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Evolving Bipedal Locomotion with Genetic Programming — A Preliminary Report —

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Abstract-

This paper shows how Genetic Programming can be applied to the task of evolving the neural oscillators that produce the coordinated movements of human-like bipedal locomotion. In the research of biomechanical engineering, robotics and neurophysiology, to clarify the mechanism of human bipedal walking is of major interest. It serves as a basis of developing several applications such as rehabilitation tools and humanoid robots. Nevertheless, because of complexity of the neuronal system that interacts with the body dynamics system to make walking movements, much is left unknown about the details of locomotion mechanism. Researchers were looking for the optimal model of the neuronal system by trials and errors. In this paper, we applied Genetic Programming to induce the model of the nervous system automatically and showed its effectiveness by simulating a human bipedal gait with the obtained model. Our experimental results are preliminary but they show some promising evidences for further improvements.

1 Introduction

A bipedal locomotion is one of the most important aspects of the human body movement. Its control mechanism has been extensively studied both in biological science and engineering, but many problems still remain unsolved in designing an optimal controller of the biped gait to be adopted in the applications such as robotics and computer animation.

On the other hand, from basic neurophysiological experiments it is known existence of a *central pattern generator* (CPG) in the spinal cord, which is an intra-spinal network of neurons capable of producing rhythmic outputs. CPG is a name given to a group of nerve cells in the central nervous system that interact to produce a coordinated pattern of signals that stimulate muscles to contract in sequence. In the past research of biomechanical engineering, CPG has been formulated as a set of *neural oscillators* to produce the patterns of oscillations necessary for rhythmic movements such as locomotion and swimming. Here, one neural oscillator is represented with two sets of mutually inhibited neural elements. The important characteristics of the neural oscillator is its ability to entrain to an incoming frequency. The self-excited oscillation of the neural oscillator is synchronized to a certain frequency range of oscillation inputs.

In [4] it was shown that the simplified mechanical system performed different modes of walking efficiently based upon the oscillator model for generating several locomotion patterns. And, in [10] mathematical models of walking were presented based on the theory asserting that the interaction between rhythms generated by the neural and the musculo-skeletal systems produces autonomous walking movements.

In the above systems, design of the neural oscillators was carefully hand-tuned by the experts to achieve desired movements. In [1] and [2] the method for autonomously determining optimal values of connection coefficients and parameters for neural oscillators was studied using Genetic Algorithm. However, in their studies the structure of neural system still had to be predetermined by trial and error, which is quite often the most painful and time-consuming task for a human designer of neural oscillators.

This paper reports the preliminary experimental results of our research that aims to construct the neural network modules for generating bipedal walking without any human interaction. Since there is no systematic way to determine the structure of the neural system that can generate a desired walking movement, the evolutionary approach using *Genetic Programming* (GP) [7] is applied to explore the space of possible neural networks.

From the beginning of GP research, evolving a neural network has obtained much interest from researchers [6, 11]. In the research of *evolutionary robotics*, there are some works that developed recurrent neural networks for controlling multi-legged (4-8) robot's behaviors using evolutionary algorithms and succeeded to outperform the controller designed by a human expert [8]. Compared with multi-legged walking which can easily stop (and start) without fear of falling down, a bipedal walking is much more fragile with its unstable limit cycle. Hence, as far as we know, there has been no reported research attempt to develop a bipedal locomotion controller without human intervention.

In the next section, we briefly explain the biological model for bipedal locomotion, and then show how we applied GP for generating human-like walking patterns. The details of system implementation and experimental results are then presented and analyzed for evaluation. The paper ends with a

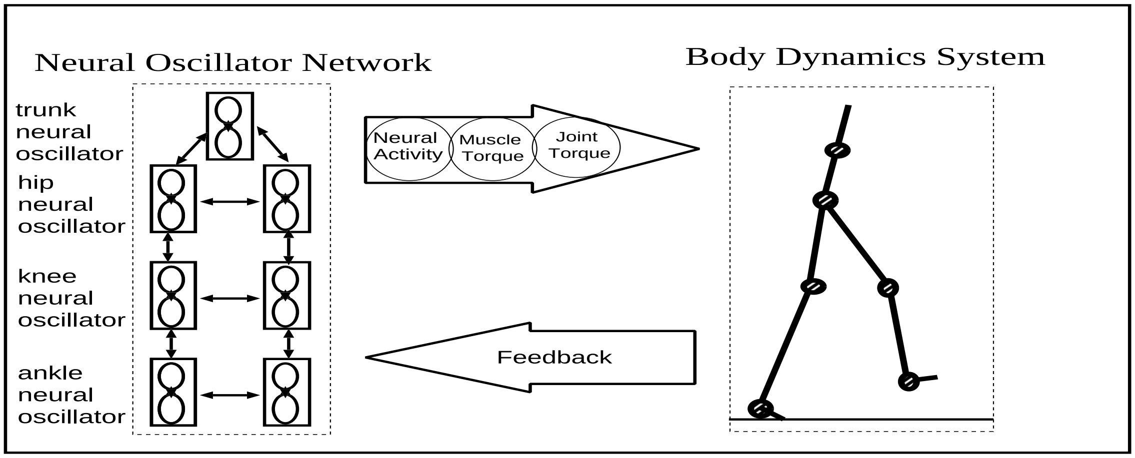

Figure 1: Interaction between Neuronal System and Body Dynamics

discussion of the results and proposals for future work.

