Evolution of Biped Walking Using Neural Oscillators and Physical Simulation*

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Abstract. Controlling a biped robot with a high degree of freedom to achieve stable movement patterns is still an open and complex problem, in particular within the RoboCup community. Thus, the development of control mechanisms for biped locomotion have become an important field of research. In this paper we introduce a model-free approach of biped motion generation, which specifies target angles for all driven joints and is based on a neural oscillator. It is potentially capable to control any servo motor driven biped robot, in particular those with a high degree of freedom, and requires only the identification of the robot's physical constants in order to provide an adequate simulation. The approach was implemented and successfully tested within a physical simulation of our target system - the 19-DoF *Bioloid* robot. The crucial task of identifying and optimizing appropriate parameter sets for this method was tackled using evolutionary algorithms. We could show, that the presented approach is applicable in generating walking patterns for the simulated biped robot. The work demonstrates, how the important parameters may be identified and optimized when applying evolutionary algorithms. Several so evolved controllers were capable of generating a robust biped walking behavior with relatively high walking speeds, even without using sensory information. In addition we present first results of laboratory experiments, where some of the evolved motions were tried to transfer to real hardware.

Keywords: Biped Walking, Humanoid Robot Simulation, Evolutionary Algorithms, Walking Controllers, Neural Oscillators.

1 Introduction

Making a biped robot walk is a complex task. Describing and calculating joint trajectories is a common way to control servo motor driven humanoid robots. In the majority of the cases, the trajectory describing coefficients are calculated based on a model of the robot and a stability criteria. As an example, Takanishi's research group in Waseda University presented the humanoid robot WABIAN, where the trajectories of the arms, legs and ZMP were described by Fourier series [1]. The coefficients were determined in simulation in a way to ensure the Zero Moment Point (ZMP,[2]) conditions. As a drawback of this approach, a detailed and valid model of the target system has to be identified, and changes in the target system require a redesign of this model.

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Another well-established approach of gaining the reference trajectories, which is emerged from studying vertebrate animals are the Central Pattern Generators (CPG, [3,4,5]). Central pattern generators are circuits which are able to produce periodic signals in a self-contained way, i.e. without having any rhythmic input into themselves. In order to build structures with similar properties to the neural oscillators found in animals, several mathematical models have been proposed (e.g. [6,7,8]). Matsuoka proposed a mathematical model of CPGs and demonstrated that the combination of simple neural models can generate the neural activities for biped locomotion [9]. This model has been applied across several biped simulations (e.g. [10]), as well as used for real robots (e.g. [11]). One of the difficulties in the application of the CPG model to real robots is to determine the weights of neural connections. This is the main reason why genetic algorithms have often been used to solve this problem [12,13].

Within this paper we present a model-free approach of biped motion generation, based on a neural oscillator. The neural architecture has a biological analogy which is particularly interesting from a cognitive point of view. Furthermore it provides a very easy and natural way to incorporate arbitrary sensory input. We demonstrate the use of physical simulation and evolutionary algorithms to identify appropriate parameter sets of the presented motion generation model. This methodology is independent of a certain robot instance and does not require the detailed physical analysis of the target system. The application of simulation and artificial evolution permits an easy adaption of the motion generation to any modifications in the target system itself or in the requirements of the motion.

2 Simulation Environment

The target system of our study is a 19-DoF *Bioloid* robot with a shoulder height of $34cm$ and a weight of approx. $2.2kg$. Due to the natural limits of real hardware experiments a physical simulation of this robot was developed. The simulation is based on the Open Dynamics Engine library (ODE, [14]) and simulates a simplified model of the real robot, consisting of 59 body parts and 19 servo motor joints. The time-integrated simulation is processed with a resolution of 100 simulation steps per second. Several isolated motor characteristic experiments were accomplished, in order to adequately simulate the servo motors torque and friction (see Fig. 1). Finally, as a weak validation of the simulation behavior, several real robot motions were transferred to the simulated one and could reproduce almost identical behavior. As an example, the handcrafted stand-up motion of the real robot is simulated accordingly (see Fig. 2).

The modular structured simulation environment was designed for exploring appropriate non-model based control structures which are potentially able to generate *robust* biped motions of our target system. Within this paper, a robust motion denotes a motion that is capable to compensate small environmental disturbances (e.g. small obstacles, impacts, rough floors, etc.). Regarding the simulation, the simulated robot had to pass at least $120s$ without falling or visible tumbling, while facing the ODE's simulated environmental noise.

