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An Intelligent Control System Using Object Model by Real-time Learning

Eriko KAWANA[1] and Seiji YASUNOBU[1]

[1]Department of Intelligent Interaction Technologies,
University of Tsukuba, Tsukuba, Japan
(Tel : +81-29-853-5019; E-mail: kawana_ ics@edu.esys.tsukuba.ac.jp)

Abstract: Safety and reliability improvement is an important for an automated system. One of the approaches to improve these is that preventing accidents even if the system malfunctions. This is difficult to ensure when using conventional control mechanisms, as these mechanisms may not be applicable if the controlled object has been changed by the malfunction. On the other hand, humans are able to adjust and act flexibly in response to a changing situation. In this paper, an intelligent control system is proposed that emulates this human capacity to adjust to a changed situation. The key feature of this control system are "hierarchical mechanism" and "acquisition of a new control rule and control according to the rule". To acquisition of a new control rule, the predictive model in real time learning the object is build into this control system. This control system is applied to a flight control system, and its effectiveness for the improvement of safety and the reliability is confirmed.

Keywords: Intelligent Control, Real-time Learning, Fuzzy Control

1. INTRODUCTION

In recent years, human work processes have been computerized and automated. Automated systems can contribute to improvements in work efficiency and safety, because they are able to do dangerous or very detailed work in place of humans [1]. However, when dangerous actions ensue because of faulty operation or breakdown of such an automated system, it can be difficult for the system to minimize its danger by itself, and may instead threaten safety. Therefore, improvement of system safety and reliability increase in importance as the use of automated systems increases.

There are two approaches to improve the safety and reliability of a system. The first approach is to ensure that the system cannot malfunction; the second is to find a method of preventing dangerous actions and accidents even in the event of a system malfunction. In this paper, the latter approach is taken.

Conventional control techniques are specialized for controlling specific objects very precisely, but these precise control mechanisms are not flexible, so they are almost impossible to adjust if the mode of control of the object has to change due to a malfunction.

On the other hand, humans manage this flexible control in normal daily life. When a situation changes, humans are able to recognize this change, consider alternative actions appropriate to the changed situation, and then act accordingly.

In this paper, an intelligent control system, which makes use of adaptable controls, is proposed to emulate this ability of humans to adjust to a changed situation. Firstly, the flexible control of a human when a situation changes is discussed. Secondly, an intelligent control system that emulates the method of this human adjustment and learning about (the changed circumstances of) the controlled object is constructed. Finally, a simulation experiment that models an airplane as a controlled object is conducted, and the effectiveness of the proposed control system is evaluated.

2. HOW HUMANS ADJUST TO A CHANGED SITUATION

In this section we consider a behavior model and a possible corresponding brain mechanism for human adjustment to a changed situation.

Firstly, The behavior model describes the process starting from sense inputs, which eventually shows how to execution of an action.

Secondly, a model for a brain mechanism that seems to control this adjustment process is presented.

We then further discuss the human process of adjustment to a changed situation.

2.1 Behavior Model

We outline here the human behavior model due to Rasmussen [2], and depicted in Fig. 1. In this model, human behavior is classified into three layers of skill-based, rule-based, and knowledge-based behavior, respectively.

Skill-based behavior is an action, such as a hand or foot movement, in response to sensory input, e.g., sight or sound. Such an action is unconsciously executed, and many actions in daily life are of this type.

Rule-based behavior is an action that results from selection and execution of the best among behavior patterns relevant to the information obtained from perception inputs that have already occurred. Such actions are performed intentionally and can be explained at a later time.

Knowledge-based behavior is an action executed in a situation in which a person without the appropriate knowledge would be unable to judge what action to take. The action is chosen once a suitable plan has been made.

