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Author(s)	Yang, W.; Chong, Nak Young; Kim, C.; You, B.J.
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Description	

Optimizing Neural Oscillators for Rhythmic Movement Control

W. Yang[1], N. Y. Chong[1], C. Kim[2], and B. J. You[2], Member, IEEE

[1]Japan Advanced Institute of Science and Technology, Ishikawa, Japan, e-mail : (woo-yang, nakyoung)@jaist.ac.jp
[2]Center for Cognitive Robotics, Korea Institute of Science and Technology, Seoul, Korea, e-mail:(ckim, ybj)@kist.re.kr

Abstract—**A parameter tuning scheme for the neural oscillator is addressed to achieve biologically inspired robot control architectures based on a neural oscillator. It would be desirable to determine appropriately unknown parameters of the neural oscillator to accomplish a task of rhythmic movement under various changes of environment. Human or animal exhibits natural dynamics with efficient and performs robust motions against unexpected disturbances or environment changes. The neural oscillator needs to be tuned using its optimal parameters to generate such natural movement. As simple examples, this paper connects the neural oscillator to a pendulum system and a rotating crank system. To determine the optimal parameters of the neural oscillator for the examples, the optimization scheme based on the Simulated Annealing (SA) method is used. We verify the performance of the given tasks with the obtained optimal parameters of the neural oscillator, showing the adaptation motions of the example systems with entrainment property in numerical simulations.**

I. Introduction

Studies on human-like movement of robots that need a biologically inspired motion generation and control have been performed by real or virtual human-like robots for the last decade. With this, many previous works have been yielded, particularly in robotic field for embodiment of humanoid locomotion. Owing that such approaches enable robots to realize autonomous dynamic adaptation motion from unknown environmental changes, its attraction has become generally gained and issued. Rhythmic movements of human or animal like walking, running, swimming, flying, breathing, turning a steering wheel, rotating a crank, etc. are dependent on both the musculoskeletal system and nervous system based on rhythmic neural oscillator inherent in their systems. In the musculoskeletal system, it is well known that functions of limbs and limb segments connected to each other with tendons are activated like a mechanical spring by means of a neural signal. The motions of those limbs may look similar to joint motions of a pendulum. The neural oscillator in the nervous system offers a potential controller, since it is known to be robust and have an entrainment characteristic as a general controller

Incorporating the artificial neural oscillator to produce and sustain rhythmic patterned outputs in a robotic system with a coupling method and network, we can realize the nervous and musculoskeletal systems of an animal in different types of artifacts such as robots. Entrainment plays a key role to adapt the nervous system to the natural frequency of the biomechanical system. A neural oscillator, the basic unit of a neural oscillator network, incorporates a sensory feedback, dealing with environmental perturbations. Therefore, more interests on the artificial neural oscillator coupled to robot dynamics have been increasing in the field of biologically inspired robots to be deployable to real-world environments.

Relating these previous works on the application of the artificial neural oscillator to humanoid locomotion, the mathematical description of the artificial neural oscillator was addressed in detail in Matsuoka's works [1]. He proved that neurons generate the rhythmic patterned output and analysed the conditions necessary for the steady state oscillations. He also investigated the mutual inhibition networks to control the frequency and pattern in the neural rhythm generator [2]. However, that work didn't include the effect of the feedback on the artificial neural oscillator. Employing the Matsuoka's neural oscillator, Taga *et al.* investigated a task with more reasonable complexities [3]. The sensory signals from the joint angles of a biped robot were used as the feedback signals. The sensory signals were entrained with the neural oscillator [4]. As a result, the robot became robust to the perturbation and could walk up the slope. And this bipedal robot walking was also simulated and applied to the 3D locomotion by Miyakoshi *et al.* [5]. According to theses works, the neural oscillator successfully realized a dynamic quadrupedal walking and bipedal locomotion with real robot by Kimura *et al.* [6] [7].

In addition to the studies on robotic locomotion, more efforts have been made to implement the neural oscillator to a real robot for various applications. Williamson showed the system that had biologically inspired postural primitives. The joint actuators of that system were implemented using spring models such that the system successfully dealt with unexpected collisions sustaining cyclic motions of the stable arms [8]. He also proposed the neuro-mechanical system that was coupled with the neural oscillator for controlling its arm [9]. Arsenio [10] suggested the multiple-input describing function technique to evaluate and design a nonlinear system based on the neural oscillator. Even though possibility and feasibility of natural dynamic motions adapting to external changes were accomplished by the works mentioned above, approaches based on a biologically inspired system for a complex task of a robotic manipulator were not clearly described.

As above, researches in the field of biologically inspired system with the neural oscillator have yielded notable results in many cases. However an approach for the behavior gen-

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eration of robotic arms or a legged robot's locomotion still has many problems undetermined due to the difficulty of parameter tuning of a neural oscillator coupled to a mechanical system for generating a desired motion. Therefore, this paper proposes a new methodology to tune parameters of a neural oscillator connected to a mechanical system to accomplish the desired task. To do this, the paper deals with a simple mechanical system that consists of a pendulum and a two-link planner arm and is coupled to the neural oscillator for control. A procedure based on optimization to choose the parameters of the neural oscillator is proposed. In the following section, we briefly describe the mathematical form of the neural oscillator. In section III, the analysis of the coupled model and the optimization algorithm to determine parameters of the neural oscillator are described. Details of dynamic responses and the verification of developed methodology are discussed in Section IV. Conclusions are drawn in Section V.

