Interconnection Structure Optimization for Neural Oscillator Based Biped Robot Locomotion

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***Abstract*—One of the problems in neural oscillator based humanoid locomotion is the interconnection structure and its weights. They influence the locomotion performance. This paper proposes an evolutionary algorithm for determining the interconnection structure in humanoid robot locomotion based on neural oscillator. The aim of this paper is to form the interconnection structure of motor neurons in order to produce the locomotion pattern in humanoid biped robot. The evolutionary system forms the connection and determines the synapse weight values of the 12 motor neurons distributed to 6 joint angles (two hip-x joints, two hip-y joints, two knee joints). One chromosome has 53 genes, where 50 genes represent the weight values between motor neurons and 3 genes represent the gain parameters in hip-y, hip-x, and knee joint. Center of gravity and speed walking analysis are required for fitness evaluation. In order to prove the effectiveness of the system model, we realized it in a computer simulation. The experimental result shows the comparison result with our previous model. The stabilization level and speed resulted by using this system are increased.**

I. Introduction

The technology of humanoid robot has increased and been implemented in many fields of life. In humanoid robot locomotion there are more difficulties than in other types of locomotion. Many problems can be found in bipedal locomotion development, such as instability, walking controller, and so on. In trajectory based locomotion, many researchers have solved those problems by using mathematical approach, zero moment point (ZMP), center of gravity (CoG), inverted pendulum etc. The developer of Darpa Robotics Challenge–Hubo (DRC–Hubo) robot has solved a ladder-climbing locomotion [1] and also walking on rough terrain [2] by using trajectory based locomotion. Zhu et al used ZMP and inverted pendulum model for dynamic walking [3]. In our previous research we dealt with trajectory based locomotion that used inverted pendulum and zero moment point approaches [4] [5] and applied evolutionary algorithm for its energy efficiency [6].

Most of the problems in trajectory based locomotion have been solved by some researchers. There are many methods for realizing the locomotion in humanoid robot. In this paper, we propose a biological approach based bipedal robot locomotion. We use neural oscillator for generating the joint locomotion. In biological approach, some researchers implemented neural oscillator that is a type of neural network for generating the rhythmic signal. Started from Taga et al who implemented neural oscillator for generating the joint signal pattern in humanoid [7] then followed by some researchers to implement this approach. Taga et al used fix interconnection structure of the neural oscillator [7]. Ishiguro et al implemented neural oscillator in their humanoid robot locomotion. They used feedback signal to control the walking pattern [8]. The problem in neural oscillator based locomotion is the walking controller. The walking pattern is controlled by the interconnection structure and its weight. Some researchers used evolutionary algorithm for optimizing the weight values. In 2010, Park et al designed a joint trajectory generator proposed for robot locomotion by using an evolutionary optimized central pattern generator (CPG). Sensory feedback is applied for supporting the walking model [9]. Baydin also implemented neural oscillator to generate the locomotion in bipedal robot locomotion. Evolutionary algorithm is used for determining the weight values in the neural oscillator structure. However, Baydin did not consider the stability and interconnection structure in the fitness evaluation [10]. In 2014, Hong et al also used evolutionary algorithm to optimize the central pattern generation based bipedal robot locomotion [11], [12]. Other researchers used the evolutionary algorithm for gait learning in 4-legged robot [13].

In our previous research we optimized the weight synapses between motor neurons without interconnection changing. Before optimizing, we built the suitable structure based on Matsuoka's interconnection structure analysis [14]. We developed the dynamic locomotion in four-legged animal robot based on neural oscillator. We investigated the coupled muscle in four-legged animal to get the mutual inhibitory and excitatory network in the neuron's structure. To optimize the synapse weight we used a multi-objective evolutionary algorithm and used fix interconnection structure of the neural oscillator [15] [16].

The contribution in this research is, that we develop the locomotion system based on biological approach. We design the learning system for finding the best interconnection structure of motor neurons and their synapse value and optimize

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its stabilization. This system is capable to form the interconnection structure between motor neurons. This proposed method optimizes 6 joints implemented in 12 degrees of freedom (DoF) of the humanoid robot. In order to prove the effectiveness of the proposed locomotion, we realized it in a computer simulation. The advantage of this proposed method is the interconnection between the neurons, that can be formed and optimized in order to realize the locomotion pattern of the humanoid robot.

