

An Intelligent Control for State-Dependent Nonlinear Actuator and Its Application to Pneumatic Servo System

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Abstract: Soft actuators, such as pneumatic actuators, have nonlinear characteristics, which are state-dependant. Therefore, it is difficult to control them using conventional linear controllers. In this paper, an intelligent controller based on predictive fuzzy control using a control rule and a forward model is proposed. This model was designed using the current state and the input-output characteristics of the actuator. The effectiveness of the proposed intelligent controller was confirmed experimentally using a pneumatic servo system.

Keywords: Intelligent Control, Fuzzy control, Soft Actuator, Pneumatic Muscle.

1. INTRODUCTION

Soft actuators have a non-rigid mechanism, which results in movement similar to that of living organisms. Consequently, soft actuators are safer when compared to electric and hydraulic actuators even in the event of a malfunction. Recently, various investigations have been conducted into soft actuators. These actuators are expected to be applied in the welfare and the medical treatment fields. One such soft actuator is the McKibben Pneumatic Muscle (PM), which uses pneumatic pressure.

Because the PM is composed of a soft tube and sheath, it is flexible and safe for humans. The PM has a high power/weight ratio and a high power/volume ratio. Due to these advantages, the PM has been used in human assistive devices and other such devices [1][2].

The output of the PM is different if the state (for example, length) is different, even if a constant value is input by the operator. Conversely, if the state of the PM differs, so does the required input value, even if the operator wants to maintain a constant output value. Thus, the PM has a state-dependant input-output characteristic. Such actuators are called state-dependent nonlinear actuators.

State-dependent nonlinear actuators are difficult to control using conventional linear controllers based on a reverse model. Before now, the effectiveness of predictive fuzzy control [4] for a nonlinear system incorporating a pneumatic rotary actuator has already been confirmed [3]. A predictive fuzzy controller predicts a future state using a forward model of the controlled object. The controller calculates a control instruction by evaluating the future state using a fuzzy set.

In this paper, an intelligent controller is proposed, based on a forward model determined in real time from the present state of the actuator. The controller performs a control instruction by predictive fuzzy control using the state-dependant forward model. This controller was applied to a pneumatic servo device incorporating a PM. For this, a pneumatic servo system was constructed. To confirm the effectiveness of the proposed intelligent controller, experiments were conducted on this pneumatic

servo system.

2. INTELLIGENT CONTROL OF A STATE-DEPENDENT NONLINEAR ACTUATOR

A schematic of the proposed intelligent controller is shown in Fig. 1. This chapter begins with a description of the controlled object and then moves on to describe the parts of the intelligent controller.

2.1 Controlled object

The object being controlled by the proposed intelligent controller has a state-dependent nonlinear actuator. This controlled object is shown as follows.

$$Q(M, P(x, u)) \quad (1)$$

where: M represents the mechanism parameters excluding the actuator, $P(x, u)$ represents the input-output characteristics of the state-dependent nonlinear actuator and $P(x, u)$ consists of the state(x) and input(u) of the actuator.

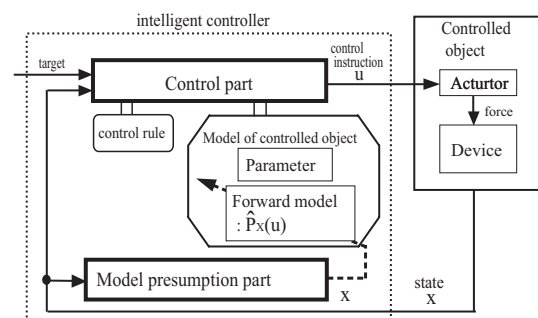


Fig. 1 Outline of the intelligent controller

2.2 Model presumption part

The model presumption part approximates a forward model ($\hat{P}_X(u)$) that represents the present input-output characteristic of the actuator. The forward model is approximated from the state of the actuator measured in real

time as follows

$$P(x, u) \xrightarrow{x=X} \hat{P}_X(u).$$

The relation between the forward model and the state of the actuator is examined in advance.

