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Gravity Compensation for Manipulator Control by Neural Networks with Partially Preorganized Structure

Toshio Tsuji, Masataka Nishida, Toshiaki Takahashi and Koji Ito

Faculty of Engineering Hiroshima University
Higashi-Hiroshima-shi, 724, Japan

The gravity torque of a manipulator can be compensated if the equation of motion can be correctly introduced, but in general industrial manipulators, there are many cases when the parameter values such as the position of center of mass are not clear, and these values largely change by the exchange of hand portions and the grasping of substances. Furthermore, in addition to unclear parameters, there are factors which occur by structural gravity compensation (spring and counter-balance) and which in many cases are difficult to express with the equation of motion. In this paper, compensation of the gravity torque of the manipulator is studied by the use of neural networks. For this purpose, a model which makes the structure known to be contained in mapping as a unit with preorganized characteristics prepared in parallel with hidden unit of error back propagation-type neural network is proposed, by which the characteristics of the link system which is the object for learning can be imbedded into the network as preorganized knowledge beforehand. Finally, the results of experiments done with the use of industrial manipulators are given, and it is made clear that the compensation of gravity torque of manipulator and adaptive learning for end-point load are possible by the use of this model.

1. Introduction

Generally, in a multi-articular manipulator, there exist interferences among each joint which largely change inertia characteristics by posture. Friction, gravity, Coriolis force and centrifugal force also exist. Therefore, the multi-articular manipulator becomes a system which has a high degree of non-linearity, and it is difficult to make high-velocity motion with high precision only using individual joint feedback control.

On the other hand, human and arival deftly move their limbs which are multi-articular mechanisms and can make a speedy and skillful motion. The superior characteristics of high velocity and pliability which the motion of a living body has indicates that it's motion control consists of not only visual and proprioceptive feedback control but also by feed-forward and program control based on an internal model which reflects the dynamical characteristics of its muscular and skeletal system.[1] To generate such an internal model, a wide range of knowledge of controlled objects. environment and motion mechanisms and also the ability to assemble these factors depending on the existing situations.conditions become necessary. It also becomes necessary to be equipped with motion-control information as a sub-system and to assemble this information to meet conditions appropriately rather than to prepare an internal model for each specific condition. Of course, it can be considered that internal representation such as a motion scheme is generated by learning for motions which occur frequently.

Recently, studies have been increasingly made to apply neural networks of coping in the central nervous system of the living body to motion control. Mr. Kawato proposed a hierarchial model for motion learning based on hetero-synapse plasticity and actualized an internal model of the inverse system which calculates input torque to each joint from a target joint angles by learning.[2] This neural network consists of two layers. One is the unit layer which non-linearly transforms the target trajectory; the other is the output unit layer which makes a linear summation, making good use of the point that the equation of motion of a link system can be represented as the linear sum of nonlinear terms. However, an industrial manipulator for general use contains a considerable amount of complicated and unclear nonlinear factors, and there are often cases in which general equations of motion are not necessarily formed. Therefore, problems arise on what kind of nonlinear transformation is to be prepared.

Additionally, Mr. Kawato et al. showed[4] that non-linear transformation itself can be obtained by learning with the use of error back propagation-type neural networks.[3] The errorback propagation-type neural network has several advantages. These include the capability of highly parallel processing, powerful learning rules which can acquire arbitrary nonlinear mappings and being strong against noise and failure. This network can become an effective means for constructing of internal models from motion control it's uniform structure. But, from it's uniform structure, it conversely has the problematic points of taking time for learning and solutions coming down to a local minimum.

Therefore, in this paper, considerations are made to imbed the characteristics of the link system which is the learning object into a network as preorganized knowledge. For this purpose, a model which makes the structure known to be contained in mapping as a preorganized-layer and which is prepared in parallel with the hidden layer of error-back propagation-type neural networks is proposed, and by the use of this model, a study is made to generate an internal model for gravity compensation by learning about the internal model of motion control.