The key points of this model are firstly, that the human behavior mechanism is hierarchical, and secondly, that behavior rules can be acquired, such that actions occur according to these rules. These points are relevant in

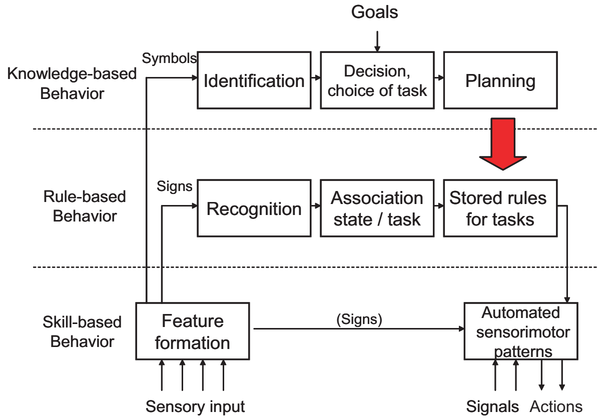

Fig. 1 Human's behavior model

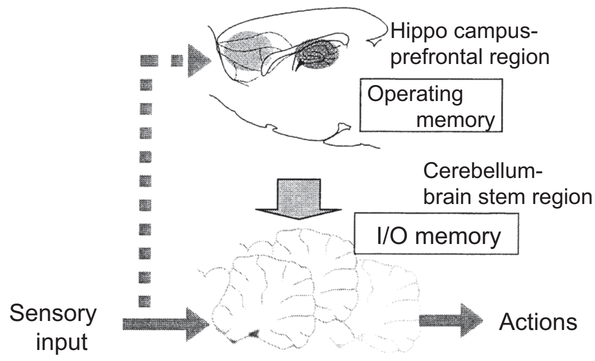

Fig. 2 Pattern diagrams of a hierarchical brain mechanism

explaining how humans can adjust to a changed situation.

2.2 A Brain Mechanism for Learning

In biology, conditioning of the eyeblink reflex has been studied [3]. This is research into the associative learning of the motor response of shutting the eyelid as a reaction to hearing a sound, combined with a nociceptive stimulus. In the experiment, at first, the animal doesn't shut its eyelid as a reaction to the sound. The time between the sound and the nociceptive stimulus is gradually lessened and this is repeated. After a while, the animal begins to shut its eyelid before the nociceptive stimulus , purely as a reaction to perceiving the sound. This is a result of learning about the situation and adjusting to it. Therefore, brain learning mechanism must be considered in discussing the adjustment to a changed situation.

It has been established that the learning circuit depends on the cerebellum-brain stem region and the hippocampus-prefrontal region. In addition, whether the learning circuit depends either on both the cerebellum-brain stem and hippocampus-prefrontal regions or on only the cerebellum-brain stem region changes by sensory input. From these two facts, Kawahara [3] describes, "The learning circuit has the possibility of a hierarchical mechanism of cerebellum-brain stem region and hippocampus-prefrontal region". Fig. 2 shows pattern diagrams of a hierarchical brain mechanism. It is thought that operating memory is formed in the hippocampus-prefrontal region and that I/O memory is formed in the cerebellum-brain stem region. Learning that uses I/O memory would thus be processed by the cerebellum-brain stem region, whereas learning that uses operating memory would be processed by the hippocampus-prefrontal region and the cerebellum-brain stem region; thus, it may be the case that the hippocampus-prefrontal region controls the cerebellum-brain stem region. In this way a learning circuit could be a hierarchical control mechanism.

In the brain mechanism described above, a hierarchical control mechanism was suggested as a key to the process of adjustment to a changed situation.

2.3 Discussion

An adjustment method for a changed situation is discussed with reference to the above model of human behavior and the suggested brain learning mechanism.

The action of driving a car is taken as an example. A learner driver trained intensively at a car driving school, and learned to drive a car, thereby acquiring a license. He was not concerned with the small size of the driving school car, nor with the particular pressure required to depress the accelerator. He subsequently bought a large car, even though he was accustomed to driving a compact car. At first he had difficulties in handling the large car; however, after a while he became able to drive the larger car similar to the way he drove the compact car.