II. GENERATION OF RHYTHMIC MOVEMENT USING A NEURAL OSCILLATOR

A. Matsuoka's neural oscillator

Our work is motivated by studies and facts of biologically inspired locomotion control employing oscillators. Especially, the basic motor pattern generated by the Central Pattern Generator (CPG) of inner body of human or animal is usually modified by sensory signals from motor information to deal with environmental disturbances. Similarly to the sensory system of human or animal, the neural oscillators are entrained with external stimuli at a sustained frequency. They show stability against perturbations through global entrainment between the neuro-musculo-skeletal systems and the ground [3]. Thus, neural oscillators have been applied to the CPG of humanoid robots with rhythmic motions [4]. The oscillators provide robust performance in a wide variety of rhythmic tasks, when they are implemented to such a system as a robotic arm. The reason is that the oscillators use sensory signals about the joint state to adapt the frequency and phase of the joint motion regardless of the references corresponding to change of the environment.

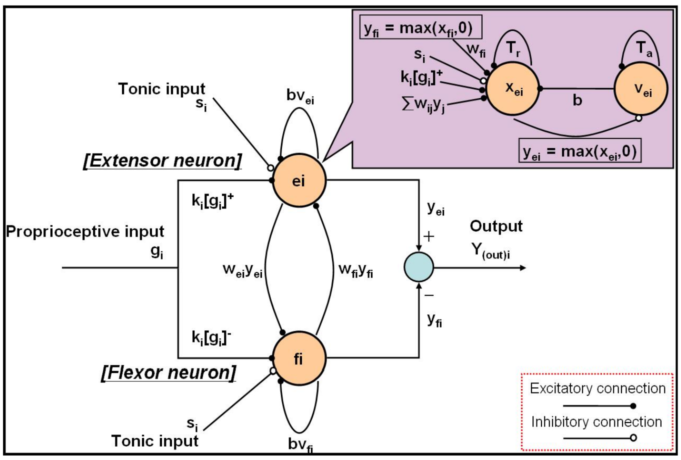


Fig. 1 Schematic diagram of the NEURAL OSCILLATOR

Matsuoka's neural oscillator consists of two simulated neurons arranged in mutual inhibition as shown in Fig. 1 [1], [2]. If gains are properly tuned, the system exhibits limit cycle behaviours. The trajectory of a stable limit cycle can be derived analytically, describing the firing rate of a neuron with self-inhibition. The neural oscillator is represented by a set of nonlinear coupled differential equations given as

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

where $x_{e(f)i}$ is the inner state of the i-th neuron which represents the firing rate; $v_{e(f)i}$ is a variable which represents the degree of the adaptation, modulated by the adaptation constant b, 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 whole oscillator as $Y_{(out)i}$; $w_{ij}y_i$ represents the total input from the neurons inside a neural network; 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; b is a coefficient of the adaptation effect; w_{ij} is a connecting weight from the j-th neuron to the i-th neuron; s_i is an external input with a constant rate. Especially, w_{ij} (0 for $i \neq j$ and 1 for $i=j$) is a weight of inhibitory synaptic connection from the j-th neuron to the i-th, and w_{ei}, w_{fi} are also a weight from extensor neuron to flexor neuron, respectively.

B. Coupling neural oscillator to mechanical systems

This subsection addresses a new control method exploiting the natural dynamics of the oscillator coupled to the dynamic system that closely interacts with environments. This method enables a robot to adapt to changing conditions. For simplicity, we employed a general 2nd order mechanical system connected to the neural oscillator as seen in lower system of Fig. 2. The desired torque input at the i-th joint can be given by [8]

$$\tau_i = k_i(\theta_{vi}-\theta_i)-b_i\dot{\theta}_i, \tag{2}$$

where k_i is the stiffness of the joint, b_i the damping coefficient, θ_i the joint angle, and θ_{vi} the desired joint position which is the output of the neural oscillator. The output of the neural oscillator drives the mechanical system corresponding to the sensory signal input (feedback) from the actuator (displacement or torque). The oscillator entrains the input signal so that the mechanical system can exhibit adaptive behaviour even under the unknown environment condition.

The key to implementing this method is how to incorporate the input signal's amplitude information as well as its phase information.