2 Model of Bipedal Walking

Neurophysiological studies on animal locomotion have revealed that the basic rhythm of locomotion is controlled by a rhythm-generation mechanism called the central pattern generator (CPG). Taga [10] and others applied the idea to human bipedal walking and presented a theory asserting that global entrainment between the neuron-musculo-skeletal system and the environment produces human walking.

The neuronal system autonomously produces rhythmic patterns of neural stimuli and the system of body dynamics generates movements according to the rhythm pattern. Information concerning somatic senses, such as information about foot-ground contact and segment angle, is fed back to the neuronal system, and the rhythm pattern of neural stimuli is regenerated based on this information. This theory holds that this interaction between the neuronal system and the system of body dynamics produces movement. Figure 1 shows a schematic model of the interaction.

Computer simulations have shown that the walking movement generated by this model can flexibly adapt to changes in the environment, such as slopes and mechanical perturbations that occur during walking. In our research, we constructed a walking model based on this theory [10].

2.1 Model of Body Dynamics

In our study, the system of body dynamics in bipedal walking is modeled by 12 three-dimensional rigid segments representing feet, shanks, thighs, lower part of torso, upper part of torso, upper arms, and forearms. This is the most basic model representing the characteristics of human biped walking. Each foot is represented by a triangle of appropriate proportions. The posterior point of the triangle represents the heel where the foot-ground contact is made. The anterior point of the triangle represents the heal of the first metatarsus where the foot-ground contact ends. The interaction between the foot and the ground is modeled as a combination of springs and dampers. The ground reaction forces produced by springs and dampers were assumed to act on four points in each foot: two points in the heel and two points in the toe of the foot. Passive joint structures such as ligaments are modeled as nonlinear, visco-elastic elements. The body dynamics models is driven by 32 muscles for the entire body, as shown in Figure 2. And, the body parameters, such as segment mass, used in the experiments are determined as summarized in Table 1.

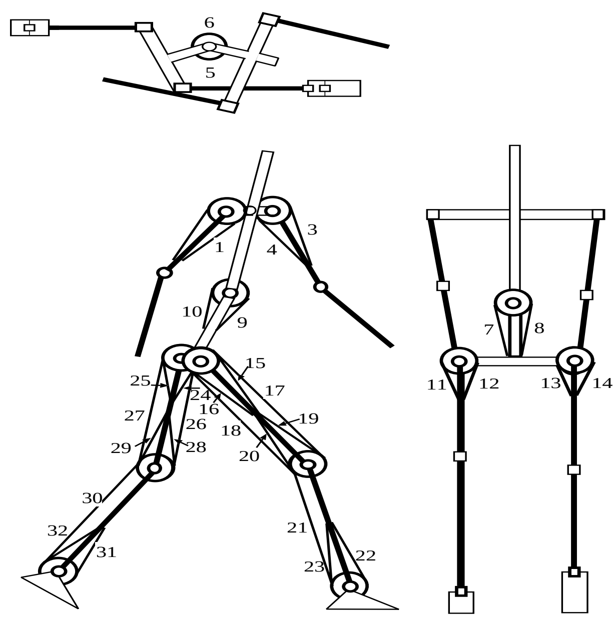

Figure 2: Body Dynamics Model

Table 1: Body Parameters

Name	Mass[kg]	Moment of inertia [kgm^2]	Link length[m]	Center of gravity[m]
Upper torso	29.482	1.6193	1.0876	0.3785
Lower torso	8.500	0.0425	0.0410	0.0500
Thigh	6.523	0.1137	0.1157	0.0224
Calf	2.685	0.0391	0.0392	0.0029
Foot	0.837	0.0033	0.0030	0.0007
Upper arm	1.842	0.0133	0.0132	0.0022
Forearm	1.513	0.0133	0.0133	0.0010

2.2 Model of Nervous System

We adopt the neural rhythm generator presented in [10] as a model of the nervous system. This neural system represents a rhythm generation mechanism with CPG and is modeled as a network system consisting of a set of neural oscillators.