It is possible to actively compensate the gravity torque of the manipulator in case the equation of motion can be correctly introduced,[5] but generally, a method to compensate the influence of gravity torque by structural balancing with the use of a counter-balance, spring, etc. is used to reduce the load by actuator. In such methods, correct compensation is not possible, and, in addition, it causes unknown factors to be built into the equation of motion and the application of active compensation method becomes difficult. The model proposed in this paper can be used to obtain the gravity torque which is represented by the equation of motion with a preorganized layer unit and unknown factors are obtained by error-back propagation-type neural network, and it becomes possible to correspond with a manipulator having a complicated structure. In Chapter 2, a mention is made of neural networks with partially preorganized structure, and in Chapter 3, a construction method for a gravity compensation internal model is shown. Finally, in Chapter 4, the results of the experiment made with the use of industrial manipulator are shown, and it is demonstrated that the improvement of position-control accuracy can be accomplished by the use of gravity compensation internal model.

2. Neural Networks with Partially Preorganized Structure

Figure 1 is the neural network proposed in this paper. Considerations are made not only of the input unit which receives input from outside and of the output unit which transmits output to the outside but also of the hidden units and preorganized units which function among them. Each unit is a feedforward network which receives the input from the previous layer and transmits the output to the following layer, and there is no connection among units in the layers.

$$x_i = \begin{cases} I_i & \text{(input unit)} \\ \sum_j w_{ij} y_i & \end{cases} \quad \cdots\cdots\cdots (1)$$

$$y_i = f_i(x_i) \quad \cdots\cdots\cdots\cdots\cdots\cdots (2)$$

Each unit receives activation value y_j from previous layer unit through weight coefficient w_{ij}, and outputs activation value in accordance to a differentiable output function f_i. Here, for the input unit, the external input I_i is the input to unit x_i. Then we have.

$$f_i(x_i) = \begin{cases} x_i & \text{(input unit, output unit)} \\ \varphi_i(x_i) & \text{(preorganized characteristic unit)} \\ \dfrac{2}{1+e^{-x}} - 1 & \text{(hidden unit)} \end{cases} \quad \cdots\cdots\cdots (3)$$

It is the characteristic of this model that is built the partially preorganized layer into the error backpropagation-type neural networks. That is, the structure contained in the mapping to be learned is imbedded in networks with the use of the output function Φ_i of partially preorganized unit and the mights to it.. By this method, the structure contained in mapping can be represented in the network as: input layer, partially preorganized layer and output layer. The other unknown factors can be represented in the network as: input layer, hidden layer and output layer. It is expected that learning velocity can be accelerated by structurally preparing preorganized knowledge.

The learning target of the model is to regulate the weight coefficient w_{ij} among units so that the target output can be obtained for the input as in the case the of ordinary error back propagation learning.[3]

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial y_i}\frac{dy_i}{dx_i} y_j \quad \cdots\cdots\cdots (4)$$

$$\frac{\partial E}{\partial y_i} = \begin{cases} y_i - t_i & \text{(output unit)} \\ \sum_k \dfrac{\partial E}{\partial y_k}\dfrac{dy_k}{dx_k} w_{ki} & \end{cases} \quad \cdots\cdots (5)$$

Here, η shows learning rate, t_i teacher signal given to output unit, k unit of the layer next to i, respectively, and the weights between input layer and partially preorganized layer unit are to be fixed.

3. Construction of Gravity Compensation Internal Model

Generally, the equation of motion of the multi-articular manipulator can be expressed by:

$$M(\theta)\ddot{\theta} + f(\theta,\dot{\theta}) + g(\theta) + B_j\dot{\theta} + B_c(\dot{\theta}) = \tau \quad . (6)$$

Here, θ represents the joint angle, $M(\theta)$ inertia matrix, $f(\theta, \theta)$ Coriolis and centrifugal force, $g(\theta)$ gravity torque, B_j viscous friction matrix, $B_c(\theta)$ nonlinear friction force τ joint torque respectively.