2.3 Control part

The control part calculates a control instruction using predictive fuzzy control [4] based on a model of the controlled object. The model of the controlled object consists of the present forward model ($\hat{P}_X(u)$) as approximated in the model presumption part and the mechanism parameters excluding the actuator (M). This is written as

$$\hat{Q}(M, \hat{P}_X(u)). \quad (2)$$

Predictive fuzzy control is an intelligent control method based on the control knowledge of humans. This human control knowledge is described as control rules. Predictive fuzzy control makes an inference based on certain control rules and decides upon a control instruction. The model of the controlled object is used to make an inference. The inference process is described in chapter 4.

3. PNEUMATIC SERVO DEVICE

3.1 Composition of the pneumatic servo device

The composition of the pneumatic servo device used as a controlled object in this research is shown in figure 2. The pneumatic servo device uses a McKibben Pneumatic Muscle (PM) as an actuator. The PM consists of a silicon inner tube and a nylon fiber braided outer sleeve. The PM expands circumferentially when the inner tube is pressurized. The outside sleeve converts this circumferential expansion into an axial contraction. The PM used in this research has a 1500 mm neutral length and ϕ 48 mm.

The length of the PM is measured using a rotary encoder through a mechanism that converts the linear contraction into an angular rotation. The output pulses of the rotary encoder are counted by a PSoC (Programmable System-On-Chip), converted into an analog voltage and sent to an A/D board. Control instructions from the PC are converted into analog voltages by a D/A board and drive the PM through an 8-ch electro-pneumatic regulator.

3.2 Modeling of the pneumatic servo device

The model of the pneumatic servo device consists of a forward model of the PM and the load M . The forward model of the PM shows the input-output characteristic with the air pressure being the input and the contractive force being the output. The forward model is obtained by finding the relation between the length, air pressure and contractive force of the PM. This relation was determined by hanging a weight on the bottom of the PM and

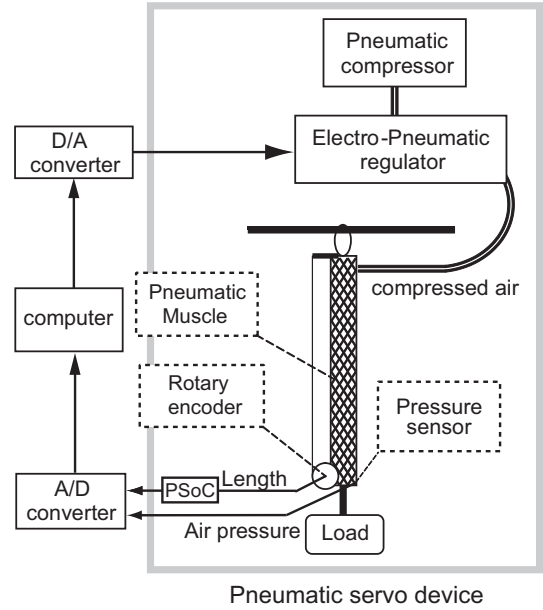


Fig. 2 Composition of the pneumatic servo device

then varying the weight and air pressure. The relationship resulting from these measurements is shown in Fig. 3. The PM exhibits hysteresis due to coulomb friction [6]. Thus, the PM has different lengths depending on whether it is expanding or contracting. Here, an average value is taken.

The relation between f and $l_0(p) - l$ is shown in Fig. 4, where l is the length of the PM, p is the air pressure, f is the contractive force and $l_0(p)$ is the length at no load and air pressure p . From Fig. 4, f and $l_0(p) - l$ are proportional for air pressures of 0.15MPa or more. Thus, the PM may be assumed to be a spring element for which the spring constant changes according with air pressure. Therefore, the contractive force f may be described as follows

$$f = K(p)(l - l_0(p)) + \hat{C} \quad (3)$$

where: $K(p)$ is the spring constant for the air pressure p , \hat{C} is the coulomb frictional force of the PM.

