From Passive to Active Dynamic 3D Bipedal Walking – An Evolutionary Approach

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Summary. Applying an evolutionary algorithm, we first develop the morphology of a simulated passive dynamic bipedal walking device, able to walk down a shallow slope. Using the resulting morphology and adding minimal motor and sensory equipment, a neural controller is evolved, enabling the walking device to walk on a flat surface with minimal energy consumption. The applied evolutionary algorithm fixes neither the size nor the structure of the artificial neural network. Especially, it is able to generate recurrent networks, small enough to be analyzed with respect to their behavior relevant inner dynamics. An example of such a controller is given which realizes also minimal energy consumption.

Key words: passive dynamic walking, evolutionary robotics, recurrent neural networks, bipedal walking

1 Introduction

A large amount of research activities has been spend on problems concerning the development and control of bipedal robots. Most of them mainly headed to mimic human motions. The most famous example is Honda's Asimo [4]. It is also a representative example for not attaching importance on efficient bipedal walking, concerning the energy consumption, as it can be found for example in human walking. Taking efficiency into account principles of bipedal walking in biological systems had to be understood first [7].

The efficency of human walking is mainly based on two aspects. On one hand, there is a very well coordinated use of muscles [1]. There is still a lack of new technology for efficient actuators to imitate such a motor system. On the other hand, the morphology is very well adapted to this kind of locomotion [11]. Considering the latter point seems to be very promising [3, 6]. A bipedal walking machine is shown, that is able to walk down a shallow slope without any energy consumption only powered by gravity (passive dynamic walking). As it is described in [6] the gravity force compensates the energy loss occurring due to the heel strike in bipedal walking. Therefore it should be possible to create a motor system which just compensates this energy loss and therefore enables the machine to walk on level surface with minimal energy consumption. To reach this goal, and to avoid tremendous mathematical calculations, for determining an efficient morphology we use an evolutionary algorithm.

In considering the strong interrelationship of morphology and control [2, 5, 8] we first evolve the morphology for a passive dynamic walking device, and secondly we add a minimal sensorimotor system to that model and evolve a recurrent neural network (RNN) as control structure. Finally the behavior relevance of the controller dynamics is analyzed.

2 Methods

2.1 Evolutionary Algorithm

For evolution the ENS^3 (evolution of neural systems by stochastic synthesis) algorithm [9] was used. A simple form of this algorithm is as follows.

1. Create an initial population $P(0)$.
2. Create an offspring population $\hat{P}(t)$ by reproducing the parent population $P(t)$.
3. Vary the structure and the parameters of $\hat{P}(t)$ by stochastic operators.
4. Evaluate each individual of $\hat{P}(t)$ and $P(t)$ and assign a fitness value to it.
5. Create $P(t+1)$ by a rank based selection of individuals out of $\hat{P}(t)$ and $P(t)$ according to their fitness values.
6. Has some stop criteria fulfilled? If yes, exit, if no, go to 2.

A population either consists of a number of neural controllers (control optimization) or a number of parameter sets (morphology optimization). In the first case the evolutionary algorithm fixes neither the size nor the structure of the artificial neural network. Parameters of the evolutionary process such as the probability of including, deleting or changing synapses and neurons, average size of a population, the steepness of the selection function, costs of neurons and synapses etc. can be modified online.

The neurons of the controller are of the additive graded type with zero bias terms. The dynamics of the controller is then given by

$$a_i(t+1) = \sum_{j=1}^{j} w_{ij}\ f(a_j(t))\ , \tag{1}$$

where the activation a_i of neuron i at time $t+1$ is the weighted sum of the outputs $f(a_j(t))$ of the connected neurons at time t, and w_{ij} denotes the strength of the connection from neuron j to neuron i. The input neurons act as buffers with identity as transfer function. The transfer function for all hidden and output neurons is given by the hyperbolic tangent $f(x) = tanh(x)$.

