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Description	

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Biologically Inspired Control for Robotic Arm Using Neural Oscillator Network

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Abstract— **It is known that biologically inspired neural systems could exhibit natural dynamics efficiently and robustly for motion control, especially for rhythmic motion tasks. In addition, humans or animals exhibit natural adaptive motions without considering their kinematic configurations against unexpected disturbances or environment changes. In this paper, we focus on rhythmic arm motions that can be achieved by using a controller based on neural oscillators and virtual force. In comparison with conventional researches, this work treats neither trajectories planning nor inverse kinematics. Instead of those, a few desired points in task-space and a control method with Jacobian transpose and joint velocity damping are merely adopted. In addition, if the joints of robotic arms are coupled to neural oscillators, they may be capable of achieving biologically inspired motions corresponding to environmental changes. To verify the proposed control scheme, we perform some simulations to trace a desired motion and show the potential features related with self-adaptation that enables a three-link planar arm to make adaptive changes from the given motion to a compliant motion. Specifically, we investigate that human-like movements and motion repeatability are satisfied under kinematic redundancy of joints.**

I. Introduction

In general, the neural oscillator based circuits on the spinal cord known as Central Pattern Generators (CPGs) might contribute to efficient motor movement and novel stability properties in biological motions of animal and human. Based on the CPGs, most animals locomote stably using inherent rhythmic movements adapted to the natural frequency of their body dynamics in spite of differences in their sensors and actuators. In our daily lives, natural rhythmic movements such as running, swimming, flying, breathing, etc and human-like motions such as turning a steering wheel, rotating a crank, etc. are dependent upon the interaction between the musculo-skeletal system and the nervous system. The CPGs composed of neural oscillator networks coupled to limbs efficiently provides alternate motor commands for the muscles through afferent feedback of sensory signal and enables the musculoskeletal system of an animal to deal with environmental perturbations properly. Also, they seem to appropriately give desired inputs for driving motors to the muscles according to environmental changes without precisely considering kinematic configurations and kinematic redundancy of joints. To accomplish the biologically inspired system, the CPG is mathematically designed and incorporated into an artificial neural oscillator network.

The mathematical description of a neural oscillator was presented in Matsuoka's works [1]. He proved that neurons generate the rhythmic patterned output and analyzed the conditions necessary for the steady state oscillations. He also investigated the mutual inhibition networks to control the frequency and pattern [2], but did not include the effect of the feedback on the neural oscillator performance. Employing Matsuoka's neural oscillator model, Taga *et al*. investigated the sensory signal from the joint angles of a biped robot as feedback signals [3]-[4], showing that neural oscillators made the robot robust to the perturbation through entrainment. This approach was applied later to various locomotion systems [5]-[7]. Besides the examples of locomotion, various efforts have been made to strengthen the capability of robots from biological inspiration. Williamson created a humanoid arm motion based on postural primitives. The spring-like joint actuators allowed the arm to safely deal with unexpected collisions sustaining cyclic motions [8]. He also proposed the neuro-mechanical system that was coupled with the neural oscillator for controlling rhythmic arm motions [9]. Arsenio [10] suggested the multiple-input describing function technique to control multivariable systems connected to multiple neural oscillators.

Even though natural adaptive motions were accomplished by the coupling between the arm joints and neural oscillators, the correctness of the desired motion was not guaranteed. Specifically, robot arms are required to exhibit complex behaviors or to trace a trajectory for certain type of tasks, where the substantial difficulty of parameter tuning emerges. The authors have presented encouraging simulation and experiment results in controlling the arm trajectory incorporating neural oscillators for a desired task [11]-[13]. Apart from such the proposed parameter optimization method, we newly address an intuitive and efficient approach for a desired task of the neural oscillator based control. In addition, we show an impressive capability such as self-adapting motions against an unknown disturbance and solving ill-posedness of inverse kinematics under redundancy of degrees of freedom (DOFs) sustaining motion repeatability of the joints. For achieving this, virtual force constraints in terms of Jacobian transpose and damping factors

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corresponding to the velocity of joints [14] are employed simply to the oscillator based controller as desired torques.

In the following section, a neural controller is briefly explained. The proposed control scheme is described in Section III to design the parameters of the neural oscillator an external force for a desired task. Details of dynamic responses for the verification of the proposed method through simulations are described and discussed in Section IV and V, respectively. Finally, conclusions are drawn in Section VI.

II. Rhythmic Movement Using A Neural Oscillator

We use Matsuoka's neural oscillator consisting of two simulated neurons arranged in mutual inhibition as shown in Fig. 1. If gains are properly tuned, the system exhibits limit cycle behaviors. Now we propose the control method for dynamic systems that closely interacts with the environment exploiting the natural dynamics of Matsuoka's oscillator.

