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A Neuro-based Adaptive Training Method for Robotic Rehabilitation Aids

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Abstract

In this paper, a new training method for robotic rehabilitation aids is proposed, in which only one neural network (NN) is simultaneously used in order to identify dynamic properties of a human-robot system and give an assist to a trainee. The model used for identification of the dynamics of the human-robot system consists of the NN and a reference model which represents a control property of a skillful operator. This paper explains a working principle of the training method and shows the validity of the proposed method through experiments by unskilled operators.

Key Words: Human-robot systems, Adaptive training, Neural network, Impedance control

1 Introduction

Let us consider a prosthetic or orthosis system for physically disabled people [1] [2]. The goal of such systems is to realize effective human assists for a limited motor capability of the operator with robotic manipulators. To attain the goal, it is necessary to not only establish the robot control technology for assisting a human, but supply an effective training system for improving the control ability of the human operator as shown in Fig.1. In the present paper, as the first step for realizing such a system, a basic training mechanism for robotic rehabilitation aids is proposed.

One method for designing such a training system is to give technical assistance to a trainee in order to alleviate a burden in the process of skill acquisition. This kind of training is based on the idea that a human understands easily a given control task and characteristics of a controlled system through appropriate assistance, so that the speed of the skill acquisition process would be accelerated. Several studies on such a training system for a human operator have been reported. For example, Kraiss [3] proposed a method to support a car driver using a neural network (NN). The NN used in his method identifies the human characteristics through learning. However, this method may require a large size of the NN and cause difficulty during the learning procedure. KrishnaKumar et al. [4] developed a training system of helicopter hovering. Since a desired control characteristic was not used as a training target of the task, however, it is difficult to

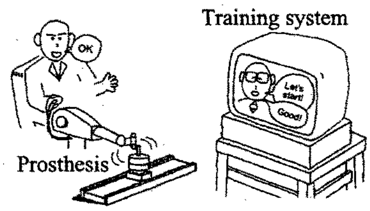

Figure 1: Examples of the training system using robotic rehabilitation aids for the physically disabled

evaluate how much a trainee has acquired the control ability and realized the desired characteristic well. Also, Suenaga [5] proposed a manual preview-predictive control system which shows a future reference signal and a predicted value of the controlled variable to the operator. Although he showed that the method was effective in compensation for human delay and improvement of the control performance, the validity of the method is strictly limited because the human operator's identified model is assumed to be linear.

In this paper, to solve the problems mentioned above, a new training method is proposed. The proposed method modifies a controlled output, that is, trainee's motion, in order to enhance task-performing ability of a trainee, while identifying nonlinear control characteristics of the overall system including the human operator by using the NN in real time. The model used for identification of the human-robot system consists of the NN and a linear reference model which represents a control property of the skilled operator.

This paper is organized as follows: Section 2 defines the structure of a human-robot system used in this paper, Section 3 describes a proposed adaptive training system. In Section 4, some basic properties of the training system are examined through experiments with subjects.

2 Structure of a Human-Robot System

In such training systems including interactions between a human and a robot, a human should take an initiative in performing a task, while the robot assists him or her. This is also true in robot systems for assisting human activities such as a master-slave manipulator, a teleoperated robot and a power-assist robot.

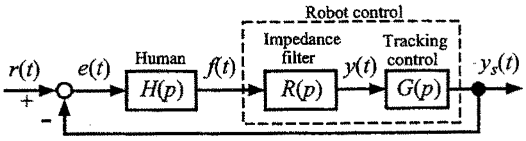

Figure 2: Human-robot system for robotic training

Figure 2 shows a block diagram of such a human-robot SISO system, where $r(t)$ denotes the desired signal, $e(t)$ the control error, $f(t)$ the operational force generated by the human operator, $y_s(t)$ the robot's position, and p the differential operator [6]. The dynamic behavior of the robot is assumed to be regulated by the impedance control [7].

During the training proposed in this paper, the operator is asked to manipulate the impedance-controlled robot with $f(t)$ so as to minimize the control error $e(t)$ displaying on a visual feedback monitor. An transfer function of the impedance-controlled robot $R(p)$ [7] [8] is given by

$$R(p) = \frac{1}{Mp^2 + Bp + K}, \tag{1}$$

where M, B, K are the inertia, the viscosity and the stiffness of the end-effector, respectively. Also, it is assumed that the robot current position $y_s(t)$ almost agrees with the desired position $y(t)$ in a certain band width of frequency so that $G(p) \approx 1$ is held.

