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Self-adapting Humanoid Locomotion Using a Neural Oscillator Network

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***Abstract*— Stable and robust dynamic locomotion has been gaining increasing attention in humanoid research. This paper presents a neural oscillator network for the generation of periodic locomotion patterns adapting to changes in the slope of the terrain. Specifically, locomotion trajectories of individual limbs are predetermined in the trajectory generator as a periodic function of the gait. The phase of the periodic function is coordinated with the output of the neural oscillator network incorporating sensory signals detecting the state of the foot in contact with the unknown changing terrain. For stability to be maintained, the neural oscillator plays an important role by controlling the trajectory of the COM in phase with the trajectory of the ZMP. In order to verify the validity of the proposed scheme, we carry out simulations and experiments. A preliminary investigation has yielded promising results, indicating that it may be applied to humanoid locomotion through uneven and uncertain terrain.**

I. INTRODUCTION

AUTOMATIC motion generation of a humanoid robot is so far undetermined in complex and dynamically changing environments. This is one of the most important challenges to deploy humanoid robots as a part of our daily lives. For a large number of vertebrates, continuous rhythmic movements are produced by central pattern generators (CPGs) in their spinal cord [1]. Specifically, CPGs, or neural oscillators, can endogenously produce rhythmic patterned outputs that can be utilized in generating rhythmic motor movement of humanoid robots. Moreover, neural oscillators can entrain to the sensory feedback, which plays a key role to adapt locomotion in a changing environment.

Mathematical descriptions of a neural oscillator were addressed in Matsuoka's works [2], [3], where neurons were proven to generate the rhythmic patterned output. His work provided necessary and sufficient conditions on the parameters to sustain self-oscillations. Employing Matsuoka's neural oscillator model, Taga *et al.* investigated mutual entrainment of neural oscillators performed by a musculo-skeletal system, which created stable locomotion in a certain environment. Specifically, sensory signals from the joints of a biped robot were fed back to entrain the oscillators [4], [5]. As a result, the robot became robust against perturbation and was able to climb an upward slope [6]. These attributes were later applied to a 3D locomotion by Miyakoshi *et al.* in [7]. In addition to these prior researches, neural oscillators were successfully implemented in a dynamic quadrupedal walking by Fukuoka *et al.* [8], and the control of rhythmic robot arm movement by Williamson [9].

The present work involves a new application of neural oscillator networks that enables humanoid robots to autonomously adapt their locomotion to changes in the terrain. Even though neural oscillators possess such desirable property as entrainment to the environment, it is difficult to design their interconnected relation and feedback pathways. This process entails an intensive and time-consuming effort of manually tuning their parameters to achieve a desired behavior [10], [11], [12]. Therefore, to decrease uncertainty and nonlinearity in the characteristics of neural oscillators and increase the predictability of adaptation of humanoid locomotion, this work employs various predetermined periodic functions of locomotion. The proposed neural oscillator network is subject to the state changes of oscillator interacting with the environment. In addition, to guarantee the stability of humanoid locomotion with regards to the rolling motion in a frontal plane, an inverted pendulum model coupled to the neural oscillators is employed.

In this paper, a neural oscillator network with phase adaptation that can compensate for the difference between the predetermined state and the current state of the humanoid locomotion is proposed by incorporating the sensory signals that detect changes in the slope of the terrain. It is verified through simulations and experiments with a real robot that the proposed approach yields a robust and efficient control of rhythmic locomotion for humanoid robots.

II. LOCOMOTION ADAPTATION FRAMEWORK

Fig. 1 describes the conceptual locomotion control algorithm organized into the neural oscillator network and the locomotion trajectory generator. The neural oscillator network generates the predetermined phases in a time domain. These phases are comprised of the main phase responding to sensory feedback from the landing foot and the phases of individual limb's trajectories. The individual limbs consist of two arms, two legs, and torso. By this algorithm, the periodic

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motions of each leg and arm are determined like the rhythmic motions of a human. The locomotion trajectory generator of individual limbs has normal trajectories in the function of the phase obtained from the output of the oscillator network.

Hence, if the main phase is adjusted reflecting the feedback signals from the landing foot, the locomotion trajectory generator autonomously modifies the normal trajectories with respect to the swing motion of two arms and the stance and swing motion of two legs in the sagittal plane. Then, the joint angle trajectories of individual limbs can be obtained by solving the respective inverse kinematics problems for the modified trajectory of the locomotion except for the joint motion in the rolling direction. The rolling of the hip joints and the motion of torso are directly controlled using the neural oscillator with the inverted pendulum model. The motor commands for the rolling of hip joints and the motion of torso are modulated by sensory feedback from a gyro sensor in the body. In humanoid locomotion, the necessary condition is that the resulting motions should satisfy the criterion on dynamic stability. Therefore, the main problems are how to make a stable trajectory and how to maintain the stability for locomotion, when the proposed approach incorporates the sensory signals detecting changes in a slope of the terrain. In the following sections, we describe how to maintain stability and adapt to a new environment.