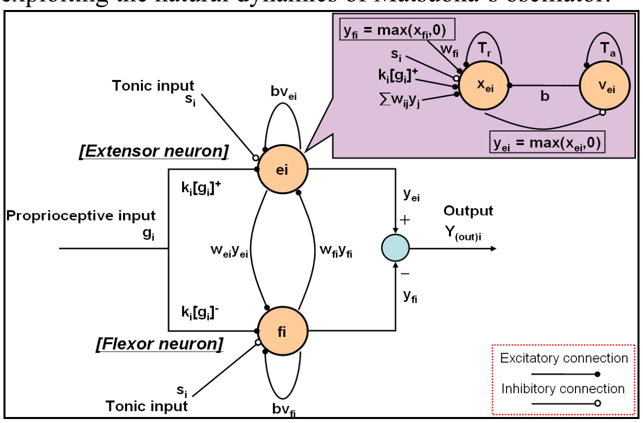


Fig. 1. Schematic diagram of Matsuoka Neural Oscillator

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

where x_{ei} and x_{fi} indicate the inner state of the i-th neuron for $i=1\sim n$, which represents the firing rate. Here, the subscripts 'e' and 'f' denote the extensor and flexor neurons, respectively. $v_{e(f)i}$ represents the degree of adaptation and b is the adaptation constant or self-inhibition effect of the i-th neuron. The output of each neuron $y_{e(f)i}$ is taken as the positive part of x_i and the output of the oscillator is the difference in the output between the extensor and flexor neurons. w_{ij} is a connecting weight from the j-th neuron to the i-th neuron: w_{ij} are 0 for $i\neq j$ and 1 for $i=j$. $w_{ij}y_i$ represents the total input from the neurons arranged to excite one neuron and to inhibit the other, respectively. Those inputs are scaled by the gain k_i. T_r and T_a are the time constants of the inner state and the adaptation effect, respectively, and s_i is an external input with a constant rate. $w_{e(f)i}$ is a weight of the extensor neuron or the flexor neuron and g_i indicates a sensory input from the coupled system which is scaled by the gain k_i.

Fig. 2 shows two types of mechanical systems connected to the neural oscillator. The desired torque signal to the i-th joint can be given by

$$
\tau_i = -k_{oi}(q_i - q_{odi}) - b_i \dot{q}_i, \tag{2}
$$

where k_{oi} is the stiffness of the joint, b_i the damping coefficient, q_i the joint angle, and q_{odi} is the output of the neural oscillator that produces rhythmic commands of the i-th joint. The neural oscillator follows the sensory signal from the joints, thus the output of the neural oscillator may change corresponding to the sensory input. This is what is called "entrainment" that can be considered as the tracking of sensory feedback signals so that the mechanical system can exhibit adaptive behavior interacting with the environment.

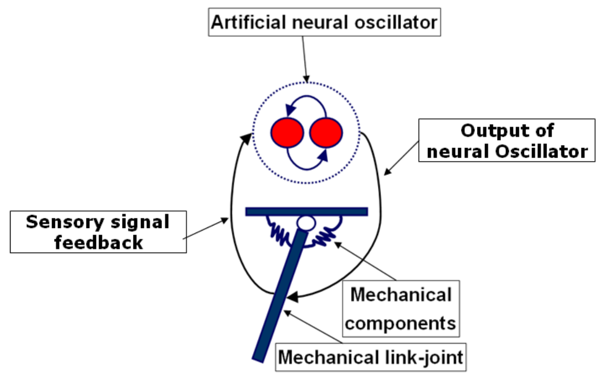


Fig. 2. Mechanical system coupled to the neural oscillator

III. Control Scheme

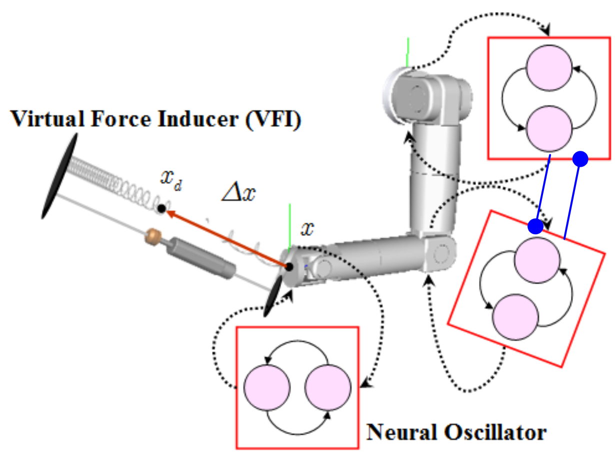


Fig. 3. Schematic robot arm control model coupled with neural oscillators

The neural oscillator is a non-linear system, thus it is generally difficult to analyze the dynamic system when the oscillator is connected to it. Therefore a graphical approach known as the describing function analysis has been proposed earlier [15]. The main idea is to plot the system response in the complex plane and find the intersection points between two Nyquist plots of the dynamic system and the neural oscillator. The intersection points indicate limit cycle solutions. However, even if a rhythmic motion of the dynamic system is generated by the neural oscillator, it is usually difficult to obtain the desired motion required by the task. This is because many oscillator parameters need to be tuned, and different responses occur according to the inter-oscillator network. Hence, we propose the control method that enables a robot system to perform a desired motion without precisely tuning parameters of the neural oscillator within the range of its well-known stable condition.