This paper is organized as follows. Section II explains the design of locomotion generator. Section III discusses the interconnection optimization. Section IV presents the stability support system. Section V shows experimental results and Section VI concludes the paper.

II. Locomotion Model

The proposed paper is implemented in biped robot that has 6 DoF in each leg as illustrated in Fig. 1. The robot in this proposed method is equipped with inertial sensor. This robot is designed in the Open Dynamic Engine (ODE) [17].

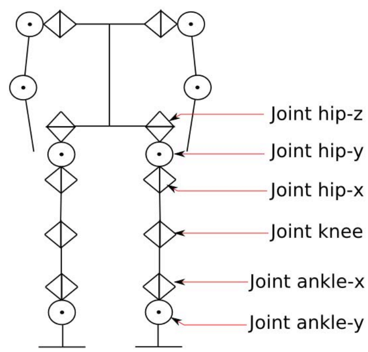


Fig. 1. Mechanical structure of the robot

We used neural oscillator as the signal generator in joint angle level. Neural oscillator is generated by mutual inhibition between n neurons. The neural network model depicted in Fig. 2 was also implemented in our previous research for locomotion generation of a 4-legged robot [15]. The general mathematical model of the neural oscillator based on [14] is presented in Eqs. (1), (2), and (3). In our model as depicted in Fig. 2, we constructed the nonlinear oscillator equipped with external feedback S_i.

$$\tau_l \dot{x}_i = x_i - \sum_{j=1}^{n} w_{ij} y_j + S_i - b v_i \tag{1}$$

$$\tau_r \dot{v}_i + v_i = y_i \tag{2}$$

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

$$\theta_n = (y_{2n} - y_{2n+1}) \mu_n \tag{4}$$

where x_i, y_i, and v_i are the inner state, the output, and a variable representing self-inhibition effect of the ith neuron;

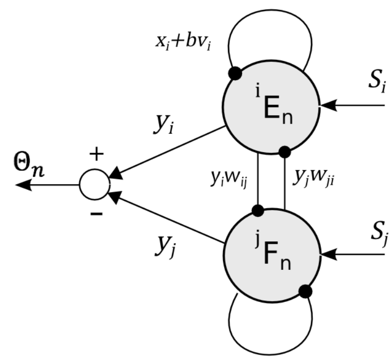


Fig. 2. Coupled neuron

b is a coefficient of self-inhibition effect; μ is a constant parameter representing the gain value in each joint angle; τ_l and τ_r are time constants of the inner state and the adaptation effect, respectively.

In Eq. (1), w_{ij} represents the strength of the inhibitory connection between the neurons, $\sum_{j=1}^{n} w_{ij} y_j$ represents the total signal input from the neurons inside the interconnection structure, and S_i is a constant value representing the input from outside the neuron structure.

Equation (4) explains 2 neurons (flexor and extensor) representing the union of the joint system. The joint angle in the neuron locomotion system has 6 DoF, 2 legs, and each leg has 3 joints: knee joint, hip-x joint which is rotational about the x axis, and hip-y joint which is rotational about the y axis. The joint limitations are implemented as: $-\pi/2 < \theta_1^i < \pi/2$, $-\pi/2 < \theta_2^i < 0$, $-\pi/4 < \theta_3^i < \pi/4$. The interconnection structure of the neural oscillator has 12 neurons illustrated in Fig. 3 representing 6 joints. This interconnection structure is optimized by using evolutionary algorithm.

In our previous research, in order to form the interconnection structure, we investigated the muscular structure, and the relationship between the neurons is separated as server neurons and client neurons [15].