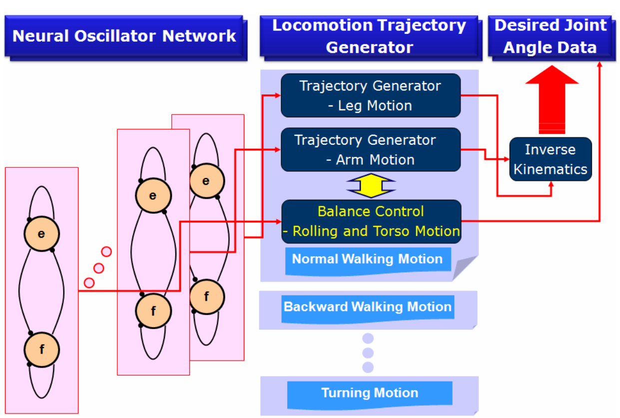

Fig. 1 The proposed locomotion control algorithm

III. PHASE ADAPTING NEURAL OSCILLATOR NETWORK

A. A neural oscillator network

We design a neural oscillator network to realize the phase generator using Matsuoka's CPG model as shown in Fig. 2. This model consists of two simulated neurons arranged in mutual inhibition [2], [3]. If gains are properly tuned, the system exhibits limit cycle behavior. The trajectory of a stable limit cycle can be derived analytically and describes the firing rate of a neuron with self-inhibition. The model is represented by a set of nonlinear coupled differential equations given by

$$
\begin{aligned}
T_r\dot{x}_{ei}+x_{ei} &= -w_{fi}y_{fi}-\sum_{j=1}^{n}w_{ij}y_j-bv_{ei}-\sum k_i[g_i]^+ + s_i\\
T_a\dot{v}_{ei}+v_{ei} &= y_{ei}\\
y_{ei} = [x_{ei}]^+ &= \max(x_{ei},\ 0)\\
T_r\dot{x}_{fi}+x_{fi} &= -w_{ei}y_{ei}-\sum_{j=1}^{n}w_{ij}y_j-bv_{fi}-\sum k_i[g_i]^- + s_i\\
T_a\dot{v}_{fi}+v_{fi} &= y_{fi}\\
y_{fi} = [x_{fi}]^+ &= \max(x_{fi},\ 0)\ ,(i=1,\ 2,\ \cdots,\ n)
\end{aligned}
\qquad (1)
$$

where $x_{e(f)i}$ is the inner state of the i-th neuron which represents the firing rate; $v_{e(f)i}$ represents the degree of the adaptation, modulated by the constant b, or self-inhibition effect of the i-th neuron; the output of each neuron $y_{e(f)i}$ is taken to be the positive part of the firing rate and the output of the whole oscillator is denoted as $Y_{(out)i}$; $w_{ij}y_i$ represents the total input from the neurons inside a neural network; w_{ij} is a weight of inhibitory synaptic connection from the j-th neuron to the i-th neuron, and w_{ei}, w_{fi} are also a weight from extensor neuron to flexor neuron, respectively; the input is arranged to excite one neuron and inhibit the other by applying the positive part to one neuron and the negative part to the other; the inputs are scaled by the gains k_i; T_r and T_a are time constants of the inner state and the adaptation effect of the i-th neuron, respectively; s_i is an external input with a constant rate.

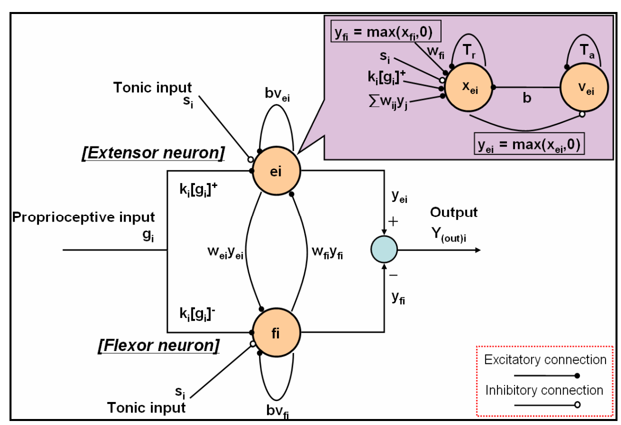

Fig. 2 Schematic diagram of the half-center CPG model

B. Neural oscillator network for phase adaptation

Neural oscillators exhibit such characteristics as self-organization of the phase synthesis of an outer oscillatory signal, robustness to external and internal parameter changes, and entrainment to environments. Specifically, using the phase synthesis and entrainment by sensory signals, we propose a novel design of the neural oscillator network. Basically this network can couple two neural oscillators by establishing four connections weighted w_e, w_f, w_{ef}, and w_{fe}, addressed in above subsection A, respectively as shown in Fig. 3. The black circles at the end of the connection correspond to inhibitory connections.

Thus, if two oscillators are connected vertically, the phase of the flexor neuron, f1, of oscillator 1 will be in phase with the extensor neuron, e2, of oscillator 2. The cross connection between two oscillators will have the opposite effect such that the outputs of neural oscillators have phase differences of $\pm\pi$ or 0. Generally, if w_e and w_f exist, w_{ef} and w_{fe} can be omitted due to mutual inhibition of the output's phase of each neuron. If not, the inputs/outputs of neurons will be complicated and the final phase relies on initial conditions of each neural oscillator. The oscillator network could have a variety of periodic motions that plays an important role to control the state of phase in individual limbs. Note that stable human locomotion exhibits a coordinated periodic limb movement even though there are unexpected motor disturbances or abnormalities. Therefore, the phase generating oscillator network impacts on the protective effect against irregular motor rhythm.