The dynamics of a single neuron can be expressed by the differential equations as follows:

$$\tau_i \dot{u}_i = -u_i - \beta v_i + u_0 - w_{ij} y_j + sig(f_i), \quad (1)$$

$$\tau_i^{'} \dot{v}_i = -v_i + y_i, \quad (2)$$

$$y_i = \max(u_i, 0) \quad (3)$$

where u_i is the inner state of the ith neuron; v_i is the state variable representing the fatigue of the ith neuron; y_i is the output of the ith neuron; u_0 is the constant stimulus; τ_i and $\tau_i^{'}$ are time constants; and β is the fatigue constant; w_{ij} is connection between neurons in a oscillator. f_i represents the sensory signals fed back from receptors as well as input signals from other neural oscillators. We call this *feedback unit*. A feedback unit consists of signal information such as output of neurons($y_1 \cdots y_{24}$), joint angles, joint angles in standing posture, angular velocities at joints and ground reaction force of the leg. The range of output from a feedback unit is regulated using a sigmoid function $sig()$. Existence of the sigmoid function is not biologically grounded, but it accelerates finding promissing individuals at the early stage of evolution. Figure 3 depicts the above model of a single neural oscillator.

Our model of the nervous system network is constructed based on the following assumptions:

1. A neural oscillator consists of a pair of flexor and extensor neurons and each neuron produces a signal for either flexion or extension motion of a joint as shown in Figure 3 [5]. A neural oscillator exists for each degree of freedom of the joint, and it is expressed by the above differential equations. The neural oscillators are able to generate the basic rhythm of joint movements in walking due to their mutual inhibition. In our study, the number of neural oscillators and their inner structure are fixed a priori.

2. We postulate sensory signals of inertial angles, angular velocities, and somatic senses from sensory receptors.

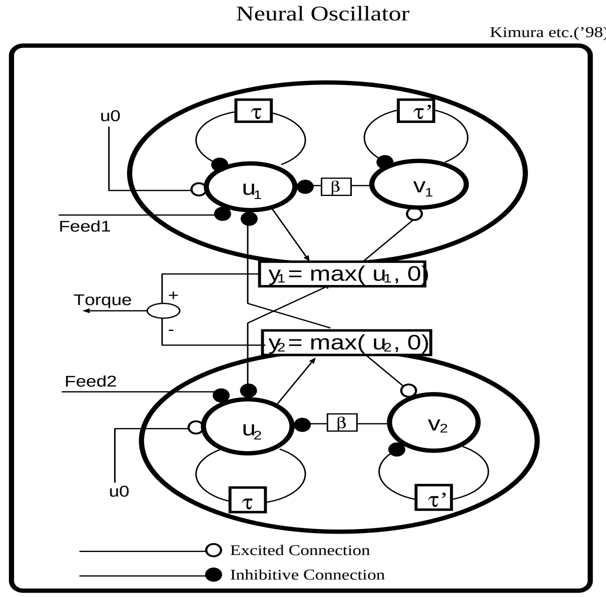

Figure 3: Neural Oscillator

3. If an output signal of a receptor is connected or fed back to a specific neural oscillator, the same output signal is input to both the flexor and extensor neurons. This linkage is reciprocal. If one of the connections is inhibitory, then the other connection is excitatory.

An example of the neural system based upon our assumptions is shown in Figure 4. As shown in the figure, our model has 12 neural oscillators (24 neurons) corresponding to 12 joints in our human body model.

The most difficult problem in constructing the neural system based upon the above model is formulation of a *feedback network*, which is the way signals from a feedback unit are input to a neuron (i.e., f_i in the equation (1)). Although neurons within a single neural oscillator are known to be connected reciprocally to each other, only little is known in the neurophysiological studies about which receptors and neurons in different neural oscillators are connected and how they are connected. Hence, in developing an artificial neural oscillator system for bipedal locomotion, the feedback networks have been developed by researchers and engineers in a trial and error manner to generate a rhythmic movement that closely matches a human walking pattern.

3 Evolving Neural System

Although the rigid properties of the body and the anatomical properties of the muscle are provided by analyzing body mechanism, it seems to be extremely difficult to predict or to predetermine the relevancy of feedback network in the nervous system. As there exists no theory about how such a nervous system can be constructed, we used the evolutionary approach as a method of choice for building the nervous

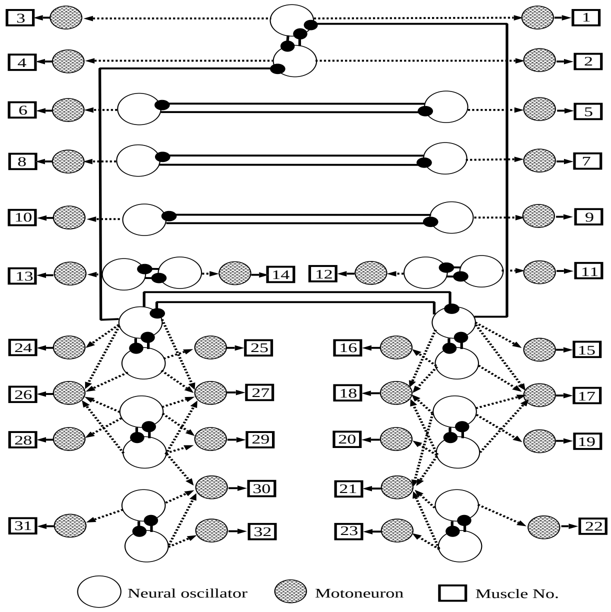

Figure 4: Example of Neural System

system to control the body dynamics system.

