ACQUSITION OF HUMAN OPERATOR'S SKILL FROM TIME SERIES DATA USING FUZZY INFERENCE : IDENTIFICATION OF INDIVIDUALITY DURING STABILIZING CONTROL OF AN INVERTED PENDULUM

Yoshihiko Kawazoe * and Jin Matsumoto*

** Department of Mechanical Engineering, Saitama Institute of Technology, ykawa@sit.ac.jp*

ABSTRACT

In order to stabilize the inherent unstable system like the inverted pendulum on a cart, severe judgment of situation by the operator is required. Accordingly, it can be expected that the human operators exhibit a complex behavior occasionally. This paper tried to identify the chaotic characteristics of human operation from the experimental time series data by utilizing fuzzy inference. It showed how to construct rules automatically for a fuzzy controller from experimental time series data of each trial of each operator to identify a controller from human-generated decision-making. Furthermore, it tried to identify the individual difference of human operator's behavior from time series data and acquire individual skill of human operator. It also investigated the chaotic behavior of human operator and the possibility of the formation of complex system composed of the human operator and the control objects. The operators in the experiment are skilled to some extent in stabilizing the inverted pendulum by training, and the data of ten trials per person were successively taken for an analysis, where the waveforms of pendulum angle and cart displacement were recorded. The maximum Lyapunov exponents were estimated from experimental time series data against embedding dimensions. It was found that the rules identified for a fuzzy controller from time series data of each operator showed well the human -generated decision -making characteristics with the chaos and the large amount of disorder. It was also found that the individual difference of the degrees of freedom and the amount of disorder in the system composed of the human operator and the control objects.

1. INTRODUCTION

Machinery and human beings are absolutely of different nature at the present stage, but most research work on man-machine system dealt with the linear characteristics of human behavior [1]. Many studies on control systems for stabilizing the inverted pendulum as an example of an inherently unstable system have been also presented in the past. There seem to be few studies and a number of unknowns regarding the nonlinear characteristics of human behavior in the man-machine system with an inherently unstable system as well as the learning process of the human operator with difficult control objects [2]-[4].

In order to stabilize the unstable system like the inverted pendulum, the severe judgment of situation is required. Accordingly, it can be expected that the human operators exhibit a complex behavior occasionally. In the author's previous papers [5]-[9], it was found that there are various nonlinear features in the stabilizing behavior of human operator. The terms of being nonlinearly stable or stabilizing in this study means that the inverted pendulum does not

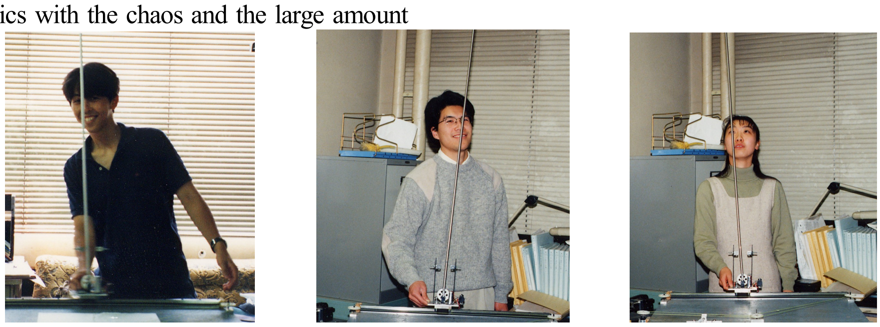


Fig.1 Stabilizing control of an inverted pendulum on a cart by a human operator.

fall down for 60 successive seconds.

The behavior during stabilizing control of inverted pendulum by human operator exhibited the random-like or limit-cycle like fluctuation. This might be robust against the disturbance, because the limit-cycle-like fluctuation with a digital computer control, which means lineally unstable, was more robust against the disturbance than the lineally stable fluctuation in the experiments [5]. Furthermore the limit cycle was very stable nonlinearly, which means very strong against the disturbance, because the trajectories near the limit cycle spiral onto it from its inside and outside [10]-[12].

This paper tries to identify the chaotic characteristics of human operation from the experimental time series data by utilizing fuzzy inference. It shows how to construct rules automatically for a fuzzy controller of each trial of each human operator. It tries to acquire the individual skill of each operator. The operators in the experiment are skilled to some extent in stabilizing the inverted pendulum by training, and the data of ten trials per person were successively taken for an analysis, where the waveforms of pendulum angle and cart displacement were recorded.

