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An Evolutionary Central Pattern Generator for Stable Bipedal Walking by the Increased Double Support Time

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***Abstract*— Central pattern generator (CPG) consisting of neural oscillators, generates rhythmic signals using simple input signal. It can modify motor patterns to handle environmental perturbations by sensory feedback. In this paper, an evolutionary CPG for stable bipedal walking by the increased double support time is proposed. The proposed CPG generates swing motion of arms as well as ankle and the center of pelvis (COP) motions in Cartesian coordinate system. Sensory feedback pathways in the proposed CPG use force sensing resistor (FSR) signals. The sensory feedback maintains humanoid robot's balance and prevents it from falling down to the ground. To optimize the parameters of the proposed CPG, evolutionary algorithm is employed. The effectiveness of the scheme is demonstrated by simulations with the Webot model of a small-sized humanoid robot, HSR-IX, developed in the RIT Lab., KAIST.**

I. Introduction

In spite of the complexity of high dimensional systems, many methods for walking pattern generation for stable walking of bipedal robots have been developed [1]-[4]. There are two typical approaches to generate robust walking patterns of humanoid robots: dynamic model based approach and biologically inspired approach. In dynamic model based approach, one of popular schemes is to use 3-D linear inverted pendulum model (3-D LIPM) [5], [6]. In biologically inspired approach, central pattern generator (CPG) is the most widely used method to generate the walking pattern for bipedal robots. It can endogenously produce multidimensional rhythmic signals without rhythmic sensory or central input. Also, it can alter motor patterns to deal with environmental perturbations using sensory feedback. Taga successfully developed to generate robust biped locomotion using CPG with appropriate feedback signals even in an unknown environment [7], [8]. Then, many researches of biped locomotion based on CPG have been studied. Nakamura *et al*. presented a learning scheme for a CPG controller called a CPG-actor-critic model, whose learning algorithm is based on a policy gradient method [9]. Righetti *et al.* developed a new architecture for building programmable CPG which can encode arbitrary periodic trajectories as limit cycles in a network of coupled oscillators [10]. Endo *et al.* introduce a learning framework for a CPG-based biped locomotion controller, which controls tip positions of legs in the Cartesian coordinate system, instead of trajectory of each joint, using a policy gradient method [11]. Heliot *et al.* developed a method for providing in real time a reliable synchronization signal for cyclical motions such as steady-state walking [12]. This approach estimates a phase variable on the basis of several implicit central pattern generators associated with a set of sensors.

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This paper proposes an evolutionary CPG for stable bipedal walking by the increased double support time. Biped locomotion consists of single and double support phases. In human's walking, the percentage of the double support time is greater than 20% for stable bipedal locomotion [13], [14]. However, in previous researches on CPG-based bipedal locomotion control, the double support phase was not considered and the percentage of the double support time was less than 5%. For stable bipedal locomotion, in this paper, the CPG, which generates swing motion of arms as well as ankle and center of pelvis (COP) motions in Cartesian coordinate system, is employed [15]. It modifies vertical and sagittal ankle motions and COP motions by the increased interval of the double support phase. The body posture for sensory feedback is obtained using the signals of force sensing resistor (FSR) sensors attached to the sole of foot. To optimize the parameters of the CPG, quantum-inspired evolutionary algorithm (QEA) is employed [16], [17]. The effectiveness of the proposed scheme is demonstrated by computer simulations with the Webot model of a small-sized humanoid robot, HSR-IX, developed in the RIT Lab., KAIST.

This paper is organized as follows: In Section II, the neural oscillator and QEA are introduced to generate rhythmic signals and to optimize the parameters of CPG, respectively. Section III proposes an evolutionary CPG. In Section IV, simulation results are presented and finally concluding remarks follow in Section V.

II. Preliminaries

A. Neural Oscillator

Neural oscillator [18], [19] is widely used as a CPG in robotic application. It is defined as follows:

$$\tau \dot{u}_i = -u_i - \sum_{j=1}^{N} w_{ij} y_j - \beta v_i + u_0 + feed_i \quad (1)$$

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

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

where u_i, v_i and y_i are the inner state, the self-inhibition state and the output signal of the ith neuron, respectively. u_0 is the input signal that affects the output amplitude and w_{ij} is the connecting weight which determines the phase

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difference between the ith and the jth neurons. τ and τ' are time constants. They have influence on the shape and frequency of output signal. β is the weight of self-inhibition. $feed_i$ is the sensory feedback signal which is necessary for stable biped locomotion.

