STUDY OF INTELLIGENT IMPEDANCE CONTROL USING A FUZZY NEURAL NETWORK

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ABSTRACT
This paper presents study of adaptive force control that takes into account object characteristics using a fuzzy neural network. This study applies fuzzy theory to position control and force control, similar to those actually implemented by industrial robots, to enable automatic establishment of optimum parameters for different environments and autonomous, flexible motion.

Keywords: adaptive force control, fuzzy neural network, Intelligent impedance control

1. INTRODUCTION

In recent years, the industrial world has been anticipating the arrival of robots capable of coping with differences in environment and object characteristics. These robots would be capable of what is called humanoid motion. This study of Intelligent Impedance Control using a Fuzzy Neural Network applies fuzzy theory to position control and force control, similar to those actually implemented by industrial robots, to enable automatic establishment of optimum parameters for different environments and autonomous, flexible motion. After the motion of a constructed control model was verified through simulation and experiments at the uniaxial stage, it was then installed into an arm robot, the ultimate target of this research, for a final confirmation of motion.

2. INTELLIGENT IMPEDANCE CONTROL

In this research, a neural network[1,3,6,7,8] and fuzzy neural network are used in the system, as shown in the block diagram, Fig. 1.

There are control systems for position and force, each composed of a two-degree-of-freedom[2] structure combining feedback and feedforward[5,10,11,12]. In the FF-NN (neural network block), even greater linear control is achieved by giving the inverse of Plan t characteristics. Also, the FB-FN (fuzzy neural network block) is utilized to cancel disturbances caused by unsteadiness and friction arising from motion that the FF-NN cannot fully absorb. These are achieved by fine-tuning the fuzzy parameters to carry out ill-defined controls and through the learning capabilities of the neural network[4,9].

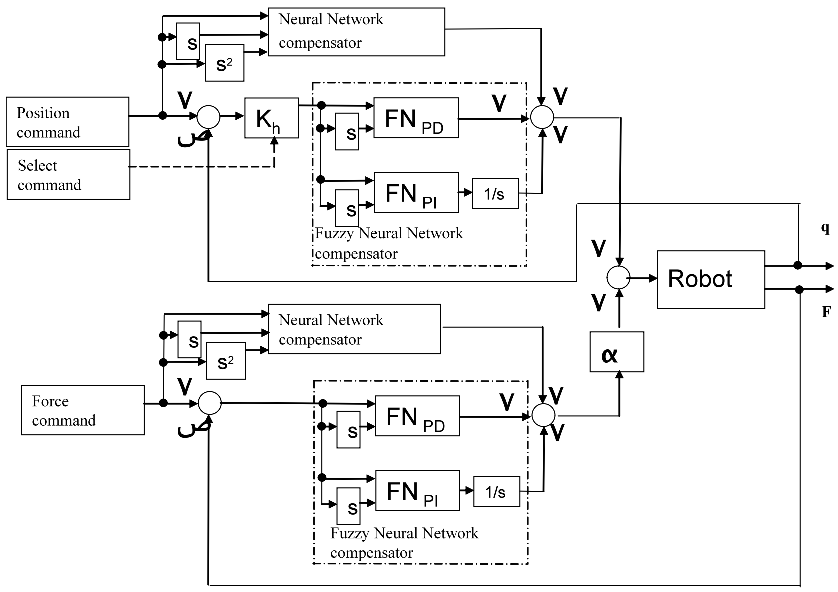


Fig.1. Block diagram of control

The structures are illustrated in Fig.2 and Fig.3.
This shows the fuzzy neural network is employing the neural network theory.

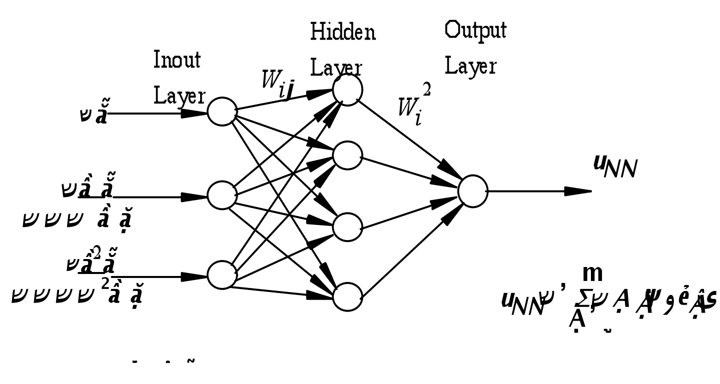


Fig.2. Neural network structure

The neural network has a 3-layer structure with an input layer, a hidden layer, and an output layer. It uses displacement, velocity, and acceleration for position input, and force, viscosity, and rigidity for force input.