Figure 3 illustrates a schematic model of a robot arm whose joints are coupled to the neural oscillators. And a virtual force leads the coupled robot arm to a given motion. The virtual force inducer (VFI) such as springs and dampers which is supposed to exist virtually at the target can be transformed into equivalent torques. This causes the end-effector of a robot arm to draw according to the target calculating position error. Also, it is shown that ill-posedness of inverse kinematics can be resolved in a natural way using without introducing any artificial optimization criterion [14], [16]. However, even in such a method kinematic configurations including redundant joints may not be guaranteed, even though the posture of a robot arm could be set only within a certain boundary.

From this point of view, it would be advantageous if neural oscillators are hardly coupled to each joint of a robot arm. When the oscillators are implemented to a robotic arm, they provide a proper motor command considering the movements of the joints with sensory signals. Since biologically inspired motions of each joint as described in section II are attained by entrainment of the neural oscillator, the coupled joint can respond intuitively according to environmental change or unknown disturbance inputs performing an objective motion. In addition, each neural oscillator can be tuned in order to give the criterion with regard to motion limitation to the joints considering the amplitude of the sensory feedback signal.

In general, dynamics of a robot system with n-th DOFs could be expressed as

$$H(q)\ddot{q} + \left\{\frac{1}{2}\dot{H}(q) + S(q,\dot{q})\right\}\dot{q} + g(q) = u, \tag{3}$$

where, H denotes the $n \times n$ inertia matrix of a robot, the second term in the right hand side of Eq.(3) stands for coriolis and centrifugal force, and the third term is the gravity effect. Then a control input for a rhythmic motion of the dynamic system shown in Eq. (3) is introduced as follows;

$$u = -C_0\dot{q} - J^T(k\Delta x + \varsigma\sqrt{k}\dot{x}) - k_o\Delta q + g(q), \tag{4}$$

where

$$C_0 = \mathrm{diag}(c_1,\ c_2,\ \cdots,\ c_n)$$

$$c_i = \varsigma_0\sqrt{k}\sqrt{\sum_{j=1}^{n}\left[H_{ij}\right]},\ (i = 1,\ 2,\ \cdots,\ n)$$

$$\Delta x = x - x_d$$

$$\Delta q = q - q_{od}$$

where k and ς_0 is the spring stiffness and damping coefficient, respectively for the virtual components. C_0 is the joint damping. k_o and q_{odi} are the stiffness gain and the output of the neural oscillator that produces rhythmic commands, respectively.

The control inputs as seen in Eq. (4) consist of two control schemes. One is based on Virtual spring-damper Hypothesis [14], [16] and the other is determined in terms of the output of the neural oscillator as illustrated in Eq. (2). In the control input of Eq. (4), the first term describes a joint damping for restraining a certain self-motion which could be occurred in a robot system with redundancy, and the second term means PD control in task space by using of Jacobian transpose, and also a spring and a damper in the sense of physics. Appropriate selection of joint damping factors C_0, stiffness k and damping coefficient ς render the closed-loop system dynamics convergent, that is, x is converged into x_d and both of $\dot{x}$ and $\dot{q}$ are become 0 as time elapses. In general, the neural oscillators coupled to the joints perform the given motion successively interacting with a virtual constraint owing to the entrainment property, if gains of the neural oscillator are properly tuned [12]-[13]. In the proposed control method, the VFI is considered as a virtual constraint. Also, the coupled model enables a robotic system to naturally exhibit a biologically inspired motion employing sensory signals obtained from each joint under an unpredictable environment change.