Fig. 4 illustrates the proposed phase generating neural oscillator network. The double solid rectangle is the main neural oscillator network that determines the reference phase of the gait cycle through interactions between individual neural oscillators, sustaining the respective motor (limb) phase inputs with respective phase shifts. Four dashed line-rectangles represent neural oscillators connected for the phase output of each limb. There are inhibitorily connected links between the respective individual neural oscillators of the opposite limbs. For instance, the phase signal of the right leg, $Y_{R,L}$, and that of the left arm, $Y_{L,A}$, (similarly, the phase of the left leg, $Y_{L,L}$, and that of the right arm, $Y_{R,A}$) are synchronized to the same phase of the generated signal as seen in Fig. 4. The phase signals of two arms and two legs are reversed, respectively. These inhibitory connections are denoted by dashed dot line at the end of connections. The line arrows indicate the flow direction of the output of the phase signal interacted between the neural oscillators, and also the dot lines show that sensory signals are obtained from the environment.

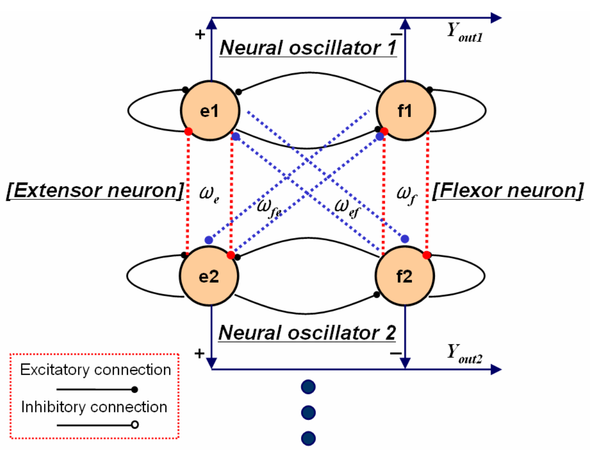

Fig. 3 Schematic diagram of neural oscillator network

The adjustment of the gait cycle due to the terrain changes will in effect by the sensory signals. The changes in the predicted phases sensed through the foot sensors result in the change in the reference phase signal generated in the main neural oscillator network. In Fig. 4, Y implies a phase signal determined in the neural oscillator network. The sum of Y_{M1} and Y_{M2} generates a reference phase signal incorporating S_1 and S_2 of sensory signals. This output is additively summed with $Y_{L,L}$, $Y_{L,A}$, $Y_{R,L}$ and $Y_{R,A}$ derived from the individual neural oscillator network of the limbs. Therefore, the combined outputs of the phases, adapted to the varying environmental condition, are fed to the locomotion trajectory generator.

The proposed neural oscillator network is simulated when the flat terrain changes abruptly to an upward slope in Fig. 5. The respective neural oscillator generates the expected phases of $\pm\pi$ or 0 by appropriately networking the neural oscillators as mentioned above. To produce the desired output of the phase, the parameters of the neural oscillator should be tuned appropriately. The tonic input, the sensory gain, and the inhibitory weight of the neural oscillator are set to 2π, 4, and 5, respectively.

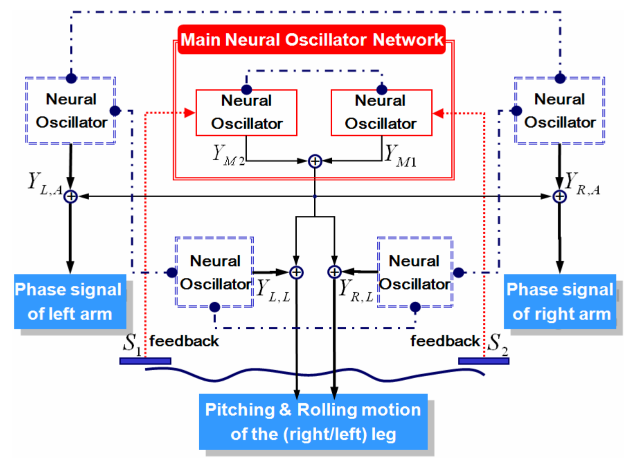

Fig. 4 Design of the proposed neural oscillator network

The middle line shows the output of the main phase, and the upper and lower lines show that the phase outputs of the both legs are reversed. The same result is obtained from the simulation of arm swinging. That is, the phases for bipedal locomotion are given such that the legs and arms swing in the opposite phase, and the legs and their contralateral arms swing in the same phase. The gait cycle is controlled by the main neural oscillator network. In the simulation, we assumed that the foot sensor processed contact information properly to enable the main neural oscillator network to adapt to terrain changes. Based on this, it was verified that the generated phases were changed at the instant when the foot stroke the ground ahead of its nominal flat terrain stride interval. The phase difference remains the same irrespective of changes in the terrain. Note that, if the foot takes off the unknown terrain, the swing or stance phase is set to the determined phase value. The torso should be moved adaptively so that the locomotion stability is satisfied. Therefore, in this work, feedback control loop was designed employing the gyro sensor for stable body attitude of a humanoid robot.