Construction of the nervous system is modeled as a search process for structure and parameters of the neural system. Effectiveness of the constructed nervous system is evaluated based upon the predefined criteria on the walking patterns obtained in the simulation resulting from interactions among the nervous system, body and environment. In this research, we assumed that parameters and structures within a single neural oscillator are known and fixed, and we focused on creation of the feedback networks between the neural system and the body dynamics system.

In our model of the nervous system, a *global feedback network* in the neural system is composed of 24 feedback networks. This is based on the assumption that each joint (i.e., each neural oscillator) has 2 feedback networks connected to the flexor and extensor neurons. And a feedback network at the joint has a reciprocal value of the other. The global feedback network can work consistently only when neural oscillators interact with each other cooperatively through their feedback networks. In this paper, we apply GP with heterogeneous populations to evolve the global feedback network of the nervous system by modeling each feedback network as an independent population of GP individuals.

3.1 Generating Feedback Networks with GP

GP is an evolutionary search algorithm which searches for a computer program capable of producing the desired solution for a given problem. In a GP population, the individuals are hierarchical computer programs of various sizes and shapes. And in this paper, individuals are s-expressions giving a desired feedback network. A run of GP begins with the initial creation of individuals for the population. Then, on each generation of the run, the fitness of each individual in the population is evaluated, then individuals are selected (probabilistically based on their fitness) to participate in the genetic operations (e.g., reproduction, crossover, mutation). These three steps (fitness evaluation, selection, and genetic operations) are iteratively performed over many generations until the termination criterion for the run is satisfied. Typically, the best single individual obtained during the run is designated as the result of the run.

Since we need to develop 12 feedback networks of neural oscillators (i.e., a half of 24 feedback networks due to the reciprocal nature of feedback networks) to construct the nervous system for human-like bipedal gait generation, our implemented GP system has 12 distinct sub-populations, each of which corresponds to breeding space for each feedback network. Figure 5 depicts the schematic overview showing how a global feedback network is evolved through our GP system.

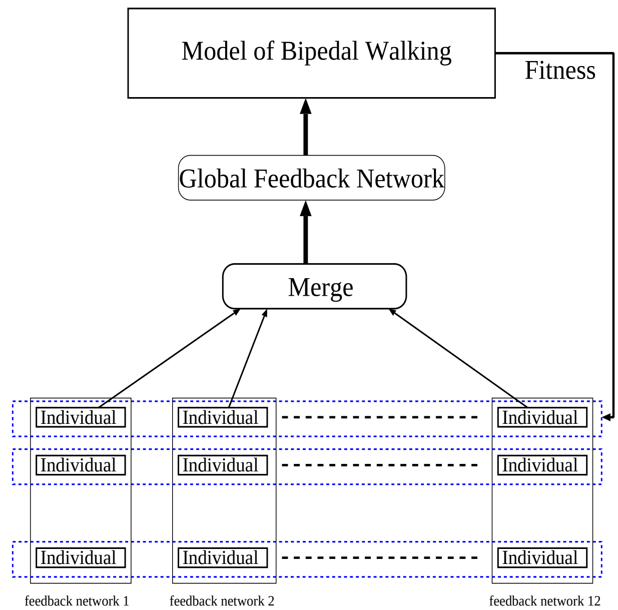

Figure 5: Evolving Feedback Networks

Although each feedback network can be bred independently within each sub-population of the GP system, fitness of a feedback network cannot be evaluated separately from the other feedback networks because the fitness should be determined based upon the quality of movements that are generated by the interactions among neural oscillators through the global feedback network in the nervous system. Hence, fitness of a single feedback network must be deduced from fitness of the global feedback network. This is a widely known difficult problem in multi-agent problem solving called *credit assignment*, which is to determine the contribution of each agent when making a solution in cooperation with other agents. Although there have been many research activities in GP that tackled to the problem [3], there is no generic methodology for rational credit assignment. To avoid this problem, we organize groups, each of which represents a global feedback network and consists of individuals from all sub-populations. The steps in the GP process (i.e., selection, evaluation and genetic operation) are executed on the population of groups. Thus, when a group is selected based upon its fitness value, the all individuals in the selected group are bred and the same genetic operator is applied to all the members in the group. This is the simplest way of breeding *heterogeneous populations* with GP, but in the experiments of generating neural oscillators for bipedal locomotion it produced some promising results.