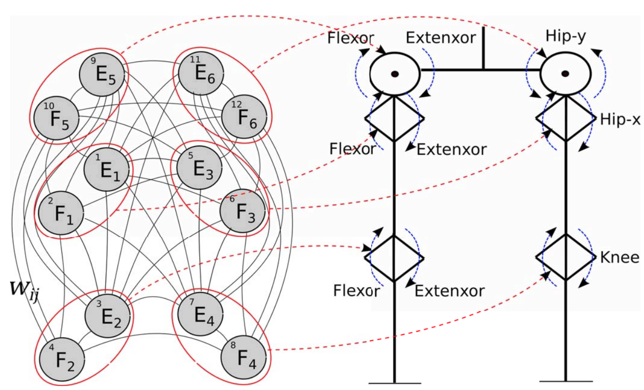


Fig. 3. Diagram of the neuron structure

Since the neural locomotion handles only 3 joint angles in each leg (hip-y, hip-x, and knee), the other joints are represented by parameter θ_1 for ankle-x joint and θ_2 for ankle-y joint computed in Eq. (5) and Eq. (6). We set the θ_6 as 0.

$$\theta_4 = \theta_2 - \theta_1 \tag{5}$$

$$\theta_5 = -\theta_3 \tag{6}$$

III. Interconnection Optimization

In this section, the strategy for interconnection structure optimization is explained. In our approach, we represent the multi-objective problem by weight factors for calculating the fitness function. We expect to form the walking pattern with stable speed, good stabilization, and length of step appropriate to the desired length of step. In order to optimize these problems, we apply steady state genetic algorithm (SSGA) [18].

A. Individual structure

One chromosome has 53 genes (x_{1-53}) converted to walking pattern (G_{1-53}), where 50 genes ($G_1, G_2, G_3, \ldots, G_{50}$) represent the weight value and the neuron structure, and 3 genes (G_{51}, G_{52}, G_{53}) represent the gain value of angle joint in hip-x, hip-z, and knee joint. The genes have minimum value x_{min} and maximum value x_{max}, which can be different for the genes that represent the synapse weight and for the genes that represent the gain value. The minimum and maximum values are decided depending on preliminary test. The interconnection weights map from source neuron to destination neuron as shown in Table I. For example, weight G_{41} represents the weight connection from neuron 1 to neuron 12 ($W_{12,1}$) and from neuron 5 to neuron 10 ($W_{10,5}$).

$$G_j = \begin{cases} x_j & \text{if } 1 < j < 50 \ \& \ x_j > 0 \\ x_j & \text{if } 51 < j < 53 \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

The conversion from the genes of the individual to the locomotion parameter is shown in Eq. (7). If the gene's number is between 1 and 50, then that gene represents the weight value of the neuron connection. If the gene's value is lower than 0, then the weight value is 0 implying that there is no connection between those neurons. If the gene's number is between 51–53, then that gene represents the gain of joint angle in each joint.

B. Fitness Calculation

The fitness function is defined by the minimization of the error of walking speed ($E^{(v)}$), the error of desired step length ($E^{(l)}$), the height of step (h), the Center of Mass (CoM) error in x-axis ($E_x^{(CoM)}$) and z-axis ($E_z^{(CoM)}$). The weight factors ($w_i^{(f)}$) represent the value of effect of each component in the evaluation.

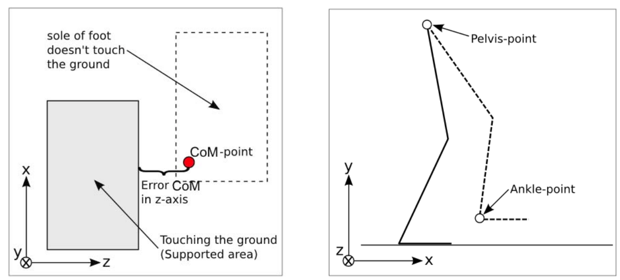
$$E^{(v)} = \sum_{j=1}^{T} \| d_v - v(t) \| \tag{8}$$