This example can be explained as follows. He acquired driving sense for the compact car (e.g., to increase the speed, depress the accelerator) by intensive training, and acquiring experience. He treated this driving sense as a number of rules: for example, he took the driving instruction (e.g., step on the gas pedal), that corresponded to the existing state of the object, (The car is not going fast enough), as such a rule.

However, when the situation changed to driving a large car instead of the compact car, he drove as if he were still driving the compact car. Then, because the results were different, he was puzzled. However, he was able to respond to the situation of the large car by executing a trial and error process based on his previously acquired driving knowledge of the compact car (e.g., the car accelerates if you step on the gas pedal). Thus, he was able to acquire the driving sense appropriate for a large car; that is, he became able to execute the appropriate driving operation suitable for the existing state of the car, without reference to scenarios involving the compact car.

Fig. 3 shows the adaptive process when the situation changed from the compact car to the large car.

Thus, humans acquire action rules like the driving sense, and can act appropriately to the existing situation based on these rules. If the situation changes, humans can adjust flexibly by recognizing that the situation has changed, and produce new actions accordingly, subse-

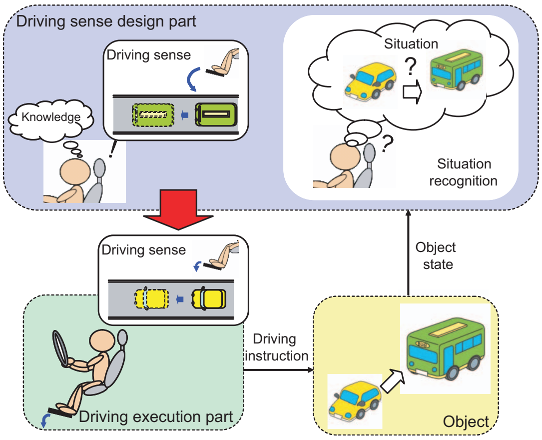

Fig. 3 The adaptive process when the situation changes from the compact car to the large car

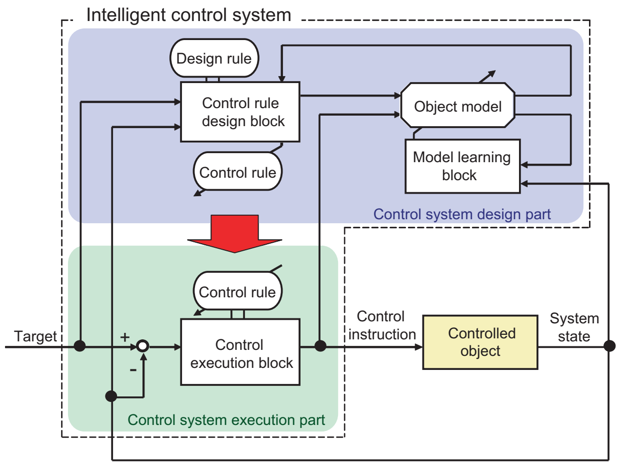

Fig. 4 The block diagram of the intelligent control system

quently acquiring a new rule.

3. THE INTELLIGENT CONTROL SYSTEM

An intelligent control system is proposed that emulates the method of human adjustment to a changed situation that we have considered in the preceding section. Fig. 4 shows the block diagram of this intelligent control system.

This control system is composed of two parts: the design part and the execution part.

The control system design part is intended to emulate the driving sense design part. It learns about the controlled object, generates the object model, and designs a new control rule, thus emulating the way in which the driving sense design part recognizes the situation and makes a new driving sense. The design part is subdivided into the model learning block and the control rule design block.

Moreover, the control system execution part is intended to emulate the driving execution part. This part controls the object based on the designed control rule corresponding to the way in which the driving execution part operates the car based on the driving sense.

Next, the control system design part and the control system execution part are described.

3.1 Control System Design Part

The control system design part generates the object model, learning about the controlled object in real time, and designing control rules for the object using this object model. This part is composed of the model learning block and the control rule design block, which are now described.

