1. INTRODUCTION

In an aging society it will be necessary that robots work for housekeeping and elderly care at home and hospitals. These robots will have to interact physically with humans. Therefore, the human-robot physical interaction is an important subject for the future robots for purposes of housekeeping, elderly care and entertainment.

It is important to synchronize the robot motion with that of human motion in order to make a natural physical interaction. However it is not possible to realize the synchronization between human and robot motions by conventional compliant control. Recently, neural oscillators have been applied to walking [1] and rhythmic motions [2] of robots in order to generate periodic motions synchronized with the environment. This research seeks to apply a neural oscillator to a human-robot physical interaction in order to realize a natural interaction based on synchronization between human and robot motions.

We focused on handshaking as an example of the human-robot interactions. When a handshake is performed between persons, there is neither master nor slave in the motions. And the motions come close to the same period naturally. We consider that the synchronization and the entrainment between both motions are the basic phenomena. Therefore to realize human-robot handshaking like a natural handshake between persons we propose to use neural oscillators. In the handshake it is possible that one person is passive and the other is active. Such passive handshake can be performed by adjusting strength of the synchronization. Output signals of neural oscillators are used for the desired trajectories of robot joints. The external force applied on the robot is fed back into the neural oscillators. Then the motion of the robot is synchronized with human motion and entrained to the same period.

There have been a number of studies concerning physical human-robot interaction, e.g. [3, 4]. Many have focused on impedance control for robots, which regulates impedance for fluctuation from the reference trajectory. Using this method, the reference trajectory of the robot must be determined in advance of the robot making such a motion. Although we anticipate human motion to determine the reference trajectory of the robot, it is very difficult to estimate future human motion exactly. To solve this problem, we first have to determine which side is the master and which side the slave in advance. Thus, the slave side follows the motion of the master side. However, in human-human natural interaction such as handshaking, there is neither master nor slave in such motions. As a result, it is very difficult to apply impedance control for natural physical human-robot interactions.

In this paper we address a framework of human-robot handshaking based on neural oscillators and examine the validity by computer simulation and the experiment. In the next chapter the proposed control method is described. In Chapter 3, a model and characteristics of the neural oscillators are outlined. Chapter 4 proposes a structure of a neural oscillator. The simulations of the handshaking using neural oscillators are performed in Chapter 5. In Chapter 6, the experiments and psychological evaluations are conducted to examine the effectiveness of the proposed method. Finally, we conclude this paper in Chapter 7.
2. SYNCHRONIZATION BASED CONTROL

This chapter addresses Synchronization Based Control (SBC) for human-robot physical interactions. Synchronization and entrainment between human and robot motions are performed by SBC. Passivity of the interaction can be changed by adjusting the strength of the synchronization.

We utilize synchronization and entrainment of neural oscillators to generate synchronized robot motion. Also the gain of the input signal adjusts the strength of the synchronization. Figure 1 shows the basic structure of SBC. Neural oscillators are installed on each robotic joint, and its input signal is the joint torque caused by interaction with the human. The output signal is the desired joint angle. Using this control technique, synchronization phenomena are realized between human and robot motions. The strength of the synchronization is adjusted continuously by the input gain.

3. NEURAL OSCILLATOR

3.1 Neural oscillator

Neural oscillators are used to create rhythmic motion like walking and breathing of animals. Neural oscillators synchronize and entrain with the input signal. The structure of a unit is shown in Fig.2. The mathematical model of a neural oscillator called the “Matsuoka model” [5, 6] is written by the following equation as

\[
 T_r \frac{dx_i}{dt} + x_i = - \sum_{j \neq i} a_{ij} g(x_i) - b_i f_i + s_i + \text{Input} \tag{1}
\]

\[
 T_a \frac{df_i}{dt} + f_i = g(x_i) \tag{2}
\]

\[
 g(x_i) = \max(0, x_i) \tag{3}
\]

where, \( x_i \) is the inner state of the \( i \)th neuron, \( f_i \) is a variable which represents self inhibition effect of the \( j \)th neuron, \( T_r \) and \( T_a \) are time constants of the inner state and the adaptation effect of the \( i \)th neuron, respectively, \( b_i \) is a constant which represents the degree of the self-inhibition influence on the inner state, \( a_{ij} \) is a connecting weight from the \( j \)th neuron to the \( i \)th neuron; \( S_i \) is a steady state input of the \( j \)th neuron, Input is an external input.