The entropy is estimated from the time series data as a measure of the amount of disorder in the system. The maximum Lyapunov exponents are estimated from time series data of the experiments and computer simulations against embedding dimensions for quantifying chaos.

2. DIAGNOSIS OF CHAOTIC BEHAVIORS AND FORMATION OF COMPLEXITY USING TIME SERIES DATA

2.1 Trials of Stabilizing Control of an Inverted Pendulum on a Cart by a Human Operator

Figure 1 shows the experimental situation. The inverted pendulum is mounted on a cart which can move along a line of sliding rail of limited length, being hinged to the cart so as to rotate in the plane [5]. A human operator manipulates a cart directly by hand. Although it takes some time and is needed intensive training for a human operator to succeed in stabilizing the pendulum for 60 seconds, it is not so difficult after the first success of stabilizing.

2.2 Amount of Disorder as the Complex System Estimated by Entropy

In order to stabilize the unstable system like the inverted pendulum, the severe judgment of situation is required. Accordingly, it can be expected that the human operator exhibit a complex behavior occasionally.

Consider a hypothetical statistical system for which the outcome of a certain measurement must be located on the unit interval. If the line is subdivided into N subintervals, we can associate a probability p_i with the i th subinterval containing a particular range of possible outcomes. The entropy of the system is then defined as

$$S = -\sum_{i=1}^{Nc} p_i \log p_i \qquad (1)$$

This quantity may be interpreted as a measure of the amount of disorder in the system or as the information necessary to specify the state of the system. If the subintervals are equally probable so that $p_i = 1/N$ for all i, then the entropy reduces to $S = \log_e N$, which can be shown to be its maximum value. Conversely, if the outcome is known to be in a particular subinterval, then $S = 0$, the minimum value. When $S = \log_e N$, the amount of further information needed to specify the result of a measurement is at a maximum. On the other hand, when $S = 0$ no further information is required [13][17]. We applied this formulation to the time series data by establishing N bins or subintervals of the unit interval into which the value of time series data may fall. We define S the net entropy calculated with Eq.(1) and $S/\log_e N$ the entropy ratio.

2.3 Diagnosis of Chaotic Dynamics

It is necessary to analyze time series data for detecting chaotic dynamics and characterizing it quantitatively when a model of a whole system is unknown. Methods for dynamical analysis of time series data are still developing, but a common method is a two-step process: (1) reconstruction of the strange attracter of the unknown dynamical system from the time series, and (2) determination of certain invariant quantities of the system from the reconstructed attracter. It is possible to glean the dynamics from a single time series without reference to other physical variables [13]. This concept was given a rigorous mathematical basis by Takens [14] and Mane [15].

Since the attracter dimension is unknown for time series data and the required embedding dimension M is unknown, it is important that the reconstruction be embedded in a space of sufficiently large dimension to represent the dynamics completely. Thus, the dimension of the embedding space is increased one by one; the attractor is reconstructed and its largest Lyapunov exponent is calculated. The process is continued until the largest Lyapunov exponent saturates against embedding dimensions and a dimension i.e. the degree of freedom of the system behavior is estimated. The largest Lyapunov exponent can be obtained from a time series data using an algorithm given by Wolf *et al.* [16]. The Lyapunov exponent can be used to obtain a measure of the sensitive dependence upon initial conditions that is characteristic of chaotic behavior. If Lyapunov exponent is positive, nearby trajectories diverge; the evolution is sensitive to initial conditions and therefore chaotic.

Consider the time series data $x(t_1)$, $x(t_2)$, - - - - -. Successive points in the phase space formed from time-delay coordinates can be written as vectors, ***Xi***;

$$\begin{aligned} \boldsymbol{X}_1 &= (x(t_1), x(t_{1+\tau}), \cdots, x(t_{1+(m-1)\tau})) \\ \boldsymbol{X}_2 &= (x(t_2), x(t_{2+\tau}), \cdots, x(t_{2+(m-1)\tau})) \\ &\vdots \\ \boldsymbol{X}_i &= (x(t_i), x(t_{i+\tau}), \cdots, x(t_{i+(m-1)\tau})) \end{aligned} \quad (2)$$

where the symbol τ denotes the time delay and the symbol m denotes the embedding dimension.