In this paper, a method to compensate gravity torque $g(\theta)$ is considered. As gravity torque becomes a factor to generate steady-state error in position control the methods to set up position feedback gain largely within the limit of satisfying the stability of control system or to adopt PID control are ordinarily used. But, there is a case in which such methods are not applicable. For example, when compliance control which needs the pliability of end-point is made, the compliant motion becomes difficult if position

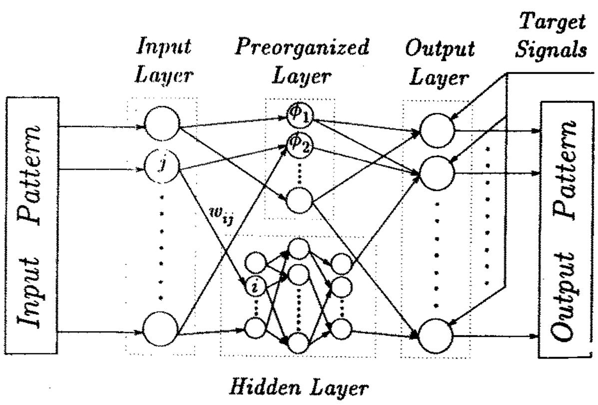


Fig. 1. Neural network with partilly preorganized structure

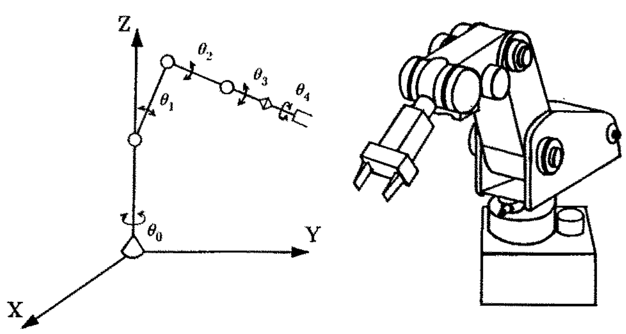


Fig. 2. A Multi-articular manipulator: MOVE MASTER II

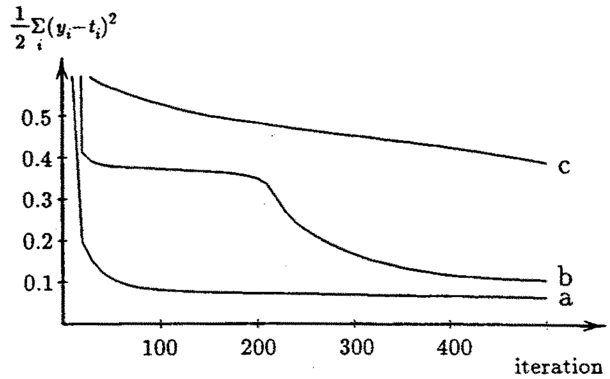


Fig. 3. Learning history of gravity compensationmodels

feedback gain becomes extremely large. Therefore, it is necessary that the gravity torque is to be compensated by some method.

The gravity torque of the manipulator can be computed in accordance with the equation of motion (6) when the parameters such as mass, position of the center of mass of each link, etc. are known. But, in the general industrial manipulator, even the mass of each link is often unclear, not to mention the position of the center of mass. Also, each parameter changes greatly at the exchange of the hand portion and the grasping of substances, etc. Furthermore, in many cases, such trials to mitigate the influences of gravity by structural contrivances (for example, a spring installed in a joint) have been made, and when such complicated mechanisms exist, the application of the equation of motion itself becomes impossible. Therefore, the gravity compensation by learning with the use of neural networks shown in the former chapter is studied separately from the introduction of gravity torque from the equation of motion.

The method of constitution which is going to be proposed is as follows.

1) Manipulator is positioned to target joint angle θ_d ($n \times 1$ vector).
The control rule is PD control and

$$\upsilon = K(\theta_d - \theta) + B\dot{\theta} \quad \ldots\ldots\ldots\ldots\ldots (7)$$

is used.
Here, K is position feedback gain ($n \times n$ matrix), B is velocity feedback gain ($n \times n$ matrix), and υ ($n \times 1$ vector) is control voltage to the servo motor.

2) When the manipulator is influenced by gravity and friction as external forces, it stands a joint angle θ_a, which is different from θ_d. When the balancing condition is considered, the link does not move upwards if

$$\tau_s + g(\theta_a) \geq f_v(k(\theta_d - \theta_a)) \quad \ldots\ldots\ldots (8)$$

is satisfied.
Here, r_s ($n \times 1$ vector) is downward stationary friction, and $fv(\,)$($n \times 1$ vector) is the function to express the relation between the joint torque and the input voltage of servo motor.