B. QEA

QEA is based on the concept and principles of quantum computing, such as the quantum bit and the superposition of states [20]. QEA handles the balance between exploration and exploitation easier than conventional genetic algorithms, such as EA and GA. QEA also needs a small number of individuals to explore the search space and quickly finds global solution in the search space.

In QEA, Q-bit is the smallest unit of information. It is defined as the pair of numbers (α, β). They satisfies $(|\alpha|^2 + |\beta|^2 = 1)$. Note that $|\alpha|^2$ and $|\beta|^2$ are probabilities that Q-bit will be 0 and 1 states, respectively. When the number of Q-bits in Q-bit individual is m, the following Q-bit individual is defined as a string of Q-bits:

$$q_j^t = \left[\begin{array}{c|c|c|c} \alpha_{j1}^t & \alpha_{j2}^t & \cdots & \alpha_{jm}^t \\ \beta_{j1}^t & \beta_{j2}^t & \cdots & \beta_{jm}^t \end{array}\right].$$

At generation t, QEA maintains the population of Q-bit individuals, $Q(t) = q_1^t, q_2^t, \ldots, q_n^t$, where n is the size of population. During the evolutionary process, more diverse individuals are generated because the Q-bit individual represents linear superposition of all possible states probabilistically. The detailed procedure of QEA and its structure for single objective optimization problems are described in [16], [17].

III. CPG Scheme

This section presents the proposed CPG, which consists of neural oscillators, for biped locomotion. The CPG is developed to generate swing motion of arms as well as ankle and COP motions for stable walking by the increased double support time. The body posture for sensory feedback is obtained using signals of FSR sensors attached to the sole of each foot.

A. Application to Bipedal Locomotion of the CPG

In the previous researches on biped locomotion control based on CPG, the CPG generates each joint's torque or trajectory [7]-[10], [12]. However, by these methods, it is difficult to know the phase difference between each neurons. Then it is difficult to set the parameters of the neural oscillator in CPG. Also, it is difficult to set initial states in CPG. Because it is difficult to know appropriate initial state of each joint's torque or angle when humanoid robot starts to walk. To overcome these problems, this paper designs the CPG, which generates swing motion of arms as well as ankle and center of pelvis (COP) motions in Cartesian coordinate system. The proposed method is simple to set up connecting weights in neural oscillator because it is easy to get the phase difference between neural oscillators and the initial states of inner states in neural oscillator and to modify the step length or foot height.

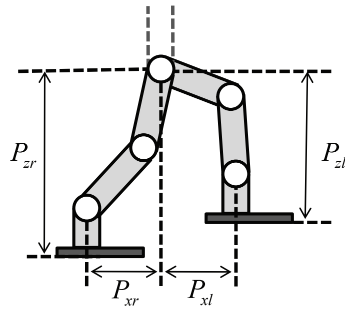


Fig. 1. The sagittal and vertical motions of both feet.

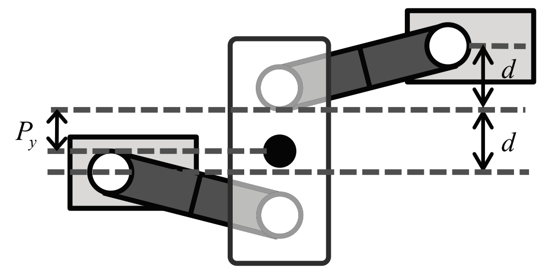


Fig. 2. The lateral motion of COP.

The CPG generates the sagittal, vertical and lateral ankle, and COP motions as follows [15]:

$$P_{zl} = Z_c - A_z(y_1 - y_2) \tag{4}$$
$$P_{zr} = Z_c + A_z(y_1 - y_2) \tag{5}$$
$$P_{xl} = -A_x(y_3 - y_4) \tag{6}$$
$$P_{xr} = A_x(y_3 - y_4) \tag{7}$$
$$P_y = A_y(y_5 - y_6) \tag{8}$$

where $P_{zl/r}$ and $P_{xl/r}$ are the vertical and the sagittal distances from COP to left and right ankles, respectively (Fig. 1). P_y is the lateral distance between COP and the center position of both ankles (Fig. 2). A_z, A_x and A_y are the amplitude scaling factors. Z_c is the offset factor.

The projected ankle's motion on X-Z plane can be approximated as a semi-ellipsoid. Thus, the desired phase difference between ankle's vertical and sagittal position trajectories should be $\pi/2$. Also, for humanoid robot's stability along the lateral direction, the lateral distance between COP and the support leg should be minimized in single support phase and the COP should be given as the center position of both ankles along the lateral direction at the double support phase. To satisfy these conditions, the phase difference between P_y and P_z, which is the vertical distance from COP to swing leg's ankle, should be zero.