The choice of an appropriate delay τ is important to the success of the reconstruction. If τ is too short then the coordinates are almost equal to each other, and the reconstruction will be useless. If τ is too large then the coordinates are so far apart as to be uncorrelated. If the system has some rough periodicity, then a value comparable to but somewhat less than that period is typically chosen. Because there is no simple rule for choosing τ in all cases, some times τ is adjusted until the results seem satisfactory. The time τ is typically some multiple of the spacing between the time series points [13]. We chose 7 times the spacing 0.0293 [s] between the time series points as the value of τ because the calculated largest Lyapunov exponents were not too sensitive to τ, and furthermore the curves of largest Lyapunov exponents against embedding dimensions were smooth within a reasonable range τ, while the dominant period of the experimental time series data were 0.5 ～ 1.0 [s].

Because the time series is presumed (by hypothesis) to be the results of a deterministic process, each x_{n+1} is the result of a mapping. That is

$$x_{n+1} = f(x_n) \quad (3)$$

The differentiation of the above equation is approximated as

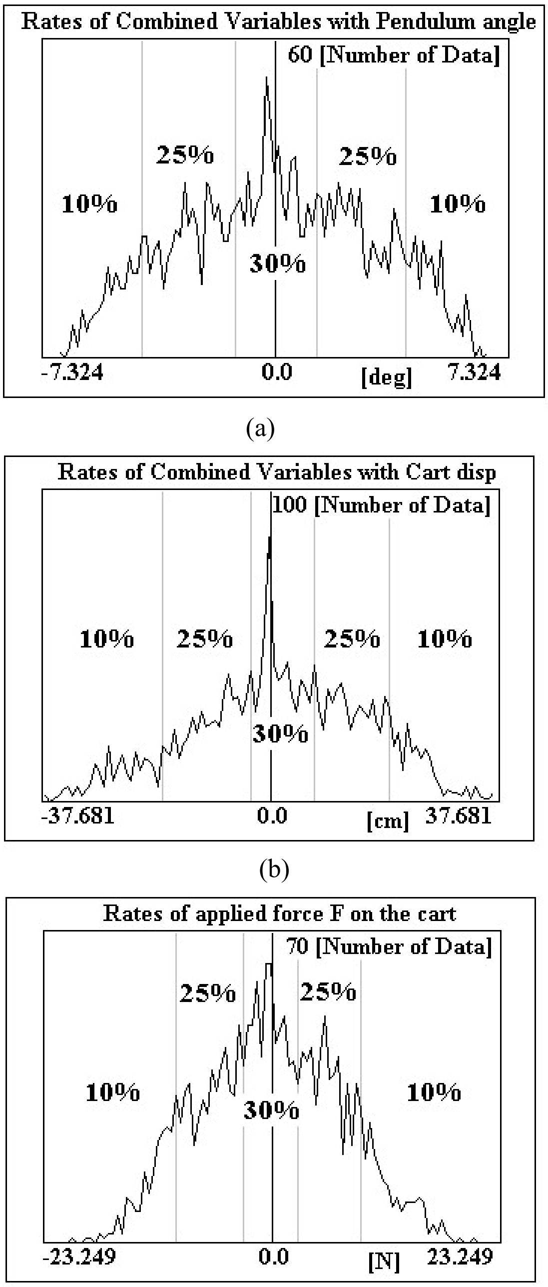
$$\frac{df(x_j)}{dx_j} = \frac{dx_{j+1}}{dx_j} = \frac{x_{j+1} - x_j}{x_j - x_{j-1}} = f'(x_j) \quad (4)$$

Thus, the general expression of Jacobian matrices and the orthogonal vectors $\boldsymbol{b}_{ij}\,(i = 1,2,\cdots,m)$ can be obtained [20]. The Lyapunov exponents λ_i against each embedding dimension i are then obtained as

$$\lambda_i = \frac{1}{t_n - t_0} \sum_{j=1}^{n-1} \log_e \boldsymbol{b}_{ij} \quad (i = 1,2,3,\cdots,m) \quad (5)$$

3. GENERATION OF FUZZY MEMBERSHIP FUNCTIONS AND CONTROL RULES FROM TIME SERIES DATA OF HUMAN OPERATORS

We choose the pendulum angle θ_t, angular velocity θ'_t, the cart displacement X_t and its velocity X'_t as input



(a)

(b)

(c)

Fig.2 Rates of input and output variables.

variables, and the force F_t that moves the cart as output of the fuzzy controller, trying to identify the nonlinear characteristics of the human operator from the experimental time series data. Furthermore, we choose the combined variables $\theta_t + \beta\,\theta'_t$ and $X_t + \gamma X'_t$ as inputs so as to eliminate the complexity of the control rule table. The β and γ are the combination variables.