3.2 Characteristic change due to the time constants

We examine how the output of the neural oscillator changed, when the various time constants \( T_r \) and \( T_a \) were used. Another parameters are set as \( S_i = 2.0, b_i = 2.5, a_{ij} = 1.2 \). These values of parameters are determined so that the output signal becomes a sinusoidal curve. The results are as follows:

1. On the output signal of a neural oscillator
   - When \( T_r \) is changed under the constant ratio of \( T_r \) to \( T_a \), the frequency is proportional to \( 1/T_r \) without the amplitude change.
   - When the ratio of \( T_r \) to \( T_a \) is smaller than 1/10, the oscillation converges to zero.

2. On the synchronization
   - When the values of the time constants \( T_r, T_a \) are small, the output signal synchronizes easily.
   - When the ratio of \( T_r \) to \( T_a \) is larger than 1/10, the phase of the oscillation is delayed.

4. PROPOSED METHOD

Handshaking is modeled as a motion on a two dimensional vertical plane. We assume that the handshaking motion is generated by two joints such as the shoulder and elbow joints. Each joint is controlled by a neural oscillator. The desired trajectories of the joint angles are determined by the output signals of the neural oscillators. The external joint torque is fed back into the neural oscillator.

The neural oscillator of each joint consists of two units as shown in Fig.3, and the output signal is computed as \( \max(0, x_i) - \max(0, x_j) \). The neural oscillators are connected to each other between joints as shown in Fig. 4. There are two kinds of the input to each neural oscillator as written by the following equation. Where, \( i \) is the joint number, \( i = 1, 2 \), and \( j \) is the unit number, \( j = 1, 2 \).

\[
 T_r \frac{dx_y}{dt} + x_y = - \sum_{k \neq j} a_{jk} g(x_k) - b_j x'_{yj} + s_{yj} + (-1)^{j-1} K_j (\sum_{l=1}^{2} (g(x_{yl}) - g(x_{yl+1}))) + (-1)^{j-1} \text{Input1} + \text{Input2} \tag{4}
\]

\[
 T_a \frac{dx'_{yj}}{dt} + x'_{yj} = g(x_{yj}) \tag{5}
\]

\[
 g(x_{yj}) = \max(0, x_{yj}) \tag{6}
\]
As described in Section 3.2, the ratio of $T_r$ to $T_a$ should be smaller than $1/10$ to get good performances in the synchronization. However, when values smaller than $1/10$ are used as the ratio, the oscillation converges to zero. To solve this problem, we make a connection between neural oscillators of Joint 1 and 2 of each arm. The connection between joints enables them maintain the oscillation with the synchronization and the entrainment. Also, the connection enables to synchronize both joints 1 and 2. The connection gains, $K_1$ and $K_2$, are set to 1.2. Figure 5 shows the outputs of the neural oscillators of joints 1 and 2. These outputs oscillate at the same frequency.

In order to synchronize the output signal of the neural oscillator to the external force applied on the robot, the signal of Input1 is utilized. Torque(1) and (2) in Fig. 4 mean joint torques caused by the interaction force between human and robot arms. Input1(1) and (2) are obtained by multiplying torque(1) and (2) by gains $C_1$ and $C_2$, respectively. We may change the strength of the synchronization by adjusting values of the gains. If we want to make a passive handshake to the partner, then large gains are selected. By using small gains, the handshake becomes active. Figures 6 and 7 show the input and output signals of the neural oscillators which are $C_1 = 0.05$ and $C_1 = 0.5$, respectively. Also the return maps between input and output signals are shown in Figs. 6 and 7. The relationships between $\Delta \theta_n$ and $\Delta \theta_{n+1}$ are plotted in the return map, where subscript $i$ is the $n$th oscillation, $\Delta \theta$ is the difference between the phases of the signals. When $C_i = 0.05$, we can see from the return map that there is no
synchronization between the input and output signals, since the plots are parallel to the straight line of \( \Delta \theta_{i+1} = \Delta \theta_i \) as shown in Fig.6. On the other hand, in the case of \( C_i = 0.5 \) the plots are located at the same position as shown in Fig.7. In this case the output signal is synchronized to the input signal.