$$E^{(l)} = \| d_l - l \| \tag{9}$$

TABLE I

Interconnection Maps Represented by Genes

Source neuron (j) \ Destination neuron (i)	1	2	3	4	5	6	7	8	9	10	11	12
1	0	G_1	G_2	G_3	G_4	G_5	G_6	G_7	G_{29}	G_{37}	G_{33}	G_{41}
2	G_8	0	G_9	G_{10}	G_{11}	G_{12}	G_{13}	G_{14}	G_{30}	G_{38}	G_{34}	G_{42}
3	G_{15}	G_{16}	0	G_{17}	G_{18}	G_{19}	G_{20}	G_{21}	G_{31}	G_{39}	G_{35}	G_{43}
4	G_{22}	G_{23}	G_{24}	0	G_{25}	G_{26}	G_{27}	G_{28}	G_{32}	G_{40}	G_{36}	G_{44}
5	G_4	G_5	G_6	G_7	0	G_1	G_2	G_3	G_{33}	G_{41}	G_{29}	G_{37}
6	G_{11}	G_{12}	G_{13}	G_{14}	G_8	0	G_9	G_{10}	G_{34}	G_{42}	G_{30}	G_{38}
7	G_{18}	G_{19}	G_{20}	G_{21}	G_{15}	G_{16}	0	G_{17}	G_{35}	G_{43}	G_{31}	G_{39}
8	G_{25}	G_{26}	G_{27}	G_{28}	G_{22}	G_{23}	G_{24}	0	G_{36}	G_{44}	G_{32}	G_{40}
9	0	0	0	0	0	0	0	0	0	G_{48}	G_{46}	G_{49}
10	0	0	0	0	0	0	0	0	G_{45}	0	G_{47}	G_{50}
11	0	0	0	0	0	0	0	0	G_{46}	G_{49}	0	G_{48}
12	0	0	0	0	0	0	0	0	G_{47}	G_{50}	G_{45}	0



(a) (b)

Fig. 4. a) Center of Mass representation for calculating one component of the fitness value b) 2-D pose walking robot

$$h = \begin{cases} y(t) & \text{if } h < y(t) \ \& \ x_p(t) < x_a(t) \\ h & \text{otherwise} \end{cases} \tag{10}$$

$$E_z^{(CoM)} = \sum_{t=1}^{T} \| CoM_z(t) \| \tag{11}$$

$$E_x^{(CoM)} = \sum_{t=1}^{T} \| CoM_x(t) \| \tag{12}$$

$$f = w_1^{(f)} E^{(v)} + w_2^{(f)} E^{(l)} - w_3^{(f)} h + w_4^{(f)} E_z^{(CoM)} + w_5^{(f)} E_x^{(CoM)} \tag{13}$$

In Eq. (8), d_v and $v(t)$ are the desired speed and the current speed. In Eq. (9), d_l and l are the desired length of step and the current length of step. In Eq. (10), $y(t)$ is the current height of step illustrated in Fig. 4b, $x_p(t)$ is the current pelvis position in x-axis, and $x_a(t)$ is the current ankle position in x-axis. In Eqs. (11) and (12), $CoM_z(t)$ and $CoM_x(t)$ are the length of CoM from supported area in z-axis and x-axis, respectively. The CoM point in this model is illustrated in Fig. 4a. T is the maximum time and t is the current time cycle.

C. Crossover and Mutation

In SSGA, the crossover and mutation process take the best individual and the worst individual in each generation. We use elitist crossover and adaptive mutation in order to replace the worst individual's genes. The genes of the worst individual is replaced by the genes of the best individual and the random individual. The calculation to acquire the jth gene of the worst individual can be seen in Eq. (14). When the uniform random number r_j is lower than r then the worst individual's gene will be replaced by the gene of the random individual. Otherwise, when r_j is higher than r then the worst individual's gene will be replaced by the gene of the best individual.

$$x_{worst,j} = \begin{cases} x_{rand,j} + \alpha \cdot N(0,1) \cdot \left(\frac{N_{gen}-t}{N_{gen}}\right) & \text{if } r_j < r \\ x_{best,j} + \beta \cdot N(0,1) \cdot \left(\frac{N_{gen}-t}{N_{gen}}\right) & \text{otherwise} \end{cases} \quad (14)$$

In Eq. (14), $x_{worst,j}$, $x_{best,j}$, and $x_{rand,j}$ are the jth gene of the worst, the best, and the random individual, respectively; N_{gen} is the number of generations, t is the current generation; r_j is a uniform random number between 0 and 1, r is a uniform random number between 0 and 0.5; $N(0,1)$ is a normal random number with 0 mean and 1 variance. The constant parameters α and β are parameters of the mutation operation.

