining the sign and the strength of the different feedback paths (see below).

The fitness measure was normally taken as the distance walked by the robot in the initial forward direction, decreased by the sideways deviation. Some attempts were made to use a multi-objective GA (MOGA), with three populations evolving simultaneously towards different fitness measures, namely (1) the distance walked, (2) the number of times an entire foot touched the ground, and (3) the sum of the shortest distance (of the two legs) in the vertical direction between the hips and the knees over all time steps. Criterion (2) was included in order to suppress running behavior where the feet hardly touched the ground, which affected the frontal plane balance. The last criterion should promote an upright posture. However, the MOGA did not lead to any significant improvement. Hence, a standard GA was eventually chosen for the simulation experiments.

For selection, a tournament scheme of size 8 was adopted. The individuals are randomly picked from the population to compete against each other, based on the fitness values. The individual with highest fitness value is then selected with a probability equal to 0.75. After selection, the mutation operator is applied, randomly changing a gene's value with the probability $10/N$, with N being the total number of genes of the individual.

D. Feedback

In order to guide the evolutionary process towards an upright and stable bipedal gait, feedback was introduced measuring the waist angle, thigh angle, and lower leg angle, all relative to the vertical axis. Also, a touch sensor in each foot was introduced in the simulation. This sensor is used both to produce a feedback signal and to enable, or prohibit, feedback to a certain joint CPG during a specific phase, e.g. the stance phase. The feedback was incorporated into the CPGs by adding an extra term to (1), which then becomes

$$\tau_u \dot{u}_i = -u_i - \beta v_i + \sum_{j=1}^{n} w_{ij} y_j + u_0 + f \qquad (4)$$

where f is the feedback. In this setup, the feedback structure is decided upon beforehand. However, the actual type of the connection (inhibitory or excitatory) and the strength of the feedback are determined by the GA. An example of the feedback paths connected to the hip joint (and a possible choice of connection type) is shown in the right panel of Fig. 3. In detail, the feedback paths are given by the following equations:

$$\begin{aligned}
\text{waist}_1 &= c_1 w_{1_{f,e}} \theta_w + p_r[w_{1_{f,e}}(c_2\theta_{r,u} + \theta_{r,l})] \\
&\quad + p_l[w_{1_{f,e}}(c_2\theta_{l,u} + \theta_{l,r})] && (5)\\
\text{waist}_2 &= w_{2_{f,e}}\theta_{l,u} - w_{2_{f,e}}\theta_{r,u} && (6)\\
\text{hip}_{1,l} &= w_{3_{f,e}}\theta_{l,u} - w_{3_{f,e}}\theta_{r,u} + c_3 w_{3_{f,e}} e_r && (7)\\
\text{hip}_{2,l} &= e_l[w_{4_{f,e}}\theta_{l,u}] && (8)\\
\text{hip}_{3,l} &= w_{5_{f,e}}\theta_{\text{hip}_{3,l}} && (9)\\
\text{knee}_l &= e_r[w_{6_{f,e}}\theta_{r,l}] && (10)\\
\text{ankle}_l &= e_l[w_{7_{f,e}}\theta_{l,u}] && (11)\\
\text{foot}_l &= e_l[w_{8_{f,e}}\theta_{l,l}] + e_r[c_4 w_{8_{f,e}}\theta_{r,l}] && (12)\\
\text{hip}_{1,r} &= w_{3_{f,e}}\theta_{r,u} - w_{3_{f,e}}\theta_{l,u} + c_3 w_{3_{f,e}} e_l && (13)\\
\text{hip}_{2,r} &= e_r[w_{4_{f,e}}\theta_{r,u}] && (14)\\
\text{hip}_{3,r} &= w_{5_{f,e}}\theta_{\text{hip}_{3,r}} && (15)\\
\text{knee}_r &= e_l[w_{6_{f,e}}\theta_{l,l}] && (16)\\
\text{ankle}_r &= e_r[w_{7_{f,e}}\theta_{r,u}] && (17)\\
\text{foot}_r &= e_r[w_{8_{f,e}}\theta_{r,l}] + e_l[c_4 w_{8_{f,e}}\theta_{l,l}] && (18)
\end{aligned}$$

where waist_1 is the joint rotating the torso in the sagittal plane, and waist_2 denotes the joint responsible for frontal plane rotation. Likewise, hip_1 rotates the leg in the sagittal plane, while hip_2 rotates the leg in the frontal plane. The hip_3 joint is responsible for rotation around the vertical axis. The strength and the sign of the feedback paths are determined by the 16 weights $w_{i_{f,e}}$, along with the four additional constants c_i.