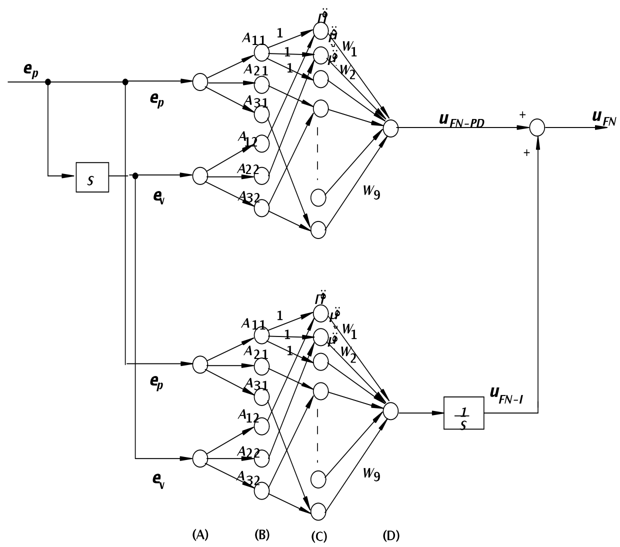


Fig.3. Fuzzy neural network structure

It is split into an antecedent and consequent, with the antecedent applying membership function to determine nonlinear function. The consequent weights the control using fuzzy rules.

$$M_x \ddot{x} + B_a(\dot{x} - \dot{x}_d) + K_h S K_d (x - x_d) = SF + \alpha(E - S)K_f(F - F_d) \qquad (1)$$

X: position, X_d: position command, M_x: inertia matrix, B_a: damper matrix,

K_d: virtual spring matrix, F: force response, F_d: force command, S: switching matrix diag(S_1,- - -,S_6), K_f: force gain, E: unit matrix

S, M, B, K are 6×6 matrices(X,Y,Z,X_M,Y_M,Z_M)

Defined as in Equation (2) the impedance as a secondary delay system in terms of the displacement force.

$$\frac{1}{M_x s^2 + B_a s + K_d} \qquad (2)$$

① ② ③

①M_x: Material rigidity (fixed)

②B_a: Virtual viscosity Parameters set by NN learning

③K_d: Virtual rigidity Parameters set by NN learning

Adjusting parameter K_h allows smooth, continuous switching of complete force control and position control through compliance control.

This method makes continuous setting of 3 modes possible by adjusting just 1 parameter.

K_h=0(α=1) force control

$$M_x(\vartheta)\ddot{x} + B_a(\dot{x} - \dot{x}_d) = SF + 1(E - S)K_f(F - F_d) \tag{3}$$

K_h=K_{hmax} (α=0) position control

$$M_x(\theta)\ddot{x} + B_a(\dot{x} - \dot{x}_d) + 1\ SK_d(x - x_d) = SF \tag{4}$$

0<K_h< K_{hmax} (1>α>0) compliance control

$$\begin{aligned} M_x(\theta)\ddot{x} + B_d(\dot{x} - \dot{x}_d) + K_h\ SK_d(x - x_d) \\ = SF + \alpha\ (E - S)K_f(F - F_d) \end{aligned} \tag{5}$$

Not directly set,α coefficient is calculated by substituting the K_h to equation (6) the following.

$$\alpha = \frac{K_c}{K_h + K_c} \tag{6}$$

K_c: Constant 0.1 , K_h: Virtual spring constant

α: Configuration parameter control mode

The control model for this research was constructed with 2 kinds of input, position command and force command. Each was integrated after fuzzifying. Fig.4 shows the actual model diagram built using MATLAB Simulink.