Denoting the length of the PM as L , the forward model of the PM can be written

$$f = \hat{P}_L(p, \hat{C}) = \hat{C} + K(p)(L - l_0(p)). \quad (4)$$

Consequently, the model of the pneumatic servo device can be written

$$\begin{aligned} M \frac{d^2 y}{dt^2} &= Mg - \hat{P}_L(p, \hat{C}) \\ &= Mg - \hat{C} - K(p)(L - l_0(p)) \end{aligned} \quad (5)$$

where: M is the load and y is the position of the load.

4. INTELLIGENT CONTROL OF THE PNEUMATIC SERVO DEVICE

The pneumatic servo system is composed of the pneumatic servo device and the intelligent controller (Fig.

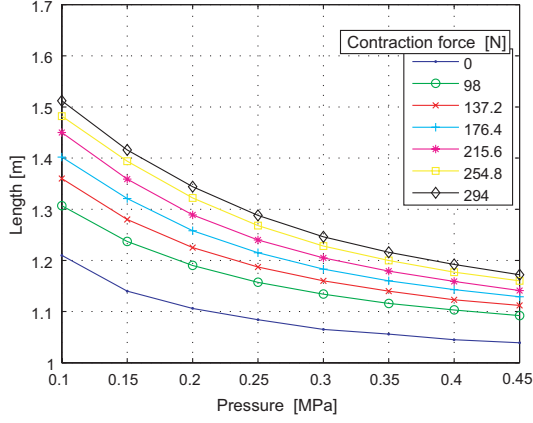


Fig. 3 Relationship between the length, air pressure and contractive force of the PM

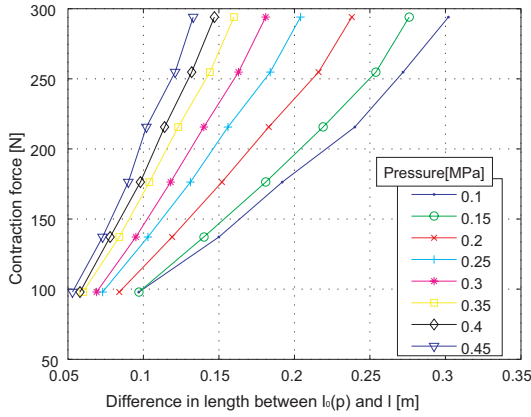


Fig. 4 Relation between f and $l_0(p) - l$

5). This system uses an intelligent pneumatic controller which adds a coulomb friction presumption part to the simple intelligent controller proposed in Fig. 1.

4.1 Model presumption part

This presumption part approximates a forward model from the present state of the PM. In the forward model, the input is the air pressure p , the output is the contractive force f and the state is the length l . An instantaneous forward model is approximated from the present state of the PM l and the approximated coulomb friction \hat{C} . The model is written

$$f = \hat{P}_L(p, \hat{C}) = K(p)(L - l_0(p)) + \hat{C}. \quad (6)$$

4.2 Control part

The control part calculates a control instruction using predictive fuzzy control based on a model of the controlled object (Eq. (5)). The model of the controlled object consists of the present forward model ($P_X(u)$) approximated in the model presumption part and the load of the pneumatic servo device (M).

The control part describes human control methodology using the if-then rule. For example
 if (control instruction U is $\hat{U}_k \rightarrow$ the error between \hat{y}_k and the target position y_t is small)
 then (control instruction U is \hat{U}_k)

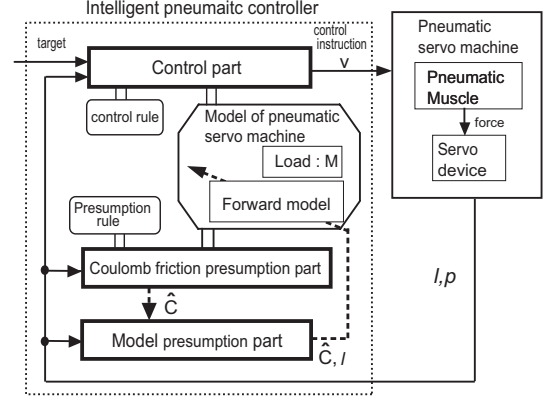


Fig. 5 Composition of the pneumatic servo system

where: \hat{y}_k is the future position of the load calculated with the model of the pneumatic servo device when U is \hat{U}_k . The control part uses a group of such rules for control. The control rule is shown as follows