When humanoid robot increases walking speed, it may slip because of yawing moment. To make up for the yawing moment, arm swing motion should be provided. The following

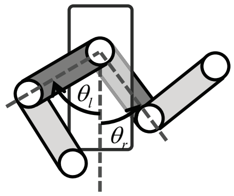


Fig. 3. The swing motion of both arms.

CPG generates the swing motion of left and right arms:

$$\theta_l = A_\theta(y_7 - y_8) \quad (9)$$
$$\theta_r = -A_\theta(y_7 - y_8) \quad (10)$$

where $\theta_{l/r}$ is the pitching angle of left/right shoulder, respectively (Fig. 3). Similarly, A_θ is the amplitude scaling factor.

The yawing moment can be approximated as follows:

$$|T| = |m_l D_l \ddot{x}_{sl} + J_b\ddot{\theta}_b + m_b D_b \ddot{x}_b + m_a D_{a_1}\ddot{x}_{a_1} - m_a D_{a_2}\ddot{x}_{a_2}| \quad (11)$$

where m_l, m_b and m_a are the mass of each leg, body and each arm, respectively. $\ddot{x}_{sl}, \ddot{x}_b$ and $\ddot{x}_{a_{1/2}}$ are the accelerations of swing leg, body, and left/right arm, respectively, along sagittal direction, respectively. $\ddot{\theta}_b$ is the yawing angle acceleration of body and D_l, D_b and $D_{a_{1/2}}$ are the distance between swing leg, body, and left/right arm, respectively, and supporting leg along lateral direction (Fig. 4). In (11), $|x_{sl}|$ and $|x_b|$ are defined as $|2A_X(y_3 - y_4)|$ and $|A_X(y_3 - y_4)|$, respectively from (6), (7). Then, $\ddot{x}_b = 0.5\ddot{x}_{sl}$, and $\ddot{x}_{a_2} = -\ddot{x}_{a_1}$, as $\theta_l = -\theta_r$. Accordingly, (11) can be approximated as

$$|T| = |\ddot{x}_l(m_l D_l + 0.5 m_b D_b) + J_b\ddot{\theta}_b + m_a\ddot{x}_{a_1}(D_{a_1} + D_{a_2})|. \quad (12)$$

For decreasing yawing moment, in (12), the phase difference of $\ddot{x}_{a_1}$ and $\ddot{x}_{sl}$ is π. x_{a_1} is proportional to $-sin\theta$, then $\ddot{x}_{A_1}$ is proportional to $sin\theta$. If $-\pi/2 < \theta < \pi/2$, when θ increases, $sin\theta$ increases, and also, when θ decreases, $sin\theta$ increases. Thus, the phase difference between the position trajectory of swing leg's ankle along the sagittal direction and the pitching angle of shoulder becomes π.

B. Increase of the Double Support Time

Biped locomotion consists of the double support phase and single support phase. The double support phase is very important for stable biped locomotion [13], [14]. In the double support phase, the cumulative error in single support phase is decreased and the COP moves near the next supported leg. Therefore, stability of bipedal locomotion is improved. However, in previous studies of biped locomotion based on CPG, the double support phase was not considered and the double support time was very short. Thus, it is hard to generate stable biped locomotion. If CPG generates sagittal and vertical ankles motions and COP motion using (4) and (5), the double support time is the moment of $y_1 - y_2 = 0$.

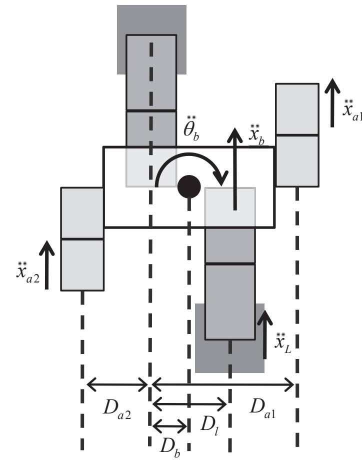


Fig. 4. The yawing moment.