IV. Stability Support System

We propose a stability system which improves the stability level of the neural oscillator based locomotion. The stability system uses the robot's hand as response actuator to minimize the oscillation of the robot's tilt angle. We use neural network with back propagation algorithm as depicted in Fig. 5.

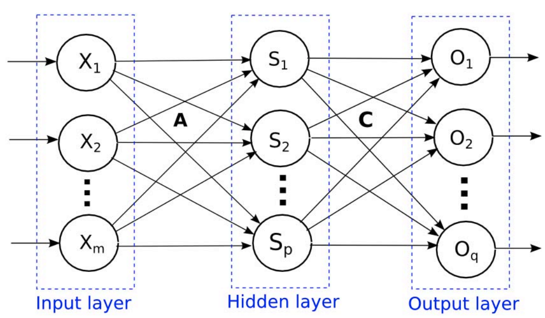


Fig. 5. Neural network back propagation model

In Eqs. (15) and (16), $X_i(t)$ is the input value of the tilt sensor from the ith input neuron; $S'_y(t)$ and S_y are the input and output value of the yth hidden neuron; and $O_k(t)$ is the output value representing the value of joint angle of hands. The output data $O_k(t)$ is converted from $-\pi/2$ to $\pi/2$. The number of neurons in the input layer, hidden layer, and output layer are denoted by m, p, and q, respectively.

In Equations (17) and (18), δ_k and δ_j are the error propagation in output neuron and hidden neuron, where d_k is the desired output, and the output function $g_k(x)$ is the output of the tilt sensor ($g_0(O_0)$ for pitch and $g_1(O_1)$ for roll direction). We normalize the data from 0 to 1, therefore we set d_k as 0.5.

$$S_y(t) = f(S'_y(t)) = f\left(\sum_i^m x_i(t)A_{ij} + b_j\right) \quad (15)$$

$$O_k(t) = g(O'_k(t)) = g\left(\sum_j^p s_j(t)C_{jk} + b_k\right) \quad (16)$$

$$\delta_k = (d_k - g_k(O_k))f'(O'_k) \quad (17)$$

$$\delta_j = \sum_k^q \delta_k C_{jk} f'(S'_j) \quad (18)$$

$$\mathbf{C}(t+1) = \mathbf{C}(t) + \eta \mathbf{s}(t)\delta_k^T \quad (19)$$

$$\mathbf{A}(t+1) = \mathbf{A}(t) + \eta \mathbf{s}(t-1)\delta_j^T \quad (20)$$

In Eq. (15), the activation function in the hidden layer $f(x)$ is a sigmoid function. The weight parameters of neurons, **A** and **C** are computed by Eqs. (19) and (20), where η is the learning rate of the weight.

V. Experimental Result

This section presents the experimental result of the proposed locomotion model. These experiments are conducted in 2-D simulation for optimizing the interconnection structure, and 3-D simulation for analyzing the stability of the optimized interconnection structure. In 3-D simulation, we used ODE for constructing the robot simulation based on real robot properties. The neural oscillator parameters used for the experiments are depicted in Table II.

TABLE II
Parameter Values of Neural Oscillator

Parameter	Time cycle	τ	τ'	τ_f	b	η
Value	0.01 second	12.0	1.2	1.0	2.5	0.01

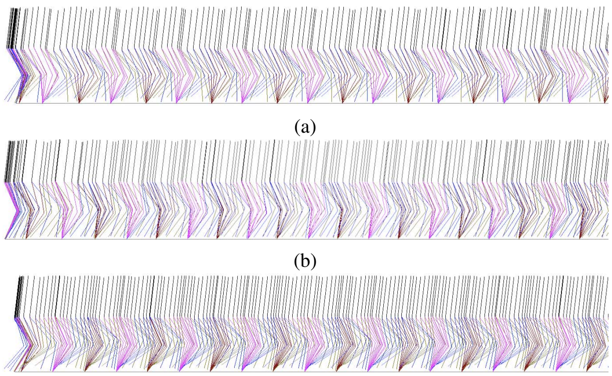
A. Interconnection optimization

In this experiment, we optimize the interconnection structure of neural oscillator for acquiring stable speed, good stabilization, and length of step appropriate to the desired length of step. We used 2-D robot simulation to optimize the structure. The parameter setting of SSGA is shown in Table III, where N_{ind} is the number of individuals.