Input(2)(1) and (2) regulate the amplitudes of the oscillations. The absolute values of torque(1) and (2) are multiplied by gains \( L_1 \) and \( L_2 \) to determine Input(2)(1) and (2), respectively. The amplitude of the oscillation depends on Input2, and then an adaptation occurs to the amplitude of the handshaking motion. Figures 8 and 9 show the outputs of the neural oscillators with \( \text{Input2} = 0 \) and \( \text{Input2} = [2 \sin(2.64 \pi t)] \). The amplitude of the output of \( \text{Input2} = [2 \sin(2.64 \pi t)] \) is larger than that of \( \text{Input2} = 0 \). Therefore we can synchronize the amplitude of the output signal with that of the input signal by increasing the value of \( L \).

Based on the discussion described above, we determined the typical values of parameters of the neural oscillator as follows, \( S_i = 2.0, b_i = 2.5, a_{ij} = 0.8, T_r = 0.1, T_a = 0.05, K_i = 1.2, L_i = 0.024, C_i = 0.02 \).

5. SIMULATION OF HANDSHAKING

In order to examine the synchronization of human-robot motions, we made computer simulations of handshaking. We assume that people shake hands using neural oscillators. Figure 10 shows an arm model for handshaking simulations. Each arm has three degrees of freedom in two dimensional space. Joints 1, 2 and 3 are shoulder, elbow and wrist joints, respectively. We assume that A arm is a robot arm, and B arm is a human arm.

5.1 Simulation method

The dynamic equation of the model is written by

\[
\tau = M(q) \ddot{q} + h(q, \dot{q}) + g(q) + A\lambda
\]  
(7)

where, \( M \) is the inertial matrix, \( h \) is the Coriolis force and centrifugal term, \( g \) is the gravity term, \( A\lambda \) is the constraint force term between A and B arms. \( A \) and \( \lambda \) are computed as follows:

\[
A = \begin{bmatrix} \lambda_x \\ \lambda_y \end{bmatrix}
\]  
(9)

\[
\lambda = \begin{bmatrix} \lambda_x \\ \lambda_y \end{bmatrix}
\]  
(10)

\[
A = \begin{bmatrix} \ddot{q}_x, \ddot{q}_y, \ddot{q}_z, \dot{q}_x, \dot{q}_y, \dot{q}_z \end{bmatrix}
\]  
(11)

\[
A = \begin{bmatrix} \ddot{q}_x, \ddot{q}_y, \ddot{q}_z, \dot{q}_x, \dot{q}_y, \dot{q}_z \end{bmatrix}
\]  
(12)

\[
\ddot{q}_x + \dddot{q}_x \phi_x + \omega_y \phi_x = 0
\]  
(13)

The equations are rewritten by

\[
A_x \ddot{q} + (A_x, A_y \dot{A}_y) \dot{q} + \omega_y \phi_x = 0
\]  
(14)

\[
A_y \ddot{q} + (A_x, A_y \dot{A}_y) \dot{q} + \omega_x \phi_y = 0
\]  
(15)

Figure 8: Outputs of the neural oscillator (Input2 = 0)

Figure 9: Outputs of the neural oscillator (Input2 = [2 \sin(2.64 \pi t)])

Figure 10: Model of the handshaking simulation. (A arm is a robot arm, and B arm is a human arm.)
where, $A_x$ and $A_y$ are the following vectors.

$$A_x = \frac{\partial \phi_x}{\partial q} \quad (16) \quad A_y = \frac{\partial \phi_y}{\partial q} \quad (17)$$

By using the vectors the equation (4) can be represented as the following equation.

$$H^*(\ddot{q}_x, \ddot{q}_y, \ddot{q}_x, \ddot{q}_y, A_x, A_y)^T = (k_i, k_x, k_y, k_i, k_x, k_y)^T \quad (18)$$

Solving equation (17) we obtain the joint torques caused by the external constraint, $A\lambda$. The values of the link parameters that are used in the simulation are listed in Table I.