Therefore, in this paper, to increase appropriate the double support time, (4) and (5) are rewritten as follows:

$$P_{zl} = \begin{cases} Zc - A'_z(y_1 - y_2 - u_z), & \text{if } y_1 - y_2 > u_z \\ Zc + A'_z(y_1 - y_2 - u_z), & \text{if } 0 \le y_1 - y_2 \le u_z \\ Zc - A'_z(y_1 - y_2 + u_z), & \text{if } y_1 - y_2 < 0 \end{cases} \quad (13)$$

$$P_{zr} = \begin{cases} Zc + A'_z(y_1 - y_2 + u_z), & \text{if } y_1 - y_2 < -u_z \\ Zc - A'_z(y_1 - y_2 + u_z), & \text{if } -u_z \le y_1 - y_2 \le 0 \\ Zc + A'_z(y_1 - y_2 - u_z, & \text{if } y_1 - y_2 > 0 \end{cases} \quad (14)$$

with

$$A'_z = A_z \frac{A_{1,2}}{A_{1,2} - u_z}$$

where u_z is a parameter for the double support phase, $A_{i,j}$ is amplitude of $y_i - y_j$ and A'_z is modified scaling factor of equal step height using (4) and (5). When $|y_1 - y_2| < u_z$, the state of biped locomotion is the double support phase. Thus, the double support time is determined as u_z.

When the state of biped locomotion is the double support phase, it is hard to satisfy (6) and (7). Thus, biped locomotion along the sagittal direction is rewritten as follows:

$$P_{xl} = \begin{cases} (A_x - 2A'_x)(y_3 - y_4), & \text{if } y_1 - y_2 > u_z \\ A_x(y_3 - y_4) - 2A'_x P'_x, & \text{if } 0 \le y_1 - y_2 \le u_z \\ -A_x(y_3 - y_4), & \text{if } y_1 - y_2 < 0 \end{cases} \quad (15)$$

$$P_{xr} = \begin{cases} (-A_x + 2A'_x)(y_3 - y_4), & \text{if } y_1 - y_2 < -u_z \\ -A_x(y_3 - y_4) + 2A'_x P'_x, & \text{if } -u_z \le y_1 - y_2 \le 0 \\ A_x(y_3 - y_4), & \text{if } y_1 - y_2 > 0 \end{cases} \quad (16)$$

where P'_x is defined as $|y_3 - y_4|$ at the beginning of the double support phase, A'_x, which is defined as $A_x|y_3 - y_4|/P'_x$ at $y_1 - y_2 = 0$, is the scaling factor for equal step length using (6) and (7). It is periodically updated when $y_1 - y_2 = 0$.

C. Sensory Feedback Design

Sensory feedback pathways are designed to maintain humanoid robot's balance and to prevent it from falling down to the ground. In this paper, sensory feedback gets the information of humanoid robot's body posture using FSR sensors which are attached to the sole of each foot. The sensory feedback pathways are defined as follows:

$$feed_1 = \begin{cases} k_1 S_v + k_2 S_l, & \text{if } y_1 - y_2 > 0 \\ -k_1 S_v + k_2 S_l, & \text{if } y_1 - y_2 < 0 \end{cases} \quad (17)$$

$$feed_2 = -feed_1 \quad (18)$$

$$feed_3 = k_3 S_s \quad (19)$$

$$feed_4 = -feed_3 \quad (20)$$

$$feed_5 = \begin{cases} k_4 S_v + k_5 S_l, & \text{if } y_1 - y_2 > 0 \\ -k_4 S_v + k_5 S_l, & \text{if } y_1 - y_2 < 0 \end{cases} \quad (21)$$

$$feed_6 = -feed_5. \quad (22)$$

with

$$\begin{aligned} S_v &= F_L + F_R - mg \\ S_l &= F_{Ll} - F_{Lr} + F_{Rl} - F_{Rr} \\ S_s &= (F_{L_f} - F_{L_b}) - (F_{R_f} - F_{R_b}) \end{aligned}$$

where S_v, S_l and S_s are the sensory informations about body postures along the vertical, lateral and sagittal directions, respectively. $F_{L/R}$ is the left/right foot's vertical reaction force and m is the mass of the humanoid robot. $F_{Lf/b}$ and $F_{Rf/b}$ are the left and right foot's front/back vertical reaction forces, respectively. $F_{Ll/r}$ and $F_{Rl/r}$ are the left and right foot's left and right vertical reaction forces, respectively. Since $feed_1$ and $feed_2$ modulate the vertical positions of both ankles and body, S_v, which is related to the vertical body posture, is considered. $feed_3$ and $feed_4$ modulate the sagittal positions of both ankles and body, so S_s, which is related to the sagittal body posture, is considered. $feed_5$ and $feed_6$ modulate the lateral position of COP, so S_l, which is related to the lateral body posture, is considered. Also, $(y_1 - y_2)$ and $(y_5 - y_6)$ are in phase, so $(feed_1 - feed_2)$ and $(feed_5 - feed_6)$ are satisfied to be in phase. Therefore, S_l should be considered in calculating $feed_1$ and $feed_2$. Similarly, S_v should be also considered in calculating $feed_5$ and $feed_6$.