Then, closed-loop dynamics with Eq. (3) and Eq. (4) is expressed as

$$H(q)\ddot{q} + \left\{\frac{1}{2}\dot{H}(q) + S(q,\dot{q}) + C_0\right\}\dot{q} + J^T(k\Delta x + \varsigma\sqrt{k}\dot{x}) + k_o\Delta q = 0 \tag{5}$$

The inner product between $\dot{q}$ and the closed-loop dynamics of Eq. (5) yields

$$\dot{q}^T\left[H(q)\ddot{q} + \left\{\frac{1}{2}\dot{H}(q) + S(q,\dot{q}) + C_0\right\}\dot{q} + J^T k\Delta x + J^T\varsigma\sqrt{k}\dot{x} + k_o\Delta q\right] = 0 \tag{6}$$

and

$$\frac{d}{dt}E = -\dot{q}^T C_0\dot{q} - \dot{x}^T\varsigma\sqrt{k}\dot{x} \le 0, \tag{7}$$

where E stands for the total energy

$$E(\dot{q},\ \Delta x,\ \Delta q) = \frac{1}{2}\dot{q}^T H(q)\dot{q} + \frac{k}{2}\|\Delta x\|^2 + \frac{k_o}{2}\|\Delta q\|^2 \tag{8}$$

In Eq. (8), the first term of the quantity E describes the kinetic energy of the robot system, the second term means an artificial potential energy caused by the error Δx in task space and the error Δq gives rise to an artificial potential energy corresponding to the third term in joint space. As it is well known in robot control, the energy balance relation of Eq. (7) shows that the input-output pair $(u, \dot{q})$ related to the motion of Eq. (6) satisfies passivity.

IV. Dynamic Motion Analysis of Three link Planar Arm coupled to Neural Oscillator

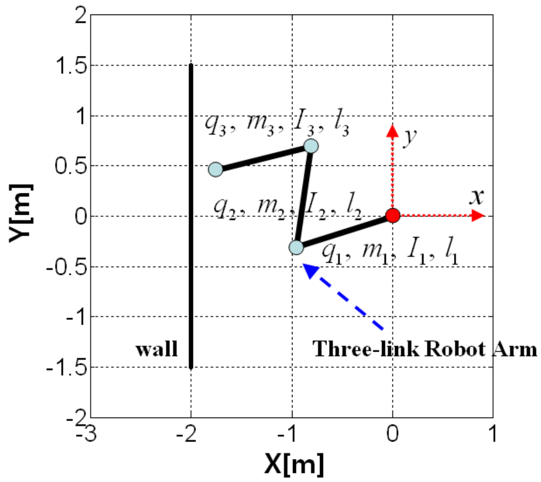


Fig. 4. Three-link planar arm model coupled with neural oscillators

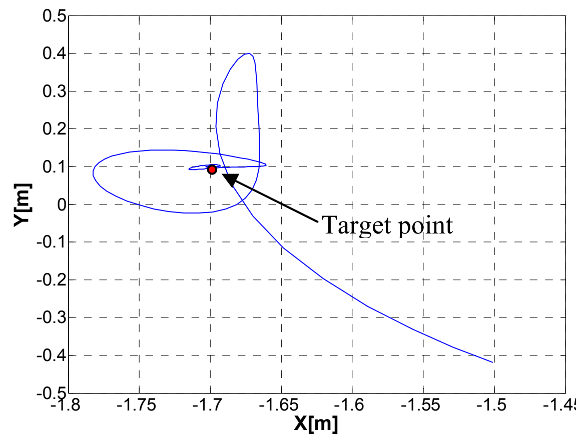
TABLE I
Parameters of the Neural Oscillators with Robot Arm Model

Parameters of Neural Oscillators			
Inhibitory weight (w)		2.5	
Time constant (T_r)		0.16	
(T_a)		0.32	
Sensory gain (k_1, k_2, k_3)	30,	15,	10
Tonic input (s)		4.0	
Robot Arm Model			
Mass1 (m_1), Mass2 (m_2), Mass3 (m_3)	0.5kg,	0.5kg,	0.5kg
Inertia1 (I_1), Inertia2 (I_2), Inertia3 (I_3)	0.042kgm^2,	0.042kgm^2,	0.042kgm^2
Length1(l_1), Length2(l_2), Length3(l_3)	1.0m,	1.0m,	1.0m

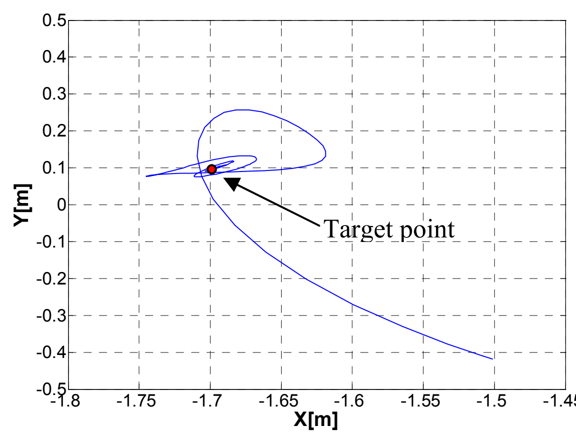
To validate the proposed control scheme, we evaluate arbitrary tasks employing a three-link planar arm whose joints are coupled to neural oscillators as seen in Fig. 4. Then, a neural oscillator network was designed and proposed for showing an efficient adaptive motion. The excitatory connection is adopted between the neural oscillators of the second and third joint. On the contrary, the VFI is coupled to the neural oscillator of the first joint with the inhibitory connection. Table I shows parameters of the neural oscillator and mechanical parameters of the three-link planar arm. With this, the gains for the outputs of the neural oscillators and the stiffness gains for the control inputs are tuned roughly under the condition of a bounded stable oscillation considering the amplitude of the gains of the VFI.