Since each joint CPG consists of two units, a flexor neuron and an extensor neuron, two different connection weights are used, w_{i_f} and w_{i_e}, respectively, as indicated in the equations. Apart from this, the feedback paths for the two CPG neurons are identical. Hence, the total number of parameters to be determined sums up to 20.

Furthermore, θ_w is the torso angle in the sagittal plane, $\theta_{l,u}$ is the left upper leg (thigh) angle, and $\theta_{l,l}$ is the left lower leg angle. Correspondingly, the angles for the right leg are denoted with $\theta_{r,u}$ and $\theta_{r,l}$. The angle of the hip$_3$ joint in the local frame is denoted $\theta_{\text{hip}_{3,i}}$, where i is either r (right) or l (left). Finally, e_i and p_i stand for *enable* and *prohibit* respectively. If the corresponding foot is on the ground, e_i is equal to one, and zero otherwise. If the corresponding foot is *not* in contact with the ground, p_i equals one, and zero otherwise.

IV. SIMULATIONS

In this section, simulation experiments of three different methods, all involving posture-support structures, will be discussed.

In order to guide the evolution towards human-like gait, and at the same time avoid the problems related to complex fitness functions (see Sect. I), simplest fitness measure, i.e. the distance covered, has been used here, in combination with a mass-less posture-support structure, as shown in the right panels of Fig. 2. Given a supporting structure, the robot is forced to an upright position, and only individuals capable of producing repetitive leg motion will gain high fitness. When the support is used, such individuals will appear early in the evolution. However, a drawback with this method is that when the repetitive leg motion is discovered, individuals will start to exploit the support mechanism in many different ways. One common result is that individuals tend to take unnaturally large steps. While this gives high fitness when the support is used, it will certainly have a negative effect on the frontal plane balance once the support is removed. Thus, in an attempt to avoid this motion pattern, a choice was made not to evolve the internal parameters of the individual two-neuron CPGs, shown in Fig. 1, simply because the evolution would strive towards lower frequencies. Also, in order to prevent crawling behaviors, each individual run is aborted as soon as the hips of a robot collide with the ground.

Information concerning the simulations is given in Table I. In the following subsections the simulation experiments will be described in more detail.

A. Method 1: Four-point support

The first experiments were made using a posture support with four contact points, as shown in the right panel of Fig. 2. The four-point support was attached to the robot in such a way that there was a predetermined distance d between the contact points of the support and the ground. Different values of d were examined, as shown in the 1^{st}, 2^{nd}, and 3^{rd} rows of Table I. Feedback was not used here, and the hip$_2$, hip$_3$ and ankle joints were locked. However, no successful gait patterns were obtained in this way. The individuals simply exploited the support too much, leading to unnatural gait patterns of different kinds, also briefly described in the table. For example, the $0.2, 2$ support configuration (3^{rd} row) led to an individual performing a running gait, which one might expect to be useful, but that individual over-exploited the support to such an extent that it could not maintain its balance at all without the support. In Fig. 4, some of the resulting motions are depicted.

In order to meet the intended goal, i.e. evolving a human-like gait for the robot, two modified strategies were also tried. In the first strategy the support was gradually removed, in the sense that d increased during evolution, as better fitness values were obtained. The assumption here was that this should eventually lead to an individual that was completely independent from the support. However, this approach did not improve the outcome, compared with the previous results.

In the second strategy, the support was not gradually removed during evolution, but instead individuals were punished for using it. The fitness measure was simply decreased by a factor, properly normalized, measuring the number of ground contacts with the support. However, this approach did not yield any improvements either.

In the case of four-point support no useful results were obtained; the individuals simply exploited the support too much, resulting in unnatural gait patterns. For example, when using the first modified strategy, gradually removing the support, a slow unstable gait pattern, which almost resembles a drunkard's walk, emerged. When using the second modified strategy, with punishment for support usage, the result was an individual using a hop gait for locomotion.