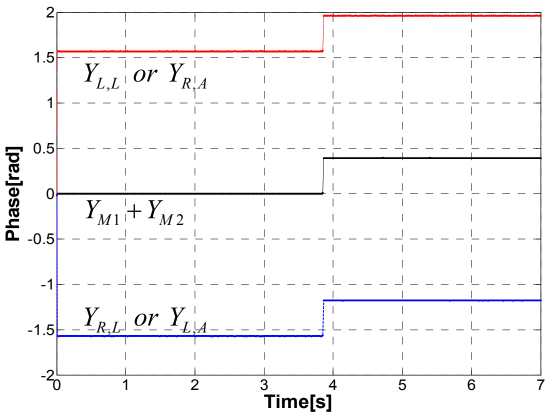

Fig. 5 Phase changes when flat terrain changes to an upward slope

IV. Self-Adapting Locomotion Generation

Fig. 6 illustrates the kinematic schematic of the humanoid robot employed in this work. In the figure, Ajoint denotes arm joints and Ljoint does leg joints. Ajoint3 and Ljoint1 are engaged in the yawing motion of an arm and a leg. Ajoint2 and Ljoints2, 6 are engaged in the rolling motion. Ajoints 1, 4, 5 and Ljoints 3, 4, 5 are engaged in the pitching motion. Hjoint and Tjoint denote the head joint and the torso joint. The locomotion trajectory generator generates the Cartesian trajectories of respective limbs. Specifically, the swing foot trajectory can be a cycloid and the hip trajectory vaults like an inverted pendulum over the supporting foot.

A. Locomotion trajectory generation

For generating appropriate locomotion trajectories, nominal trajectories in Cartesian coordinates are provided *a priori* by the trajectory generator. Each trajectory is the function of the phases as time sent from the neural oscillator networks for each limb given by

$$\begin{aligned} Y_M &= Y_{M1}+Y_{M2} \\ &= 2vt+(y_{eM1}-y_{fM1})+(y_{eM2}-y_{fM2}) \\ &= 2vt+([x_{eM1}]^+-[x_{fM1}]^+)+([x_{eM2}]^+-[x_{fM2}]^+) \\ Y_{L,L} &= vt+(y_{eL,L}-y_{fL,L})=vt+([x_{eL,L}]^+-[x_{fL,L}]^+) \\ Y_{R,L} &= vt+(y_{eR,L}-y_{fR,L})=vt+([x_{eR,L}]^+-[x_{fR,L}]^+) \\ Y_{L,A} &= vt+(y_{eL,A}-y_{fL,A})=vt+([x_{eL,A}]^+-[x_{fL,A}]^+) \\ Y_{R,A} &= vt+(y_{eR,A}-y_{fR,A})=vt+([x_{eR,A}]^+-[x_{fR,A}]^+) \end{aligned} \tag{2}$$

Note that '*L*' and '*R*' in the first subscript denote left and right, and '*L*' and '*A*' in the second subscript do leg and arm, respectively. The pre-specified joint angle velocity, v, required to track the foot trajectories, is subject to the dynamics of the coupled oscillators. Normal gait trajectory based on cycloid function is given by

$$\begin{aligned} Traj^{sw}(x,z) &= (\frac{A_x}{2\pi}(2Y-\pi-\sin 2Y),\frac{A_z}{2\pi}(1-\cos 2Y))-H \quad (0\le Y<\pi) \\ Traj^{st}(x,z) &= (A_x(\frac{3}{2}-\frac{Y}{\pi}),-H(2-\frac{Y}{\pi})) \quad (\pi\le Y<2\pi) \end{aligned} \tag{3}$$

where A_x indicates the step length of the normal gait trajectory in the *x-z* plane (or sagittal plane), and A_z does the step height in the same plane. *H* denotes the height from the ankle joint to the thigh joint (Ljoint 2 or 3). The superscripts, '*sw*' and '*st*' note foot trajectories in the swing and stance motion, respectively. Eq. (3) holds in the range of $0\le Y<\pi$. In $\pi\le Y<2\pi$, the stance motion is generated to make the hip move along the horizontal trajectory connecting two end points of the inverted pendulum-like movement. This leg motion is periodically switched at the phase of π. The joint angle trajectories of Ljoints 3 and 4 for the pitching motion are determined by solving the inverse kinematics problem. And the joint angle trajectories for the arm motion are designed as the function of the phase of $Y_{L,A}$ and $Y_{R,A}$ given by

$$\begin{aligned} \theta_{A,L,1} &= A_{arm}\cos Y_{L,A} \\ \theta_{A,R,1} &= A_{arm}\cos Y_{R,A} \end{aligned} \tag{4}$$

where A_{arm} denotes the amplitude of the arm swing motion.

In order to precisely control the both legs and arms, a PD controller is employed. The torque inputs at the joints are given as follows:

$$\tau_i = -k_p^i(\theta_d^i-\theta^i)-k_D^i(\dot{\theta}_d^i-\dot{\theta}^i), \tag{5}$$

where the superscript '*i*' denotes the *i*-th joint; k_P and k_D are the *i*-th proportional and derivative gains, respectively.

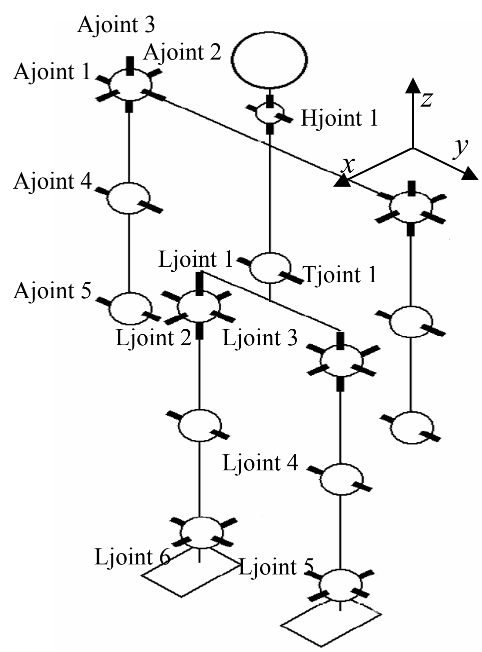

Fig. 6 Kinematic configuration of humanoid robot.