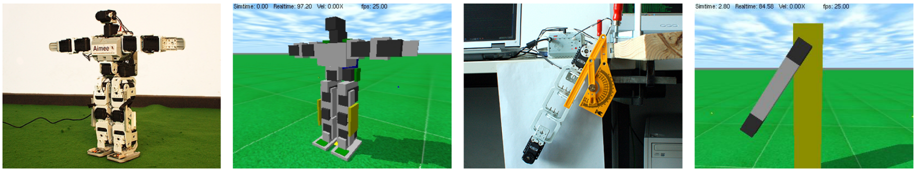

Fig. 1. Real and simulated world (left to right): Real Bioloid, Simulated Bioloid, Real servo motor torque and friction experiment setup, Simulated servo motor torque and friction experiment setup

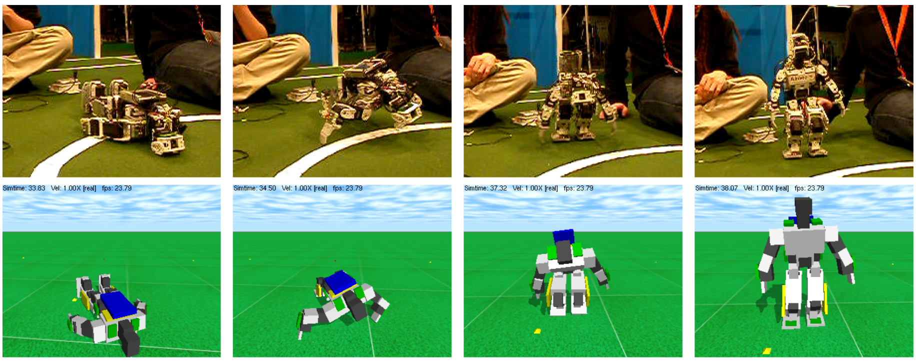

Fig. 2. A first weak validation of the simulation: The stand-up motion is based upon interpolated keyframes and was developed on the real Bioloid. The (raw) transfer of the identical keyframe structure to simulation shows almost identical behavior.

3 Motion Generation – Neural Oscillator Approach

The neural oscillator approach generates a core oscillation with the use of the discrete-time dynamics of a two neuron network. Aspects of discrete-time dynamics with recurrent connectivity have been studied extensively, e.g. in [15,16]. The basic idea behind this approach is formulated by Pasemann, Hild and Zahedi in [17], which is also a good address for its mathematical background. The network update formula is as follows:

$$a(t+1) := \tanh\left(\Omega\ a(t)\right), \quad \Omega = \begin{pmatrix} \omega_{11} & \omega_{12} \\ \omega_{21} & \omega_{22} \end{pmatrix} \tag{1}$$

It is demonstrated, that certain configurations of the weight matrix Ω cause periodic or quasi-periodic attractors in the phase space of the network [17,18]. These types of networks are able to generate different types of oscillations which in turn can be used for generating reference trajectories. An example of such a quasi-periodic orbit is displayed in Fig. 4.

The oscillations of the presented two neuron networks are now used for generating the joint's reference trajectories. The reference trajectory of a single joint is represented by the output of a dedicated (standard additive) neuron. The neuron derives its activation by two synapses coming from the two neurons oscillator and a bias term which

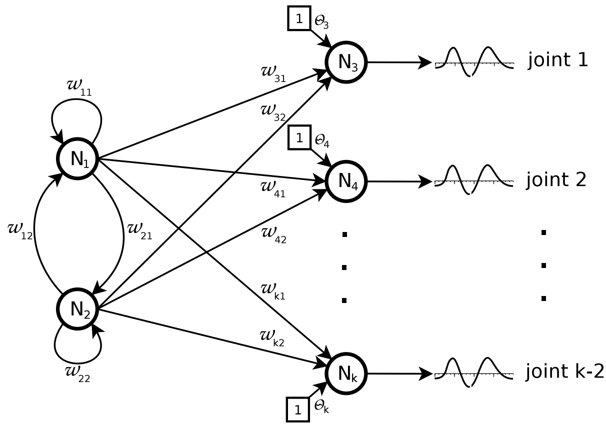

Fig. 3. Topology of the neural net controller. Each joint's reference trajectory is given by a dedicated neuron, which derives its activation by the two oscillating neurons N_1, N_2 and a bias term θ_j.