4 Experiments

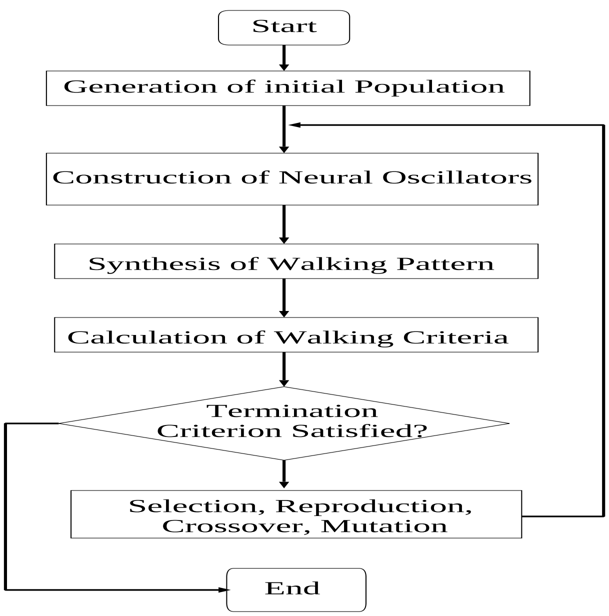

Figure 6: Flow of Implemented System

Based on the models of the neuronal system and the musculo-skeletal system described in the previous sections, we implemented a system for three dimensional simulation of human-like bipedal locomotion. The overview of the system is presented in Figure 6. For constructing neural oscillators used in the system, GP was used to find appropriate formulation of a feedback network for each neuron, which can cooperatively synthesize human-like bipedal walking movements.

4.1 Details of Implemented System

We utilized and modified the lil-gp system [12] as the platform for our GP implementation. Parameters used in the GP system are shown in Table 2.

Fitness of a GP individual is decided by simulating movements of human-like 3D model with the evolved neural oscillators. A walking pattern of the simulation was evaluated with a criterion which combines the distance it could walk before falling down and the number of steps it made while walking. By changing the weight coefficients in the fitness

Table 2: GP Parameters

Fitness	$F = 10 \times WalkingDistance + 100 \times Steps$
Misc.	Number of Multiple Populations = 12 Each population size = 1000 Generations = 1000 Depth of tree = 15 Selection = greedy over-selection
Crossover Probability	80%
Reproduction Probability	10%
Mutation Probability	10%
Termination Criterion	After completing 8 walking steps

function, we could evolve varieties of walking patterns from stepping to jumping.

The terminal and function sets used to formulate feedback networks in our experiments are summarized in Table 3.

Table 3: Terminals and Functions

Terminals	n_i	output of neurons (24)
	$a^{\{r,l\}}_{\{x,y,z\}}$	absolute angles at each side (6)
	$\dot{a}^{\{r,l\}}_{\{x,y,z\}}$	absolute angular velocities at each side (6)
	$r_i^{\{x,y,z\}}$	relative angle at each joint (36)
	$\dot{r}_i^{\{x,y,z\}}$	relative angular velocities at each joint (36)
	$s^{\{r,l\}}$	contact sensory at each side (2)
	$g_{\{x,y,z\}}$	position of center of gravity (3)
	$\dot{g}_{\{x,y,z\}}$	velocity of center of gravity (3)
	c	ephemeral random constant
Functions	$+, -, \times,$ $H(x) = \begin{cases} 1 & (\text{when } x \geq 0) \\ 0 & (\text{otherwise}) \end{cases},$ $K(x) = \begin{cases} x & (\text{when } x \geq 0) \\ 0 & (\text{otherwise}) \end{cases}$	

As shown in Table 3, the number of terminals sums up to 121. This is by far a very large terminal set in today's standard of GP applications. But, since the neurophysiological study have not clarified the details of the neuronal system that enables bipedal walking in the human body, we could not select the relevant set of terminals exclusively for our purpose but had to use many terminals as plausible members of our terminal set. Of course, the huge terminal set ruins efficiency of the GP search process, but as a first trial in this research, we expected that given high performance computing environment the GP process could eventually find useful terminals

Table 4: Specifications of Cluster Machine

CPU's	533MHz or 433MHz Celeron
Number of PE	64
Memory	128MB/PE
NIC	Fast Ethernet
Switching Hub	100 Base
OS	Redhat Linux 6.2
Library	LAM/MPI

from the redundant terminal set and develop appropriate neural oscillators for walking movements. Hence, we configured a cluster machine (Figure 7) for computing fitness of each GP individual in parallel. Since calculating fitness requires a full simulation of bipedal walking, distribution of the task to many processing elements improved the efficiency of experiments in a nearly linear fashion. Hardware and software specifications of the cluster machine we built are outlined in Table 4.