B. Posture balancing and phase adaptation

Since the dynamic stability is affected by the leg motion and the torso motion, the torso motion of humanoid robot is controlled by PD compensator as Eq. (5) to follow a referential hip joint angle, $\theta_{T,1}$, in Eq. (6). We consider a feedback signal from the gyro sensor for the current state to compensate for the reclining angle of the upper body. The referential hip joint angle is given as follow:

$$\theta_{T,1} = A_{torso} \cos Y_M \tag{6}$$

In the proposed neural oscillator network with phase adaptation, the sensory feedback is employed to detect changes in the slope of the terrain. The following equation is the sensory signal input to be incorporated in Eq. (1)

$$S_1 = k[g]^+,\ S_2 = k[g]^+, \tag{7}$$

$$\text{where } g = (\arctan(\frac{\left\| |Traj'^{st}(z)| - |Traj'^{sw}(z)| \right\|}{\left\| |Traj'^{st}(x)| - |Traj'^{sw}(x)| \right\|}))\delta(t-t')$$

Note that $Traj'^{sw}$ and t' are the current position of the swing foot in the Cartesian coordinate system and the time when the foot strikes the ground. And $Traj'^{st}$ is the current position of the supporting foot. $\delta(t)$ is the dirac-delta function. Based on this equation, the swing and stance motions of both legs are switched with each other at t', and at the same time the predetermined locomotion trajectories of both legs and arms are modified autonomously. This switching occurs when the flat terrain changes to an upward or downward slope (or the upward or downward slope flattens out).

Specifically, the changes in the slope affect the rolling motion as well as the foot placement associated with the pitching motion. We therefore devised a compensator given by Eq. (8) which eliminates the difference of the positions between the actual and nominal foot placement by checking the final position of the swing or stance state when the phase change happens.

$$\begin{aligned} Traj^{st}(x_{i+1}) &= Traj^{st}(x_{i+1}) + S_{cp}(x_i) \\ Traj^{sw}(z_{i+1}) &= Traj^{sw}(z_{i+1}) + H_{cp}(z_i), \end{aligned} \tag{8}$$

$$\text{where } \begin{aligned} S_{cp}(x_i) &= (Traj^{sw}(x_i) - Traj'^{sw}(x_i)) \\ H_{cp}(z_i) &= (Traj^{st}(z_i) - Traj'^{st}(z_i)) \end{aligned}$$

The stride interval is compensated with S_{cp} and the stride height is with H_{cp}. The posture remains balanced only if the rolling motion of each leg should be synchronized in phase with its pitching motion regardless of the changes in the phase of the gait cycle. Since the nominal joint motions are pre-designed in the flat terrain environment, the robot motions in the changing environment might result in undesirable interaction forces with its environment. This will bring about the wrong movement of the COM and violate the ZMP criterion.

V. SELF-ADAPTING LOCOMOTION CONTROL

In humanoid locomotion, the pitching motion should be performed under the stable single support phase of the rolling motion. Now we explain how to attain the stable single support phase corresponding to the locomotion generation described in the previous section. Note that rolling motions bring about significant effects on the landing stability of swing legs that may cause an unexpected perturbation with imperfect contact. To avoid this, we consider an inverted pendulum model coupled to such a virtual mechanical component as a spring and damper and the neural oscillator, as seen in Fig. 7 (a) for generating an appropriate rolling motion. The coupled model enables the inverted pendulum to stably move in a frontal plane according to a desired ZMP trajectory sustaining the stability.

Assuming that θ, the angle between the vertical axis and the pendulum in Fig. 7 (a), is small enough, the dynamic equation of the coupled inverted pendulum is given by

$$\ddot{x} = \frac{G}{l}(x-u) + f_r \tag{9}$$

where x is the displacement of the pendulum in the rolling direction, l is the length of the pendulum, and u is the position of the massless cart of the pendulum. G is the gravitational constant and f_r indicates the force that should be applied to the Center of Mass (COM) of the pendulum in the rolling direction.

If the desired ZMP trajectory, u, is given in Eq. (9), a stably periodic motion of the COM of the pendulum is generated in terms of the coupled neural oscillator with state feedback. A stable limit cycle behavior is induced and the expected periodic COM motion is caused by the impedance control with the connected virtual components, as illustrated in the block diagram in Fig. 8. Accordingly, f_r in Eq. (9) is given by

$$f_r = k_s((h\theta_o - k_p x) - k_v \dot{x}) + (i_p(\theta_d - x) - i_v \dot{x}) \tag{10}$$

where k_s is the stiffness coefficient and h is the output gain of the neural oscillator. k_p and k_v are the gains of state feedback, and i_p and i_v are the gains of the impedance controller. In the proposed controller, θ_o and θ_d denote the output of the neural oscillator and a desired ZMP input, respectively. The current COM position and velocity of the humanoid robot are obtained again by Eq. (9). For a stable rolling motion corresponding to the ZMP input, f_r in Eq. (10) is transformed into joint torque using the Jacobian that needs to be applied to Ljoint 2 and Ljoint6 of both legs in Fig. 6. As illustrated in Fig. 7 (b) and (c), the humanoid robot exhibits stable rolling motion satisfying the desired ZMP.