In this section, we compare the simulation results between an approach of the VFI model only and that of the VFI with the neural oscillator. Various tasks in cases I through II with the results of Figure 5 and 6 are verified with respect to given motions. Specifically, an adaptive motion of the arm against environmental change is investigated through simulation of Case III. It is important to be verified whether the proposed control scheme brings about complementary characteristics in viewpoint of biologically inspired robotic motion or not.

A. *Case I*: Point to Point Reaching Movement



(a)

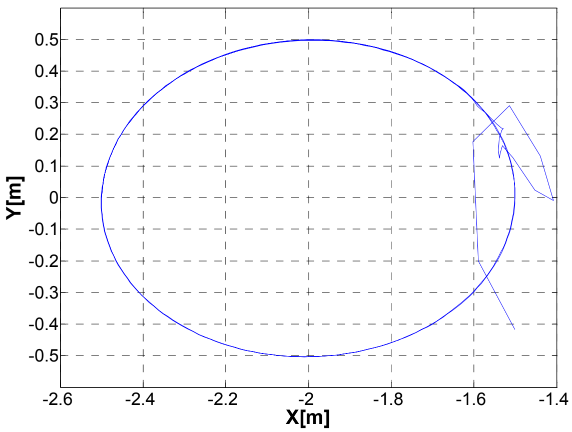


(b)

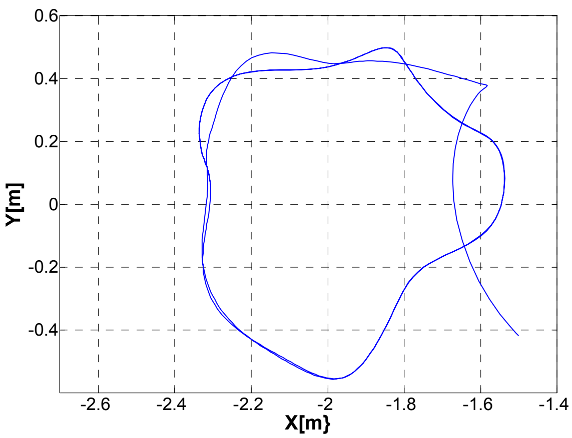
Fig. 5. The trajectory drawn by the end-effector of the robot arm without coupling to the neural oscillator (a) and with coupling to the neural oscillator (b)

We first confirm a reaching motion of the three-link planar arm implementing the proposed control approach. In simulation of case I, the target position is set with (-1.7, 0.1) in Cartesian coordinates. We can observe that the end-effector of the robotic arm is precisely moved to the target position as shown in Fig. 5 (a) and (b). In particular, existing works exploiting the neural oscillator based control have been faced with problems that the correctness of the desired motion is not guaranteed. However, Fig. 5 (b) shows that the robotic arm coupled neural oscillators with the VFI can follow the given position. In addition, comparing Fig. 5 (a) and (b), it can be verified that both of two models show smooth movements from the initial point to the target point.

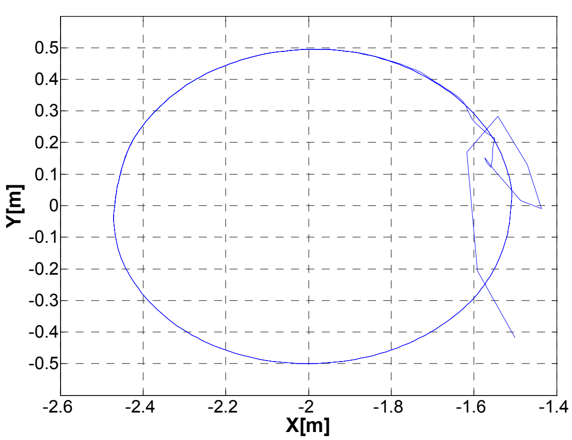
B. Case II: Dynamic Motion in Given Trajectory



(a)

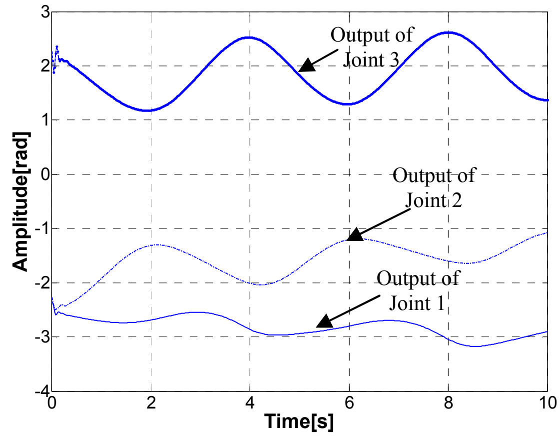


(b)