3.1.1 The model-learning block

The model-learning block learns about the controlled object in real time from the state of the system in terms of the control instruction and the controlled object, and generates a predictive model of the controlled object. The predictive model is used to forecast the state of the system from the control instruction. When the predictive model inputs a certain control instruction, the state of the system corresponding to the instruction is output. The predictive model can thus forecast the state of the system will execute if this control instruction is entered.

This block acquires the state of the system x_t that is output of object when the control instruction u_t is input, and the state of the system $\hat{x}_t$ that is output of the object model when the control instruction u_t is input in real time. This block accumulates these control instructions, and learns the goodness-of-fit of an actual controlled object and the object model. It generates the one with the highest goodness-of-fit on each occasion as an object model.

3.1.2 The control rule design block

The control rule design block designs the control rule matched to a present controlled object by predictive-fuzzy logic [4] using the object model generated in the model learning block.

Concretely, this block designs the control rule so that the control purposes are "Follow to the control target early" and "The error margin and the overshoot are reduced". This block uses predictive-fuzzy logic for the design. It evaluates the future state by a predictive-fuzzy logic rule, and decides $u(e,\dot{e})$ that composes the control rule.

The design rules are groups of the following types of if-then rules. "If the control instruction u_t at time now is assumed to be u_{t-1}*a(a is constant), the state of the system in the future is near ($x_{ft} - x_{Tft}$ is Small) the targeted value, the speed is also good $\frac{d}{dt}(x_{ft} - x_{Tft})$ is VeryGood), then the control instruction u_t is u_{t-1}*a."

An example of a design rule is as follows.

- If (u_t is u_{t-1}*0.9 $\rightarrow$ $x_{ft} - x_{Tft}$ is Small and $\frac{d}{dt}(x_{ft} - x_{Tft})$ is VeryGood),
  then u_t is u_{t-1}*0.9.

$\vdots$

- If (u_t is u_{t-1}*0.99 $\rightarrow x_{ft} - x_{Tft}$ is Small and $\frac{d}{dt}(x_{ft} - x_{Tft})$ is VeryGood), then u_t is u_{t-1}*0.99.
- If (u_t is u_{t-1}*1.0 $\rightarrow x_{ft} - x_{Tft}$ is Small and $\frac{d}{dt}(x_{ft} - x_{Tft})$ is VeryGood), then u_t is u_{t-1}*1.0.

$\vdots$

- If (u_t is u_{t-1}*1.01 $\rightarrow x_{ft} - x_{Tft}$ is Small and $\frac{d}{dt}(x_{ft} - x_{Tft})$ is VeryGood), then u_t is u_{t-1}*1.01.

$\vdots$

- If (u_t is u_{t-1}*1.1 $\rightarrow x_{ft} - x_{Tft}$ is Small and $\frac{d}{dt}(x_{ft} - x_{Tft})$ is VeryGood), then u_t is u_{t-1}*1.1.

This block inputs the candidate value of some control instruction $u(t)$ described in this design rule to the object model, and performs the forecast calculation of each candidate value. From this forecast calculation, the system state x_{ft} at a future time $ft(t+\Delta t)$ is obtained. Whether the obtained state x_{ft} of the system agrees with the control purpose is multipurpose evaluated by fuzzy logic, and the control instruction which results in the best evaluation is selected.

Here, because "Followed to the control target early" and "The error margin and the overshoot were reduced" were the control purposes, fuzzy multipurpose evaluation was done based on the difference $x_{ft} - x_{Tft}$ between the control target x_{Tft} and the system state x_{ft} at the future time tf, and the differentiated value $\frac{d}{dt}(x_{ft} - x_{Tft})$. As a result, the control instruction u_t is decided. Fig. 5 shows the control rule designing process of the control system design part.