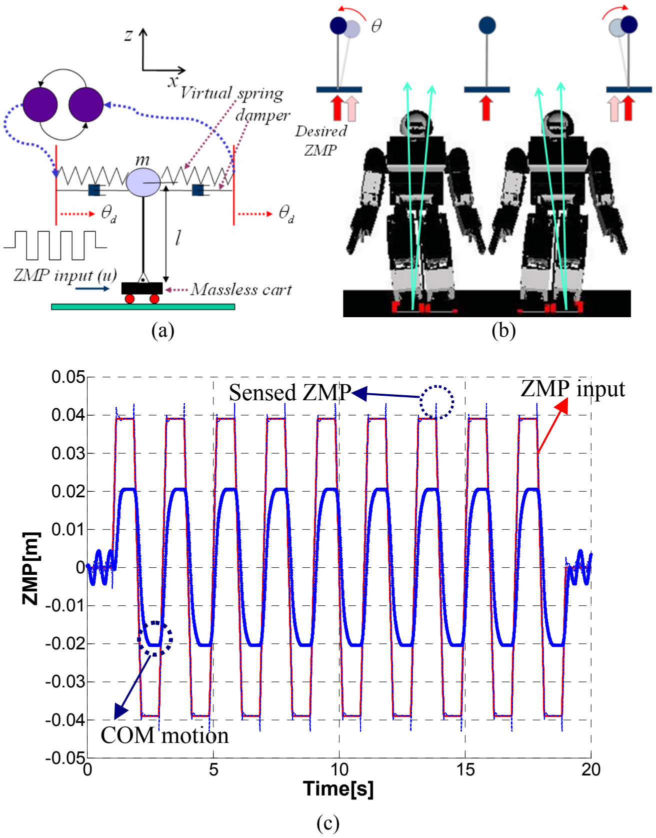

Fig. 7 (a) The proposed control model for stable inverted pendulum motion (b) Simulation result with respect to rolling motion of humanoid robot (c) The rolling COM motion of humanoid robot

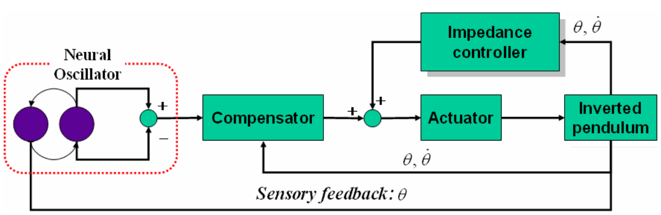

Fig. 8 Control block diagram of the coupled inverted pendulum

VI. Simulation and Experimental Results

We performed simulations to verify the proposed locomotion control algorithm using Fujitsu's HOAP model. In Fig. 9, the foot trajectories predetermined by the locomotion trajectory generator are illustrated. The upper and lower figures show the trajectories of the right and left foot, respectively. The first step of the right foot is designed to have the half interval. Figs. 10 and 11 are the simulation and experimental results showing that the robot walks straight on flat ground employing the foot trajectories in Fig. 9. Moreover, various locomotion gaits can be designed based on the proposed phase generator network such as turning while walking as shown in Fig. 12. This motion can be realized by applying a sinusoidal input to Ljoint1. This input should be synchronized in phase with the rolling motion.

Additionally, we investigate how the adapted locomotion is acquired in the unknown terrain. In Fig. 13, it is observed that the foot trajectories are modified to appropriate trajectories adapting to an unknown slope. The foot pressure sensor detects the changing period of foot strike with the ground and sends this information to the main phase generator. Fig. 14 shows the results of phase changes in individual limbs. The three lines in the figure correspond to those in Fig. 5, respectively. The phases abruptly jumped by about 6° at the instant when the sensory signals, S_1 and S_2, are fed from the foot pressure sensor (see Fig. 4). Thus, locomotion trajectories associated with the pitching motion can be switched appropriately.

However, the changes in the pitching phase do not affect the rolling motion that should be synchronized in phase with each other. Therefore it is important to design the rolling motion compensator in the locomotion trajectory generator. When the phase jumped at an instant, this jumped phase should be kept constant until the phase returns to the original phase. This means that the joint motions not engaged in the rolling motion remain stationary. In the double support phase, the position of the COM should be located at the middle point of both feet, and at the same time the joint angles engaged in the rolling motion should return to zero. In the red dash lined boxes in Fig. 15, it is observed that the pitching joints, LJoint 3, 4, and 5, all remain stationary. They are displayed with the blue dashed line, lower blue solid line, and upper black solid line in sequence in the figure.

It is also important to plan the trajectory of the ankle joint, LJoint 5, appropriately, to make the landing foot strike the unknown slope smoothly yet completely. Thus, if the robot can estimate the position of the support foot from the slope, it is possible to plan the ankle trajectory using the gradient in the stance trajectory in Eq. (3). Since the contact condition between the foot and the slope affects the stability, this ankle trajectory design is an important part of stable locomotion. Fig. 16 shows the ankle trajectory planned for a 6° slope. The blue solid and red dashed lines are the ankle trajectories of the right leg and the left leg, respectively.