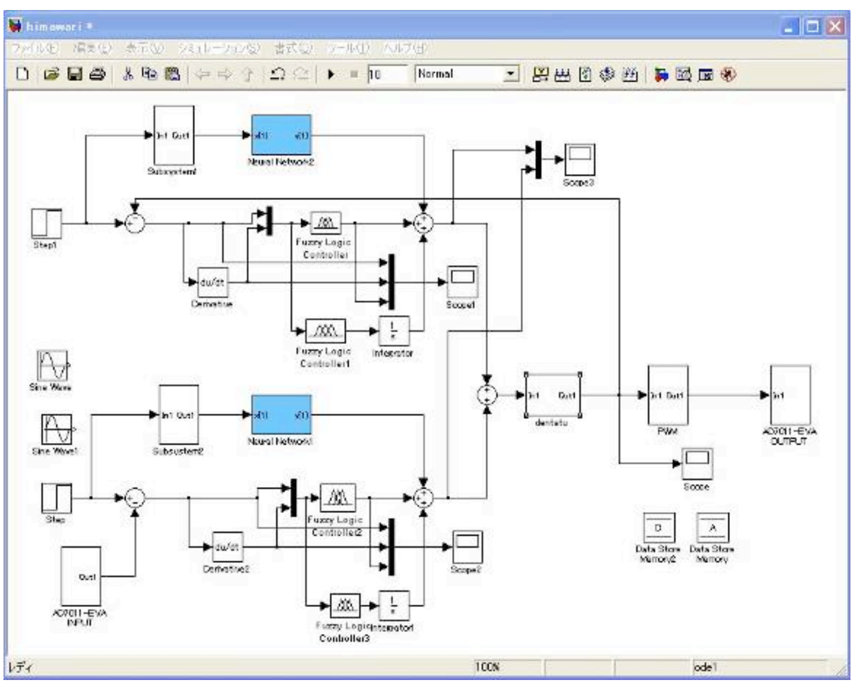


Fig.4 Fuzzy model diagram

3 EXPERIMENT

3.1 System configuration

A DC motor-driven, uniaxial table was used for control to conduct a grasping experiment. A metal plate was also attached to the moving table for grasping an object, and a strain gauge was attached to the center of the metal plate to acquire strain data. The aim was to grasp the object without placing load on either the object or instrument. Fig. 5 shows an external view of the control instrument.

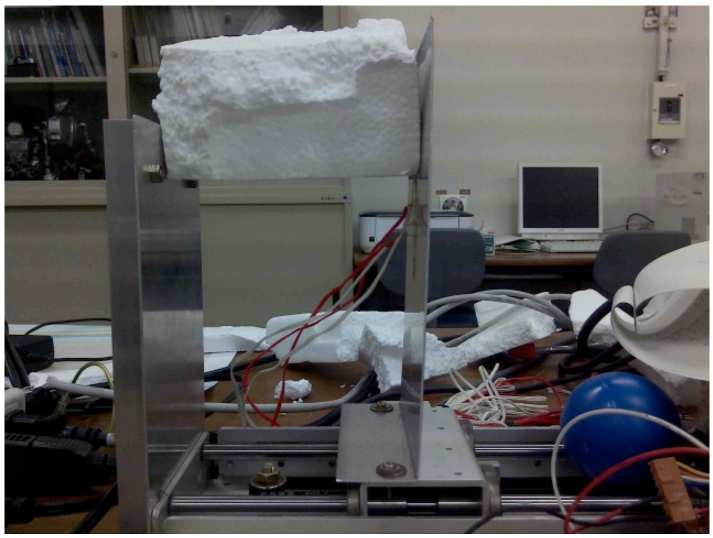


Fig. 5 External view of the control instrument

3.2 MATLAB

The system architecture of this study utilized MATLAB, Simulink, and Real-Time Workshop. Simulink was used to link to the block to allow the establishment of parameters for the constructed model diagram and simulation. This method is advantageous because it facilitates system changes and enables visual construction. First, an experiment was conducted with a system built using only PID control. Then, the Fuzzy Logic Controller from the Fuzzy Logic Toolbox in the Simulink Library Browser was added to the system to build a control model diagram using a fuzzy neural network.

The top and bottom have identical configuration, but position control is on top and power control on the bottom. Both use a neural network for feedforward and a fuzzy neural network for feedback. The output of the strain gauge attached to the metal plate was used to obtain power data for power control. The model diagram built with Simulink was converted to C source with Real-Time Workshop and entered into an embedded computer to operate the instrument.