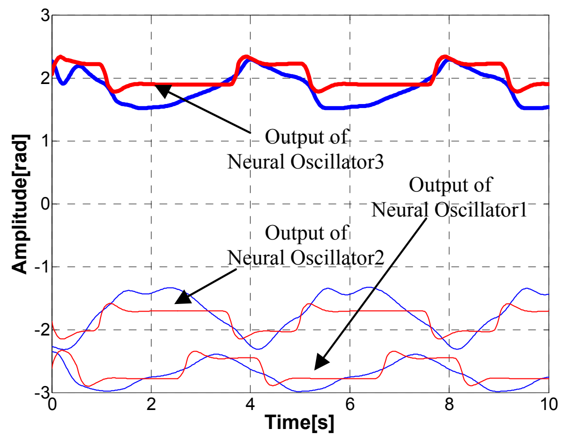


(c)

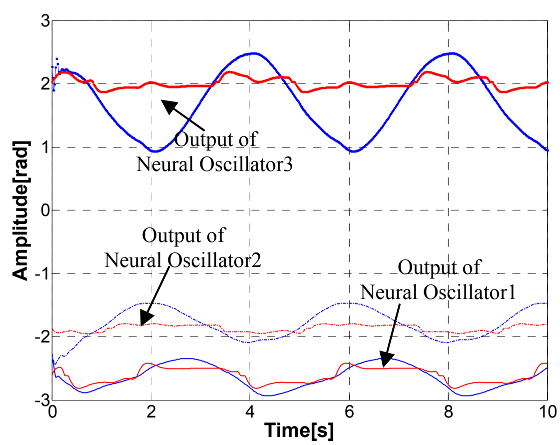
Fig. 6. The trajectory drawn by the end-effector of the robot arm without coupling to the neural oscillator (a) and with coupling to the neural oscillator (b), (c)



(a)



(b)

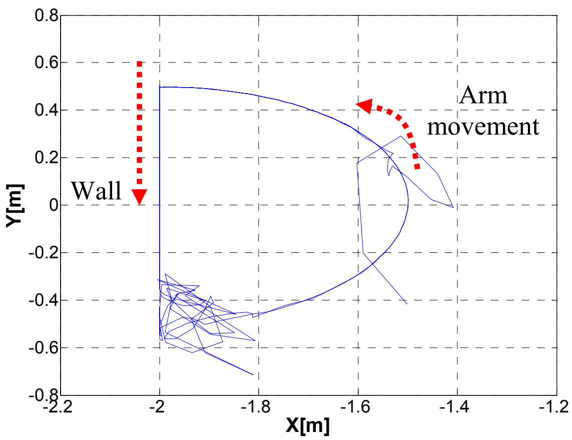


(c)

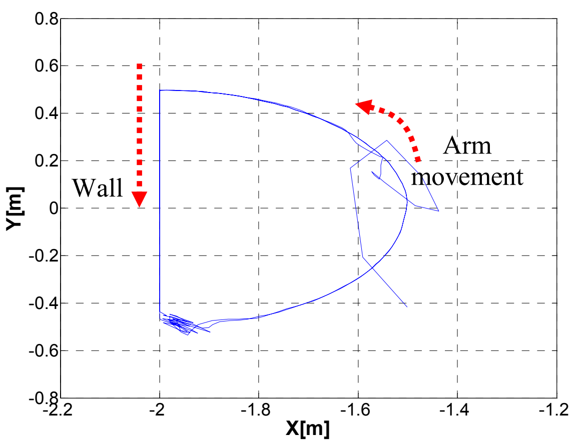
Fig. 7. The joint angle trajectories actuated by the neural oscillator and the output of the neural oscillators. In graphs, the thin line is the first joint angle, the dashed line indicates the second joint angle and the third joint angle is drawn by the thick line.

In case II, the end-effector of the planar arm performs a circular motion as illustrated in Fig. 6. Figure 7 (a), (b) and (c) show the joint angle trajectories corresponding to Fig. 6 (a), (b) and (c), respectively. As expected, it can be observed through Fig. 7 (a) that a problem in kinematic configurations regards as repeatability is exposed. Coupling the neural oscillators to each joint of the robot arm, the related weakness can be complemented as mentioned in section III. In Figs. 7 (b) and (c), we can confirm that repeatability of the joint angle trajectories is maintained owing that each neural oscillators entrain the joint angle trajectories properly. A change in the output of the neural oscillator causes a change in the joint torque. The difference of motion between Fig. 6 (b) and Fig. 6 (c) is induced according to internal network of neural oscillators. We use independently the neural oscillators in simulation of Fig. 6 (b) and the better result in the circle motion of Fig. 6 (c) is caused by efficiently connecting the neural oscillators corresponding to adequate joint motion.