3) To balance the driving force upwards with the sum of stationary friction force acting downward and the gravity force the position feedback gain K is gradually increased in a stationary condition, and the control voltage is made higher. Also, the control voltage at the instant when the joint begins to move is measured.

$$\upsilon_d = K^*(\theta_d - \theta_a) \quad \ldots\ldots\ldots\ldots\ldots\ldots (9)$$

4) The above procedures are repeated M times by changing the target joint angle, and by making the control voltage which deducted the voltage corresponding to stationary friction V_{di} ($i = 1,\cdots,M$) a teacher signal, and making θ_{ai} ($i = 1,\cdots,M$) an input signal, neural networks are learned until the square sum of the error between the teacher signal and the output of the network becomes small.

In partially preorganized layer trigonometric functions contained in $g(\theta)$ of the equation of motion are prepared for an example, by which the parameters of the mass of the link and the position of the center of mass, etc., can be learned by a partially preorganized layer, and unknown factors such as mechanism for gravity compensation can be learned by the network through its hidden units. By learning on voltage levels, it is not necessary to be conscious of the function f_v contained in equation (8). In the next chapter, an appraisal of this method is made by the actual use of the manipulator.

4. Experiment of Manipulator Control

The above-mentioned procedures were applied to the industrial manipulator shown in **Fig.2** (MOVE MASTER II manufactured by Mitsubishi Electric, mass appr.27kg), and the generation of gravity compensation internal model was studied. In the experiment, the joints at the wrist (θ_3, θ_4) and waist (θ_0) were fixed, and gravity compensation was made on the joints at the shoulder (θ_1) and elbow (θ_2).

4-1. Learning History

First, target joint angle θ_d were made into ten patterns in the step width of 10° from 0° to 90° for each shoulder and elbow joint, and learning was done with the use of a total of 100 patterns of teacher signals. **Figure 3** shows the learning history. (a) in the figure is the learning history which used a neural network with partially preorganized structure proposed in this paper, (b) is that which used an error-back propagation-type neural network,[3] and (c) is that which used an adaptive filtering model.[(7)] As for (a), two pieces of hidden layers, ten pieces of hidden units for each layer and six pieces of partially preorganized units were prepared. The nonlinear functions used for partially preorganized layer units were of six types; $\sin\theta_1$, $\sin\theta_2$, $\sin(\theta_1+\theta_2)$, $\cos\theta_1$, $\cos\theta_2$, $\cos(\theta_1+\theta_2)$. Two hidden layers and ten pieces of hidden units for each layer for (b), and six kinds of nonlinear functions for (c), the same as (a), were used. In each case, the number of units of input layers and output layers are two pieces each, and the learning rate was set at 0.01.

By the way, as wrist and waist joints are fixed in this experiment, this manipulator can be considered to have 2-link arms, shown in **Fig.4.** If the motion of manipulator is perfectly described by the equation of motion for equation (6), gravity torque $g(\theta)$ becomes[8];

$$g_1(\theta) = (m_1 l_{g1} + m_2 l_1)\, g\sin(\theta_1) + m_2 g l_{g2}\sin(\theta_1+\theta_2) \quad \cdots\cdots (10)$$