In this experiment, we take the result in 10000-th, 20000-th, and 30000-th generation. The locomotion pattern resulted by the evolutionary algorithm process can be seen in Fig. 6 and its neural interconnection structures can be seen in Fig. 7. The pelvis speed of locomotion pattern resulted in 10000-th and 20000-th generation are still not stable, but in 30000-th generation, the pelvis speed is stable enough. The fitness evolution depicted in Fig. 8 is decreasing implying that the interconnection structure results in better locomotion pattern.

TABLE III
SSGA PARAMETERS

Parameter	Value
N_{ind}	5000
N_{gen}	20000
α	0.01
β	0.01
$x_{min,(1-50)}$; $x_{min,(51-53)}$	-3.5; 0.8
$x_{max,(1-50)}$; $x_{max,(51-53)}$	3.5; 3.0
$w_1^{(f)} - w_5^{(f)}$	{0.2, 0.3, 0.2, 0.2, 0.1}



(a) (b) (c)

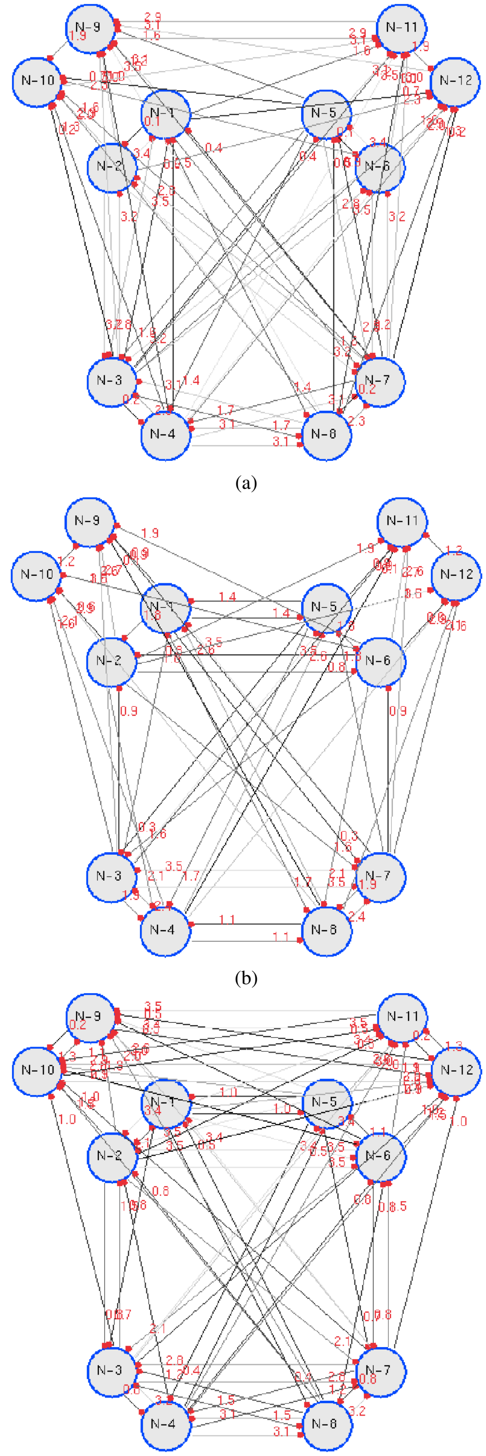
Fig. 6. Locomotion pattern resulted by the evolutionary process in generation a) 10000 b) 20000 c) 30000