Figure 7: Cluster Machine

As a second approach to handle a huge terminal set, we advocated *adaptive terminal selection* and showed its effectiveness for the symbolic regression problems [9]. The adaptive terminal selection method was able to eliminate irrelevant terminals from a redundant terminal set by means of the in-process terminal weighting mechanism. We plan to apply this method to the problem of bipedal walking.

4.2 Experimental Results

The results of GP evolution were evaluated by simulating a walking pattern with the evolved neural oscillators. In the simulation, the equations (1 - 3) were numerically solved with the Euler method. The integration interval for solving the equations was 0.5 ms. The parameters in the equations such as the time constants τ_i were determined a priori so that they could oscillate at a rate of about 1 second per cycle.

As a preliminary study before full scale experiments of evolving every neural oscillator of 12 joints, we tried evolution of 1 neural oscillator. We chose to evolve a neural oscillator of a waist joint because the waist is considered to have an important role in human's bipedal walking. Configurations of the other neural oscillators were derived from the past research results [2], and the equations of the hand-tuned feedback networks are as follows:

$$
\begin{aligned}
f_0 &= 134.5054\,(r_5^y - r_2^y) + 10.8311\,(\dot{r}_5^y - \dot{r}_2^y)\\
&\quad -(n_2 + n_9 - n_3 - n_8)\\
f_2 &= 2.3615\,r_7^y - 1.3880\,r_{11}^y + 0.7623\,r_8^y\,s^r\\
&\quad -1.0420\,s^r - 29.8467\,r_2^y\,s^r\\
&\quad -11.1777\,\dot{r}_2^y\,s^r - (n_8 - n_9)\\
f_4 &= -1.8263\,r_7^y\,s^l + 1.0680\,r_{12}^y\,s^l\\
&\quad +3.3566\,(s^r - s^r\,s^l\,H(a_x^l - a_x^r))\\
&\quad -(n_2 + n_3)\\
f_6 &= -3.8349\,r_7^y\,s^r + 039.0429\,r_8^y\,s^r\\
&\quad +4.3012\,(\dot{r}_9^y - \dot{r}_8^y)\,s^r - 5.0983\,s^r\\
&\quad +5.0983\,(1.0 - s^r)/2.0 - (n_2 + n_3)\\
f_8 &= 2.3615\,r_{11}^y - 1.3880\,r_7^y + 0.7623\,r_{12}^y\,s^l\\
&\quad -1.0420\,s^l - 29.8467\,r_2^y\,s^l\\
&\quad -11.1777\,\dot{r}_2^y\,s^l - (n_2 - n_3)\\
f_{10} &= -1.8263\,r_{11}^y\,s^r + 1.0680\,r_8^y\,s^r\\
&\quad +3.3566\,(s^l - s^r\,s^l\,H(a_x^r - a_x^l))\\
&\quad -(n_8 + n_9)\\
f_{12} &= -3.8349\,r_{11}^y\,s^l - 39.0429\,r_{12}^y\,s^l\\
&\quad +4.3012\,(\dot{r}_{13}^y - \dot{r}_{12}^y)\,s^l - 5.0983\,s^l\\
&\quad +5.0983\,(1.0 - s^l)/2.0 - (n_8 + n_9)\\
f_{14} &= 0.5\,r_{14}^y - 0.5\,r_{16}^y + r_7^y + r_8^y - r_{11}^y - r_{12}^y\\
&\quad -(n_2 + n_9 - n_3 - n_8)\\
f_{16} &= -901.2270\,(g_y - a_y^r - 0.8711/20.0)\\
&\quad (1.0 - s^r)\,K(-r_7^y - r_8^y)\\
&\quad -232.2408\,r_1^z\,s^r - 27.3127\,\dot{r}_1^z\,s^r\\
&\quad +89.7301\,\dot{a}_y^r\,(1.0 - s^r)\,K(-r_7^y - r_8^y)\\
&\quad -541.7639\,\dot{g}_y\,(1.0 - s^r)\,K(-r_7^y - r_8^y)\\
f_{18} &= -901.2270\,(a_y^l - g_y - 0.8711/20.0)\\
&\quad (1.0 - s^l)\,K(-r_{11}^y - r_{12}^y)\\
&\quad +232.2408\,r_1^z\,s^l + 27.3127\,\dot{r}_1^z\,s^l\\
&\quad -89.7301\,\dot{a}_y^l\,(1.0 - s^l)\,K(-r_{11}^y - r_{12}^y)\\
&\quad +541.7639\,\dot{g}_y\,(1.0 - s^l)\,K(-r_{11}^y - r_{12}^y)\\
f_{20} &= -100.0\,r_3^z - 10.0\,\dot{r}_3^z - 10.0\,r_5^x - \dot{r}_5^x\\
f_{22} &= -10.0\,r_4^z - \dot{r}_4^z - 20.0\,r_0^z + 10.0\,r_7^y\\
&\quad +10.0\,r_8^y - 10.0\,r_{11}^y - 10.0\,r_{12}^y
\end{aligned}
$$