B. Method 2: Two-point support in 2D, then 3D

Since no acceptable results were found with the four-point support, the support structure was changed to one having only a single contact point on each side of the robot, as seen in the rightmost panel of Fig. 2. Rather than evolving 3D balance at once, as in the previous case, the idea now was to divide the problem into two phases; first evolving gait in 2D, and second, to generalize it to a full 3D gait.

In this procedure, a CPG network capable of producing a stable upright gait in the sagittal plane should first be evolved using the two-point support, with the hip$_2$, hip$_3$ and ankle joints locked at this stage. Second, when a stable individual has been obtained, it should be cloned creating a new population consisting of copies of this individual. At this stage, the support should be removed and the GA should find a way to balance the robot in the frontal plane as well. Before

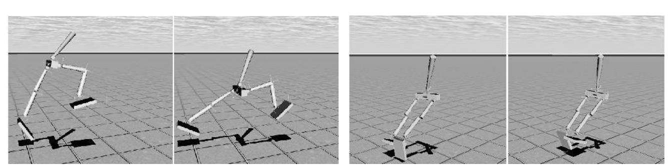

Fig. 4. The left panel shows the simulated robot taking unnaturally large steps. The right panel shows the robot exploiting the four-point support. Note that the supporting structure is not shown in the pictures.

the evolution starts, the hip_2 and ankle joints should be unlocked and the corresponding genes, including the genes encoding the waist joint parameters, should be randomly initiated for each individual in the population. Since the remaining genes (which are identical for all individuals) ensure sagittal plane balance they should not be changed in the second step.

1) Phase 1: Evolving balance in the sagittal plane: During this first phase the hip_2, hip_3 and ankle joints were locked. Balance in the frontal plane was evolved using a two-point support, with contact points placed 2 m from the robot and 0.25 m above the ground. This configuration was chosen since it ensures low sideways leaning angle and at the same time allows the robot to bend its knees without the support touching the ground. Furthermore, if a robot's hips collide with the ground, the evaluation of that particular individual is terminated.

In order to balance in the sagittal plane the evolutionary procedure started misusing the torso as a third leg, achieving speeds up to 0.3 m/s. This problem was solved by simply removing the contact point in the torso which is used to detect the collision with the ground. Once the torso could not be used for support, evolution found the large step motion, as described earlier, ensuring balance in the sagittal plane with a speed of approximately 0.45 m/s, see the 4^{th} and 5^{th} rows of Table I.

In order to reduce the step length, hand-tuned feedback paths were introduced measuring torso, upper leg, and lover leg angles, as described in Sect. III. Adding feedback, significant reduction in evolution time was observed. The same fitness value as before could now be reached approximately 5 times faster. However, the individuals were still taking unnaturally large steps.

Success in obtaining an upright human-like gait, with normal step size, was achieved using the following rule: during the evaluation of each individual, if the robot's hip fell below a certain value, the support was removed until the end of that run. If the step length is large and the support is removed in this way, the robot will most likely be unable to maintain the frontal plane balance. Thus, it will fall to the ground ending the run. Forced by this rule, evolution was able to find individuals moving at a speed of 1.13 m/s, see Table I, 6^{th} row. However, even after 400 generations, these individuals could not walk more than 10 to 15 meters before falling to the ground. In order to improve the performance, the GA was allowed to evolve the feedback paths as well. As a result, a stable individual, i.e. one that did not fall even after the end of the nominal evaluation time, was obtained within 50 generations, walking at a speed of 0.4 m/s, see Table I, 7^{th} row. To ensure stability, the whole foot sole was on the ground during almost the entire stance phase, resulting in a perfect condition for full 3D balance.

2) Phase 2: Evolving balance in full 3D: Once a satisfactory stable individual had been obtained using the support, evolution in the full 3D environment could begin. In the initial population at this stage, all individuals were mutated copies of the best individual from the previous step, as described above. The GA should now only consider the hip_2, ankle, and waist joints, as well as their feedback paths. The fitness measure was still taken as the distance covered in the initial forward direction, decreased by the sideways distance.