C. *Case III:* Dynamic Motion under Unknown



(a)



(b)

Fig. 8. The trajectory drawn by the end-effector of the robot arm without coupling to the neural oscillator (a) and with coupling to the neural oscillator (b)

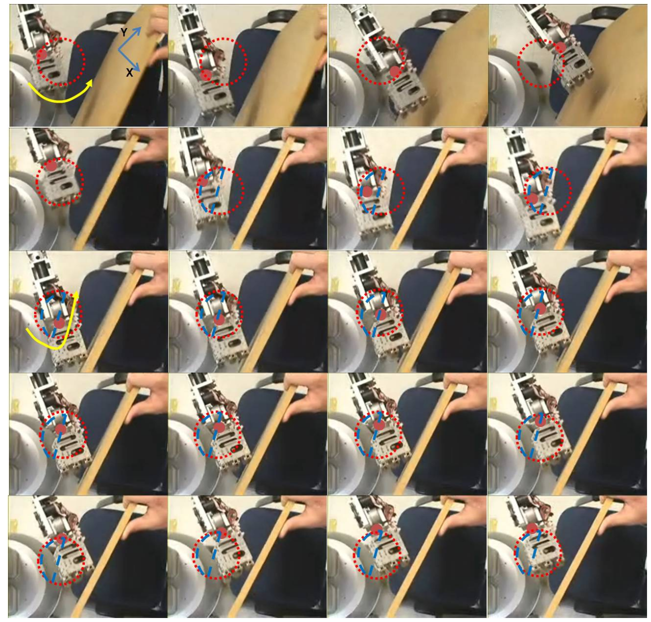


Fig. 9. Snap shots of the arm motion in collision

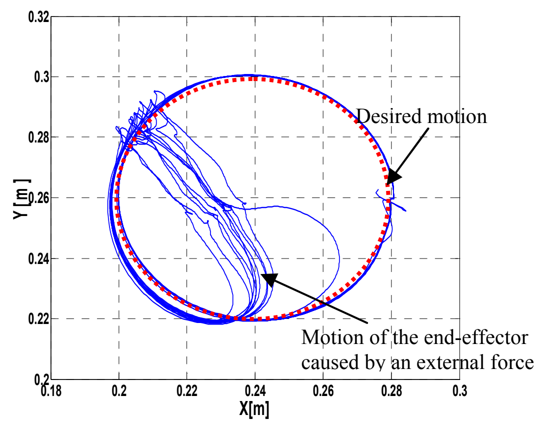


Fig. 10. The trajectory drawn by the end-effector of the real robot arm

Now, we will examine what happens in the arm motion if additive external disturbances exist. For this, an arbitrary wall is considered as seen in Fig. 4. The wall is modeled as a spring with a damper vertically. Figure 8 in case III illustrates the simulation result with respect to the trajectory of the end-effector of the robot arm. Figure 8 (b) shows better adaptive motion than motion of the VFI model only seen in Fig. 8 (a). This is because that though a desired task changes unexpectedly owing to an unknown environment, the entrainment function of the neural oscillator adjusts the control commands in an adaptive way so as to maintain rhythmic movement. It is also demonstrated through the related experiment as shown in Figs. 9 and 10. The end-effector of the robot arm was collided against an arbitrary wall 7s to 15s and 19s to 27s sequentially. Fig. 9 shows the snap shots of the circular motion by the robot arm, where we can observe that the end-effector traces the circle well, and adapts its motion when an external force in terms of unknown environmental change such as the wall is applied to it. Thus we can observe from experiment of Fig. 10 that the robotic arm is well moved along the wall. From these results, it is confirmed that the neural oscillator enables the coupled joint to exhibit a biologically inspired motion to enhance adaptive property sustaining motion stability. Incorporating the proposed control approach to 7-DOF robotic arm, we finally verify a desired motion generation and the repeatability of each joint motion as seen in figure 11.