D. Evolutionary Optimization for the CPG algorithm

In the proposed CPG, connecting weights and feedback scaling factors should be optimized for stable biped locomotion. In this paper, these parameters are optimized by QEA [16], [17]. This optimization is performed through two separated QEA processes.

In the first process, connecting weights are obtained by QEA to satisfy the phase difference conditions derived in the above. The phase differences between y_{2n-1} and y_{2n} (n = 1,. . . ,4) is π, then the phases of y_{2n-1} and $y_{2n-1} - y_{2n}$ are equal. The phase difference between $(y_1 - y_2)$ and $(y_5 - y_6)$, and $(y_3 - y_4)$ and $(y_7 - y_8)$ are equal to zero. Also, the phase difference between $(y_1 - y_2)$ and $(y_3 - y_4)$ is $\pi/2$, then the phase difference between y_1 and y_3 is $\pi/2$, y_1 and y_4 is $3\pi/2$, y_2 and y_3 is $3\pi/2$, and y_2 and y_4 is $\pi/2$. The connecting weights determine the phase difference between the ith and the jth neurons, then if each phase difference is equal, each connecting weight is also equal. The connecting weights are determined as shown in Table I. The key objectives in optimizing w_1 and w_2 are to make the phase difference between $(y_1 - y_2)$ and $(y_3 - y_4)$ as $\pi/2$ and the amplitudes of $(y_1 - y_2)$ and $(y_3 - y_4)$ are equal to 1. Considering these objectives, the objective function is defined as follows:

TABLE I
CONNECTING WEIGHTS

$w_{1,2}$	2.0	$w_{2,1}$	2.0	$w_{3,4}$	2.0	$w_{4,3}$	2.0
$w_{5,6}$	2.0	$w_{6,5}$	2.0	$w_{7,8}$	2.0	$w_{8,7}$	2.0
$w_{1,6}$	0.5	$w_{6,1}$	0.5	$w_{2,5}$	0.5	$w_{5,2}$	0.5
$w_{3,8}$	0.5	$w_{8,3}$	0.5	$w_{4,7}$	0.5	$w_{7,4}$	0.5
$w_{1,3}$	w_1	$w_{1,4}$	w_2	$w_{2,3}$	w_2	$w_{2,4}$	w_1
$w_{3,1}$	w_2	$w_{3,2}$	w_1	$w_{4,1}$	w_1	$w_{4,2}$	w_2
$w_{5,7}$	w_1	$w_{5,8}$	w_2	$w_{6,7}$	w_2	$w_{6,8}$	w_1
$w_{7,5}$	w_2	$w_{7,6}$	w_1	$w_{8,5}$	w_1	$w_{8,6}$	w_2

$$f_1 = k_p |\Delta T_m - T_p/4| + k_a(|A_{1,2} - 1| + |A_{3,4} - 1|) \quad (23)$$

with

$$\Delta T_m = t_{m(3,4)} - t_{m(1,2)}$$

where k_p and k_a are the scaling factors, $t_{m(1,2)}$ and $t_{m(3,4)}$ are the times when $(y_1 - y_2)$ and $(y_3 - y_4)$ have maximum values and T_p is the period of $(y_1 - y_2)$. $A_{1,2}$ and $A_{3,4}$ are the amplitudes of $(y_1 - y_2)$ and $(y_3 - y_4)$, respectively.

In the second process, to maintain humanoid robot's balance, feedback scaling factors are obtained by QEA and the objective function is defined as follows:

$$f_2 = k_p f_p + k_r f_r + P \quad (24)$$

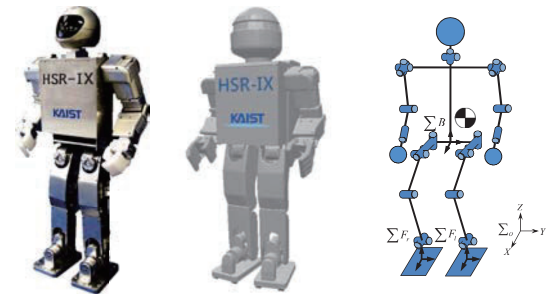
with

$$\begin{aligned} f_p &= \sum_{T=0}^{T_1} |\theta_p| \\ f_r &= \sum_{T=0}^{T_1} |\theta_r| \end{aligned}$$

where k_p and k_r are the scaling factors. $f_{p/r}$ is the sum of pitching/rolling angle of COP for T_1. When humanoid robot rocks while walking, $|\theta_p|$ and $|\theta_r|$ increase and bipedal locomotion is unstable. P is the penalty which is given if humanoid robot loses its balance and collapses.