How to make the membership functions and the control rules are shown as follows [8][20]-[22]. Figure 2 shows a typical example of rates of $\theta_t + \beta\,\theta'_t$ and $X_t + \gamma X'_t$ as inputs, and rates of F_{t+1} as output with the 1st trial of Human Operator *NK* (data *NK*01).

The values of β and γ are identified with the identification of membership functions and control rules by a trial and error method after repeating many simulations. In order to partition the data and determine the border of the data with the fuzzy sets under the assumed values of coefficient β and γ, for example, G_{NB}=10%, G_{NS}=25%, G_{ZR}=30%, G_{PS}=25%, G_{PB}=10% were chosen and the borders were denoted by D_{NB_NS}, D_{NS_ZR}, D_{ZR_PS}, D_{PS_PB} as shown in Fig.3.

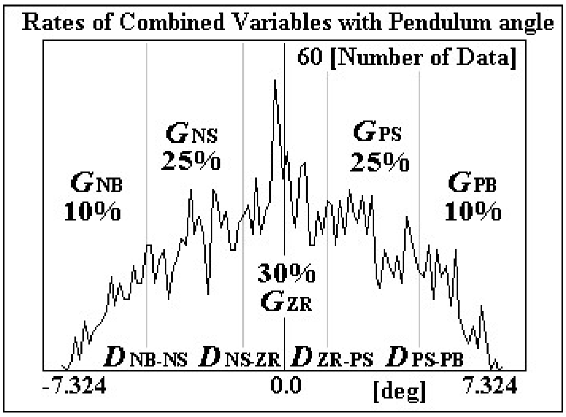


Fig.3 Fuzzy partition and the border of the data.

The labels of the membership functions with $\theta + \beta\,\theta'$ and $X + \gamma X'$ were determined as follows.
NB = minimum of the data: D_{MIN}, *NS* = $(D_{NB\_NS} + D_{NS\_ZR})/2$, *ZR* =average of the data: D_{AVE}, *PS* = $(D_{ZR\_PS} + D_{PS\_PB})/2$, *PB* = maximum of the data: D_{MAX}.

The labels of the membership function with *F* are also determined as follows.
NB= minimum of the data: D_{MIN}, *NMB* = (*NB* + *NS*)/2, *NS*= $(D_{NB\_NS} + D_{NS\_ZR})/2$, *NMS*= *NS*/2, *ZR*= average of the data: D_{AVE}, *PMS*= *PS*/2, *PS*= $(D_{ZR\_PS} + D_{PS\_PB})/2$, *PMB*= (*PB* + *PS*)/2, *PB*= maximum of the data: D_{MAX}.

Suppose that $\theta_t + \beta\,\theta'_t$ is G_{NB}, $X_t + \gamma X'_t$ is G_{ZR}, and F_{t+1} is G_{NS}, we count to the cell of label *F*= *NS* in the numbered grid to which $\theta + \beta\,\theta'$= *NB* and $X + \gamma X'$= *ZR* are given as inputs. The output is derived using the label frequencies and Eq.(6).

$$F_{OUT} = \frac{(-4.4 \cdot NB) + (-2.0 \cdot NS) + (0.0 \cdot ZR) + (2.0 \cdot PS) + (4.4 \cdot PB)}{NB + NS + ZR + PS + PB} \qquad (6)$$

We can determine the output label by using table 1 and construct the operator's control rule for balancing the inverted pendulum.