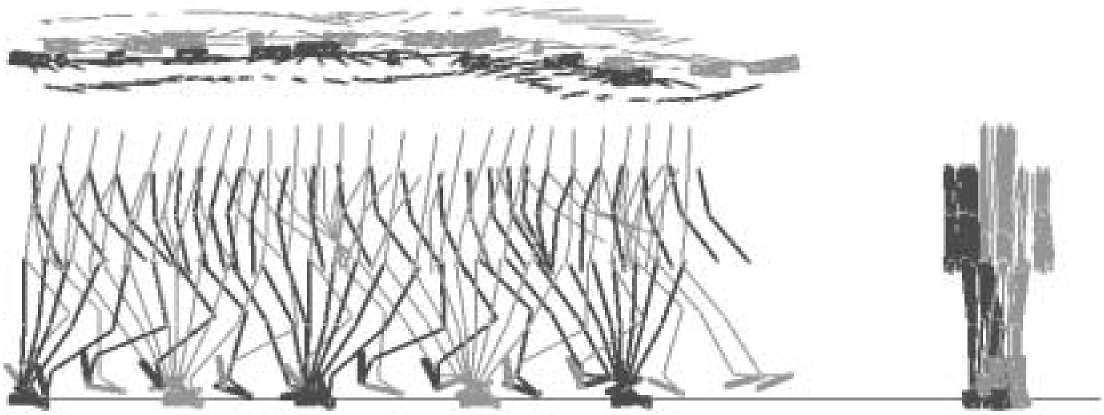

Figure 8: Example of Emerged Walking Pattern (only a single neural oscillator of the waist joint was evolved using GP)

In the experiment, we could generate a human-like walking pattern which was compatible with the result of hand-tuned neural oscillators as shown in Figure 8. Although the resultant walking pattern was similar to that of the hand-tuned neural oscillators, when we analyzed a formula of the waist neural oscillator evolved with GP, we found it was quite different from the original formula (f_0 in the above equations) described in [2], as shown in the following equation of the feedback network:

$$
\begin{aligned}
f_0 \quad = \quad & ((\dot{g}_x + \dot{r}_5^y + H(H(n_{21}))((\dot{r}_{11}^y - r_{12}^x) - \dot{r}_{12}^x r_{12}^x) \\
& (\dot{r}_8^x + r_{11}^y) + r_{14}^x - r_9^z - H(H(n_{14}) - H(H(n_{14}))) \\
& (\dot{g}_x + \dot{r}_5^y)) + ((\dot{r}_8^x + r_{11}^y + H(H(n_{21}))((\dot{r}_2^z + r_7^x \\
& -H(n_{14}))(\dot{r}_2^z + r_7^x)(\dot{r}_2^z + r_7^x)) + r_{14}^x - r_9^z - \\
& H(r_{12}^x))(\dot{r}_{11}^y - r_{12}^x - \dot{r}_{12}^x r_{12}^x)((\dot{r}_8^x + r_{11}^y)(\dot{r}_2^z + r_7^x)) \\
& \dot{r}_{12}^x r_{12}^x)) + (\dot{g}_x + \dot{r}_5^y + H(H(n_{21}))((\dot{r}_{11}^y - r_{12}^x - \\
& \dot{r}_{12}^x r_{12}^x) r_{12}^x) + (r_{14}^x - r_9^z - H(H(n_{14})) - \\
& H(H(n_{14})))(\dot{g}_x + \dot{r}_5^y))(\dot{r}_8^x + r_{11}^y + H(H(n_{14})) \\
& ((\dot{r}_{11}^y - r_{12}^x - (\dot{r}_{11}^y - r_{12}^x - \dot{r}_{12}^x r_{12}^x))((\dot{r}_8^x + r_{11}^y) \\
& (r_{16}^y - 15.32862))) + H(x)H(x)r_{12}^x) - H(n_{14})
\end{aligned}
$$

Hence, we predicted that there might be a large possibility that GP could evolve the better neural oscillators for bipedal locomotion than those ever developed by human researchers.