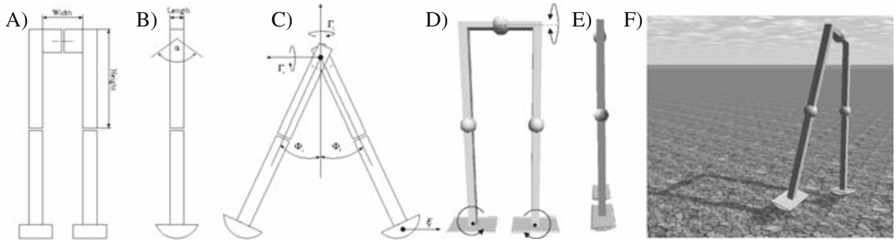

Fig. 1. A-C: Evolvable parameters of the passive dynamic walking device. **D-F**: The active dynamic walking device within the simulation environment

2.2 Evolution of Body and Brain

Hence we evolved the morphology and control in a sequential order, the parameters of the passive dynamic walking device has to be introduced first. But as far as the main concern of this paper is the use of the principles of passive dynamic walking for an active controlled bipedal walking machine, for information we want to mention that 10 morphology parameters (dimensions and mass distributions) and 5 initial conditions which were evolved (Fig. 1a–1c). A detailed description of the experimental setup and the results in pure passive dynamic walking can be found in [10]. The used model is sketched in Fig. 1.

The fitness value of each individual i was computed as follows.

$$F_{V_i} = (S_i + 1) \cdot W_i \ , \tag{2}$$

where S_i denotes the number of completed steps, and W_i the distance covered by the center of the hip. One is added to the number of steps to exclude a fitness value of zero if the walking device isn't able to make at least one step. For evaluation the model is implemented within the physical simulation environment *Open Dynamics Engine*[a] (ODE). The evaluation process was stopped when the walking device was falling over.

Once a suitable passive dynamic walking device was evolved, we applied a sensorimotor system to this model which should be as minimal as possible. Therefore, the model has just three motors. A servo motor model in each ankle is able to shorten or lengthen the leg respectively. The motor at the hip joint is controlled by torque. If no torque is applied to this motor the leg can swing freely around the joint axis. The rotation axis of all motors are sketched in Fig. 1d. As it can be seen the hip motor is the only one which is able produce forward motion.

The output of the control architecture is represented by the desired angles of the foot motors and the desired torque of the hip motor. The actual angles of these three joints are fed into the controller as internal sensors. Additionally

[a] ODE is an open source library with an C/C++ API for simulating rigid body dynamics. More information about ODE can be found at http://www.ode.org

a foot contact sensor is given as an external sensor, which provides information about which foot is in contact with the ground. This sensor can have three discrete states. The output of the according input neuron is +1, if the left foot is in contact with the ground, and −1 vice versa. If both feet are in contact with the ground, the signal is 0. Because we wanted to encourage walking, not running, the case that no feet is in contact is excluded. If no foot is contact with the ground the signal maintains its last value.

For evaluation the following fitness function was used.

$$F_V = k_1 \cdot (S_i + 1) \cdot W_i - k_2 \cdot \Delta E \tag{3}$$

It is an extended version of Formula (2) with an additional energy term ΔE to reduce the energy consumption. The energy term is given as follows:

$$\Delta E = \sum_{t=1}^{n} \sqrt{(\Delta T_H(t))^2 + (\Delta A_{Fr}(t))^2 + (\Delta A_{Fl}(t))^2} \, , \tag{4}$$

where $\Delta T_H(t) = T_H(t) - T_H(t-1)$ denotes the torque difference of the hip motor between two time steps and $\Delta A_F(t) = A_F(t) - A_F(t-1)$ denotes the difference of the desired angle of the foot motor of consecutive time steps and n denotes the maximum time steps. The two weights k_1 and k_2 can be varied online during the evolutionary process. The sum of these two terms was always 1 to normalize the fitness value. At the beginning of the evolution $k_1 \gg k_2$ was chosen to encourage the development of a gait pattern at all. Since a suitable gait pattern was obtained we set $k_1 = k_2$ to encourage control structures which additionally produce an energy efficient walking behavior. The neural network was updated with an frequency of 10 Hz, whereas the simulation was updated with 100 Hz.

The active dynamic walking device had to fulfill two tasks. First it has to produce a stable walking pattern on flat surface with minimal energy consumption, and second, it had to initialize the gait by itself. For the latter case all evolved starting conditions of the passive dynamic walking device were set to zero.

3 Results

The model taken for the active dynamic walking device was able to make about 9 steps and cover a mean distance about 3.4 meters on a descending slope of 4 degrees. This achievement seemed good enough to continue with the evolution of a neural network for an active dynamic walking device.

Therefore we applied the previously described sensorimotor system to the passive dynamic walking device. At the end of the evolutionary process the *RNN* displayed in Fig. 3a turned out to be the best result.