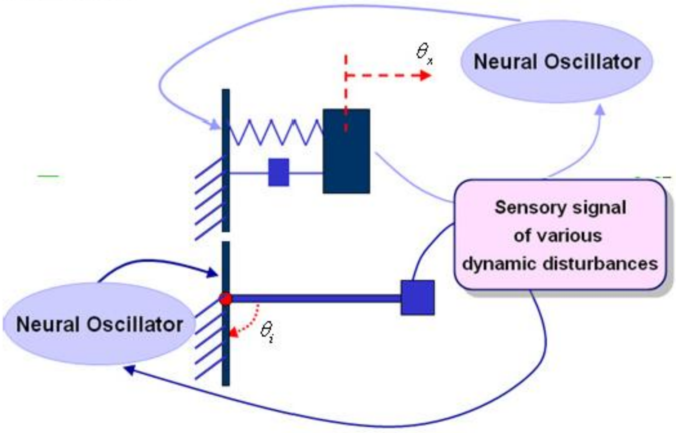


Fig. 2 Mechanical system model coupled to the neural oscillator

III. Parameters Optimization of the coupled Neural Oscillator

A. Function analysis

The neural oscillator connected to a mechanical system is a non-linear system. So it is generally difficult to solve this equation analytically. Therefore a graphical approach has been taken by some researchers. This method is known as describing function analysis [11]. The main idea of the method is to plot the equation in the complex plane and find the intersection points of the two curves. The intersection points of the two curves with match the natural frequency, ω , indicate limit cycle solution. However, even if rhythmic movement of the mechanical system coupled with the neural oscillator is generated, it may be difficult to obtain the peculiar motion to satisfy the requested task due to a number of the parameters of neural oscillator and the different dynamic response of the model according to connection structure of the neural oscillator networks. Hence, in subsection *B*, we describe how to determine the parameters of neural oscillator using optimization to sustain stability of the oscillator.

B. Optimization of neural oscillator parameters

Metropolis method based on the SA for optimization [12], is employed to obtain the optimal parameters of the neural oscillator coupled to the mechanical system. *Metropolis* method has been used to search the global extremum (minimum or maximum) of a cost function in many applications. This optimization algorithm based on the SA is said to guarantee the global optimality [13].

In optimization, the essential starting parameters minimizing cost function E to evaluate an energy equation are T_0, initial temperature; X (e.g. $X=[T_r, T_a, w, s, \cdots]^T$, optimization variables of the neural oscillator; and v, the step size, called learning rate, for X. A function evaluation equation is given by;

$$X_i = X_{i-1} + v \cdot N, \tag{3}$$

where N notes a distributed random number from [-1, 1] such as Gaussian noise. By means of Eq. (3) is generated new solution of the given cost function at i-th trial. If the cost function, ΔE, computed at i-th trial is less than zero, X_i is accepted and stored. If otherwise, the transition probability, $Prob_i(E)$ of the i-th unit is given by the following equation,

$$Prob_i(E) = (\frac{1}{Z(T)})\exp(-\frac{\Delta E}{c}) > \gamma, \tag{4}$$

where ΔE is change in the cost function value, $\Delta E = E_i - E_{i-1}$; γ is random value uniformly distributed between 0 and 1. If $\Delta E \geq 0$ and $Prob_i(E)$ is less than γ or equal zero, X_i is rejected. Cooling schedule is $c_i = k \cdot c_{i-1}$ (k is the Boltzmann constant or effective annealing gain) and $Z(T)$ is a temperature-dependant normalization factor. Here the lower cost function value and large difference of ΔE indicate that X_i is the better solution.

However, even though the SA has several potential advantages over conventional algorithms, if the SA is applied for achievement of the objective task of a mechanical system coupled with the neural oscillator, a crucial problem may be happened. On searching for objective variables, this is annealing process in viewpoint of the SA, we can't recognize whether the task is successively performed with the selected parameter values or not. If the probability to be driven errors which wrong parameters are taken exists in processing of the SA in terms of such reason, the final stable values at the lowest level of cost function is unbelievable. We newly, accordingly, designed a cost function comparator and a distinguishable module of a task performance in this work as shown in Fig. 3. The process for embodiment of these modules is added to the SA and is illustrated with thick-lined box of Fig. 3. In our work, the comparator finds the optimized parameters of the lowest cost function level to be normalized and whether objective task is feasible or not results from the distinguishable module. If a failure task is happened after examining the desired task, the process is terminated at a moment and the two modules proposed in this research are activated in sequential. And than again this optimal process is operated with parameters and initial values to perform the objective task at the lowest cost function value.

IV. Simulation Results

For validation of the proposed scheme on optimal dynamic systems control based on the neural oscillator to adapt to an environmental variation, we evaluate swing task of pendulum model and crank-rotation task of two-link planner robot arm in this section. And then, we discuss and prove on entrainment property in point of view of dynamic property when the neural oscillator is coupled to mechanical systems. The coupled models are illustrated in Fig. 4 (a) and (b). Here, the oscillators are individually connected with mechanical joints. In this work, inner networks of the neural oscillators isn't considered owing that same signed initial conditions drive an identical effectiveness with excitatory connection of neural oscillator network.