3.3 System flow

Numbers ①–⑥ illustrate the system flow.

① C source converted with Real-Time Workshop is entered into an embedded computer.

② The motor is driven according to simulation.

③ Strain gauge voltage is produced at the moment an object is grasped.

④ Voltage amplified by an amp is converted to a digital value by an A/D converter.

⑤ Strain gauge output is received as power data, and power control starts.

⑥ Voltage applied to the motor and strain gauge output are displayed on the computer in real time.

VC Designer software was used for the computer display (⑥) to create a system showing a real-time graph display of voltage applied to the motor and strain gauge output.

3.4 Experiment method

As previously noted, this study aimed to construct a system capable of flexibly handling differences in object rigidity. That is, even when the characteristics of a component on a manufacturing line suddenly change, the conventionally required resetting of parameters is omitted, object-appropriate autonomous adjustment of pressure is achieved, and motion can be executed without load.

Since a variety of instances had to be anticipated in this grasping experiment, objects with totally different properties and rigidity were used. Observations and indications for improvement were derived from outcome disparities between a conventional PID control system and an adaptive force control system using a fuzzy neural network. Fig. 6 shows the objects used in the experiment.

Styrofoam Building block Sponge

Coil Chalk Stuffed animal

Fig. 6 Objects used in the experiment

(1) Experiment using PID control

First, a grasping experiment was conducted with a model diagram using PID control. This system also had a built-in neural network for feedforward because, ultimately, this study attempted to prove the outcomes of a fuzzy neural network. Also, PID block parameters for control were set at parameters more appropriate than experimental values to observe output waveform and show even greater efficient convergence. The established parameters were P=1, I=0, D=0.1.

(2) Experiment using a fuzzy neural network

The model diagram for the PID block constructed in the previous step was changed to a fuzzy neural network, at which time displacement and velocity were input, so the input signal and first-order differentiation signal were bundled and linked to the block. The fuzzy block treated this displacement, velocity, and output during PID control as an instruction signal, and learned from these 3 pieces of data. In addition, though not stated in item (1), a neural network was needed. This bundled 4 pieces of data—displacement, velocity, acceleration, and, like the fussy neural network, PID control output—into a single-file instruction signal as an array, from which it learned.

(3) Learning

(a) Neural network learning

Data on displacement, velocity, acceleration, and instruction signal were collected and input into the "NN TRAIN1.m" file, and learning was completed through execution. At this time, the various signals required for learning used a block data storage function called scope that was utilized when waveform was observed during simulation. Since the saved data became quite large, it was culled to adjust data quantity. Data was stored in the MATLAB workspace.

The data stored in the workspace was input into "NN TRAIN1.m." The 3 pieces of data, displacement, velocity, and acceleration, were assigned to the P array in the M file, and the instruction signal was assigned to the T array. Fig. 7 shows an actual screenshot.

```
P = [0.02094389 0.2303019   0.439256    0.6474394   0.854487    1.060
     1.047189    1.046091    1.043158    1.038395    1.031811    1.023
     -0.000872767    -0.01005629 -0.01922216 -0.02835432 -0.03743673 -
T = [0.3141584  2.454529    2.83884 2.961591    3.067305    3.150533
net=newff([-5 5 ; -5 5 ;-5 5],[3 1],{'tansig','purelin'},'trainlm');
```

Fig. 7 Screenshot of "NN TRAIN.m"

(b) Fuzzy neural network learning

Like the neural network, the 3 pieces of data—displacement, velocity, and instruction signal—were saved as a single data array. The FIS Editor screen for the fuzzy block that was to be learned was opened, input was doubled, and the Gaussian function was applied to the function. In this way, input/output were set and rules were established in the FIS Editor. Next, Anfis was selected from the edit tab. Fuzzy block learning took place in Anfis. Learning was executed by loading the created file. Learning frequency was set with the number of Epochs in Train FIS.

4. EXPERIMENT RESULTS

4.1 Results from the experiment using PID control

A grasping experiment was conducted using the previously noted 6 objects. Here, Fig. 8 shows representative results from the building block, Styrofoam, and stuffed animal. Even using PID control, it proved possible to grasp the objects without overloading them.