3 Adaptive Training System

3.1 Formulation

In this paper, a human-robot system is dealt as a discrete time system because the system is constructed with a digital computer.

From Fig.2 under $G(p) = 1$, the kth output signal of the impedance filter with a sampling interval Δ_t is given as

$$y(k) = R(z^{-1})H(z^{-1})e(k), \tag{2}$$

where $H(z^{-1})$ denotes a human characteristic and $R(z^{-1})$ is a characteristic of the impedance filter. Then, the term $R(z^{-1})H(z^{-1})$ is expressed as

$$R(z^{-1})H(z^{-1}) = [1 + \Delta_{RH}(z^{-1})]R_n(z^{-1})H_n(z^{-1}), \tag{3}$$

including an unknown multiplicative modeling error $\Delta_{RH}(z^{-1})$ [9], where $R_n(z^{-1})H_n(z^{-1})$ is the reference model, namely, the target training property of the human-robot system.

On the other hand, an open-loop transfer function with robotic assistance is defined as

$$R_s(z^{-1})H_s(z^{-1}) = [1 - \Delta_s(z^{-1})]R(z^{-1})H(z^{-1}), \tag{4}$$

where $\Delta_s(z^{-1})$ is a controller for robotic assistance. So, if the target property $R_n(z^{-1})H_n(z^{-1})$ is equivalent to (4), the system output with the robotic assistance agrees with one of the target property. From (3) and (4), the following relationship can be derived:

$$\Delta_s(z^{-1}) = \frac{\Delta_{RH}(z^{-1})}{1 + \Delta_{RH}(z^{-1})}. \tag{5}$$

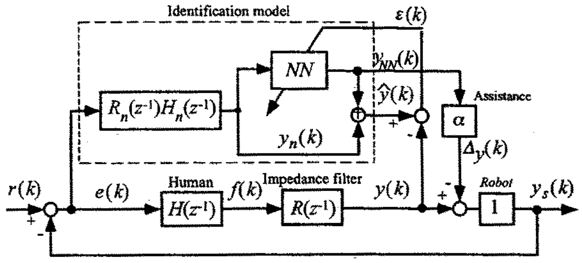

Figure 3: Block diagram of the proposed training system

The modeling error $\Delta_{RH}(z^{-1})$, however, is unknown, so that it is impossible to obtain the controller for assistance $\Delta_s(z^{-1})$ directly. In the next section, a neural network (NN) is introduced into the training system to overcome this problem on $\Delta_s(z^{-1})$.

3.2 Structure of the Proposed Training System

Figure 3 shows a block diagram of the proposed training system. The identification model consists of the reference model $R_n(z^{-1})H_n(z^{-1})$ and the NN. The output of the identification model $\hat{y}(k)$ is the sum of the NN's output $y_{NN}(k)$ and the reference model's output $y_n(k)$. The NN is trained in order to minimize or locally minimize the identified error $\epsilon(k)$ which is the error between $\hat{y}(k)$ and $y(k)$.

The assisting signal Δ_y is defined using $y_{NN}(k)$ as

$$\Delta_y(k) = \alpha y_{NN}(k), \tag{6}$$

where α $(0 \le \alpha \le 1)$ is the assisting ratio. By changing α, amount of the robotic assistance for a trainee can be adjusted. Under $\alpha = 1$, characteristics of the training system is agreed with the reference model $R_n(z^{-1})H_n(z^{-1})$ as explained below. It can be expected that the effective training for a trainee can be realized by adjusting α according to his/her control ability.

Here, the dynamic behavior of this control system is analyzed. Using (2) and (3), $y(k)$ is expressed as

$$y(k) = y_n(k) + \Delta_{yn}(k), \tag{7}$$

where

$$y_n(k) = R_n(z^{-1})H_n(z^{-1})e(k), \tag{8}$$

$$\Delta_{yn}(k) = \Delta_{RH}(z^{-1})y_n(k). \tag{9}$$

Also, from (4), $y_s(k)$ is represented as

$$\begin{aligned} y_s(k) &= R_s(z^{-1})H_s(z^{-1})e(k) && (10)\\ &= y(k) - \Delta_y(k), && (11) \end{aligned}$$