The walking device with this control structure was able to initialize a walking pattern and to maintain stable walking. It covers a mean distance

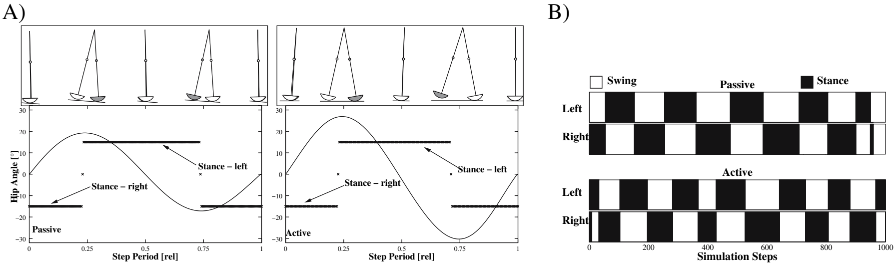

Fig. 2. Passive vs. active dynamic walking. (**A**): One step cycle. (**B**): Swing and stance phases

about 7.1 meters by making mean 12 steps. So we got an improved result in comparison to pure passive dynamic walking.

The small structure of the *RNN* has yet another advantage as we will see in the next section by analyzing the dynamics of the control architecture.

4 Analysis

In Fig. 2b the swing and stance phases of both devices are plotted. In the passive walking device a nearly regular pattern can be found. Here only the morphology and the environment (slope, gravity, friction etc.) defines the walking pattern. By way of contrast in the active walking device the pattern is additionally controlled by the *RNN*, thus it is less regular in comparison to the passive dynamic walking device.

A whole step cycle for both walking devices is shown in Fig. 2a. The pattern of the hip angle, the swing and stance phases and their switching points are very similar except of the amplitude of the hip angle. The reason for the higher amplitude is a little offset in the hip motor signal as it will be described later.

We will now see how the output activity of the sensor inputs and motor outputs (Fig. 3b and 3c) are related to the internal dynamics of the *RNN* (Fig. 3a). Therefore we first discuss the behavior of the foot motors on the basis of the left foot motor neuron N_6.

There are two strong excitatory connections w_{61} and w_{64} (describing the synapsis from N_1 to N_6 and accordingly from N_4 to N_6). As it can be seen in Fig. 3b the absolute output of N_1 is always lower than that of N_4 due to the fact that N_4, representing the foot contact sensor, can only have 3 states. So the influence of w_{64} is dominant. Whenever the left leg is in stance, the output of N_4 is $+1$ and so, because of the strong connection w_{64} and the strong excitatory self-connection w_{66} of N_6, the output of N_6 is also $+1$. If the left leg is in the swing phase, the output of N_4 is -1 and at the same time the output of N_6 is also -1. So, due to the strong self-connection of N_6 the output of this neuron switches between two states. These states correspond

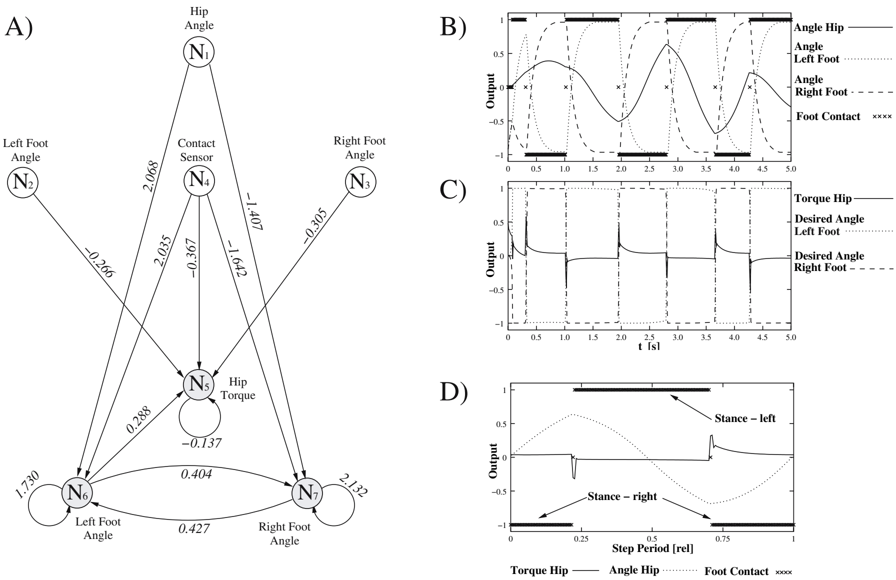

Fig. 3. (**A**): The *RNN* of the active dynamic walking device. (**B**): Output of the input neurons ($N_1 - N_4$). (**C**): Output of the output neurons ($N_5 - N_7$) (**D**): Hip motor output for one step cycle

to motor positions of 15 degrees or 0 degrees, meaning the leg is lengthen, if it is in stance and shorten if it is in the swing phase. The reaction of the servo motor in the left foot joint can be seen in the curve of the actual angle sensor (N_2) in Fig. 3b.