IV. Simulations

The proposed CPG was implemented on the computer simulations with the Webot model of a small sized humanoid robot, HSR-IX (Fig. 5) [21]. HSR-IX is the latest one of HSR-series. HSR is a small-sized humanoid robot that has been in continual redesign and development in RIT Lab, KAIST. Its height and weight are 52.8cm and 5.5kg, respectively. It has 26 DOFs that consists of 14 RC servo motors in the upper body and 12 DC motors with harmonic drive for reduction gears in the lower body. Webot is the 3-D robotics simulation software. Users can conduct the physical and dynamical simulation using Webot [22]. $\tau/\tau' = 1/2$ and $\tau = A_\tau$ were used. The parameters in the CPG were optimized by QEA.



(a) (b) (c)

Fig. 5. (a) HSR-IX. (b) Simulation model. (c) Configuration.

TABLE II

INITIAL STATE OF INNER STATE

u_1	0.3055	u_2	0.3055	u_3	-0.3788	u_4	0.8783
u_5	0.3055	u_6	0.3055	u_7	-0.3788	u_8	0.8783
v_1	0.1242	v_2	0.5591	v_3	0.2319	v_4	0.5280
v_5	0.1242	v_6	0.5591	v_7	0.2319	v_8	0.5280

A. Evolutionary Optimized Connecting Weight in the CPG

In the simulations, Z_c was set as 23.95cm. The initial states of $u_1, \ldots, u_8$ and $v_1, \ldots, v_8$ were set as shown in Table II to make the initial state of $P_{Z_l} = P_{Z_r}$ to Z_c. k_p and k_r were taken as 5.0 and 1.0. w_1 and w_2 in Table I were obtained as 4.718 and -3.907, respectively, by QEA.

B. Walking Simulation Results

Fig.6 shows the COP vertical, sagittal, and lateral trajectories generated by the proposed CPG with increase of the double support time. The thick and thin lines represent the COP trajectories in the single and the double support phases, respectively.

Fig. 7 shows pitching and rolling angles of the COP while walking with increase of the double support time. $A_x = 1.5$, $A_y = 3.0$, $A_z = 1.0$ and $A_\tau = 1.0$ were used. As shown in the figure, humanoid robot was more stable when $u_z = 0.4$. When $u_z = 0.4$, the double support time increases and COP is able to move toward the next support leg in the double support phase. Therefore, COP is closer to the support leg than $u_z = 0.0$ in single support phase and it improves stability of bipedal locomotion.

The sensory feedback pathways in the CPG maintain humanoid robot's balance and prevent it from falling down to the ground. In this paper, the sensory feedback pathways were designed by FSR signals. Fig. 8 shows the effect of including sensory feedback pathways. $A_X = 3.0$, $A_y = 3.0$, $A_Z = 1.0$, $A_\tau = 1.7$ and $u_z = 0.6$ were used. The parameters in sensory feedback pathways were evolutionary optimized by QEA. In this simulation, the amplitudes of humanoid robot's COP rolling and pitching angles while walking with sensory feedback were smaller than without sensory feedback. This result illustrates that sensory feedback based on FSR sensor maintains humanoid robot's balance and prevents it from falling down to the ground.

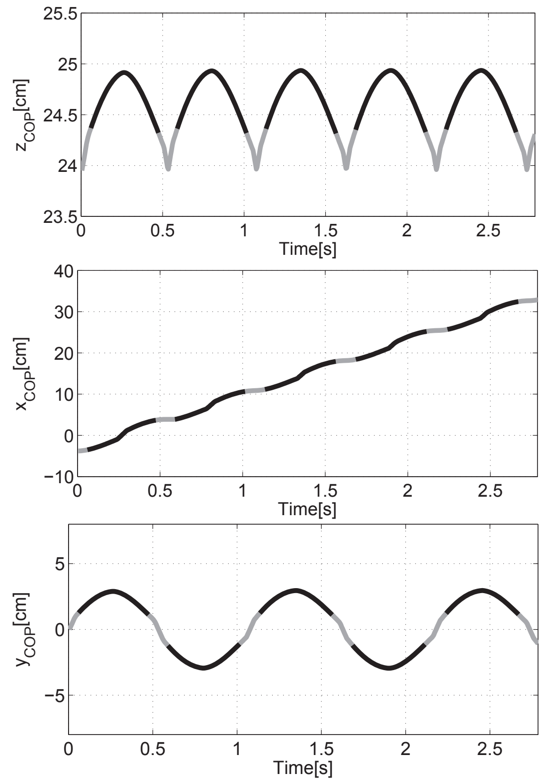


Fig. 6. The COP trajectories generated by the proposed CPG with increase of the double support time. The thick and thin lines represent the COP trajectories in the single and the double support phases, respectively.