### 5.2 Simulated results

Joints 1 and 2 of each arm are controlled by the neural oscillators. Joint 3 is controlled by compliant control to reduce the internal force between arms. The desired trajectories of Joints 1 and 2 are the output signals of the neural oscillators. Each joint is controlled by PD local feedback control to follow the desired trajectory.

The joint torque consist of the constraint torque $A\lambda$, the inertial torque $M(q)\dot{q}$ and the Coriolis force and centrifugal torque $h(q, \dot{q})$ in equation (7). The interaction force between arms is computed by the constraint torque $A\lambda$. In the experiment it was not easy to obtain the joint torque caused by motion of the partner only, because the gravity, the inertial and Coriolis force and centrifugal terms are included in the output signal of the joint torque sensor. Therefore, we assume that the inertial torque and Coriolis force and centrifugal torque are very small compared with the constraint torque. The gravity torque $g(q)$ is only removed from the joint torque to obtain the interaction torque between arms.

When $T$ is changed under the constant ratio of $T_a$ to $T_r$, the frequency becomes proportional to $1/T_r$ without any amplitude change. Then we make handshaking simulations with various frequencies to examine the entrainment effects. The typical values for other parameters of the neural oscillators are used in the simulation.

Figure 11 shows an example of the independent motion of robot and human arms without handshaking. The basic frequencies of robot and human arms are 1.33 [Hz] and 1.66 [Hz], respectively. The amplitude of human oscillation is modulated. The simulated results of handshaking are shown in Fig. 12. The synchronization and entrainment occurs between robotic and human motions. The oscillations of both arms coincide, and the frequency resembles that of human arm, since the value of the gain $C$ of robot arm is twice that of human arm. The amplitude of the robot arm adapts with that of the human arm. The return map in Fig.12 shows that the robot arm motion synchronizes with the human arm motion.

### 5.3 Analysis

We assumed in the simulation that the inertial and Coriolis force and centrifugal terms are included in the interaction torque between human and robot motions. Then, we examined the magnitude and the frequency of each term in the joint torque. Figure 13 shows each term in the input1. It is found that the constraint torque is larger than the inertial torque. Also the Coriolis force and centrifugal term is very small. The main contribution to Input1 signal is the term of the constraint torque, $A\lambda$. Figure 14 shows the results of FFT spectra of each term. In the inertial term high frequency signals are mainly included. The high frequency signal in Input1 does not greatly affect the output of the neural oscillator as shown in Fig. 15. From these results, it is found that the neural oscillator plays as a low pass filter to the input signal. The neural oscillator does not synchronize with the input signal, which differs from their own basic frequencies.

To analyze the performance of the proposed method for robots with different parameters, we simulated handshaking motions with different robotic parameters. We doubled the length and tripled the weight of those listed in Table I for the robot arm (A arm). The parameters of the human arm (B arm) were the same as those in Table I. The simulated results are shown in Fig. 16. We can find the synchronization between human and robot motions. Therefore, it is found that the proposed method is also effective for different robotic arms.

Figure 17 shows the experimental results of handshaking when the frequency of the robotic arm is changed from 1.66[Hz] to 1.33[Hz] at the middle point of time. We can see from the return map that the robotic and human

---

**TABLE I: LINK PARAMETERS**

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<th>Link Length [m]</th>
<th>Link Mass [kg]</th>
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</tr>
<tr>
<td>12</td>
<td>m2</td>
</tr>
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<td>13</td>
<td>m3</td>
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![Figure 11: Original oscillation (A arm 1.33 [Hz], B arm 1.66 [Hz])](image)
Figure 12: Simulated result of handshaking and its return map

Figure 13: Each term in the input

Figure 14: FFT

Figure 15: Output signal of the neural oscillator

Figure 16: Simulated results of handshaking with different mechanical parameters of the robot arm

Figure 17: Simulated results of handshaking with a change in frequency and its return map
6. EXPERIMENTS

6.1 Experimental method

The proposed framework using neural oscillators is examined by experiments of human-robot handshaking. The adopted arm in the experiment has been developed by Hashimoto et al. [8, 9], and it has 7 degrees of freedom. Each joint has a joint torque sensor. The torque sensing technique utilizes a flexible part of a harmonic drive gear (Fig.18). The strain gauges are cemented on the flexspline as shown in Fig.19. The technique provided joint torque sensing without reducing stiffness of the robot and changing the mechanical structure of the joint. Since the torque sensor is compact and light weight, it is considered that the technique is useful for robots with many DOF such as humanoid robots. The mechanical specifications of the robot arm and the torque sensing technique are presented in [8], and the cancellation method of gravity term from the joint torque information is performed in [9].