- If (U is $U_{old} \rightarrow e$ is “Good” and \dot{e} is “Good”) then U is U_{old} .
- If (U is $U_{old} + 1.0 \rightarrow e$ is “Very Good” and \dot{e} is “Very Good”) then U is $U_{old} + 1.0$.
- ⋮
- If (U is $e_{now} * kp + \dot{e}_{now} * kd \rightarrow e$ is “Very Good” and \dot{e} is “Very Good”) then U is $e_{now} * kp + \dot{e}_{now} * kd$.

In the control rule, U_{old} is the last control instruction, e is the error between the presumed length of the PM (\hat{l}) and the target length (l_t) and \dot{e} is the differential of e . e_{now} is the error between the present length of the PM and the target length (l_t), \dot{e}_{now} is the differential of e_{now} and kp and kd are the respective gains.

The inference process of the control part based on this control rule is shown in Fig. 6. Firstly, a candidate control instruction is assumed and the future state is calculated using the model of the controlled object. Next, a fuzzy multipurpose evaluation is done using a fuzzy set and the control rule with the maximum evaluation value is determined. Finally, the calculated value based on this control rule is output as a control instruction.

4.3 Coulomb friction presumption part

The PM has coulomb friction. The coulomb friction presumption part approximates the coulomb friction of the PM using the predictive fuzzy method [4]. This presumption part uses the model of the pneumatic servo device and a presumption rule as follows
 if (coulomb friction C is $\hat{C}_k \rightarrow$ the error between \hat{y}_k and the actual position of the load y is small)
 then (coulomb friction C is \hat{C}_k)
 where: \hat{y}_k is the present position of the load calculated using the model of the pneumatic servo device when C is \hat{C}_k .

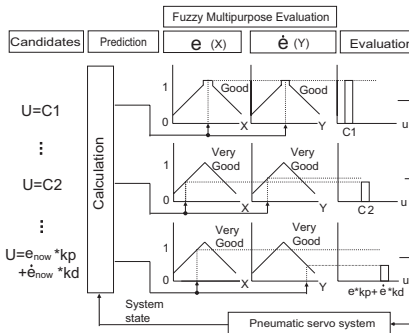


Fig. 6 Inference process of the control part

5. EXPERIMENT

To confirm the effectiveness of the proposed intelligent controller, experiments were performed on a pneumatic servo system.

5.1 Experimental apparatus

A pneumatic lift device was manufactured in order to serve as an experimental apparatus. This device, which lifts a seat, incorporates two PMs arranged in parallel. The layout of pneumatic lift device is shown in Fig. 7. An overview of the device is shown in Fig. 8

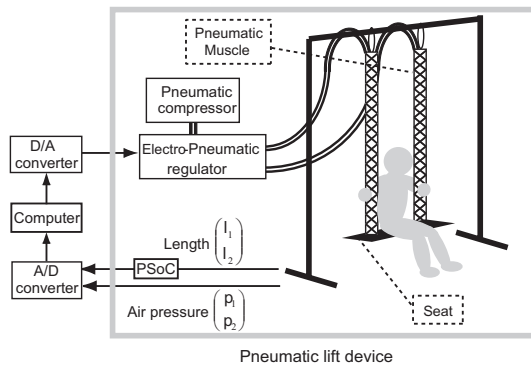


Fig. 7 Composition of the pneumatic lift device

5.2 Length control experiment

The length control experiment is one that focuses on only one of the PMs of the pneumatic lift device. In the length control experiment, the objective is to lift the load to a target length quickly and without an overshoot. The initial PM length was 1.61 [m], the target length was 1.35[m] and the load was 20[kg]. The experiment was performed using three control methods: step input, PD controller, and intelligent controller.

step input

The results using a step input are shown in Fig. 9. The input voltage is 1.72 [V] when the time is 0 seconds. The input voltage was obtained in advance from the static characteristics of the PM in consideration of the load and target length. It took about 4.8 seconds to reach the target length with no overshoot.