Table1 Conformity of output F_{out}

Output Label	NB	NMB	NS	NMS	ZR	PMS	PS	PMB	PB
F_{OUT}	-3.5	-2.5	-1.5	-0.5	0.5	1.5	2.5	3.5	

4. IDENTIFICATION OF INDIVIDUAL SKILL OF HUMAN OPERATOR AND GENERATION OF FUZZY CONTROLLER

4.1 Identification of Individual Skill and Fuzzy Control Simulation

Figure 4 shows a model of an inverted pendulum on a cart. The differential equation of motion of this pendulum- cart system would be described as

$$\begin{cases} M\ddot{X} - (mL\cos\theta)\ddot{\theta} + \mu_X \dot{X} + (mL\sin\theta)\dot{\theta}^2 = F \\ -(mL\cos\theta)\ddot{X} + I\ddot{\theta} + \mu_\theta \dot{\theta} = mgL\sin\theta \end{cases}$$

(7), (8)

where *m* denotes the mass of pendulum, *M* denotes the mass of pendulum plus cart with equivalent mass of a human arm, *L* is the half-pendulum length, *I* is the inertial moment of pendulum about the supporting point,

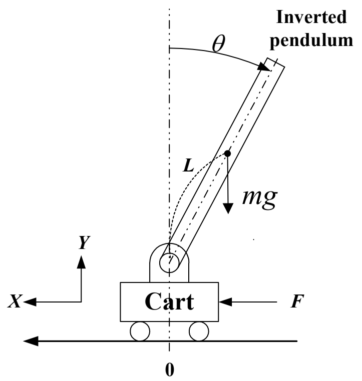


Fig.4 Model of an inverted pendulum on a cart.

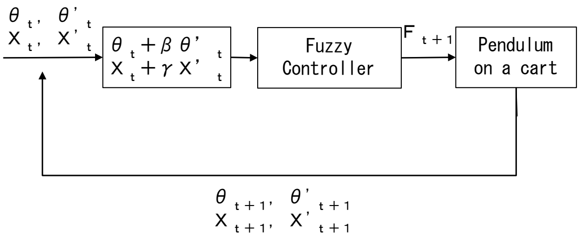


Fig.5 Stabilizing control simulation of the pendulum using the constructed fuzzy controller from human operator's time series data.

F is the force that moves the cart, μ_θ is the frictional coefficient of pendulum supporting point, μ_x is the frictional coefficient between a cart and the rail. The coefficients μ_θ and μ_x are derived from the experiment. Figure 5 shows a block diagram of stabilizing control simulation of the pendulum on a cart using the constructed fuzzy controller from human operator's time series data. The sampling time for control is 0.06[s] and the initial pendulum angle is 3.0[deg].

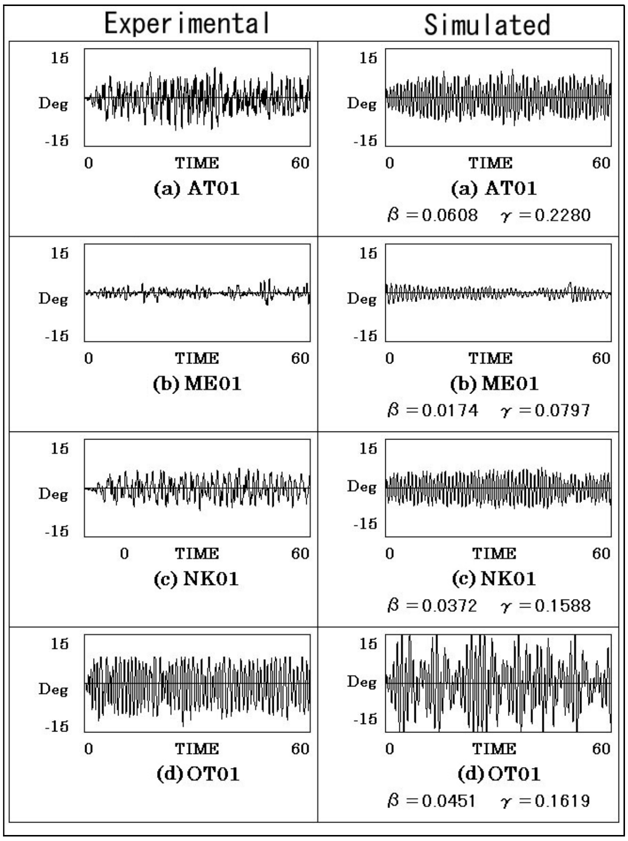


Fig.6 Simulated results using the fuzzy control rules and the membership functions constructed from the experimental time series data, being compared with the experimental results,