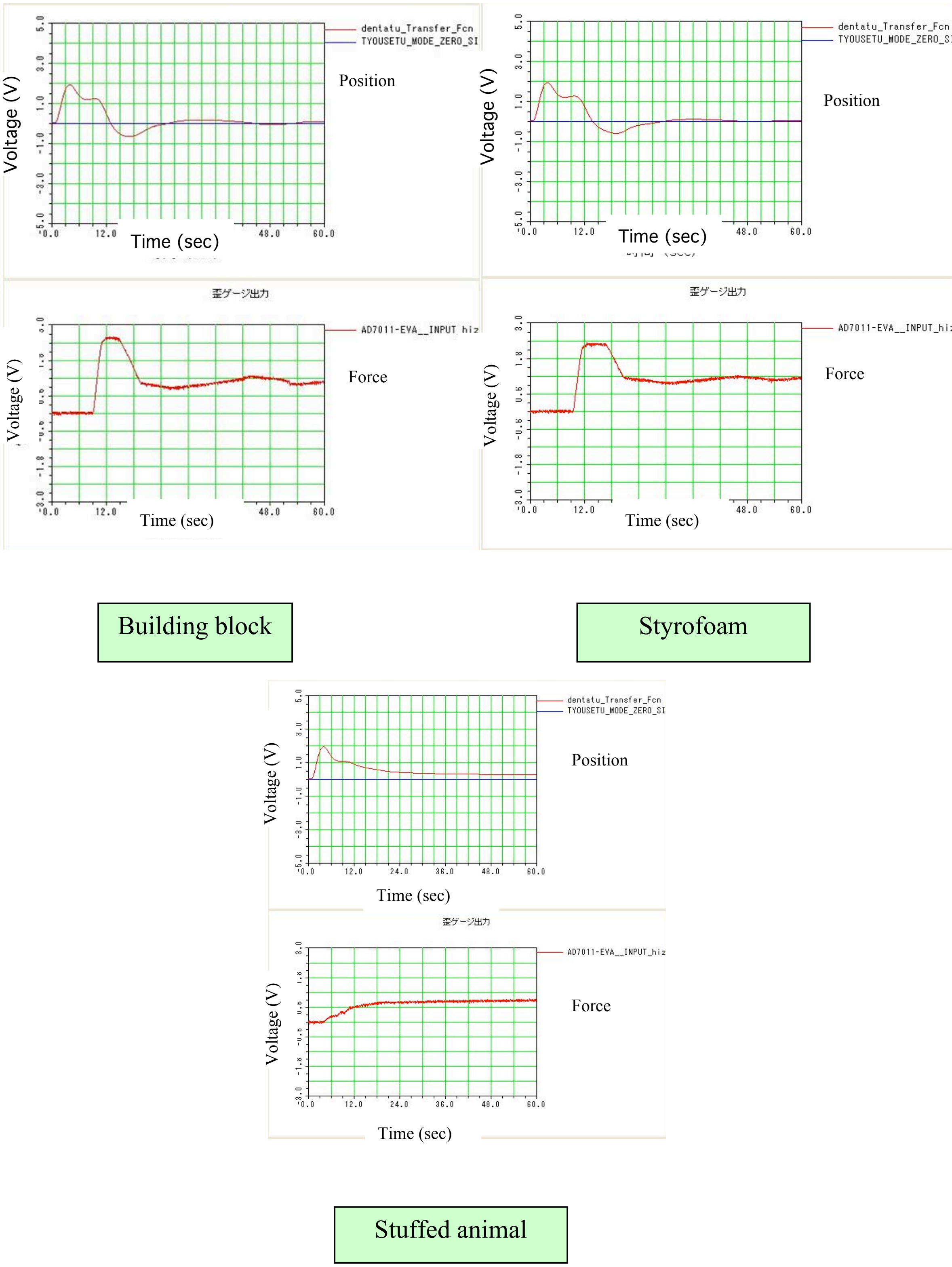


Fig. 8 Experiment results for the building block, Styrofoam, and stuffed animal

Each of the upper graphs show voltage applied to the motor, or changes to the trajectory of the voltage applied to the motor, while the lower graphs show strain gauge output when the objects were grasped.