TABLE I

PARAMETERS AND RESULTS OF THE SIMULATION RUNS

In the column labeled *support*, the numbers i, j denote the initial placement of the contact points in a given run, where i is the height above the ground [m], and j is the horizontal distance from the hip [m]. Evaluation time is denoted by t [s], and the f column indicates whether or not feedback was used. F [m] is the obtained fitness, v is the average locomotion speed [m/s] of the robot during the evaluation period, and the last column gives a short description of the resulting gait. Note: † denotes phase 1, and ‡ denotes phase 2.

Support	t	f	F	v	Gait
4-point, 0.1, 1	7	No	3.85	0.55	hop gait
4-point, 0.3, 2	7	No	4.60	0.66	large steps
4-point, 0.2, 2	7	No	6.55	0.93	running
2-point, 0.25, 2 †	7	No	2.10	0.30	tripod gait
2-point, 0.25, 2 †	7	No	3.15	0.45	large steps
2-point, 0.25, 2 †	7	Yes	7.91	1.13	running
2-point, 0.25, 2 †	20	Yes	8.00	0.38	slow, stable
no support ‡	40	Yes	18.26	0.46	slow, stable
1 sec. 0.25, 2 †	40	Yes	19.54	0.56	slow, stable
1 sec. 0.25, 2 ‡	40	Yes	23.09	0.58	slow, stable
1 sec. 0.25, 2	40	Yes	35.56	0.90	fast walk

Within 150 generations, the best individual was able to maintain balanced walking for up to 60 seconds. After an additional 100 generations, the best individual was generally able to maintain balance indefinitely, see Fig. 5 and Table I, 8^{th} row. Since the robot was unaware of its direction of motion and because of the fact that the hip_3 joints were locked, the smallest perturbation would set it out of course, resulting in a lower fitness value.

Given the best individual from phase 2, it was possible to continue evolving the parameters for the hip_3 joint. The feedback for the hip_3 joint is defined as described in Sect. III. Evolution found a solution (not shown in the table) that resembles a PD controller, striving towards keeping the feet facing forward. A similar gait as before, with the hip_3 joint locked, emerged.

C. Method 3: 2D one second support, then 3D

The reason for introducing the two-point posture-support structure in Method 2 was mainly that it is much harder to maintain balance in the frontal plane than in the sagittal plane. By using the supporting structure, the problem was separated into two stages of evolution; first, generating a stable gait in 2D, and second, generalizing the 2D gait to three dimensions. The assumption here was that this way of splitting up the problem should make it easier for evolution to find a good solution to the overall problem of generating a robust 3D gait. However, since the hip_2 and ankle joints were locked during the 2D stage the balance in the frontal plane is then only ensured by the torso. As a consequence, evolution most often creates individuals that solve the problem in an unnatural way, i.e. individuals that exploited the supporting structure too much. Such individuals are usually not suitable for further evolution in 3D. Another drawback of Method 2

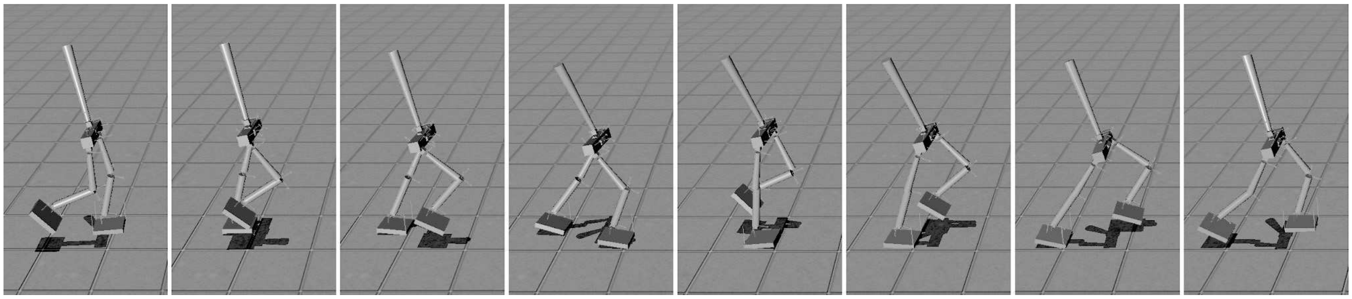

Fig. 5. The best evolved stable gait pattern in the full 3D environment. The details of the corresponding individual are shown on the $10^{\rm th}$ row of Table I.

is that there is no obvious way of deciding at what point to interrupt the 2D evolution stage, and thus to enter the 3D phase: This simply has to be judged by the experimenter in an *ad hoc* manner. Hence, there is no guarantee that the individuals evolved in 2D will perform well in the 3D stage.