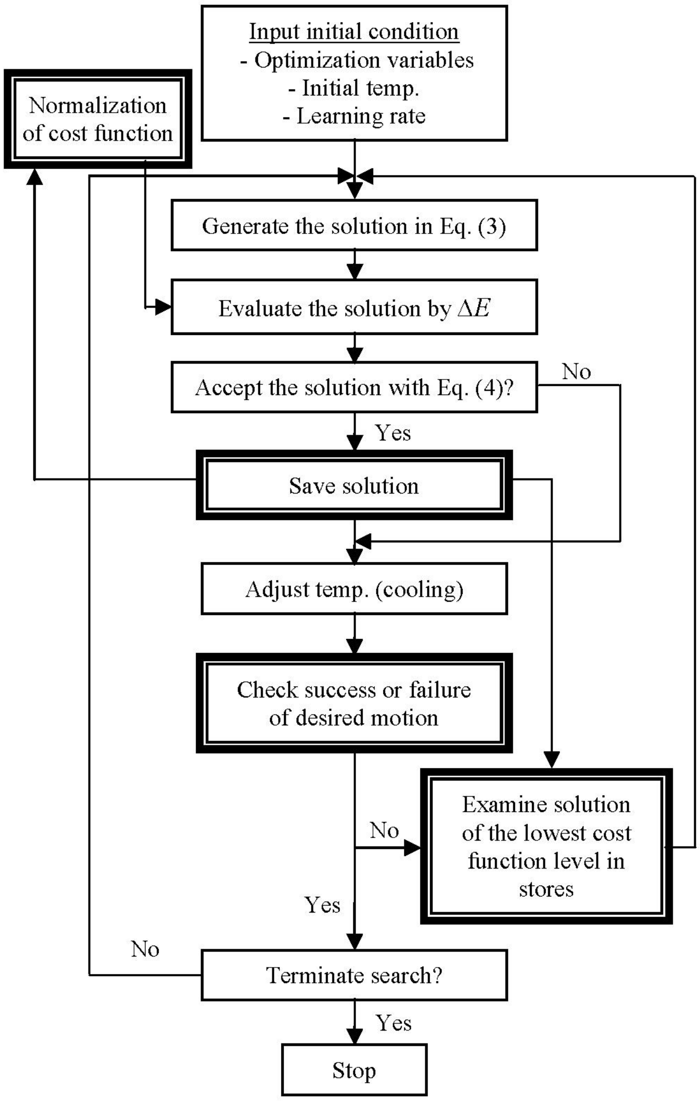
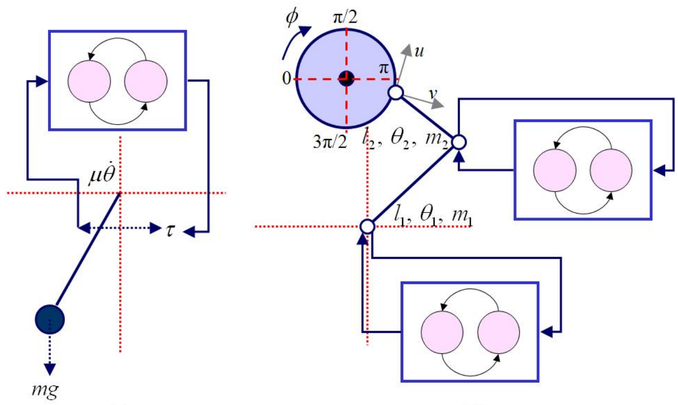


Fig. 3 Flowchart of the upgraded SA for task based parameter optimization



(a) (b)

Fig. 4 (a) Schematic model of pendulum coupled with the neural oscillator (b) Schematic model of crank rotation task of two-link planner elbow arm coupled with the neural oscillator

A. Swing of a single pendulum

This subsection explores the optimization process of parameters of the neural oscillator for swing task of pendulum and describes the discrepancy of behavior generated by the mechanical system coupled with the neural oscillator employing the optimized parameters. The pendulum model is described by the following equation:

$$ml^2\ddot{\theta} + \mu\dot{\theta} + mgl\sin\theta = \tau \qquad (5)$$

where τ is induced by means of the output of the neural oscillator. This output is given by:

$$\tau = y_{ei} - y_{fi} = [x_{ei}]^+ - [x_{fi}]^+ \qquad (6)$$

In addition, the output, θ, of Eq. (5) is fed again into the input, $k_i \cdot [g_i]^+$, of the neural oscillator as sensory signal. This coupled model is incorporated for validation of the proposed parameter turning method based on the SA according to an objective. Hence, the objective task in this simulation is to generate the most efficient swing motion of the one-link pendulum.

To technically accomplish this objective, cost functions to exhibit performance of dynamic motion are employed, respectively, as followings:

1. Energy generated by torque (E_1)
2. Energy consumption caused by viscosity (E_2)
3. Potential energy (E_3)

While the coupled oscillator-pendulum model periodically moves to do the given task, the energies called cost functions in this paper are generated and consumed. Here, the lowest level of the summation of each cost function notes that the coupled model considering parameters of the neural oscillator acquired from the improved SA is superior to its model using arbitrary parameters in the viewpoint of motion's efficiency. Motion's efficiency indicates the ratio of the in/output as follow:

$$M_e[\%] = \frac{\theta}{\tau} \times 100 \qquad (7)$$

The optimization variables, X, of the neural oscillator are T_r, T_a and w. And initial parameters of the neural oscillator and mechanical model in order to perform this given task are seen in Table I. Fig. 5 indicates cooling state in terms of cooling schedule and cooling or annealing gain K is set as 0.95. We are convinced in Fig. 6 that the optimization process is well operated and obtains better solution at the lowest cost function level converged by steps. Figures 7 (a) and (b) illustrate the procedure in order to select parameters of the neural oscillator. The behavior of the coupled oscillator-pendulum model shows oscillatory motion converging quickly to a steady state frequency and amplitude of motion. This motion is illustrated in (c) of Fig. 7, where the red thin line is the output of the neural oscillator and the blue thick line is the output of the pendulum. In Fig. 8, the proposed optimization process is verified employing Eq. (7). When appropriate parameters are applied to the neural oscillator within neighborhood of the pendulum's length such as $0.5 \le l \le 1.5$, respectively, the output of coupled oscillator-pendulum larger than that of coupled model incorporating parameters optimized in case of l=1.0. The upper blue-dash line (●) indicates the former and the result of the latter is drawn by lower red line (■). By means of this, we are able to confirm that the motion of the swing pendulum is under the best condition when the parameters through the proposed parameter turning method are adapted.

Table I. Initial parameters of the neural oscillator and mechanical model

Neural Oscillator	
Inhibitory weight	2
Adaptation constant	2
Tonic input	3
Sensory gain	8
Time constant (T_r)	0.5
(T_a)	1
Mechanical Model	
Mass	1kg
Viscosity	4.5Ns/m
Length	1m

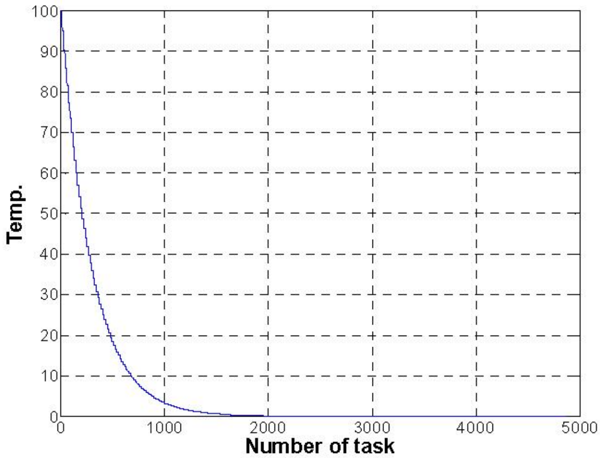


Fig. 5 Temperature transition for cooling schedule

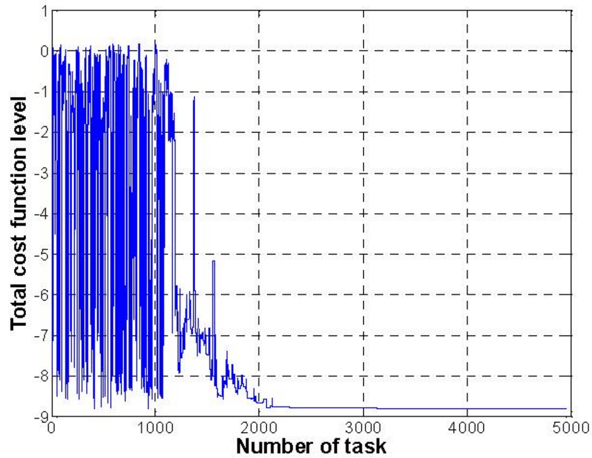


Fig. 6 A transition of total cost function level of the neural oscillator

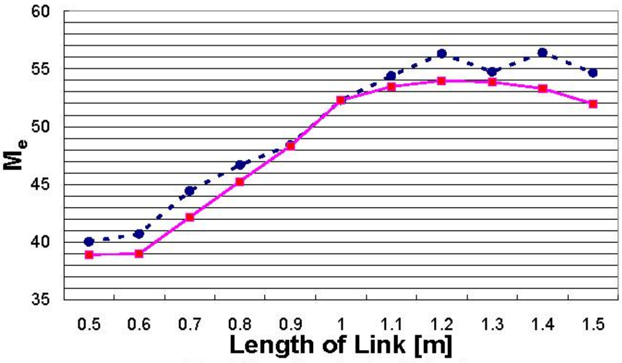


Fig. 8 Plot of motion's efficiencies

B. Crank rotation of two-link planner arm

As shown in Fig. 4 (b), two-link planar arm is considered to evaluate the improved SA and the dynamic entrainment property of the neural oscillator. Also, the dynamic model for the crank rotation is designed to generate a constraint and an appropriate external force. The crank model has moment of inertia I and derives torque with viscosity, C, from a motor. If arbitrary Cartesian coordinate of the end-effector of the two-link arm is defined as (x, y) on the crank dynamic model and the origin of the crank centre in Cartesian coordinate is (x_0, y_0), the coordinates x and y are given as

$$\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} -r\sin\phi + x_0 \\ r\cos\phi + y_0 \end{pmatrix} = \begin{pmatrix} l_1 c_1 + l_2 c_{12} \\ l_1 s_1 + l_2 s_{12} \end{pmatrix}$$
$$\begin{pmatrix} \ddot{x} \\ \ddot{y} \end{pmatrix} = \begin{pmatrix} r\sin\phi\dot{\phi} - r\cos\phi\ddot{\phi} \\ -r\cos\phi\dot{\phi} - r\sin\phi\ddot{\phi} \end{pmatrix} = \frac{\partial J(\theta)^2}{\partial^2\theta} \tag{8}$$