where

$$\Delta_y(k) = \Delta_s(z^{-1})y(k). \tag{12}$$

Therefore, with (2), (3) and (12), the assisting signal $\Delta_y(k)$ is obtained by

$$\Delta_y(k) = \Delta_s(z^{-1})[1 + \Delta_{RH}(z^{-1})]y_n(k). \tag{13}$$

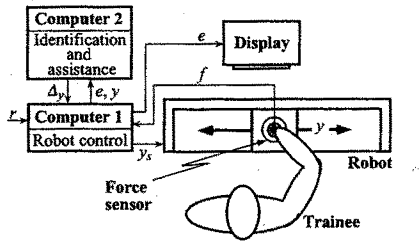

Figure 4: Experimental apparatus

Moreover, from (13), (5) and (9), the following equation is derived:

$$\Delta_y(k) = \Delta_{yn}(k). \tag{14}$$

On the other hand, $\epsilon(k)$ can be calculated with Fig.2 and (7) as follows:

$$\epsilon(k) = \hat{y}(k) - y(k) = y_{NN}(k) - \Delta_{yn}(k). \tag{15}$$

If the NN is well trained, we can expect that the identified error $\epsilon(t)$ becomes zero in (15). Consequently, from (14) and (15), we have

$$\Delta_y(k) = y_{NN}(k). \tag{16}$$

This reduces to (6) with $\alpha = 1$. In other words, the assisting signal Δ_y can be determined by the output signal of the NN.

As a result, the proposed method can control a human-robot system with a modeling error according to the characteristics of the given reference model if the NN learns to make the identified error $\epsilon(t)$ in (15) into zero in real time. It should be noticed that the proposed method identifies the control property including characteristics of the human operator. The reason why we focused on the overall dynamic property of the human-robot system is that it dose not change so much, although the dynamic property of a human changes greatly depending on the robot impedance property [10]. For implementation of the proposed training system, of course, the reference model as the target property of the training is needed to be determined. Next section describes a method to determine the reference model in detail.

4 Experiments

4.1 Experimental Apparatus

Figure 4 shows an experimental apparatus for the proposed training system with a one-degree-of-freedom linear robot (NIPPON THOMPSON CO., LTD.: encoder resolution is 2 [μm]). The robot adopts a moving magnet driving system which can control its driving force, where the maximum force is $\pm 10 \times 9.8$ [N]. The hand force generated by a human operator is measured by a six-axis force/torque sensor (BL Autotec Co'Ltd.: resolutions, force x and y axes, 0.05 [N]; z axis, 0.15 [N]; torque, 0.003 [Nm]) attached on the handle of the robot.

The target signal is a white noise filtered by the second order Butterworth filter, where the cut-off frequency is 0.5 [Hz]. A subject is asked to minimize the

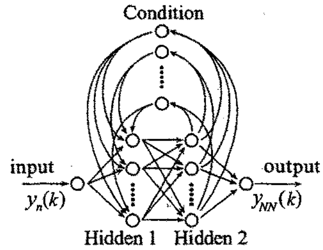

Figure 5: The Elman network used in the proposed system

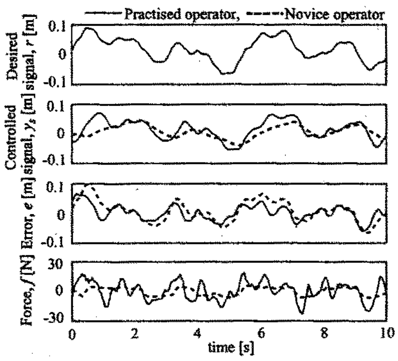

Figure 6: Examples of experimental results

control error e indicating on the display. In the experiment, the damping coefficient ζ of the robot was set at $\zeta = \frac{B}{2\sqrt{MK}}$ = -0.5, 0.0, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, and the natural frequency $\omega_n = \sqrt{\frac{K}{M}} = 4$ [rad/s] with the robot stiffness $K = 55$ [N/m]. The maximum amplitude of the desired signal $R = 0.1$ [m]; the experimental time per trial is 60 [s]; and the sampling frequency of data is 25 [Hz]. To avoid effects of the external disturbance, output signals of the force sensor and the NN are filtered by the Butterworth filter, where the cut-off frequencies are 25 Hz and 3 Hz, respectively.