V. CONCLUSION

This paper proposed an evolutionary CPG for stable bipedal walking by the increased double support time. The proposed CPG generates swing motion of arms as well as ankle and center of pelvis (COP) motions in Cartesian coordinate system. The sensory feedback pathways in the CPG were designed by using FSR signals. The parameters in the CPG were optimized by using QEA. It optimized connecting weights to satisfy appropriate phase differences between each neurons and feedback scaling factors to maintain humanoid robot's balance. To demonstrate the performance of the proposed scheme, computer simulations were carried out with the Webot model of the small-sized humanoid robot, HSR-IX, developed in the RIT Lab., KAIST.

VI. ACKNOWLEDGMENTS

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REFERENCES

[1] Y. Sakagami, R. Watanabe, C. Aoyama, S. Matsunaga, N. Higaki, and K. Fujimura, "The intelligent ASIMO: system overview and integration," in *Proc. IEEE/RSJ Int. Conf. Intell. Robot. Syst.*, pp. 2478–2483, 2002.

[2] K. Akachi, K. Kaneko, N. Kanehira, S. Ota, G. Miyamori, M. Hirata, S. Kajita, and F. Kanehiro, "Development of humanoid robot HRP-3P," in *Proc. IEEE-RAS Int. Conf. Humanoid Robots*, pp. 50–55, 2005.

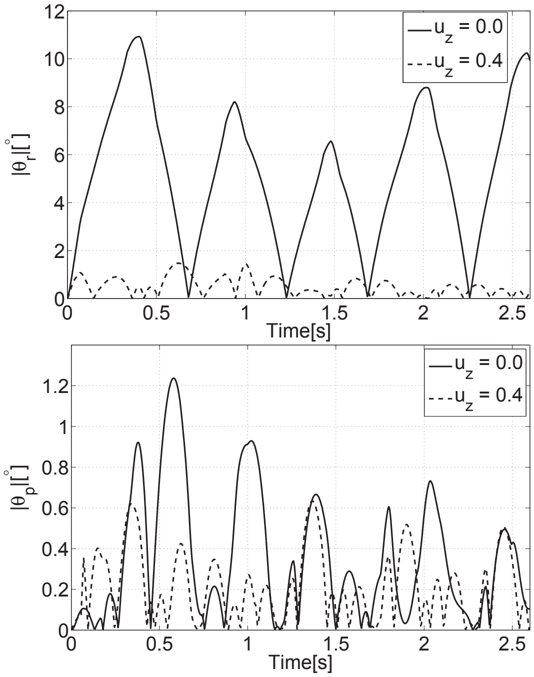

Fig. 7. The rolling and pitching angles of the COP while walking with increase of the double support time.

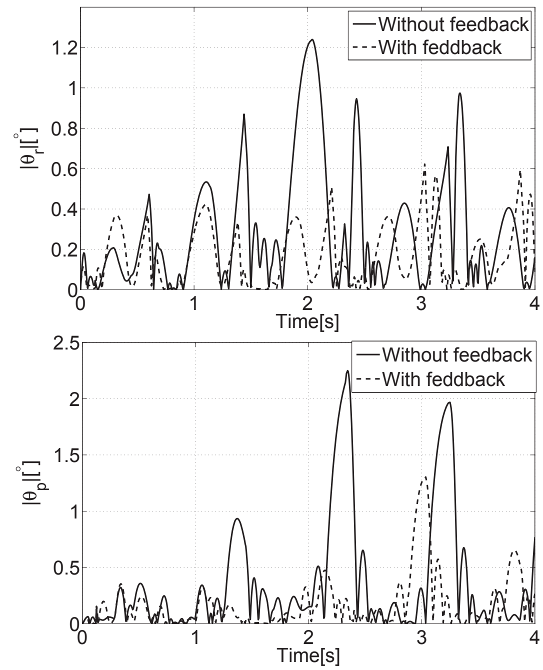

Fig. 8. The rolling and pitching angles of the COP while walking with feedback.