4.2 Identification of the Skill and the Individuality

Figure 6 shows the simulated results using the fuzzy control rules and the membership functions constructed from the experimental time series data, being compared with the experimental results, where (a) Human Operator *AT*'s 1st trial, (b) Human Operator *ME*'s 1st trial, (c) Human Operator *NK*'s 1st trial, and (d) Human Operator *OT*'s 1st trial are shown. The simulated waveform and its phase plane representation of each trial exhibit the feature of those of each trial of the experiment. The simulated results exhibited the feature of those of each trial of each operator in the experiment. The result indicates that the rules identified for a fuzzy controller from time series data of each trial of each operator show well the human-generated decision-making characteristics during stabilizing control of an inverted pendulum on a cart. These waveforms showed the characteristics of the chaos and the large amount of disorder.

Figure 7 shows the individual skill of each operator captured in the entropy ratios of the simulation being compared with those of the experiment. The entropy ratio is the measure of the amount of disorder.

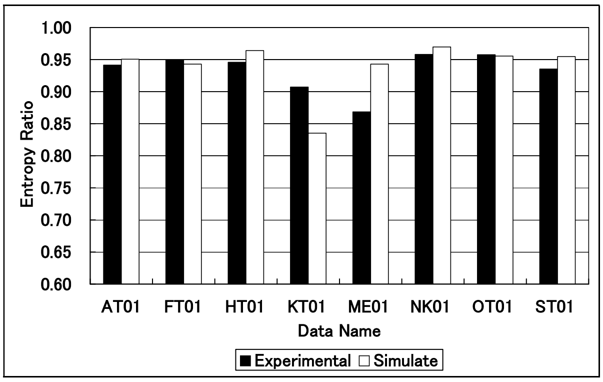


Fig.7 Individual skill of each operator captured in the entropy ratios of the simulation being compared with those of the experiment.

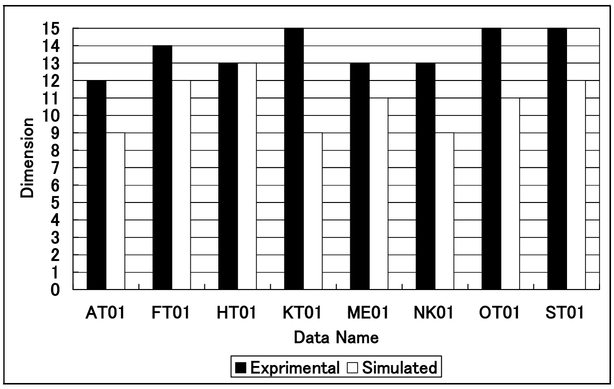


Fig.8 Individual skill of each operator captured in the estimated dimension i.e. the degree of freedom of the system behavior of the simulation being compared with those of the experiment.

Figure 8 shows the individual skill of each operator captured in the estimated dimension i.e. the degree of freedom of the system behavior of the simulation being compared with those of the experiment. The degree of freedom of the system behavior was estimated by the dimension when the curves of largest Lyapunov exponents saturated against embedding dimensions.

4.3 Skill and Individuality captured in the Fuzzy Rules and the Membership Functions

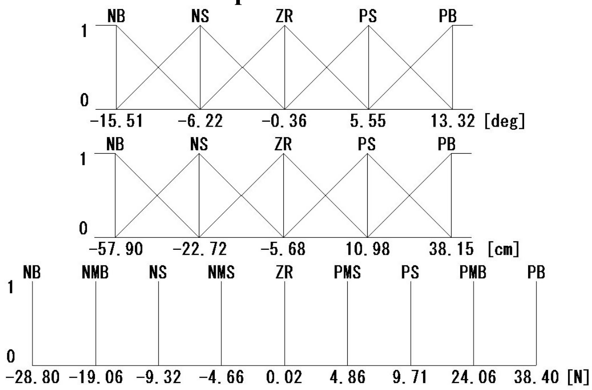


Fig.9 Identified membership function (operator *OT*01)

Figure 9 and Fig.10 show the membership functions of pendulum angle and its angular velocity, the membership function of cart displacement and its velocity, and the membership function (Singleton) for output force, which are identified from experimental time series data of Human Operator *OT*'s 1st trial and *ME*'s 1st trial.