Fig. 8 Overview of the pneumatic lift device

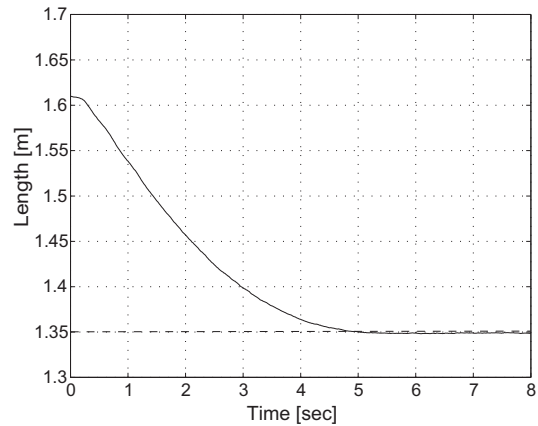


Fig. 9 Length control using "Step input"

PD controller

The results using the PD controller are shown in Fig. 10. Two sets of proportional gain (kp) and the derivative gain (kd) were assumed. These were $kp=17$ and $kd=19$, and $kp=8.5$ and $kd=10.7$. For $kp=17$ and $kd=19$, though the rise time did shorten, both an overshoot and vibration occurred in the response. For $kp=8.5$, $kd=10.7$, it took about 3.8 seconds to reach the target length with no overshoot.

intelligent controller

The results using the intelligent controller are shown in Fig. 11. It took about 2.5 seconds to reach the target length with no overshoot. From the above-mentioned results, it is clear that the length control performance was better when using the proposed intelligent controller compared to either the step input or PD controller.

5.3 Simultaneous operation control experiment

In the simultaneous operation control experiment, both of the PMs of the pneumatic lift device are simultane-

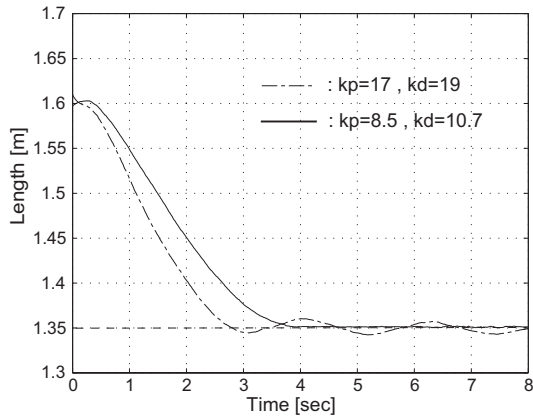


Fig. 10 Length control using “PD controller”

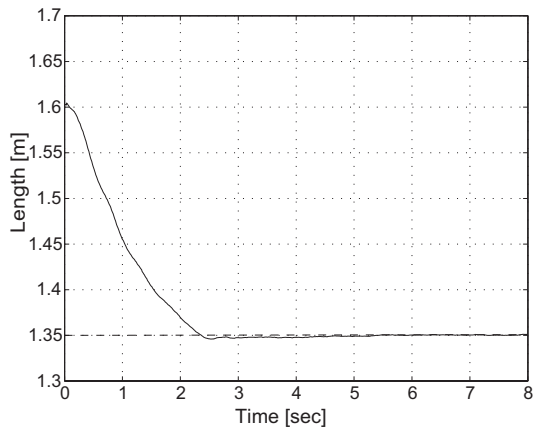


Fig. 11 Length control using “Intelligent controller”

ously contracted to a target length. In this experiment, the objective is to keep the seat level, in addition to lifting it to a target length quickly and without an overshoot. To lift the seat horizontally, it is necessary to match the contraction of the right and left PMs. When two PMs are independently controlled, the balance of contraction is poor because the PMs respective characteristics differ. Consequently, for this experiment, a purpose that is reducing difference of the length of two PMs was added to the fuzzy multipurpose evaluation of the predictive fuzzy control. An additional fuzzy set for this evaluation is shown in Fig. 12, where *cooe* is the difference of the length of two PMs.