For the motor neuron N_7, controlling the right foot joint, we observe the same behavior. In contrast to N_6 there are two strong inhibitory connections w_{71} and w_{74}. The resulting behavior is the same for N_6, because here the output of N_4 is -1 whenever the right leg is in stance and $+1$ when it is the swing leg.

We will now discuss the behavior of the hip motor. Whenever the left leg is in the swing phase, we need positive torque at the hip motor to support forward swinging, and consequently we need negative torque if the right leg is in the swing phase. As it is shown in Fig. 3d, we have three characteristics for the produced hip torque (N_5). There are peaks always at the moment of changing the swing and stance leg (i), and a damped transition (ii) to a specific offset (iii). This is controlled by five connections including one inhibitory self-connection. The damped transition is the result of the negative self-connection w_{55}.

Additionally, there are two inhibitory connections w_{52} and w_{53} from the two foot angle sensor neurons. If we look at the outputs of the neurons N_2 and N_3 (Fig. 3b) we see that most of the time both have the same value with different signs. Notice that there is a little difference of 0.039 between the weights w_{52} and w_{53}. We will later come back to this point.

Further on we see a inhibitory connection w_{54} from the foot contact sensor and a excitatory w_{56} from the motor output neuron of the left foot. We remember both outputs of the neurons are identical for most of the time, either -1 or $+1$. Notice the little difference of 0.079 between these weights.

Assume that the left leg is in stance. The output of N_2 is positive and of N_3 negative with the same absolute value. So we have a little excitatory influence because of the difference between the two weights w_{52} and w_{53}. The output of N_4 and N_6 is $+1$. So here we have a little inhibitory influence from these two connections because of the difference between w_{54} and w_{56} (compare with Fig. 3a). The difference of the described differences of the weights, in this case -0.04, is exactly the offset which can be observed in the output activity of N_5. Therefore, there is a little negative torque which supplies the swinging right leg. Correspondingly, if the left leg is in the swing phase we have an supporting offset output of $+0.04$.

Let us now consider the peaks of the produced hip torque. When both feet are in contact with the ground the inhibitory influence of w_{54} from the contact sensor is gone because the output of N_4 is zero. But the output of N_7 is either -1 or $+1$ due to the strong self-connection of N_7. So the balance between w_{54} and w_{56} is disturbed and a peak in the output of N_5 appears due to the excitatory connection w_{56}. The sign depends on which leg is in stance, as discussed before. Thus, the peak in the hip motor signal appears only at the switch between swing and stance leg when both feet are in contact with the ground. It is illustrated more clearly in Fig. 3c, where the produced output for the hip torque, the hip angle and the swing and stance phases are described for one step cycle. We can see the peak and the smooth transition to the offset, to which leg is in stance, respectively.

To summarize, we can say, that the walking pattern of the active dynamic walking device is mainly generated by the rigid body dynamics of the evolved morphology. Only at the moment of energy loss, at the heel strike, the *RNN* produce the required compensating hip torque. Only the motor at the hip joint is able to produce forward motion and so the energy consumption is minimal. We saw that the contact sensor is essential for controlling the foot motors. And it is also very essential for producing an appropriate torque at the hip joint.

5 Conclusions

We have presented a method to develop efficient control structures for generating a simple gait pattern in bipedal walking. We showed how important the optimization of the morphology is, how an evolved minimal sensorimotor system looks like, and how to interpret the dynamics of the evolved *RNN* as that of an efficient control structure. We minimized the number of parameters of the walking device as well as its control architecture, its sensorimotor system, and the energy consumption in active dynamic walking.

We showed how to optimize the morphology of a bipedal walking device, so that it is adapted to a specific environment (walking down a slope only driven by gravity). Than we changed the environment (to flat surface) and evolved a control architecture which was able to adapt to this change by using the advantages of the models morphology.

There was only one type of information about the model-environment-interaction coming from the foot contact sensor having three possible discrete values. This was enough to enable the system, controlled by the evolved *RNN*, to adapted successfully to the changed environment.

In our opinion considering the optimization of morphology and control is an important aspect in developing and building bipedal walking devices, if the reduction of energy consumption is desired.

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