Figure 11 shows the Individual skill of each operator captured in fuzzy rules constructed from the experimental time series data.

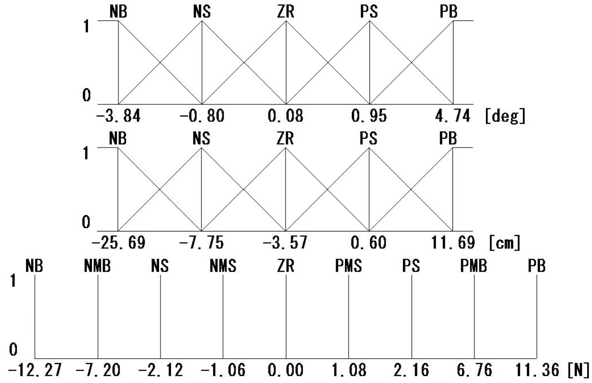


Fig.10 Identified membership function (operator *ME*01)

		$\theta+\beta\theta'$				
		NB	NS	ZR	PS	PB
$X+\gamma X'$	NB	PS	PMS	NMS	ZR	ZR
	NS	PMB	PMS	NMS	NMB	ZR
	ZR	PB	PS	ZR	NS	NMB
	PS	ZR	PB	PMS	NMS	NMB
	PB	ZR	ZR	PS	ZR	NS

(a) Human operator *AT*01
β=0.0608, γ=0.2280

		$\theta+\beta\theta'$				
		NB	NS	ZR	PS	PB
$X+\gamma X'$	NB	PMB	ZR	ZR	NMS	NB
	NS	PMB	PMS	ZR	NS	NB
	ZR	PMB	PMS	ZR	NMS	NS
	PS	PB	PMS	ZR	NMS	NMB
	PB	ZR	PS	PS	NMS	NS

(b) Human operator *ME*01
β=0.0174, γ=0.0797

		$\theta+\beta\theta'$				
		NB	NS	ZR	PS	PB
$X+\gamma X'$	NB	PMB	PMS	NMS	ZR	ZR
	NS	PMB	PS	NMS	NB	ZR
	ZR	PB	PMB	ZR	NMB	NB
	PS	ZR	PB	PMS	NMS	NMB
	PB	ZR	ZR	PMS	NMS	NMB

(c) Human operator *OT*01
β=0.0451, γ=0.1619

		$\theta+\beta\theta'$				
		NB	NS	ZR	PS	PB
$X+\gamma X'$	NB	PMB	PMS	NMS	NMB	NB
	NS	PS	PMS	NMS	NMB	NB
	ZR	PMB	PS	ZR	NS	NB
	PS	PMB	PB	PMS	NMS	NS
	PB	ZR	PB	PS	NMS	NMB

(d) Human operator *ST*01
β=0.0595, γ=0.6806

Fig.11 Individual skill of each operator captured in fuzzy rules constructed from the experimental time series data

It is seen that the fuzzy rules depend on the individual operator and are not symmetrical.

5. CONCLUSION

This paper tried to identify the individual difference of human operator's behavior from time series data and acquire individual skill of human operator. It also investigated the chaotic behavior of human operator and the possibility of the formation of complex system composed of the human operator and the control objects. The degree of freedom of the system behavior was estimated by the dimension when the curves of largest Lyapunov exponents saturated against embedding dimensions. It was found that the rules identified for a fuzzy controller from time series data of each operator showed well the human -generated decision -making characteristics with the chaos and the large amount of disorder. It was also found that the individual difference of the degrees of freedom and the amount of disorder in the system composed of the human operator and the control objects.

The author is grateful to Mr. K Tanaka for his suggestions and encouragement. Sincere thanks are extended to Messrs K. Hashimoto, T. Ohta and K. Shimura for their help in carrying out this study when senior students at Saitama Institute of Technology. This work was supported by the High- Tech Research Center of Saitama Institute of Technology.

REFERENCES

[1] Iguchi M , *Man-machine system* (in Japanese), Kyoritsu Shupan. (1970)

[2] Ito K. & Ito M.: On the human operator's learning process and nonlinear behavior in stabilizing an unstable system (in Japanese), *Trans. IEE of Japan*, Vol.96, No.5, pp.109-115 (1976).