Figure 21 shows the joint configuration and the overview of the robot arm. Joints 1 and 4 are controlled by the neural oscillators. The output signals of neural oscillators are used for the desired trajectory of Joints 1 and 4, and local PD feedback control is performed on each joint. The typical values of parameters of the neural oscillator are used to generate the desired trajectories of Joints 1 and 4. The other joints are controlled with the desired angle of 0[deg] by the local PD feedback control. The joint torque information with cancellation of the gravity term is used as the input signal to Input1 and Input2 of the neural oscillator. The overview of human-robot handshaking is shown in Fig. 21. After the robot moves to an initial position, a subject grasps the robot hand, and shakes hands with the robot.

The joint angles and joint torques of robot arm are measured by encoders and torque sensors, respectively. The joint angle of human shoulder and elbow joints are measured. Makers are attached on human joints, and the positions in two dimensional space are measured by a CCD camera with a template matching method. The template matching is performed on an image processing board, IP7000.

6.2 Experimental results

The results are shown in Fig. 22. The joint motions are synchronized between human and robot motions. Also synchronization occurs between the shoulder and elbow joints of the robot arm. The amplitudes of the robot joints change with that of the human motion together. This proves that the proposed method has adaptability in the amplitude of the motion with that of human motion.

The basic frequency of the neural oscillator of the robot is 1.5 [Hz] until 12 [s], and it remains 1.1 [Hz] after that. We can find in Fig. 17 that the synchronized frequency is 1.7 [Hz] until 12 [s], and then it changes into 1.4 [Hz]. Consequently we cannot say that one part between a human being and a robot is a master and the other part is a slave. Human and robot motions are entrained into a synchronized frequency.

We change the gains $C_i$ from the typical value to investigate the strength of the synchronization with a human motion. Figures 23 and 24 show the results with the gain values of 0.04 and 0.01, respectively. In the case of $C_i = 0.04$, the joint torque of the robot arm is very small, and the synchronization occurs as shown in Fig. 23. In this case the robot is very passive and adapts itself to the human motion. On the other hand, in the case of $C_i = 0.01$ the joint torque of the robot arm is very large as shown in Fig.24. In this case the robot is active and moves with its'...
own trajectory against to the human motion. Figure 25 shows the return maps between the elbow motions of human arm and those of the robot arm. When the gain value of $C_i$ is 0.04, the plots are concentrate around the origin of the return map. On the other hand, in the case of $C_i = 0.01$ the plotted region is broader than that of $C_i = 0.04$. This result means that the strength of the synchronization is dependant on the gain value of $C_i$.

From the results described above, it is concluded that the strength of the synchronization can be changed by adjusting the values of $C_i$ gains for Input1, and passive and active handshakes are realized by adjusting a degree of the synchronization.

### 6.3 Psychological evaluation

The proposed control method of handshaking is evaluated psychologically by using a paired comparison method proposed by Bradley [8]. Four samples with various control methods are utilized in the evaluation experiment. Samples (a) and (b) use the proposed control method with $C_i = 0.04$ and $C_i = 0.02$, respectively. Sample (a) is more flexible than sample (b). The values of parameters of the neural oscillators are listed in Table II. Samples (c) and (d) use...
conventional impedance control in order to compare with the proposed method. The impedance parameters are listed in Table II. The values of parameters of sample (c) are determined as small as possible with maintaining stability of impedance control. The stiffness parameter of sample (d) is larger than that of sample (c). The stiffness of sample (c) is smaller than that of sample (d). Impedance control is performed on each joint. The frequency and amplitude of the desired trajectories is common to all samples.