B. Simulation experiment

After the evolutionary process has completed at 30000-th generation, we take the best solution of weight parameters shown in Table IV and the gain parameters $\mu_0 = 1.069$, $\mu_1 = 1.389$, and $\mu_2 = 2.830$. These parameters are used for the robot simulation in Open Dynamic Engine. However, the evolutionary process considers the locomotion pattern without stability analysis. We improve the stability level of the locomotion by using neural network with back propagation for

TABLE IV
WEIGHT SYNAPSE SOLUTIONS RESULTED BY THE EVOLUTIONARY PROCESS

		Destination neuron (i)											
		1	2	3	4	5	6	7	8	9	10	11	12
Source neuron (j)	1	*0*	0.00	0.00	0.00	2.09	0.00	3.07	0.87	0.00	1.23	1.02	1.09
	2	0.00	*0*	3.45	0.00	1.96	0.00	3.50	2.21	0.92	2.92	0.00	0.00
	3	1.65	0.00	*0*	1.58	0.67	0.43	1.50	0.23	2.92	1.97	0.38	2.77
	4	0.00	0.00	0.00	*0*	1.39	0.00	0.00	0.51	3.32	0.00	2.02	3.50
	5	2.09	0.00	3.07	0.87	*0*	0.00	0.00	0.00	1.02	1.09	0.00	1.23
	6	1.96	0.00	3.50	2.21	0.00	*0*	3.45	0.00	0.00	0.00	0.92	2.92
	7	0.67	0.43	1.50	0.23	1.65	0.00	*0*	1.58	0.38	2.77	2.92	1.97
	8	1.39	0.00	0.00	0.51	0.00	0.00	0.00	*0*	2.02	3.50	3.32	0.00
	9	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	0.80	2.89	1.97
	10	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	0.00	*0*	2.81	0.00
	11	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	2.89	1.97	*0*	0.80
	12	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	2.81	0.00	0.00	*0*



(a) (b) (c)

Fig. 7. Interconnection structures of neural oscillator in generation a) 10000 b) 20000 c) 30000

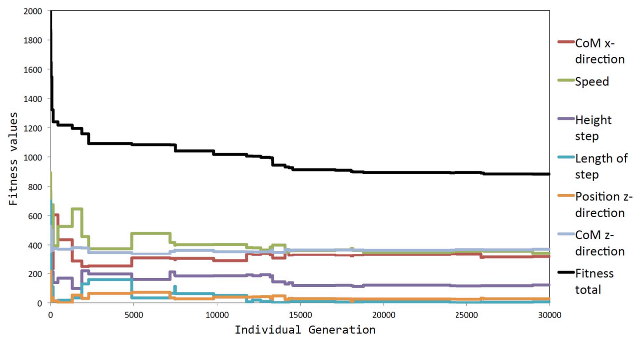


Fig. 8. Fitness evolution

learning system. This system uses hand-x and hand-y joints as the response actuator depending on the robot's tilt condition. The experimental process in simulation is shown in Fig. 9.

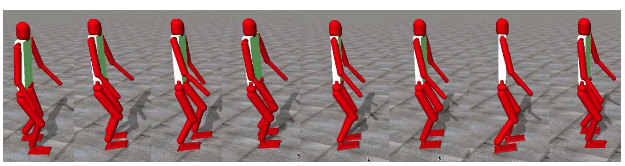
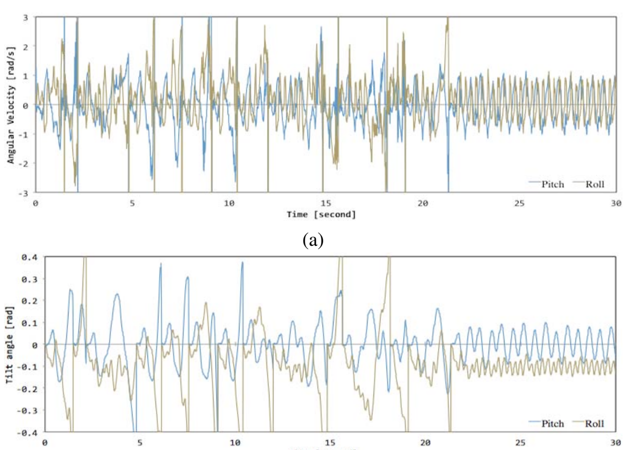


Fig. 9. Robot walking in ODE simulation

The signal oscillation representing the learning process can be seen in Fig. 10. Figures 10a and 10b represent the signal from angular velocity sensor and tilt angle sensor, respectively. The robot can walk stably after learning the environmental condition in 21 seconds. Before that, the robot fell down several times.