$$g_2(\theta) = m_2 g l_2 \sin(\theta_1+\theta_2) \quad \cdots\cdots (11)$$

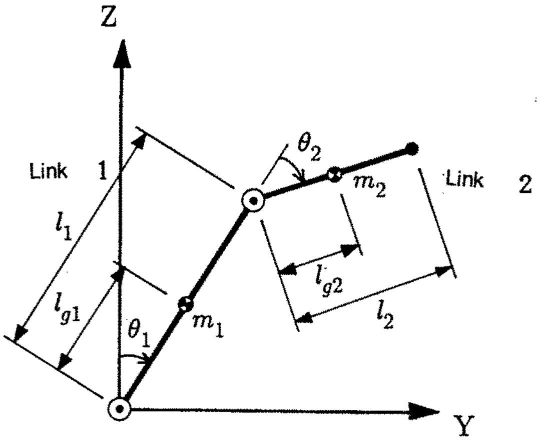


Fig. 4. Two-link model

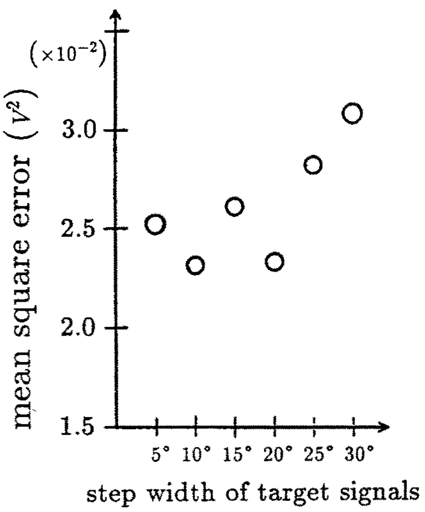


Fig. 5. The relationship between teacher signals and their mean square errors

θ_i is joint angle, m_i mass of each link, l_i the length of each link, l_{gi} distance from joint to the center of mass, g gravity acceleration. As for affixed letter i, 1 shows the shoulder joint and 2 shows the elbow joint. Therefore, nonlinear transformation necessary for the calculation of gravity torque becomes the only sin function contained in equations (10) and (11). But, in the adaptive filtering model (**Fig.3(c)**) which prepared these sin functions, the decrease in errors is late and it is known that learning does not proceed well. This is because influences other than the equations (10), (11) are contained in the gravity torque of the manipulator. On the other hand, in errorback propagation-type neural network (**Fig.3(b)**), errors decrease but learning velocity is considerably late. In contrast to the above, in the model (Fig.3(a)) proposed in this paper, fast learning velocity is achieved while sustaining accuracy. This is because nonlinear transformation which is known beforehand at the time of the internal model generation is prepared as a partially layer characteristics unit.

4-2. Number of Teacher Signals Patterns

In the experiment of the former chapter, learning was with the use of 100 pieces of teacher signals. In this chapter, study is made of the influence which the number of patterns of these teacher signals give to learning.