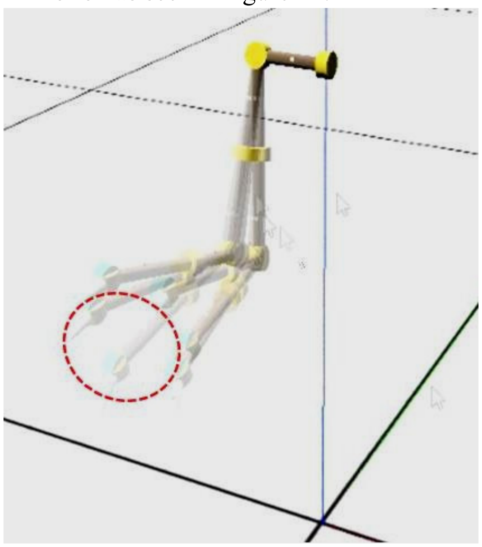


Fig. 11. Simulation result of 7-DOF robotic arm with respect to a circular motion

V. Conclusion

We have proposed a control scheme for technically attaining a biologically inspired robotic motion. The proposed control approach basically consists of the neural oscillator and the virtual force inducer (a spring and a damper) with the joint angle damper. In contrast to existing works that were only capable of rhythmic pattern generation, our approach allowed the robot arm to trace a trajectory correctly through entrainment. For achieving this, we exploit virtual components to easily carry out given tasks without calculating inverse dynamics and considering the ill-posedness problem in redundant systems. The neural oscillator coupled with each joint of a robot arm contributes to sustaining repeatability and naturally setting kinematic configurations of a robotic arm with redundancy. Simulation results showed the effectiveness of the proposed approach. Moreover, it was demonstrated that the robot arm could adaptively behave responding to environmental changes in experiment. This approach will be extended to a more complex behavior with a robotic arm of multi-DOFs toward the realization of biologically inspired robot control architectures.

References

[1] K. Matsuoka, “Sustained Oscillations Generated by Mutually Inhibiting Neurons with Adaptation,” *Biological Cybernetics*, 52:367-376 (1985).

[2] K. Matsuoka, “Mechanisms of Frequency and Pattern Control in the Neural Rhythm Generators,” *Biological Cybernetics*, 56:345-353 (1987).

[3] G. Taga, Y. Yamagushi and H. Shimizu, “Self-organized Control of Bipedal Locomotion by Neural Oscillators in Unpredictable Environment,” *Biological Cybernetics*, 65:147-159 (1991).

[4] G. Taga, “A Model of the Neuro-musculo-skeletal System for Human Locomotion,” *Biological Cybernetics*, 73:97-111 (1995).

[5] S. Miyakoshi, G. Taga, Y. Kuniyoshi, and A. Nagakubo, “Three-dimensional Bipedal Stepping Motion Using Neural Oscillators-Towards Humanoid Motion in the Real World,” *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, 84-89 (1998).

[6] Y. Fukuoka, H. Kimura and A. H. Cohen, “Adaptive Dynamic Walking of a Quadruped Robot on Irregular Terrain Based on Biological Concepts,” *The Int. Journal of Robotics Research*, 22:187-202 (2003).

[7] G. Endo, J. Nakanishi, J. Morimoto and G. Cheng, “Experimental Studies of a Neural Oscillator for Biped Locomotion with QRIO,” *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, 598-604 (2005).

[8] M. M. Williamson, “Postural Primitives: Interactive Behavior for a Humanoid Robot Arm,” *Int. Conf. on Simulation of Adaptive Behavior*. MIT Press, 124-131 (1996).

[9] M. M. Williamson, “Rhythmic Robot Arm Control Using Oscillators,” *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, 77-83 (1998).

[10] A. M. Arsenio, “Tuning of neural oscillators for the design of rhythmic motions,” *Proc. IEEE Int. Conf. on Robotics and Automation*, 1888-1893 (2000).

[11] W. Yang, N. Y. Chong, C. Kim and B. J. You, “Optimizing Neural Oscillator for Rhythmic Movement Control,” *Proc. IEEE Int. Symp. on Robot and Human Interactive Communication*, 807-814 (2007).

[12] W. Yang, N. Y. Chong, Jaesung Kwon and B. J. You, “Self-sustaining Rhythmic Arm Motions Using Neural Oscillators,” *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, accepted (2008).

[13] W. Yang, N. Y. Chong, C. Kim and B. J. You, “Entrainment-enhanced Neural Oscillator for Rhythmic Motion Control,” *Journal of Intelligent Service Robotics*, 6:.303-311 (2008).

[14] S. Arimoto, M. Sekimoto, H. Hashiguchi and R. Ozawa, “Natural Resolution of ill-Posedness of Inverse Kinematics for Redundant Robots: A Challenge to Bernstein’s Degrees-of Freedom Problem,” *Advanced Robotics*, 19: 401-434 (2005).

[15] Jen-Jacques E. Slotine, Weiping Li, “Applied Nonlinear Control,” Englewood Cliffs, N. J., Prentice Hall. (1991).

[16] S. Arimoto, M. Sekimoto, J.-H. Bae and H. Hashiguchi, “Three-dimensional Multi-Joint Reaching under Redundancy of DOFs,” *Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, 1898-1904 (2005).