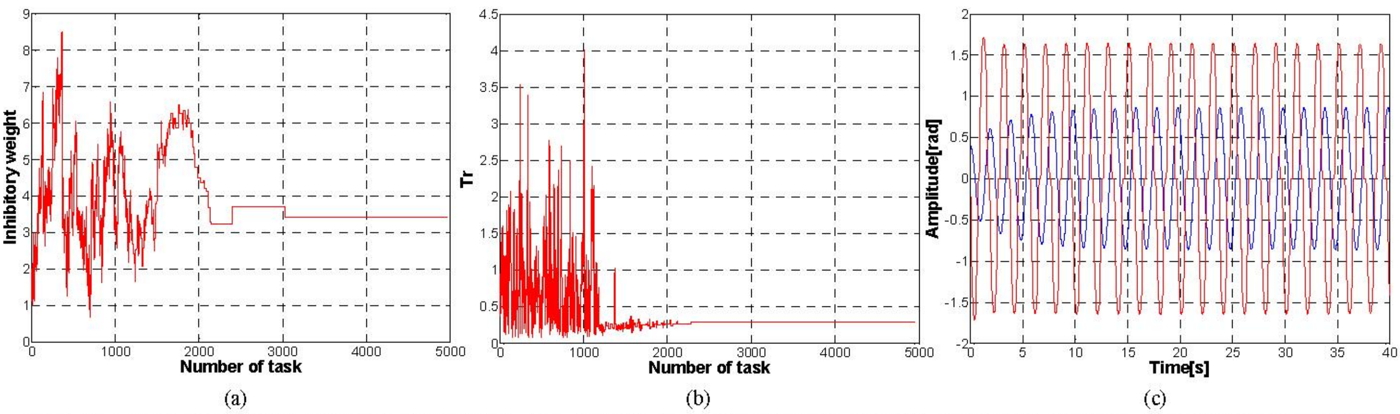
Equation (8) can be rearranged as follows:

$$J(\theta)\ddot{\theta} + \dot{J}(\theta,\dot{\theta})\dot{\theta} = r(u(\phi)\ddot{\phi} - v(\phi)\dot{\phi}^2), \tag{9}$$

where J is the Jacobian matrix of $[x, y]^T$. φ and θ_i are the crank angle and the i-th joint angles, respectively. l_i is the i-th joint length. c_1, c_{12}, s_1 and s_{12} denote cos θ_1, cos($\theta_1+\theta_2$), sin θ_1 and sin($\theta_1+\theta_2$), respectively. r is the radius of the crank. u is the tangential unit vector and v is the normal unit vector at the outline of the crank model. These vector directions are shown in Fig. 2, respectively.

The dynamic equilibrium equations of the crank and two-link arm are in the standard form

$$I\ddot{\phi} + C\dot{\phi} = ru(\phi)^T F \tag{10}$$
$$M(\theta)\ddot{\theta} + V(\theta,\dot{\theta}) + G(\theta) = \tau' - J(\theta)^T F \tag{11}$$



(a) (b) (c)

Fig. 7 (a) A weight transition of inhibitory connection of neural oscillator (b) A rising time constant transition of neural oscillator (c) The output of the coupled pendulum and neural oscillator. The red thin line is the output of neural oscillator and the blue thick line is the output of the coupled pendulum.

where M is the inertia matrix, V the Coriolis/centripetal vector, and G the gravity vector, where $\tau' = \tau - b\dot{\theta}$ and b denotes the joint viscosity matrix [14]. F is the contact force vector interacted at the connecting joint between the crank and two-link arm. By solving Eqs. (10) and (11) simultaneously using Eq. (9), F is given as

$$F = \{J(\theta)M(\theta)^{-1}J(\theta)^{T} + r^{2}I^{-1}u(\phi)u(\phi)^{T}\}^{-1} \cdot \{J(\theta)M(\theta)^{-1}(\tau' - V(\theta)) + \dot{J}(\theta,\dot{\theta})\dot{\theta} + r\dot{\phi}(v(\phi)\dot{\phi} + CI^{-1}u(\phi))\} \tag{12}$$

In this dynamic model, not only F has unique solution, but a general dynamic system has only unique solution without kinematic redundancy. In a system of this kind, it is so hard to select appropriate parameters of the neural oscillator for the given task even though this system dynamics is a redundant system where the number of D.O.F. is short in comparison with the number of actuators. Turning approach based on the SA has necessary cost functions to embody the objective task of a robot system. In the SA, the given task motion is performed repeatedly and, at same time cost functions are calculated according to annealing schedule with various parameters. However, the failure of the process may be happened frequently owing that the objective task isn't successively done with various parameters and, what is more, this dynamic model is a unique system, not redundant system. By means of such reasons, we improved the parameter turning method based on the SA to cope with various tasks with the coupled oscillator-mechanical system as mentioned in section III.