The system utilizes the Elman NN [11] with a five-layered structure including an input layer, two hidden layers, an output layer and a condition layer (See Fig. 5): The number of units in the input layer is 1, in the hidden layers 15×2, and in the output layer 1. In the second hidden layer, the recurrent connections with the condition layer (15 units) exist. An initial value of the weight ω_{ij} is given in a uniform random number under $|\omega_{ij}| < 0.01$, and a learning rate of the NN is set at 0.1. Also, the sigmoid function is used for the units in the hidden layers and the condition layer, while the identity function is used for other units. It should be noted that the NN are trained on-line, that is, the weights of the NN are updated within one control sampling time (1 [ms]) using the back-propagation through time algorithm [12].

Figure 6 shows an example of experimental results by a novice and a practised operator with $\alpha = 0$ under $\zeta = 3$, $K = 55$ [N/m], $\omega_n = 4$ [rad/s]. The top figure in Fig.6 shows the time history of the desired signal r, the second the controlled signal y_s, the third the control error e, and the bottom the force f. The solid lines in Fig. 6 show experimental results with the practised operator and the dotted lines with the novice operator. The controlled signal of the novice operator does not follow a high frequency component of the desired signal. On the other hand, the controlled signal of the practised operator follows much better.

4.2 Reference Model of the Human-robot System

The proposed training system uses the reference model of a human-robot system as a training target. To determine the reference model, the dynamic property of the human-robot system $R(j\omega)H(j\omega)$ is estimated by means of the subspace-based state space model identification method (N4SID) [13] [14] from experimental results of the practised operator. Then, the estimated describing function was approximated as the following transfer function model [15], where each parameter was estimated by the least squares method:

$$R_n(p)H_n(p) = \frac{K_s}{1+T_s p}e^{-\tau p}, \tag{17}$$

where K_s denotes the gain; T_s is the time constant; and τ represents the delay time of the system. For the estimation of the parameters, 10 trials after considerable repeated practice were used as data.

Before estimating the dynamic property of the system, to evaluate the control performance of the experimental results, the following two control indices J and U are calculated:

$$J = \int_0^{t_f} e^2(t)dt \Big/ \int_0^{t_f} r^2(t)dt, \tag{18}$$

$$U = \int_0^{t_f} f^2(t)dt \Big/ \int_0^{t_f} r^2(t)dt, \tag{19}$$

where J is a normalized square sum of the error $e(t)$, and U a normalized square sum of the hand force $f(t)$ during the trial time t_f=60 [s]. Figure 7 (a), (b) show the calculated J and U from the experimental results, respectively. From these figures, it can be seen that J is greatly increasing when ζ becomes negative, because the subject must control unstable robot dynamics. On the other hand, as ζ increases, U also greatly increases because the subject needs large force to control the robot.

Figure 8 shows the predicted response of the subject using the transfer function model defined in (17), where the measured controlled signal y_s of the practised operator and the predicted signal are shown. In the middle, the solid line is the measured control signal y_s, and the dashed line the predicted controlled signal, where the predicted signal is an output of the transfer function model when the control error e is given as an input. The predicted controlled signal almost coincides the practised operator's one and follows the corresponding desired signal r.

In this paper, the reference model with the damping coefficient $\zeta = 1.0$, which corresponds the minimum of J shown in Fig. 7 (a), is used as a training target.

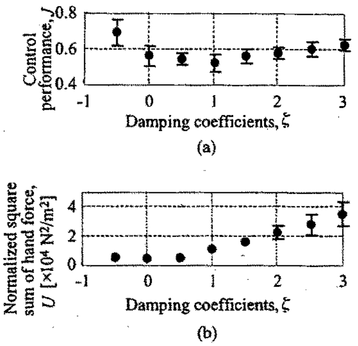

Figure 7: Change of the control performance J and the normalized square sum of hand force U of the practised subject depending on the damping coefficient ζ. Mean values and standard deviations for 10 trials are shown.

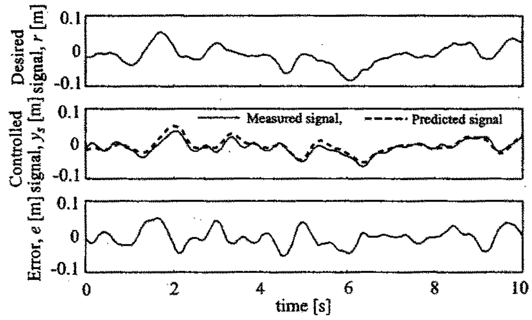

Figure 8: Response of the estimated reference model of the human-robot system ($\zeta = 1.0$)

Therefore, a novice operator is asked to perform the most difficult training among the experimental conditions used in this paper.