In full scale experiments, we evolved the entire neural oscillators with GP. In the experiments, so far we could only succeed to generate 4 steps of walking as shown in Fig. 9. An example of the evolved feedback networks are as follows:

$$
\begin{aligned}
f_0 &= (s^r + r_5^x)K(a_y^r) - H(\dot{r}_2^x \dot{r}_{15}^z) \\
f_2 &= ((r_2^x + r_{12}^x)n_{17} - H(n_{12}))H(K(r_5^x)) \\
f_4 &= a_x^r a_y^l n_{11} \dot{r}_{15}^z - H(r_2^y)(r_8^x + n_{16}) \\
f_6 &= r_{14}^z n_{10} + K(n_8) \\
f_8 &= (\dot{r}_{15}^y - r_7^z)K(H(K(\dot{r}_{14}^z) + H(\dot{r}_{16}^z))) \\
& \quad -(\dot{r}_2^z + H(\dot{r}_8^z)) - (K(18.65870) + \dot{a}_y^r) \\
f_{10} &= K((r_2^x - n_0) + H(\dot{r}_8^y)) \\
f_{12} &= n_9 + \dot{r}_{11}^y + K(r_{12}^x + n_8) - H(a_x^l) - (n_4 - \dot{r}_{15}^y) \\
f_{14} &= H(n_{16} - \dot{r}_{13}^y) + H(\dot{r}_{11}^z s^l) + K(n_0) + \dot{r}_{14}^z a_x^l \\
f_{16} &= \dot{r}_8^z r_{17}^z - (r_{12}^z a_y^l + \dot{r}_9^z r_9^z) - n_0 r_{12}^z(\dot{g}_x + n_2) \\
f_{18} &= g_x + n_6 - n_{16} \\
f_{20} &= H(r_{11}^x) + K(\dot{r}_8^z) + (\dot{r}_{12}^z + \dot{g}_y)H(r_2^z) \\
f_{22} &= K(H(n_{11}))\dot{g}_x
\end{aligned}
$$

The resultant feedback networks are simple enough to be further evolved for generating improved locomotion. Nevertheless, we need to make the evolution process more efficient for the improvement. We think the following ideas are effective for producing more stable feedback networks:

- More sophisticated fitness function
  The current fitness function evaluates only walking distance and steps, thus it tends to give a high score to irregular walking movements such big jumping and rapid vibration. By considering more biomechanical insights on human walking such as walking frequency and step width, the fitness function can direct GP search process to evolve the desirable bipedal locomotion more efficiently.

- Symmetric neural oscillators
  Since a human body has a left-right symmetric geometry and walking is left-right alternate movements of the legs, we may safely assume that neural oscillators for bipedal locomotion also have left-right symmetric structures. If this might be the case, we can reduce the number of neural oscillators from 12 to 8 and anticipate a more stable walking pattern comes out of them more efficiently.

5 Conclusion

In this paper, GP was applied to make a computer simulation of bipedal locomotion. Using GP for constructing the ner-

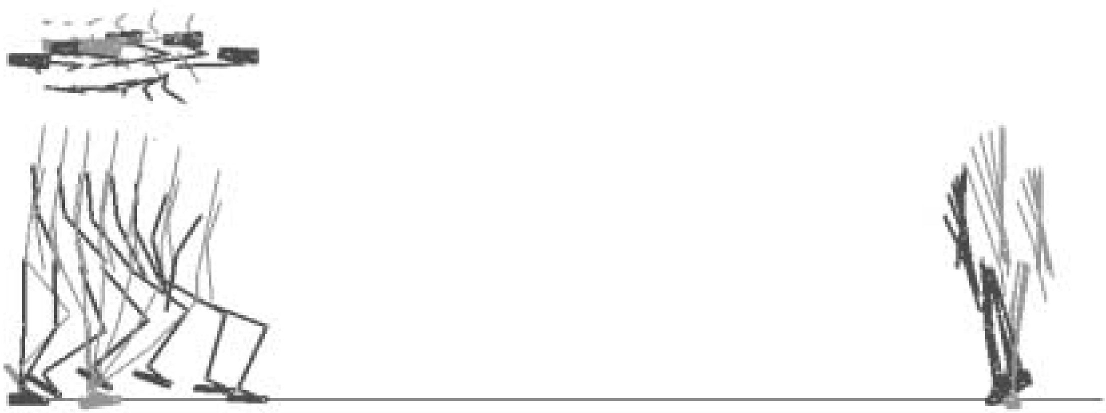

Figure 9: Example of Emerged Walking Pattern (all neural oscillators of 12 joints were evolved using GP)

vous system model for bipedal walking, we could automate a tedious task of searching for appropriate parameter values and network structures of neural oscillators that cooperatively work as CPG interacting with body dynamics for making a human bipedal gait. Comparing with the past research activities which built the neuronal models in a hand-crafted manner, our approach requires much less burdens from human experts, thus enabling to produce a wide variety of walking patterns for different body configurations efficiently. Hence, our approach makes it affordable to utilize a flexible human model for generating locomotion patterns in several practical applications such as rehabilitation planning and computer animation. In the future work, we apply the adaptive terminal selection method to reduce the GP search space by selecting the relevant nervous attributes for bipedal locomotion, and improve efficiency of the GP process for constructing a model of the neuronal system.

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