Incorporating the above-mentioned techniques into the locomotion control, we demonstrate that the robot can walk through changing terrain balancing like a human. Fig. 17 is the snapshots showing that the robot climbs a 6° slope. In Fig. 18, the robot climbs the same slope passing through the flat terrain.

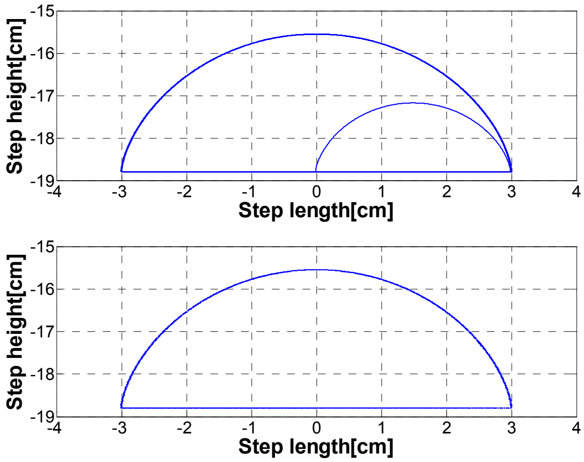

Fig. 9 Predetermined foot trajectories

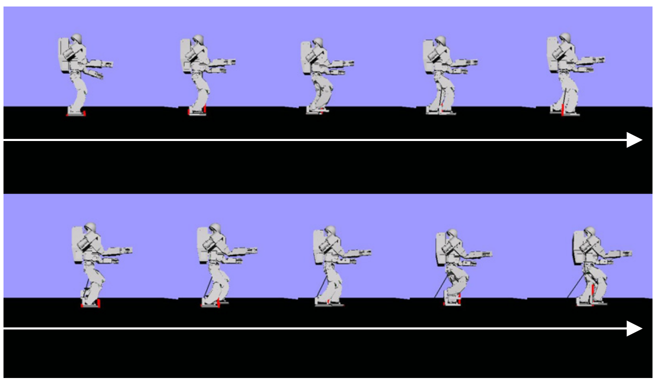

Fig. 10 Simulation of HOAP flat terrain walking

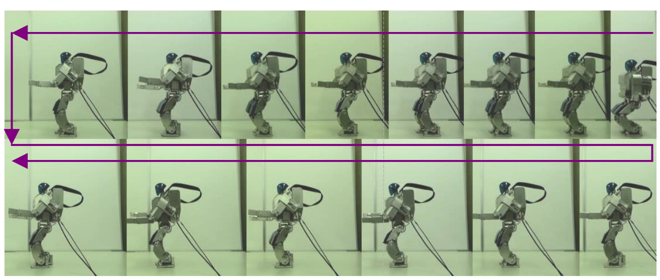

Fig. 11 Experiment of HOAP flat terrain walking

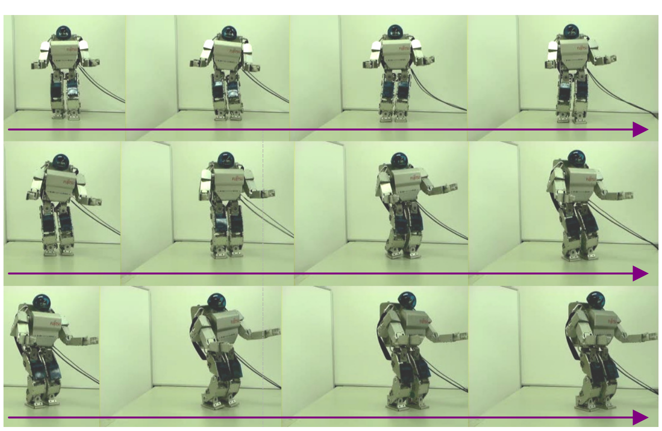

Fig. 12 Experiment of HOAP turning while walking forward

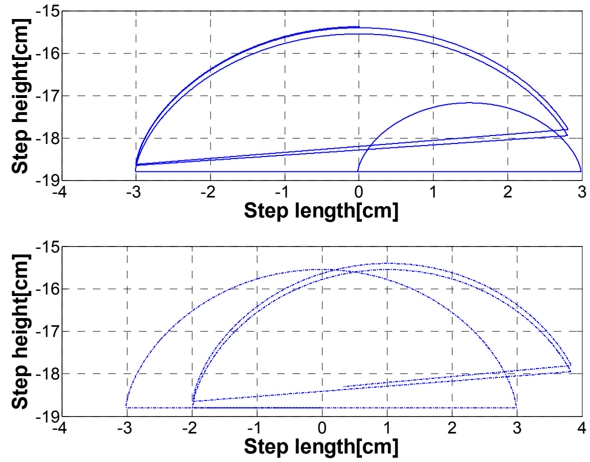

Fig. 13 Foot trajectories when flat terrain changes to 6° upward slope

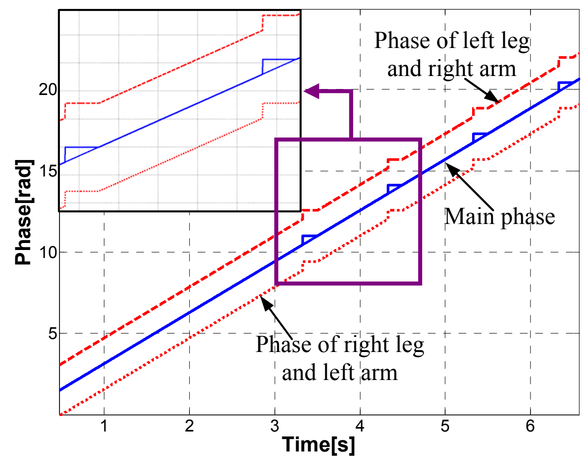

Fig. 14 Phase signal from neural oscillator network

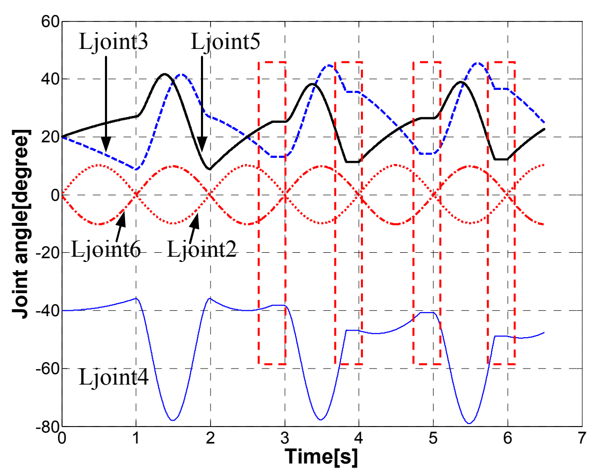

Fig. 15 Joint angle data of right leg

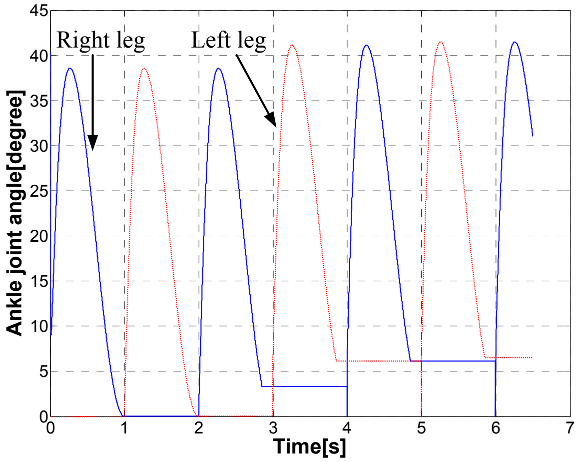

Fig. 16 Ankle trajectory in case of 6° uphill slope

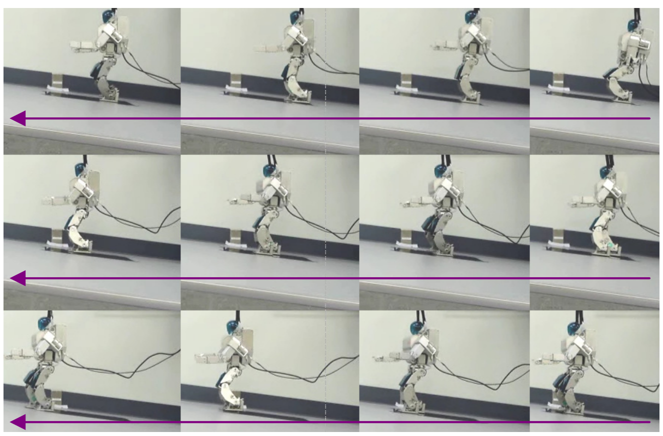

Fig. 17 Snap shots of a 6-degree uphill walking

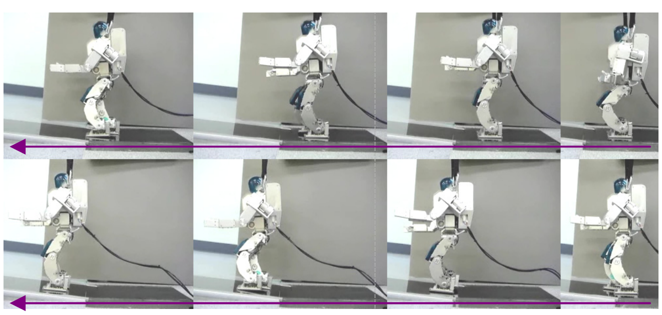

Fig. 18 Snap shots of gait adaptation to changing slope

VII. CONCLUSION

To attain a stable periodic locomotion of a biped humanoid robot, we proposed a biologically-inspired locomotion control framework consisting of the neural oscillator network for phase generation and the trajectory generator. For sustaining the stability according to a desired ZMP, the inverted pendulum model coupled with a virtual spring and damper and a neural oscillator was employed for the rolling motion. In addition, controlling the torso for the posture of the upper body enabled the humanoid robot to stably locomote under a small perturbation or disturbance.

In this work, biped locomotion was controlled by the trajectory generator that was composed of a time-varying phase function with phases obtained from the neural oscillator network. Synchronizing the motions of individual limbs, the configuration of the limbs, which determines body posture, can be modified appropriately using the proposed neural oscillator network as the slope of terrain changes. The robustness of locomotion is therefore maintained by incorporating sensory signals that detect changes in the terrain. Implementing the proposed control framework, we can develop a new type of humanoid locomotion that will adapt naturally to varying environment conditions from flat terrain to slope or vice versa.

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