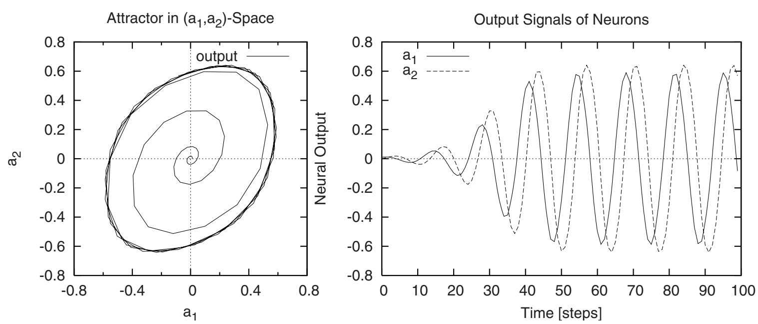

Fig. 4. Example dynamics of a two neuron network output: Phase trajectory in (a_1, a_2)-space (left), and output signals of neuron 1 and 2 (right) for $\omega_{11} = 1.17$, $\omega_{12} = 0.61$, $\omega_{21} = -0.47$, $\omega_{22} = 0.83$. Graphs show the initial phase up to reaching the quasi-periodic attractor within the first 100 time steps. The initial activation was set to $a_1 = 0.01$, $a_2 = 0.0$.

represents the offset of the trajectory's amplitude. In this way, the reference trajectory of a single joint is described by three parameters, ω_{j1}, ω_{j2} and θ_j, where ω_{ji} denotes the synaptic weight coming from neuron $i = 1, 2$ and θ_j the bias of joint j. Figure 3 illustrates the neural topology of the controller's network.

In order to reduce this parameter space, we further made use of a sagittal symmetry assumption, which states same movements between corresponding left and right sided joints with a half-period phase shift. In doing so, all trajectories are described by 10 output neurons, and the parameter space has a dimension of 34 synaptic weights.

4 Evolution of Walking Motions

Within this simulation environment, artificial evolutions were processed for identifying applicable parameters sets of the neural net controller. The primary object was to

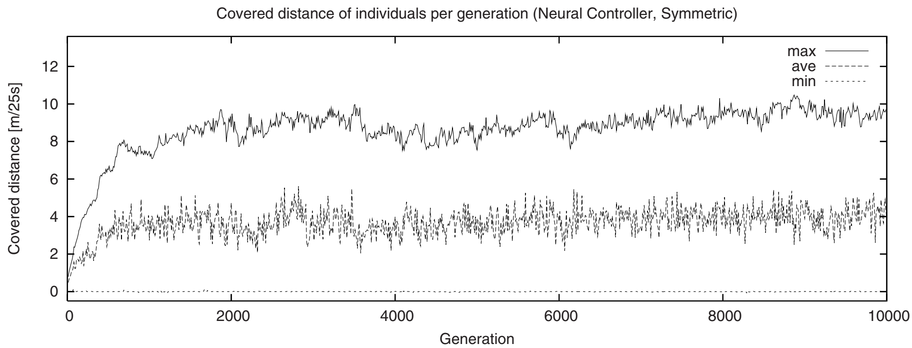

Fig. 5. Fitness development of an exemplary evolution experiment using the neural oscillator approach

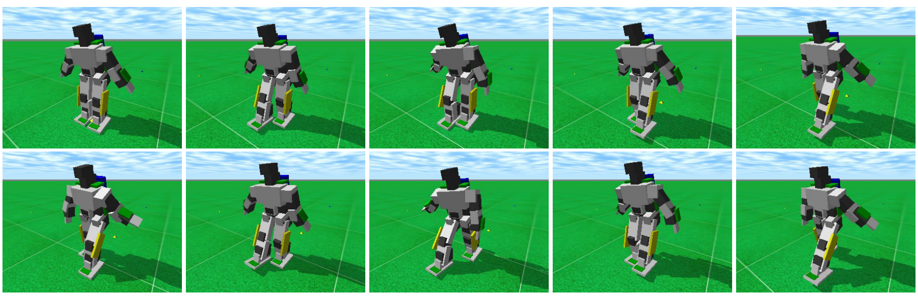

Fig. 6. Evolution of Walking Pattern: Example of an evolved walking pattern applying the neural oscillator approach. Pictures illustrate the start of walking and first steps. The displayed motion reaches a walking speed of about $0.45m/s$, which corresponds to a human walking speed of approx. $7km/h$.

identify motion patterns, that could pilot the robot a maximum possible distance within a certain time. Each individual has to pass an episode, in which the corresponding distance is measured. An episode starts with the relocation of the robot to its initial position. Subsequently the robot is given time to adopt its starting pose, in order to pass the episode run. The episode run is aborted if either the maximum episode duration is exceeded, if the robot falls or if it loses the desired path. The fitness value of an individual was set to its covered distance in stated walking direction. The actual 'position' of the robot was defined as the center of both feet. In doing so, the fitness is defined as follows:

$$fitness = min\,(\Delta y_{rfoot},\ \Delta y_{lfoot}) \tag{2}$$

$$\Delta y_{rfoot} = y_{rfoot_{end}} - y_{rfoot_{start}} \tag{3}$$

$$\Delta y_{lfoot} = y_{lfoot_{end}} - y_{lfoot_{start}} \tag{4}$$

where $y_{xfoot_{start}}$ denotes the y-coordinate of the right/left foot at the beginning of the episode, and $y_{xfoot_{end}}$ the y-coordinate of the right/left foot at the end of the episode.