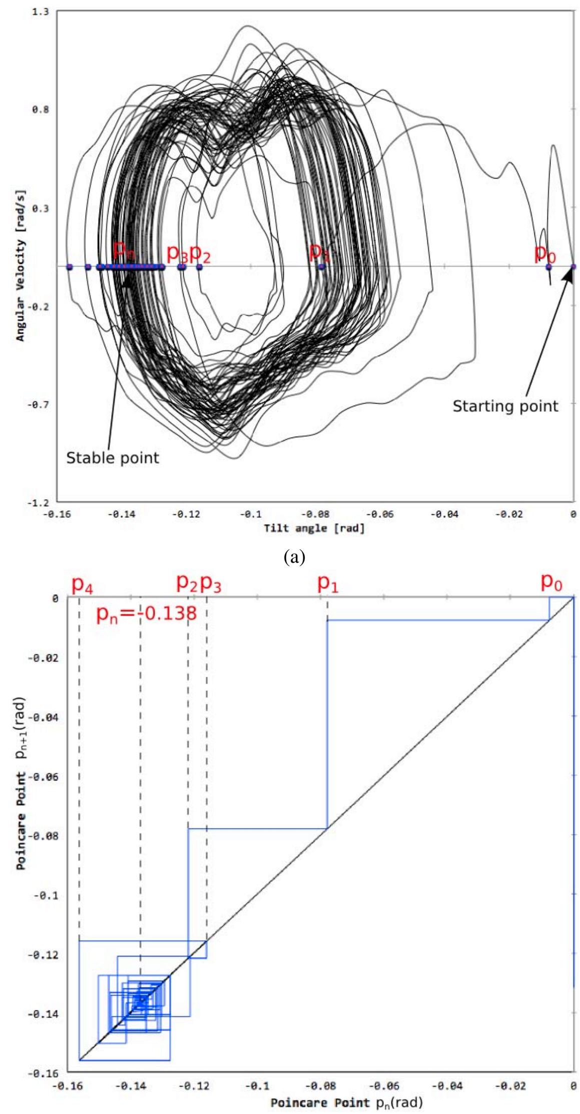
In order to analyze the stability, we transferred the tilt angle data resulted by the robot simulation experiment into Poincare diagram and Cobweb diagram depicted in Figs. 11a and 11b.



(a)

(b)

Fig. 10. Signal oscillation representing the stability learning process. a) Angular velocity signal in pitch and roll direction b) Tilt angle of robot body in pitch and roll condition



(a)

(b)

Fig. 11. a) Phase diagram of robot's tilt angle and stability analysis based on Poincare map b) Cobweb diagram representation of Poincare map for analyzing the stability

The initial condition of robot's tilt when the robot stands up was 0 rad, when the robot was walking, the robot's tilt changed to stable tilt angle (0.138 rad).

VI. Conclusion

This paper proposed the optimization model to form the interconnection structure of neural oscillator by using evolutionary algorithm. Walking speed, CoM estimation, height of step, and length of step as the fitness minimization successfully form the interconnection structure of neural oscillator, therefore it resulted in well locomotion pattern. However, the locomotion resulted by this optimization method has low stability level, therefore the robot in this implemented simulation fell down. This proposed method considers only the walking pattern. In order to improve the stability level, we implemented hand response learning system. By using neural network with back propagation algorithm for stability learning system, the robot in the simulation can walk stably after learning the environmental condition in 21 seconds. The effectiveness of this method has been analyzed by Poincare and Cobweb analysis diagram.

In the future research, we aim to classify the important connections and non-important connections in the neural oscillator structure. Therefore, we expect that we can control the walking speed or walking direction by adjusting the weight values of the important connections.

Acknowledgment

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