[3] Fujii K & Taguchi J: The role of human controller in man machine system (in Japanese), *System and control*, Vol.25, No.6, pp.328- 335 (1981).

[4] Inooka H: Swinging control of a pendulum: manual control approrch, *Theoretical and Applied Mechanics*, Vol.40, pp.3- 9 (1991).

[5] Kawazoe Y: Manual control and computer control of an inverted pendulum on a cart, *Proc. of the First International Conf. on Motion and Vibration Control,* pp.930 –935 (1992).

[6] Kawazoe Y & Ju DY: Nonlinear characteristics of human operator with the stabilizing control of an inverted pendulum on a cart, *Proc. 2nd International Conf. on Motion and Vibration Control*, pp.645- 650 (1994).

[7] Kawazoe Y, Ohta T, Tanaka K & Nagai K : Nonlinear behavior in stabilizing control of an inverted pendulum on a cart by a human operator: remarks on chaotic behavior and a complex system (in Japanese), *Proc. 5th symposium on Motion and Vibration Control*, No.97-31, pp.395 – 398 (1997).

[8] Kawazoe Y , Nonlinear characteristics of a human operator during stabilizing control of an inverted pendulum on a cart: Fuzzy identification from experimental time series data and Fuzzy control simulation, *Motion and vibration control in Mechatronics*, Edited by Seto K, Mizuno T & Watanebe T, pp.133-138.(1999)

[9] Kawazoe Y , Measurement and analysis of chaotic behavior of human operator stabilizing an inverted pendulum on a cart, *Proc. of ICMA2000-Human friendly mechatronics*, pp.457-462.(2000)

[10] Kawazoe, Y., Low Speed Hunting of Pneumatically Governed Compression-Ignition Engine: 1st Report, Various Experiments for Identifying the Cause, *Bulletin of JSME*, 28-243, 2022-2027. (1985).

[11] Kawazoe, Y., Low Speed Hunting of Pneumatically Governed Compression-Ignition Engine: 3rd Report, Computer Simulation of the Low Speed Hunting, *Bulletin of JSME*, 29-253, 2211-2217. (1986).

[12] Kawazoe, Y.; Equilibrium Instability and Limit Cycle of Pneumatically Governed Engine, *Proc. of the International Conf. on Mechanical Dynamics '87*, pp.484-489. (1987).

[13] Baker GL and Gollub JP , Chaotic dynamics: an introduction, Cambridge University Press.(1996)

[14] Takens F , Detecting strange attracters in turbulence, In Rand DA and Young LS (ed), *Lecture Notes in Mathematics*, Vol.898, Springer-Verlag, Berlin, pp.366-81. (1981)

[15] Mane R , On the dimension of the compact invariant sets of certain nonlinear maps. In Rand DA and Young LS (ed), *ibid,* Vol.898, Springer-Verlag, Berlin, pp.230-42. (1981)

[16] Wolf A, Swift JB, Swinney HL, and Vastano JA , Determining Lyapunov exponents from a time series, *Physica,* 16D, 285. (1985)

[17] Baierlein R , *Atoms and information theory*, W.H.Freeman & Co., San Francisco, Chapter 3. (1971)

[18] Fraser A M and Swinney H: Independent coordinates for strange attractors from mutual information, *Phys. Rev.A,* 33, pp.1134-1140 (1986).

[19] Fraser A M: Information and entropy in strange attractors, *IEEE Trans. On Information Theory*, 35, pp.245-262 (1989).

[20] Kawazoe Y and Matsumoto J: Acquisition of Human Operator's Skill Using Fuzzy Inference: Identification from Chaotic and Complex Time Series Data during Stabilizing Control of an Inverted Pendulum, (in Japanese), *17th Fuzzy System Symposium*, pp.715-718 (2001).

[21] Kawazoe, Y.: Fuzzy identification of chaotic and complex behavior of human operator stabilizing an inverted pendulum on a cart., *Proc. 6th Int. Symp. on Artificial Life & Robotics*, pp.9-12 (2001).

[22] Kawazoe, Y.: Measurement of Chaotic Behavior of Human Operator stabilizing an Inverted Pendulum and Its Fuzzy Identification from Time Series Data, J. Robotics & Mechatronics, 13-1, pp.23-29 (2001).