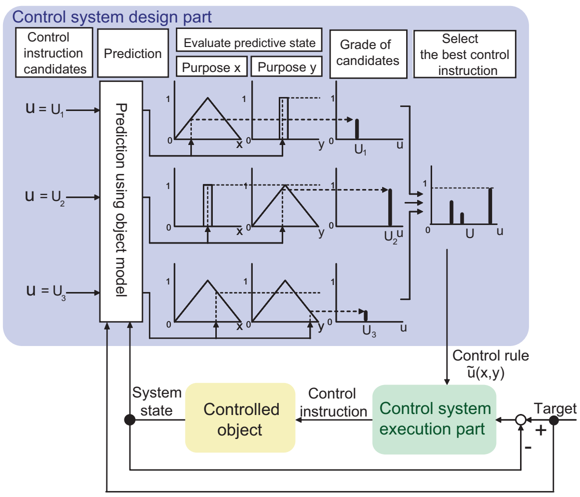

Fig. 5 The control rule designing process of the control system design part

The control rule used in the control system execution part is constructed from the control instruction u_t obtained by predictive-fuzzy logic. The control rules are groups of If-then rules of the following type. "If the difference $e(=x_t - x_{Tt})$ between the control target and the system state at the present time is A_i and the deflection $\dot{e}(=\frac{d}{dt}(x_t - x_{Tt}))$ is B_i, then the control instruction u is u_i."

In this control rule, the difference e between the control target and the state of the system at the present time, and the differentiated value $\dot{e}$ are the evaluation values. At this present time t, the value of the control instruction u_t is decided by predictive fuzzy logic, and the evaluation values e_t, and $\dot{e}_t$ are recorded. These values are accumulated repeating this process. It is possible to plot the accumulating values as a surface in three dimensions, where the x axis is the difference e, the y axis is the differentiation of the difference $\dot{e}$, and the z axis is the control instruction u corresponding to the evaluation value e and $\dot{e}$. This surface corresponds to the fuzzy control surface.

In the control rule, the evaluation uses five fuzzy sets, denoted as follows: negative big (NB), negative small (NS), zero(ZO), positive small (PS), and positive big (PB). Fig. 6 shows the fuzzy sets used by the control rule.

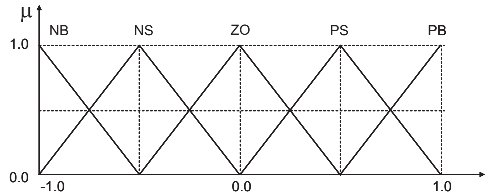

Fig. 6 The fuzzy set

These fuzzy sets NB, NS, ZO, PS, and PB are combined, and 25(= 5 × 5) if-then rules are generated. The control instruction u is decided by the fuzzy control surface $\tilde{u}(e, \dot{e})$. The fuzzy control rule was defined as follows.

- If e is NB and $\dot{e}$ is NB, then u is $\tilde{u}(e_{NB}, \dot{e}_{NB})$.
- If e is NS and $\dot{e}$ is NB, then u is $\tilde{u}(e_{NS}, \dot{e}_{NB})$.
- If e is ZO and $\dot{e}$ is NB, then u is $\tilde{u}(e_{ZO}, \dot{e}_{NB})$.

$\vdots$

- If e is NS and $\dot{e}$ is NS, then u is $\tilde{u}(e_{NS}, \dot{e}_{NS})$.

$\vdots$

- If e is ZO and $\dot{e}$ is ZO, then u is $\tilde{u}(e_{ZO}, \dot{e}_{ZO})$.

$\vdots$

- If e is PS and $\dot{e}$ is PS, then u is $\tilde{u}(e_{PS}, \dot{e}_{PS})$.

$\vdots$

- If e is ZO and $\dot{e}$ is PB, then u is $\tilde{u}(e_{ZO}, \dot{e}_{PB})$.
- If e is PS and $\dot{e}$ is PB, then u is $\tilde{u}(e_{PS}, \dot{e}_{PB})$.
- If e is PB and $\dot{e}$ is PB, then u is $\tilde{u}(e_{PB}, \dot{e}_{PB})$.