4.3 Experimental Results

4.3.1 Basic behavior of the proposed system

First, in order to confirm if characteristics of the human-robot system under the proposed adaptive control with $\alpha = 1$ would agree with of the reference model, a series of experiments were performed. Figure 9 shows an example of experimental results.

Each profile shows, in the order from the top, a time history of the desired signal r, the control signal y, the assisted signal y_s, the control error e, the hand force f, the assisting signal Δ_y, and the identification error ϵ. It is clear that the tracking ability was significantly improved by adding assistance from the system, although it was difficult for a novice operator to track the given desired signal well by himself.

Next, Fig.10 shows the estimated describing functions with experimental results. In this figure, the solid line shows the reference model $R_n(j\omega)H_n(j\omega)$, the dotted line the estimated overall system characteristics with the assisting signal, $R_s(j\omega)H_s(j\omega)$, and the dashed line the system characteristics without the assisting signal, $R(j\omega)H(j\omega)$.

It was found that the gain characteristic of $R(j\omega)H(j\omega)$ is considerably lower in the high frequency range than the reference model's one, and that there

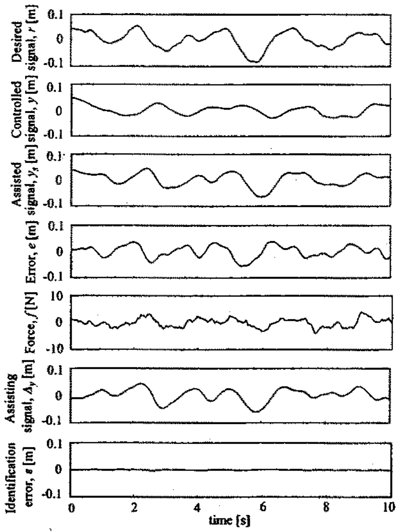

Figure 9: Examples of experimental results under the proposed method ($\alpha = 1$, a novice operator)

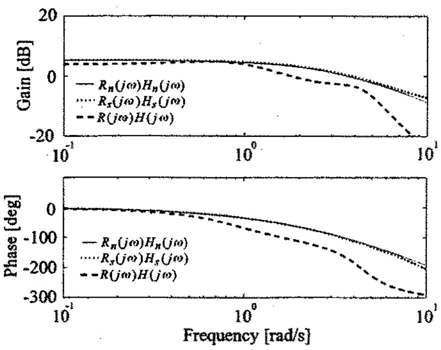

Figure 10: Describing functions estimated from experimental results under the proposed method

exists a serious phase lag in $R(j\omega)H(j\omega)$. However, by giving assistance, the gain characteristic is improved in the high frequency range and the phase lag is also compensated as shown in $R_s(j\omega)H_s(j\omega)$. As a result, we can see that the system characteristics with robotic assistance almost agree with the one of the reference model. The basic behavior of the proposed system has been confirmed.

4.3.2 Change of the training effect by the assisting ratio

In order to investigate the influence of α on human movements, experiments were conducted using the different assisting ratios as $\alpha = 0.8, 0.6, 0.4$. Each subject who was not practised was asked to perform the tracking tests in the order of α = 0.8, 0.6, 0.4. The number of trials was three for each assisting ratio α having the brief intervals when α was changed.

Figure 11 shows examples of the experimental results. The figure shows, from the top, the time history of the desired signal r, the controlled signal y, the as-