The take away from the 3 experiment results is the fact that output from the strain gauge abruptly rose from the moment an object was grasped. This shows that load was placed on the objects, and that it took time for the appropriate pressure to be applied. Therefore, the motor also tried to compensate for the too-tight grasp by easing it through counter-rotation, but in the end, it required time to converge power control. Ideally, the system would instantaneously apply appropriate pressure to grasp an object so that convergence efficiently occurs. This was the goal of the experiment conducted next that used adaptive force control through a fuzzy neural network. Table 1 shows a comparison of experiment results for the 6 objects.

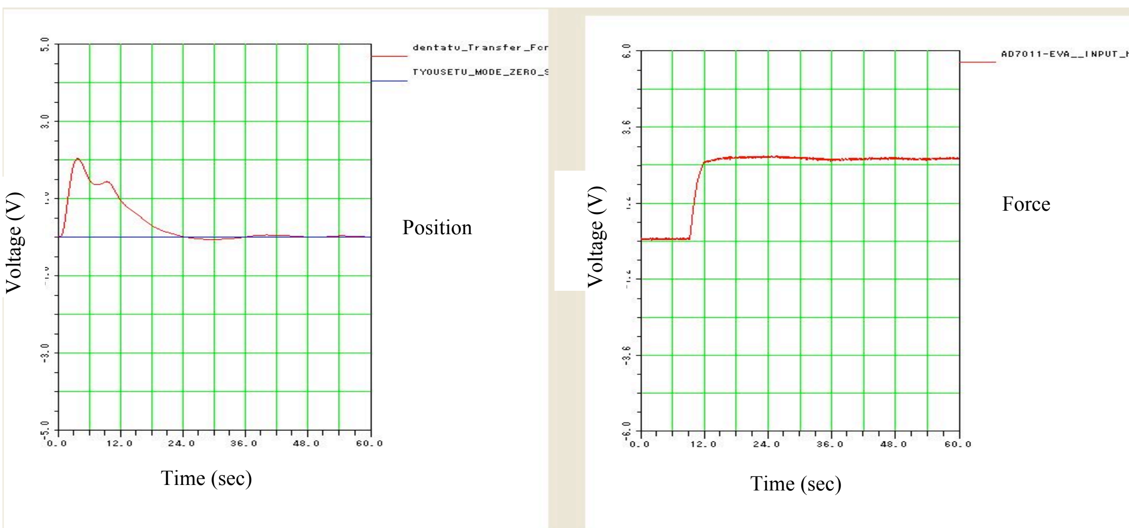
Table1. Experimentresults

	Convergence time to 0	Time to strain stability	Max. strain voltage
Styrofoam	36sec.	12sec.	approx. 2.3V
Sponge	36sec.	11sec.	approx. 2.6V
Building block	45sec.	25sec.	approx. 1.5V
Coil	24sec.	13sec.	approx. 2.1V
Chalk	38sec.	9sec.	approx. 2.7V
Stuffed animal	over 60sec.	15sec.	approx. 0.9V

The convergence time shown as “0” in the table indicates the time it took for voltage applied to the motor to reach “0,” which can also be expressed as the time it took to switch to power control. The table shows that, when grasping soft objects like the stuffed animal, necessary pressure is not applied and convergence can never be accomplished, as is also apparent from the experiment results graph. Convergence also took time for other soft objects like the sponge. Time to strain stability indicates the time it takes for the instrument to stabilize and necessary pressure to be applied. As expected, highly rigid objects took a certain amount of time due to abrupt output. It also took time for mildly rigid objects because, although strain gauge output was gained as the metal plate bent when the object was grasped, there was no abrupt output with the mildly rigid object, so acquiring enough output unavoidably took time. The maximum strain gauge output from when the object was grasped was also compiled. On average, 1.2V of output was sufficient to steadily grasp an object. However, as anticipated, highly rigid objects had over twice the output. Eliminating this abrupt output is the biggest issue.

4.2 Results from the experiment using intelligent impedance

In this study, the output from the building block PID was learned as an instruction signal. A comparison was made with the previous experiment between the building block and Styrofoam, which has relatively similar rigidity. Fig 9 shows the two experiment results.