We made six pairs of Samples (a) to (d) for the paired comparison. Number of the subjects is 12. The subjects shake hands with a pair of different samples. The subjects determined the period of handshake themselves. Then the subjects answer which is better according to the terms “Flexible”, “Natural”, “Kind” and “Affinity”. The results of the comparison in terms of “Natural” and “Kind” are listed in Table III and IV, respectively. The table shows number of subjects who answer that the sample listed on the left row is better than that on the top line. From these results we can find that many subjects select Samples (a) and (b) of the proposed control methods in terms of “Flexible”, “Natural”, “Kind” and “Affinity”. Table V lists the judging scale values and $\chi^2$. For all questions, the following inequality is satisfied, $\chi^2 > \chi^2 (3, 0.05) = 7.82$. Then the statistical test using $\chi^2$ distribution function shows that there are differences in rank among four samples. Consequently, the proposed method is more predominant than conventional impedance control in handshaking.

Since the impedance control for robots regulates impedance for fluctuation from the reference trajectory, the reference trajectory affects much the performance of human-robot handshaking. However it is very difficult to determine the appropriate reference trajectory in advance. It is considered that this is the reason why the results of psychological evaluation are negative.

Table II: Parameters of Evaluation Experiment

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Table III: Result of Evaluation Experiment

**Flexible**

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</table>

7. CONCLUSIONS

We have proposed a framework for human-robot handshaking using neural oscillators. The output signal of the neural oscillator is used for the desired trajectory of each robot joint. Joint torque information of the robot is fed back into the neural oscillator. The proposed method realizes synchronization and entrainment between human-robot handshaking motions. Also the passiveness of the handshake can be changed by adjusting strength of the synchronization. The validity of the proposed method was examined by psychological evaluations, and it was found that the proposed method is better than conventional impedance control according to the terms “Flexible”, “Natural”, “Kind” and “Affinity”.

This method is also effective for other periodic physical interactions such as dance motions, a walking assistant and rehabilitation training.

Table IV: Result of Judging Scale Values and $\chi^2$

<table>
<thead>
<tr>
<th>Parameters</th>
<th>$\pi_r$</th>
<th>$\pi_i$</th>
<th>$\pi_c$</th>
<th>$\pi_d$</th>
<th>$\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>flexible</td>
<td>0.46</td>
<td>0.37</td>
<td>0.11</td>
<td>0.06</td>
<td>25.46</td>
</tr>
<tr>
<td>natural</td>
<td>0.34</td>
<td>0.47</td>
<td>0.11</td>
<td>0.08</td>
<td>21.15</td>
</tr>
<tr>
<td>kind</td>
<td>0.40</td>
<td>0.45</td>
<td>0.11</td>
<td>0.04</td>
<td>31.41</td>
</tr>
<tr>
<td>affinity</td>
<td>0.37</td>
<td>0.46</td>
<td>0.10</td>
<td>0.07</td>
<td>24.37</td>
</tr>
</tbody>
</table>
As for future work, it is important to develop a method of synchronization based control for un-periodic motion. For this purpose we may consider the use online design of dynamics.

In this study we have focused on the robot arm motion during the handshake with human. However, there are many processes for handshaking such as grasping hand, contacting eyes so on. Therefore, in order to make a natural handshake between human and robot, we have to consider the whole processes of handshaking. As the future works, it is important to investigate the whole processes of handshaking.

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REFERENCES

Minoru HASHIMOTO
Minoru Hashimoto received M.S. and Ph.D. degrees from University of Tokyo in 1980 and 1983, respectively. From 1982 to 1988 he was a research associate of the robotics laboratory in the Department of Mechanical Engineering in University of Electro-communications. From 1988 to 1998 he was an associate professor of Department of Mechanical Engineering, Kagoshima University. Since 1999 he has been a professor of Department of Kansei Engineering, Shinshu University. His research interest is robotics, mechatronics, virtual reality and control engineering.

Tomofumi KASUGA
Tomofumi Kasuga received B.S. and M.S. degrees in Kansei engineering from Shinshu University in 2003 and 2005, respectively. Since 2005 he has been an engineer of FUJITSU Social Science Laboratory Ltd.