3.2 The Control System Execution Part

The control system execution part performs state evaluation fuzzy control using the control rule designed by the control system design part. Fig. 7 shows the inference process of the state evaluation fuzzy control mechanism.

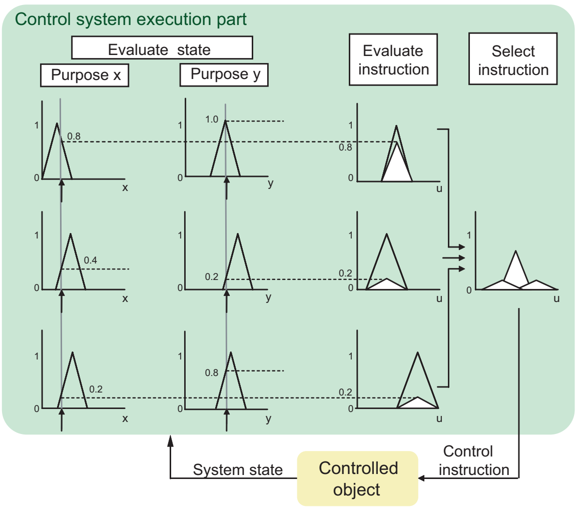

Fig. 7 The inference process of the state evaluation fuzzy control mechanism

4. APPLICATION TO FLIGHT CONTROL SYSTEM

4.1 Control of Airplane

An airplane is controlled by a pilot's operating the control stick and the foot pedal, and moving the aerodynamic control surfaces. The controls that the pilot can operate include the throttle, brakes, flaps, elevators, supplementary wings, and the vertical rudder. However, because only control concerning the stability of length, and direction of pitch is targeted in this research, only the elevator is dealt with here as a control input.

In general, the plane-force control method is adopted for airplanes such as the flying boxcar and the supersonic transport. This is a method whereby variations in the pilot's steering result in signals being transmitted to the servo of the oil pressure electronically, and the aerodynamic control surface is operated by a combination of oil pressure changes and an electrical signal. When the pilot pulls the control stick, the signal, amplified by the oil pressure and electricity, can move the aerodynamic control surface by δ_theta.

4.2 Airplane

The targeted airplane is a small supersonic transport, the F-14 model. Fig. 8 shows the F-14 model.

Fig. 8 The F-14 model

The equations of motion are shown below. Table 1 shows parameter of the F-14 model.

$$\dot{\delta}_e = \frac{1}{T_a} \cdot \delta_e + u \quad (1)$$

$$\dot{q} = M_\omega \cdot \omega + M_d \cdot \delta_e + M_q \cdot q \quad (2)$$

$$\dot{\omega} = Z_\omega \cdot \omega + Z_d \cdot \delta_e + U_o \cdot q \quad (3)$$

$$\Delta N_{zcp} = \frac{-\dot{\omega} + 22.8 \cdot \dot{q} + U_o \cdot q}{g} \quad (4)$$

$$C* = \Delta N_{zcp} + (\frac{V_{co}}{g}) \cdot q \quad (5)$$

Table 1 Parameter of F-14 model

$u[rad]$	Pilot input
$\delta_e[rad]$	Elevator angle
$\dot{\delta}_e[rad/\sec]$	Elevator angular acceleration
T_a	Actuator damping time constant
$q[rad]$	Pitch angle
$\dot{q}[rad/\sec^2]$	Pitch angular acceleration
$U_o[m/\sec^2]$	Airspeed
$\omega[m/\sec]$	Fluctuation velocity in vertical direction
$\dot{\omega}[m/\sec^2]$	Fluctuation acceleration in vertical direction
M_ω M_d Z_ω Z_d	Coefficient
ΔN_{zcp}	Fluctuation of the dynamic factor in the control compartment
$g[m/\sec^2]$	Gravitational acceleration
$C*[rad]$	Airplane Response
$V_co[m/\sec^2]$	Crossing over speed

5. SIMULATION

5.1 Scenario of Breakdown

The control system was simulated under the assumption that the pilot's steering had become ineffective because the oil pressure of the actuator had decreased due to a breakdown.