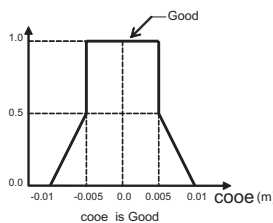


Fig. 12 Added fuzzy set for the evaluation of simultaneous operation

The initial PM length was 1.61 [m], the target length was 1.35 [m] and the load was 20kg for both the right and left PMs. The experiment was performed using two

control methods, PD controller and intelligent controller.

pd controller

The results using the PD controller are shown in Fig. 13. The proportional gains (kp) and derivative gains (kd) assumed were $kp=8.5$ and $kd=10.7$ for the right PM and $kp=11$ and $kd=11.7$ for the left PM. Because the right and left PMs are independently controlled, the balance of contraction is poor. That is to say, the seat does not remain level during the lifting process.

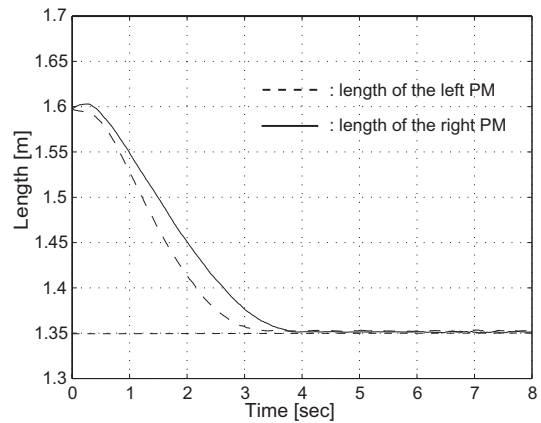


Fig. 13 Cooperated operation control using “PD controller”

intelligent controller

The results using the intelligent controller are shown in Fig. 14. The purpose that is reducing difference of the length of two PMs was added as mentioned above. The contraction of each PM is controlled in consideration of the future state of the other PM. Therefore, the balance of contraction improves between the right and left PMs, and the seat is lifted horizontally.

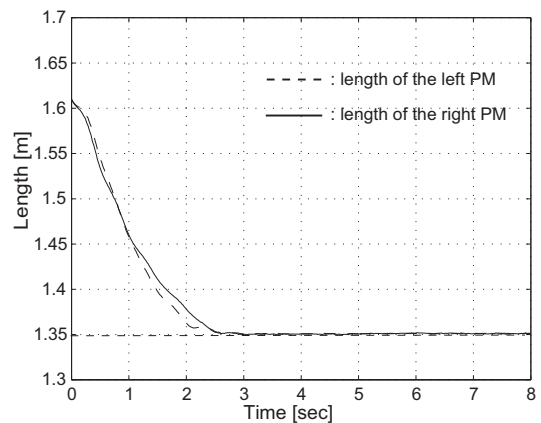


Fig. 14 Simultaneous operation control using “Intelligent controller”

From the above-mentioned result, it was confirmed that, compared to using the PD controller, the performance under simultaneous operation improves when using the proposed intelligent controller with the evaluation of *cooe*.

6. CONCLUSIONS

In this paper, an intelligent controller was constructed for a nonlinear actuator for which the characteristics were state-dependant. The intelligent controller approximates a present forward model of the actuator from the current state of the actuator. Subsequently, the controller decides the most appropriate input instruction by using this forward model to calculate the future state of the actuator and then identifying the best candidate for the input instruction.

This intelligent controller was applied to a pneumatic servo system using Pneumatic Muscles and was then subjected to experimentation. The experimental result confirmed that it was possible to control the PMs well using this intelligent controller. Therefore, it has also been shown that the proposed intelligent controller is effective in controlling state-dependent nonlinear actuators.

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