[3] Y. Ogura, H. Aikawa, K. Shimomura, H. Kondo, A. Morishima, H.-O. Lim, and A. Takanishi, "Development of a new humanoid robot WABIAN-2," in *Proc. IEEE Int. Conf. Robot. Autom.*, pp. 76–81, 2006.

[4] J. Morimoto, G. Endo, J. Nakanishi, and G. Cheng, "A biologically inspired biped locomotion strategy for humanoid robots: modulation of sinusoidal patterns by a coupled oscillator model," *Robotics, IEEE Trans.*, vol. 24, no. 1, pp. 185–191, 2008.

[5] S. Kajita, F. Kanehiro, K. Kaneko, K. Fujiwara, K. Yokoi, and H. Hirukawa, "A realtime pattern generator for biped walking," in *Proc. IEEE Int. Conf. Robot. Autom.*, vol. 1, pp. 31–37, 2002.

[6] Y.-D. Hong, B.-J. Lee, and J.-H. Kim, "Command state-based modifiable walking pattern generation on an inclined plane in pitch and roll directions for humanoid robots," *IEEE/ASME Trans. Mechatronics*, vol. 16, no. 4, pp. 783-789, 2011.

[7] G. Taga, "Emergence of bipedal locomotion through entrainment among the neuro-musculo-skeletal system and the environment, *Physica D: Nonlinear Phenomena*, vol. 75, no. 1–3, pp. 190–208, 1994.

[8] G. Taga, "A model of the neuro-musculo-skeletal system for human locomotion," *Biol Cybern*, vol. 73, pp.97–111, 1995.

[9] Yutaka Nakamura, Takeshi Mori, Masa-aki Sato, and Shin Ishii, "Reinforcement learning for a biped robot based on a CPG-actor-critic method," *Neural Networks*, vol. 20, no. 6, Pages 723–735, 2007.

[10] L. Righetti and A. J. Ijspeert, "Programmable Central Pattern Generators: an application to biped locomotion control," in *Proc. IEEE Int. Conf. Robotics and Automation*, pp. 1585–1590, 2006.

[11] Gen Endo, Jun Morimoto, Takamitsu Matsubara, Jun Nakanishi, and Gordon Cheng, "Learning CPG-based biped locomotion with a policy gradient method: application to a humanoid robot," *International Journal of Robotics Research*, vol. 27, no. 2, pp. 213–228, 2008.

[12] R. Heliot and B. Espiau, "Multisensor input for CPG-based sensory–motor coordination," *Robotics, IEEE Trans.*, vol.24, no.1, pp.191–195, 2008.

[13] T. A. McMahon, "Muscles, reflexes, locomotion," *NJ: Princeton Univ. Press*, 1984.

[14] V. T. Inman, H. J. Ralston, and F. Todd, "Human Walking. Baltimore," *MD : Willams & Wilkins*, 1981.

[15] C.-S. Park, Y.-D. Hong, and J.-H. Kim, "Full-body joint trajectory generation using an evolutionary central pattern generator for stable bipedal walking," in *Proc. IEEE/RSJ Int. Conf. Intelligent Robots and Systems*, pp.160–165, 2010.

[16] K.-H. Han and J.-H Kim, "Quantum-inspired evolutionary algorithm for a class of combinatorial optimization," *IEEE Trans. Evolutionary Computation*, vol. 6, pp. 580–593, 2002.

[17] K.-H. Han and J.-H. Kim, "Quantum-inspired evolutionary algorithms with a new termination criterion, He gate, and two-phase scheme," *IEEE Trans. Evolutionary Computation*, vol. 8, no. 2, pp. 156-169, 2004.

[18] K. Matsuoka, "Sustained oscillations generated by mutually inhibiting neurons with adaptation," *Biol Cybern*, vol. 52, no. 6, 367–376, 1985.

[19] K. Matsuoka,"Mechanisms of frequency and pattern control in the neural rhythm generators," *Biol Cybern*, vol. 56, no. 5, pp. 345–353, 1987.

[20] T. Hey, "Quantum computing: an introduction," *Comput. Control Eng. J.*, vol.10, no. 3, pp.105–112, 1999.

[21] J.-K. Yoo, B.-J. Lee, and J.-H. Kim, "Recent Progress and Development of Humanoid Robot HanSaRam," *Robotics and Autonomous Systems*, vol. 57, no. 10, pp. 973-981, 2009.

[22] O. Michel, "Cyberbotics Ltd. WebotsTM: Professional mobile robot simulation, *Int. J. Advanced Robot. Syst.*, vol. 1, no. 1, pp. 39.42, 2004.