Building block (after learning)

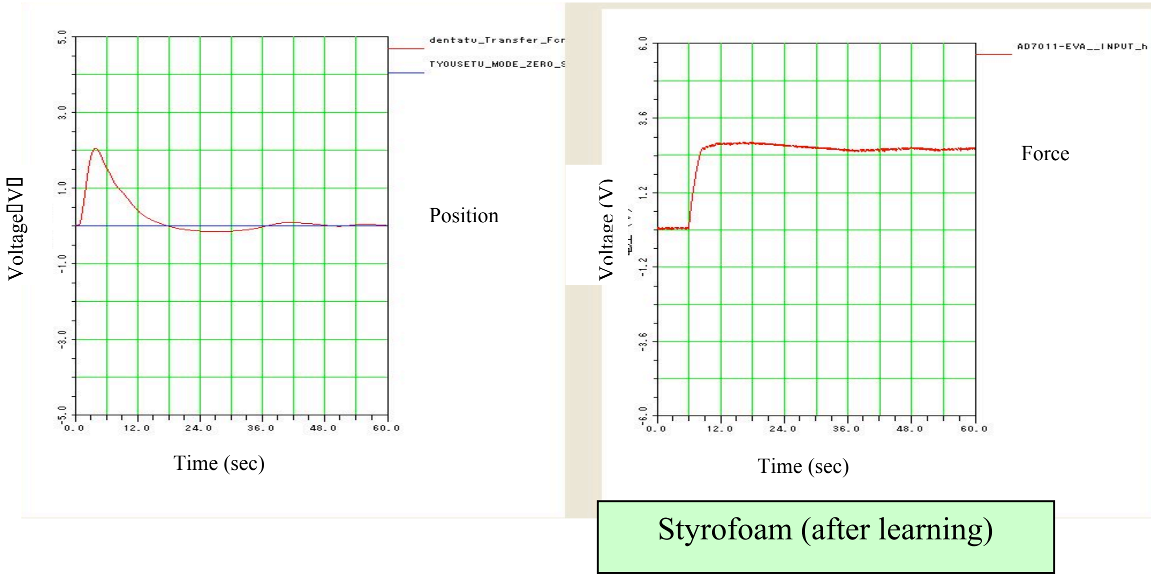


Fig. 9 Experiment results after learning

Compared to the previous experiment outcomes, the abrupt output of the strain gauge seen during PID control and the accompanying applied voltage overshoot were successfully eliminated, enabling the efficient application of optimum pressure needed to grasp the objects. A system was successfully constructed that did not place load on either the object or instrument. A comparison of experiment results was conducted using time to convergence.

Building Block:

Convergence time to “0”: 36sec. (before learning) → 12sec. (after learning)

Time to strain gauge output stability: 11sec. (before learning) → 3sec. (after learning)

These results show that each convergence time improved by approximately a third.

5. DISCUSSION

A comparison of the two experiments reveals that learning through a fuzzy neural network is extremely effective for intelligent impedance control. It can curb abrupt output from the strain gauge and allows operation that does not place load on either object or instrument. In addition, since the PID parameters used in the instruction signal were provided by the author based on appropriate experiment values and it is possible that a slight deviation from the ideal trajectory occurred, establishing even more appropriate PID parameters for the instruction signal will enable the construction of a system that operates even more efficiently.

This study conducted learning using a building block, but utilizing the system to conduct a grasping experiment with a stuffed animal revealed that a wide range of object rigidity is covered since identical improvements were seen with other objects. However, because the strain gauge currently utilized for power input performs more poorly than electrostatic power sensors of the kind that are actually installed on an arm, the grasping experiment could not be conducted at high velocity. Thus, there is a need to conduct an experiment with the table moving at high speed and confirm the difference in accompanying outcomes.

6. CONCLUSION

The implementation experiment confirmed that efficient impedance control is possible through learning that uses a fuzzy neural network. In addition, because objects such as chalk that are easily broken could also be grasped when diagonal force was applied without placing load on the object, a system was successfully built that made possible the original goal of "human-like action" that uses appropriate force. Therefore, this study reaffirmed that efficiently applying the necessary pressure to objects with any kind of rigidity requires the construction of a system that automatically adjusts gain using a learning function.

These results illustrate the necessity of a flexible system that uses appropriate force not only in the industrial world where robotic arms and various precision equipment are utilized, but also in medical fields related to nursing where care robots provide personal care for the elderly by grasping a variety of objects and making direct bodily contact. This kind of robust, intelligent impedance control system is now being eagerly awaited, and it is thought that its use will spread to many other fields aside from those noted above.

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