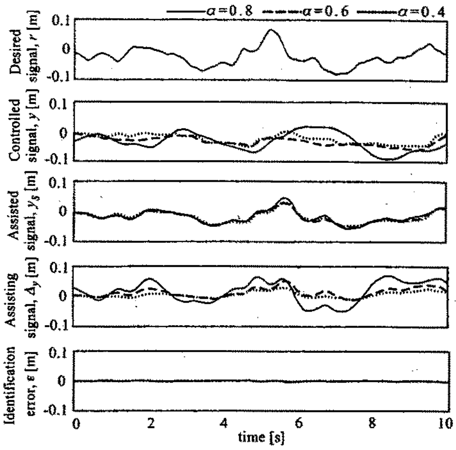

Figure 11: Changes of the control results depending on the assisting ratio α

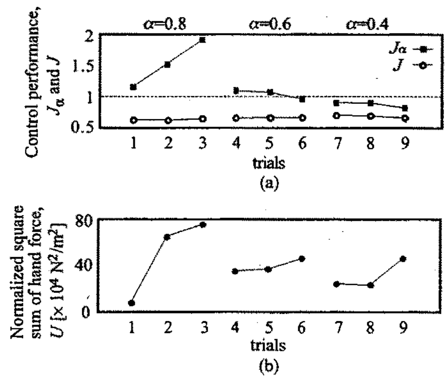

Figure 12: Changes of the control performances and the normalized square sum of hand force U depending on the number of trials

sisted signal y_s, the assisting signal Δ_y, the identification error ϵ. In the figure, the solid line shows the case of $\alpha = 0.8$, the dashed line $\alpha = 0.6$ and the dotted line $\alpha = 0.4$. As the assisting ratio decreases, the assisting signal Δ_y also does. However, it is interesting that the assisted signals y_s are almost the same in all α. This is the training effects, since the subject has to control by himself in order to keep y_s almost the same.

In addition to two indices J and U defined by (18), (19), an index on the control performance of a human without robotic assistance is defined as

$$J_\alpha = \int_0^{t_f} (r(t) - y(t))^2 dt / \int_0^{t_f} r^2(t) dt. \qquad (20)$$

The difference between J and J_α is caused by the assistance. Figure 12 (a) shows J and J_α, while Fig.12 (b) represents the normalized square sum of the hand force U under the trial time t_f=60 [s]. In spite of a reduction of the assistance, the control performance J_α was improved during the trials under $\alpha = 0.6$ and $\alpha = 0.4$, that is, the control skill of the operator was trained. It is found that the training under $\alpha = 0.8$ is not effective since both J_α and U increases. In all

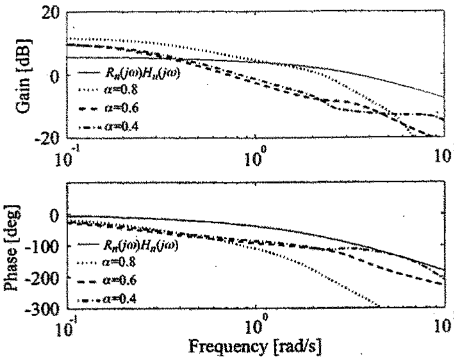

Figure 13: Changes of the estimated describing functions depending on the assisting ratio α

α, however, the control performance of the system, J, is kept around 0.6. Therefore, the overall system is always stable in these cases.

Finally, Fig.13 shows describing functions of the human-robot system $\hat{R}(j\omega)\hat{H}(j\omega)$ estimated from experimental results. In this figure, the solid line shows characteristics of the reference model, the dotted line the case of $\alpha = 0.8$ in the third trials, the broken line $\alpha = 0.6$, the alternate long and short dash line $\alpha = 0.4$, respectively. In comparison between the cases of α=0.6 and 0.4, the phase lag of the system increases under $\alpha = 0.8$. In other words, even if a human operator achieves a large gain, the control performance J_α becomes worse because of a large phase lag. From the facts, it is shown that the operator changes his own control property according to the degree of the assistance, and that a desirable value of the assisting ratio α is less than 0.6. It is expected that adaptive adjustment of α according to the control performance of a trainee improves the effectiveness of the proposed method.

5 Conclusion

In this paper, the training method for robot rehabilitation aids using the NN has been proposed. The proposed training system can identify human characteristics using an adaptive learning ability of the NN, and simultaneously assist an operator according to the results of the identification in real time. From experimental results with subjects, it was shown that the proposed method can attain the desired control property of a human-robot system with a modeling error, and that the control ability of a trainee can be trained by using the proposed method.

A notable feature of the proposed system is that desired control characteristics can be expressed by the reference model including in the identification model. Therefore, by utilizing the motor control characteristics of a healthy person as the reference model, the system can be useful a physically disabled person who uses a prosthesis or an orthosis as shown in Fig. 1.

Future research will be directed to develop an algorithm of adaptive adjustment of the robotic assistance α according to the level of trainee's skill.

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