5.2 Simulation Result

The F14 model was constructed using the control system design supporting tool SIMULINK (The Math Works Inc.). The proposed intelligent control system controls the longitudinal stability of the F14 under the assumption that the above breakdown has occurred.

The initial state of the F14 at time $t = 0$ is $q = 0$, $\omega = 0$, and $\delta_e = 0$. The sampling interval is 1ms. The breakdown was assumed, and the actuator parameter was varied accordingly, making a 1 second change from 1 to 0.2. The simulation experiment was done under these conditions.

The results are shown below. Fig. 9 shows the resulting movement of the airplane when it is controlled by the proposed system and also by the past PD control machine. Fig. 10 shows the result of the control instruction input to the controlled object.

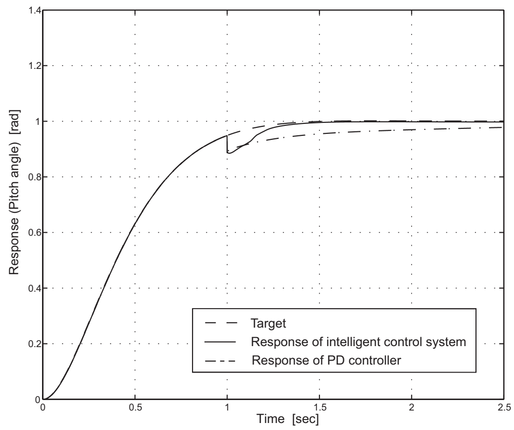

Fig. 9 The resulting movement of the airplane

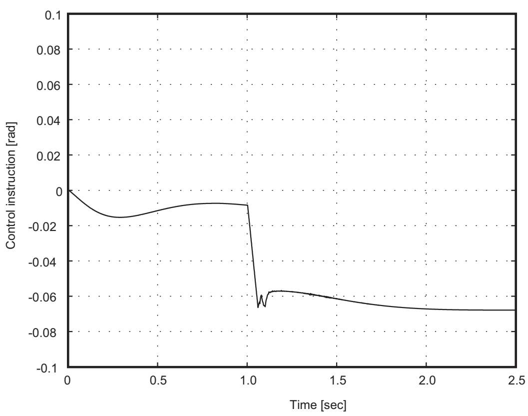

Fig. 10 The result of the control instruction

From the results above, it is clear that the control instruction has changed according to a change in the controlled object. The control instruction reacts immediately the airplane breaks down. The settling time from the large change due to the breakdown to follow to the targeted value by the past PD control was 3.8 seconds. On the other hand, the settling time under the proposed intelligent control system was 0.3 seconds, and the response followed to the targeted value without vibration.

5.3 Discussion

By comparison with the control result by a past PD control machine, we found that the proposed intelligent control system was able to achieve excellent control, even though the controlled object was changed due to the breakdown.

This is because the best control rule is designed by building real time learning the object model into the control system, and then allowing control according to a new control rule.

The effectiveness of the proposed intelligent control system was thus confirmed by this simulation experiment.

6. CONCLUSION

In this paper, an intelligent control system that adjusts to a change in the controlled object was proposed. This system emulates the method of human adjustment to a changed situation. A hierarchical model of human behavior and a corresponding possible hierarchical brain concerning learning mechanism were considered; our proposed system adopts a "hierarchical mechanism" and "acquisition of a new control rule and control according to the rule" as an adjustment method in a changed situation.

This system uses a predictive model to acquire a new control rule. Because the model can foresee the future state of the controlled object, the system that was constructed for this model can design a control rule for the controlled object. In this system it is possible to adjust to changes in the controlled object by using a new control rule.

This system was applied to the airplane as a controlled object, and was simulated. As a result, it was confirmed that this system was able to make an adaptive control change when the object changed. This adaptive control when an object changes is useful for the improvement of safety and the reliability of automated systems.

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