In addition to the teacher signals in the former chapter in

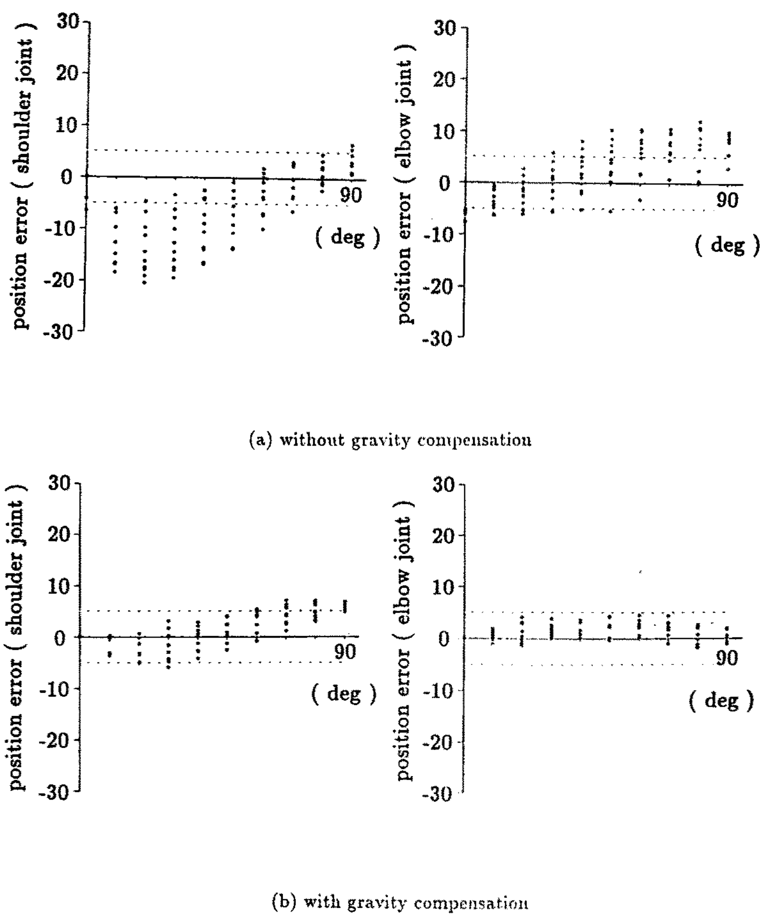


Fig. 6. Experimental results of position control

which target joint angle θ_d was set in step widths of 10°, learning was done with the use of six kinds of teacher signals with step widths of 5°, 15°, 20°, 25° and 30° (the number of patterns becomes 361, 49, 25, 16 and 16 pieces each). **Figure 5** shows mean square errors after 10,000 trials. Input (361 pieces) in the step width of 5° is given to each network and square errors with actually measured values averaged by the number of datum input. Therefore, in the case of teacher signals of 5° step widths, they coincide with the mean values of square errors at the time of learning, and input patterns which are not used at the time of learning increase with the step width of the angles. From the figure, it is known that errors increase with the increase of the step width of the angles. But, in the teacher signals between 5° and 20° step widths, the increase of a wide range of errors is not seen, and the interpolation by neural networks is made well. Therefore, it was made clear in the conditions of this experiment that a gravity compensation internal model can be generated by the small teacher signals of 20° step widths totalling 20 pieces both for shoulder and elbow joints.

4-3. Position Control Accuracy

Next, for verifying the effectiveness of the internal model (after learning of 10,000 trials) obtained by the result of learning, control voltage was made

$$\upsilon = K(\theta_d - \theta) + B\dot{\theta} + \upsilon_g(\theta) \quad \ldots\ldots\ldots \quad (12)$$

and the position control was made. $\upsilon_g(\theta)$ is gravity compensation voltage computed by the use of models. Here, K, B are diagonal matrices, and K = diag.[11.191 11.191](v/rad), B = diag.[26.857 26.857](v/(rad/sec)). As the purpose of this experiment is to verify the propriety of the gravity compensation internal model, the position gain K was set considerably low so that the steady-state error remains at the time of position control.

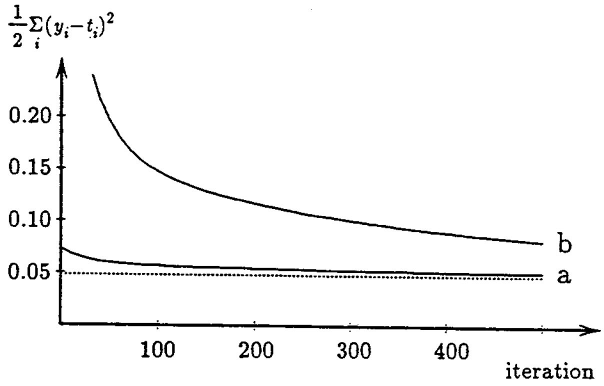
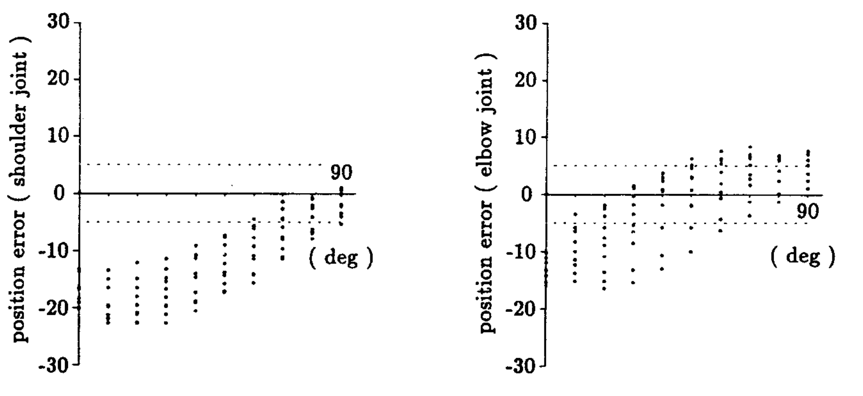
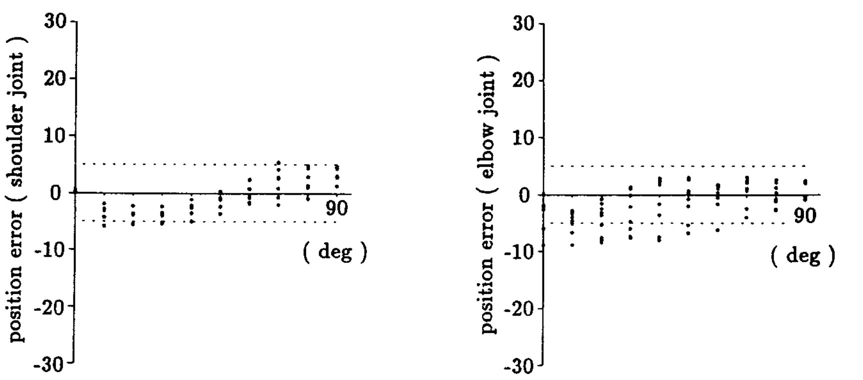