Individual joints of the dynamic model considered in this paper are coupled to the neural oscillators as shown in fig. 4. With this, the objective task is to rotate the crank with each joint output of manipulator controlled in terms of the neural oscillator. In this simulation, the neural oscillator network doesn't construct. The individual neural oscillators are able to entrain multi-body system without network such as direct inter-oscillator inhibitory connection. Entire process of the parameter turning approach is divided into two steps as follows:

1) Step 1: To roughly make the appropriate initial inputs of the neural oscillator corresponding to desired inputs of each joint, the cost function is given by:

$$\varphi = \left|\frac{T - T_G}{T_G}\right| + \nu \cdot \max\left(\frac{|A_d - C|}{B} - 1, 0\right) \tag{13}$$

subject to

i) $A_{\min} \le A_d \le A_{\max}$

ii) $|A_d - C| \le B$

where $C=(A_{\max}+A_{\min})/2$, $B=(A_{\max}-A_{\min})/2$; A_d is the desired amplitude, $A_{\max}$ and $A_{\min}$ are the maximum and minimum of amplitude, respectively; T denotes the natural frequency of a signal. v is performance gain.

2) Step 2: Incorporating the initial parameters obtained by Step1, the improved SA is operated with process illustrated in Fig. 7. In cost function for the crank rotation, we employ velocity of the rotating crank, generating torque and consumed energy.

Implementing Step1 and Step2 in sequential, we are able to acquire the appropriate initial and properly tuned parameters as seen in Table II. As expected, when tuned parameters are employed in order to perform the given task, appropriate stable motion could be accomplished. This result is shown well in Fig. 9. In Fig. 9 (b), a transient region in the early part of the simulation appears and disappears on account of the particular entrainment property of the neural oscillator. This property enables a manipulator to implement and sustain the given task under various environmental changes such as change of a manipulator's platform, outer disturbances, etc.

Hence, in order to verify the possibility of such adaptation performance, we apply various circumstances to the coupled oscillator-two link arm model. Since the neural oscillator for the objective task totally dominates the kinematic constraints of the crank and two-link arm, we alter the conditions with respect to geometric parameters of the two-link arm and the crank dynamic properties up to about two and three times; joint length and mass, crank radius and inertia, viscosity, etc. In Fig. 10, the coupled model tuned properly is enforced to fast and smoothly revolve the crank in terms of the changed circumstance. Fig. 10 (a) and (d) indicate the desired trajectories that an alternation is enforced according to environmental variety. Although severe changes as previously mentioned are applied, the coupled model with adaptation time successfully performs the given tasks as illustrated in Fig. 10 (b), (c), (e) and (f). With the above simulation result, therefore, it can be verified that the neural oscillators enable the two-link planner arm to skillfully perform the desired task regardless of somewhat change of the used mechanical model dynamics and outer circumstance if the desired joint input for a task is closed to periodic angle.

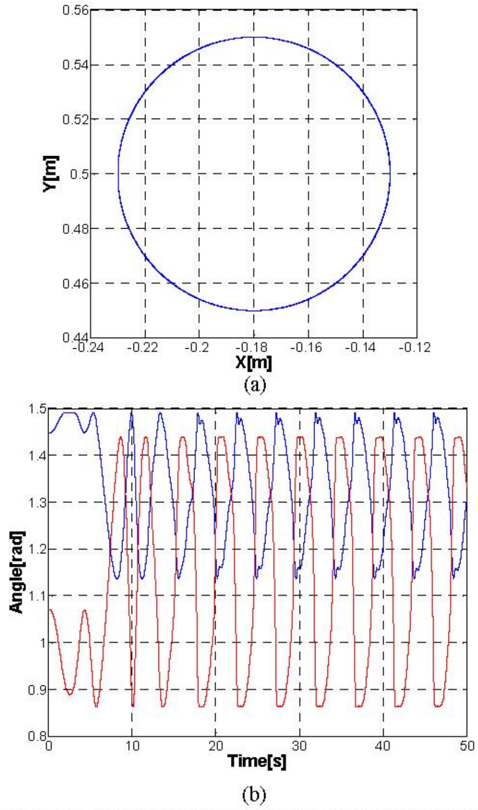


Fig. 9 (a) The end-effector trajectory of two-link arm (b) The output of joint angle. The red dash line is the first joint angle and the second joint angle is drawn by the blue thin line