Therefore, a third method was investigated as well. The same two-point supporting structure as described in the 2D case in the previous method, was used. The difference here, as compared to the other method, is that under the first stage in 2D the individuals were evaluated in a procedure where the supporting structure was present only during the first second of the evaluation, and was then completely removed. This arrangement is motivated by the fact that it is during the start sequence, before entering the gait cycle, that the individuals are most vulnerable, in terms of frontal plane balance. Here, the hip_2, hip_3 and ankle joints were still locked. However, after some generations most individuals in the population should be able to walk without the supporting structure present, except during the initial second. This has been confirmed to work well in simulation experiments. The goal in this stage is to obtain a large portion of individuals that can walk in cautious manner, which is essential for individuals to be able to generalize to 3D. In the next stage, evaluations were performed in full 3D. That is, the evaluation procedure was performed in the same way as described above, but all joints except the hip_3 joints were unlocked. The $9^{\rm th}$ row of Table I shows the results from evolution in 2D (joints locked and 1 second support), and the $10^{\rm th}$ row of the table shows the results from phase 2 (evolution based on the best individual from the previous run, with hip_2 and ankle joints unlocked). A visualization of the gait for the best individual, corresponing to the $10^{\rm th}$ row in the table, is shown in Fig. 5.

Moreover, the results from a run with hip_2 and ankle joints unlocked, performed in a single step, i.e. without the two-phase procedure described above, is shown in the last row. The gait obtained in this last run was fast, but appeared to be rather unstable.

V. DISCUSSION AND CONCLUSIONS

The outcome of the examinations and experiments described in this paper indeed fulfilled the intended goal, i.e. to generate robust bipedal gaits for a simulated robot by means of structural evolution of CPG networks: Two of the three methods introduced in this paper solved the problem of generating gaits for the simulated bipedal robot in 2D and 3D environments. However, Method 2 was affected by some drawbacks, compared to the third method. Firstly, since the support structure is present the whole time during phase 1 (evolution in 2D), evolution might very well find solutions that receive high fitness score in 2D, but are less successful in generalizing to 3D. Examples of such solutions are individuals that walk with too long foot steps, giving high fitness in 2D because of their ability to cover large walking distances in short time. However, this kind of walking behavior seriously affects the frontal plane balance in 3D. Thus, evolution in 2D has to be aborted at an appropriate time, before this kind of behavior emerges which, in turn, requires that the evolutionary process is monitored more or less continuously in order to determine when it should be interrupted.

Secondly, while it is possible (at least in principle) to monitor the progress and stop the evolution when sufficient locomotion speed is achieved, it is not always the case that evolution chooses a path, i.e. relatively small steps with a high speed, that is suitable for further evolution in 3D. Often the large step motion behavior emerges before any stable, small-step gait pattern is obtained.

In the case of the third method the two problems described above are not present: Evolution is biased towards generating gaits capable of handling the 3D environment from the beginning. Thus, Method 3 seems to be the most promising candidate for future investigations.

The need for the support structure during the initial second, as described in the second method, indicates that the CPG network cannot fully handle the start-up of the walking cycle in an appropriate way. Thus, one should, in future work, consider a dedicated controller, either a CPG-based controller or some other type of controller, for the start-up sequence of the walking cycle. It should then be tuned to enter the walking cycle and hand over to a CPG network in a more smooth way. Then, ultimately, it would be possible to skip totally the support structure.

In this paper only straight-line walking has been considered, i.e. no turning motions were involved. However, one could include such motions using the hip_3 joint in order to change deliberately the direction of walking, preferably by using vision for feedback.

Another topic for future work would be to investigate whether one could evolve the over-all feedback network, without having to pre-specify certain feedback paths, as is currently done. However, such an approach would probably increase the evaluation time considerably, since the likelihood of finding a set of feedback paths in an early generation that generates any gait at all would most probably be very small. On the other hand, evolving the feedback network could lead to better overall performance, compared to specifying the paths *ad hoc*.

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