Fig. 7. Learning history for an end-point load (500 g)



(a) without gravity compensation



(b) with gravity compensation

Fig. 8. Position control accuracies of the manipulator with an end-point load

Results of the experiment are shown in **Fig.6**. (a) concerns shoulder and elbow joints without gravity compensation and (b) concerns shoulder and elbow joints with gravity compensation. Target angles are shown in the axis of abscissa and errors (θ_d - θ_a) between target angles and actual angles are shown in the axis of ordinates, so their relations can be known. From Fig.6(a), it is known that errors decrease when the angle of shoulder joint approaches 90° (the position when the arm is horizontal). This is an influence contrary to the ordinary gravity, and the effect of the spring for gravity compensation which is built into the joint of the manipulator. As this spring is set to meet the posture which is most influenced by gravity (θ_1=90°, θ_2=0°), the influence of gravity which is different from equation (10), (11) appears in the position control errors of the manipulator. In contrast to the above, when compensation is made by the internal model (Fig.6(b)), errors come within the range of almost ±5° both for shoulder and elbow joints, and position control accuracy is increased by the addition of an internal model. Furthermore, the postures which were not used as teacher signal are contained in these errors and it is known that the neural network is making good gravity compensation also on the postures besides the teacher signal. But, further improvement was not seen even when the number of times of learning was increased. It is considered that this is caused by the influence of the noise contained in the teacher signal and the learning of method the neural network. It will be necessary to find out the method of obtaining a more robust teacher signal and develop the method of learning of neural network in the future.

Next, by giving load to the end-point of the manipulator, an experiment of generating a gravity compensation internal model for it was made. **Fig.7** shows the result of learning with the use of teacher signals (10° step width, total 100 patterns) at the time of grasping the substance of 500g by the end-point. In the figure, (a) concerns the case of relearning with the network at the time of no-load learned in 4-3. as initial value, and (b) concerns the case of learning with only teacher signals with load. The dotted line shows the square sum of the errors in output unit after learning (10,000 trials) in the network at the time of no-load. From the figure, it is known that the increase of errors by end-point load is small when the network at the time of no-load is re-learned, and errors decrease with the small number of learning times, as low as 300 times. **Figure 8** is the result of position control in the above case. The errors of the elbow joint increased a little compared with Fig.6, and is considered to be caused by the change of friction force by end-point load. It is necessary to study this further, but, compared with the case without gravity compensation (**Fig.8(a)**), position control accuracy is largely improved and it is known that the gravity compensation internal model has been adaptably adjusted against load variation.

5. Conclusion

In this paper, for the purpose of constructing a motion control internal model by learning, it was attempted to imbed link system characteristics into neural network beforehand. To this end, a model which builds a partially preorganized layer into an errorback propagation-type neural network is proposed, and a method of generating an internal model which makes gravity compensation by learning with the use of this model is shown.

In general industrial robots, there exist complicated and unclear nonlinear characteristics such as backlash accompanying to gear mechanisms and friction, and these nonlinear characteristics contain many functions whose forms are known. The method shown in this paper can effectively utilize such preorganized knowledge and can acquire the relations of mappings whose characteristics are unknown by learning too. In future, the modelization of internal models related to dynamics and kinematics will be made, and the construction of a whole motion program by a method of exchanging these internal models in compliance to conditions is considered.

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