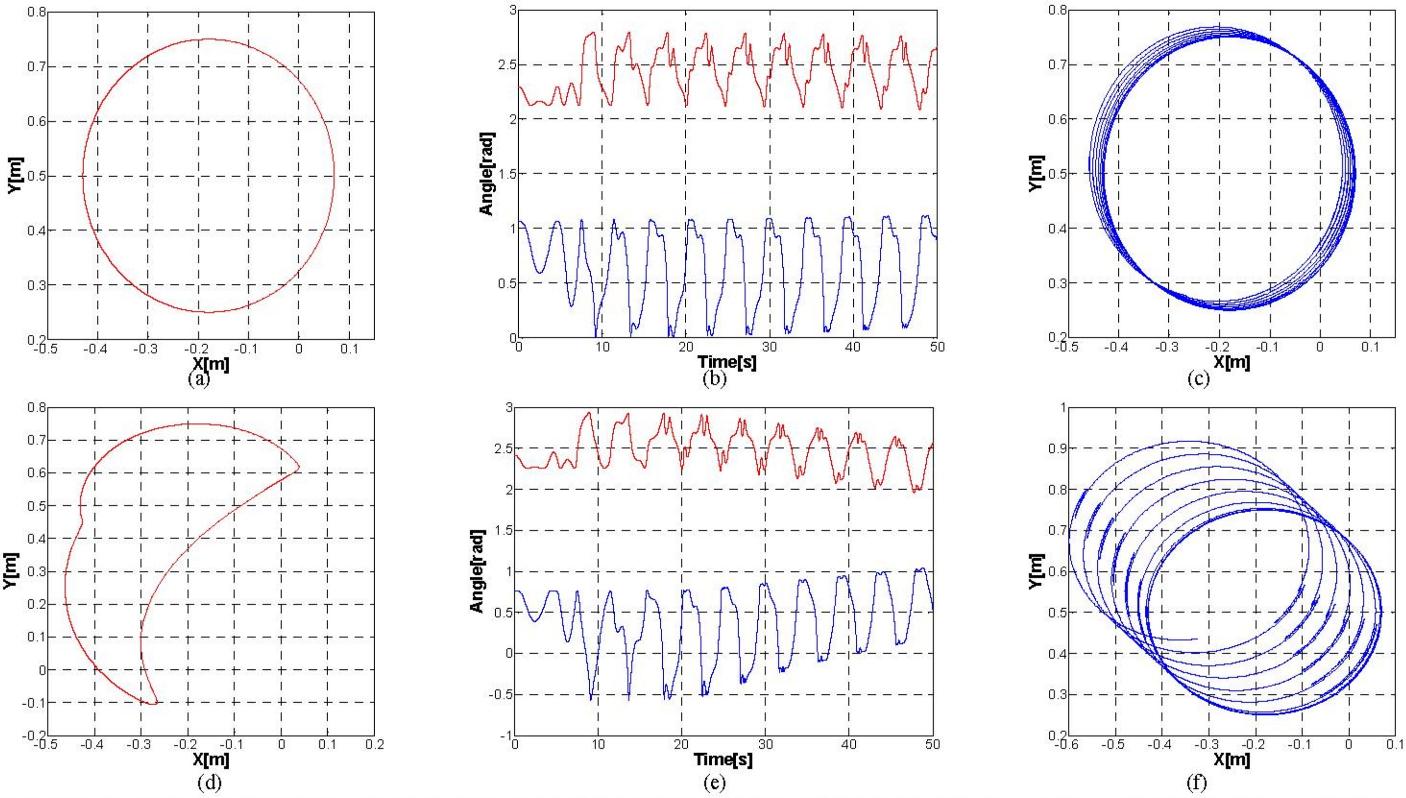


Fig. 10 (a) The desired trajectory of end-effector (b) The output of joint angle. The red dashed line is the first joint angle and the second joint angle is drawn by the blue thin line (c) The trajectory of end-effector of two-link model coupled with neural oscillator (in case of about two times change)
(a) The desired trajectory of end-effector (b) The output of joint angle. The red dashed line is the first joint angle and the second joint angle is drawn by the blue thin line (c) The trajectory of end-effector of two-link model coupled with neural oscillator (in case of about three times change)

Table II. Comparison between initial parameters and parameters of the neural oscillator tuned optimally by the modified SA

Initial parameters		Optimized parameters	
Inhibitory weight	2.0	Inhibitory weight	1.8922
Time constant (T_r)	0.25	Time constant (T_r)	1.0075
(T_a)	0.5	(T_a)	2.0150
Sensory gain	1	Sensory gain	2.4210
Tonic input	60	Tonic input	59.9575

V. Conclusion

We have described a dynamic response of a mechanical system coupled with the artificial neural oscillator with entrainment capability which can be applied under the condition of unknown environment. Even if there exist some approaches to design and analyze the coupled system, existing works on the neural oscillator did not distinctively address how to cope with the possible parameter designing and the entrainment property when the objective task was given under various states. Our aim was to optimally tune parameters of the artificial neural oscillator connected into a mechanical system with regard to the given task. For this, we newly improved the optimal method based on the SA and proposed how to deal with the coupled model with the procedure of the approach.

Our scheme to select appropriate parameter and by this, adaptable movements of the modelled manipulator were clearly verified under environmental change through efficient numerical simulations. Particularly, the adaptation motion in terms of the entrainment property of the virtual coupled model was investigated with some different conditions. Also, it was observed from simulation results of the model was investigated with some different conditions. Also, it was observed from simulation results of the appropriately tuned coupled model that transient regions corresponding to alternation of conditions appear. This approach will be a new contribution toward the realization of biologically inspired robot control architectures. A rigorous feasible possibility with the various tasks and entrainment property based on the proposed scheme is currently under way within the framework of control theory. Relating to the future research, we will show the practical validity of this approach through experiments with real robots.

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