We already processed several hundreds of evolutions experiments, and the present results are the outcome of about 210,000 (simulated) hours.

Figure 5 shows the fitness development of such an evolution experiment.

The genotypes of the first generations were initialized with a (weak) Gaussian distribution ($\sigma = 0.01$) around $m = 0.0$. Only the synaptic weights of the two neuron network were chosen in a way, that the two neurons had already oscillating dynamics, which could significantly speed up the evolution progress. The chosen parameters were: $\omega_{11} = 1.1$, $\omega_{12} = 0.7$, $\omega_{21} = -0.7$ and $\omega_{22} = 1.1$, which corresponds to a oscillating frequency of approx. 8 periods per 100 net-update steps. The net-update frequency was set to $10Hz$ (10 updates per simulated second), hence the initial overall step frequency was $0.8Hz$.

5 Motion Transfer to Real Robot

Subsequently to the simulated evolutions, we transfered and tested several of the evolved motions patterns on the real robot. In general, the real robot was capable to reproduce all motions with a similar visual motion phenotype - as long as the robot acts free and does not touch the floor. Actually, none of the transfered motions could reproduce a robust walking motion. All walking motions need manual stabilization to avoid a fall down of the robot (see Fig. 7).

Fig. 7. Transfer of motion pattern to hardware: The 'grounded' real robot shows similar behavior compared to its simulated counterpart, but still needs manual support for walking

We identified two major issues that raise serious gaps between simulation and real world behavior. One refers to the considerable gears tolerances. Due to these (currently not simulated) tolerances, the actual trajectory of a joint crucially diverges from the controlled reference trajectory. As a result, whole-body motions are not reproduced with the required accuracy. To exemplify the problem: The present bodywork of the *Bioloid* robot does not even allow for standing on one foot due to the joint tolerances.

The other issue refers to the complicated motion characteristics of the servo motors. The simplified motion model of a servo motor does not sufficiently match the real servo motor behavior. This again results in significant differences between the actual whole-body movement and the desired one.

6 Conclusion and Outlook

Physical simulation is an effective and practical method, to study and explore motion generation techniques of complex biped robots. We presented a neural net controller, that could generate several robust biped walking motions for the simulated robot. The parameters of the neural net structure were identified by processing artificial evolutions within the simulation environment. Finally the simulated robot could walk with relatively high walking speeds of up to $0.51 m/s$, which corresponds to a human walking speed of about $8 km/h$. Interestingly while identifying the motor coupling weights, the evolution slightly modified the frequency of the neural oscillator from initially $0.8 Hz$ to $0.75 Hz$.

In laboratory experiments, several evolved motions were then transfered to the real robot. However, due to discrepancies between simulated and real world behavior, none of these transfered motions could actually generate a robust biped walking pattern on the real robot. Nevertheless, this paper outlines how simulation may enhance real robot motions. Generally, the presented approach may be applied to any biped robot with trajectory driven joints. In particular it can be applied to the new simulator of the 3D-Soccer-Simulation-League, that employs a physical model of the *Fujistu HOAP-2* humanoid robot.

The presented work comprises of just the first step, involved in using simulation to explore and optimize different controller models of biped robots. Several points could further expand on the completed work: For the first instance, we are currently engaged in enhancing the simulation in order to reduce the gap between real and simulated behavior. Primarily, this includes developing an enhanced servo motor joint model which describes all relevant characteristics of the applied AX-12 servos.

For the second instance we are studying the use of sensor feedback. At present, the implemented walking controller does not incorporate any sensory information. In generating a robust biped motion, the system has to be sensitive to external environmental influences, such as obstacles or various impacts, and must be able to react appropriately. This issue includes the exploration of the appropriate sensors (e.g. touch or acceleration sensors) as well as how sensor information is incorporated into the generation of motion. The synaptic architecture of the presented controller allows for several sensor coupling techniques. In conjunction with evolutionary algorithms the physical simulation enables exploring appropriate coupling structures as well as alternative neural net architectures. Regarding this point, first successful sensor coupling experiments were accomplished which we will present in a forthcoming paper.

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