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Chaos-Entropy Analysis and Acquisition of Human Operator's Skill Using a Fuzzy Controller: Identification of Individuality during Stabilizing Control of an Inverted Pendulum*

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Abstract

In order to stabilize the inherent unstable system like the inverted pendulum on a cart, severe judgment of situation is required. Accordingly, it can be expected that human operators exhibit complex behavior intermittently. This paper investigated the identification of the individual difference of human operator's behavior from time series data by using fuzzy inference and acquired individual skill of human operator. It also investigated the chaotic behavior of human operator and the formation of a complex system in the learning process of human operators with objects difficult to control. 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 and the individual difference of chaotic and complex human operation can be identified with fuzzy inference.

Key words: Skill, Human's Dexterity, Identification, Fuzzy Control, Chaos, Entropy, Individuality, Estimated Degree of Freedom of Motion, Estimated Amount of Disorder, Time Series Data, Inverted Pendulum

1. Introduction

There is an infinite variety of motions ranging from our daily activities to the exceptional movement of an athlete or a musician(1). Based on his extensive observation of child growth, Gesell (1945) stated some empirical rules. In particular, he noted that the development of motion progresses from a generally integrated state to an individualized state in which individual sections have specialized functions. He also noted that the number of degrees of freedom of the motion increases with development, and that periods of unstabilization and stabilization are repeated to advance development by taking advantage

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of such fluctuations well. Finally, he observed that chaos plays a very important role in motion[1]. The human process of learning motion can also be studied by focusing on the degrees of freedom. When a person who normally writes with his or her right hand (i.e., their dominant hand) is asked to write with the left hand (i.e., their non dominant hand), the number of degrees of freedom of each joint is initially fixed; but, after training, each joint moves according to a peculiar phase relationship after training (Newell & Van Emmerik, 1989). This implies that we are rigid when we attempt a new motion, but become more relaxed after getting accustomed to it [1].

Machinery and human beings are absolutely of a different nature at the present stage, but most research work on man-machine systems has dealt with the linear characteristics of human behavior [2]. As an example, many studies on control systems for stabilizing the inverted pendulum as an inherently unstable system have been presented. These studies focus on the linear characteristics of human behavior. There seem to be few studies and a number of unknowns regarding both the nonlinear characteristics of human behavior in an inherently unstable man-machine system as well as the learning process of human operators with objects difficult to control [3]-[4].

In order to stabilize an unstable system such as the inverted pendulum, strict judgment of the situation is required. Accordingly, it can be expected that the human operators exhibit complex behaviors or contingencies, that is, the mixture of regular and random things intermittently[5][6].

In the author's previous papers[6]-[11], it was found that there are various nonlinear features in the stabilizing behavior of a human operator. In this study, the definition of nonlinear stability means that an inverted pendulum does not fall for 60 consecutive seconds. The behavior during stabilizing control of an inverted pendulum by a human operator exhibits a random-like or limit-cycle like fluctuation, and the stabilizing control by the human operator is robust against the disturbance. This may be because the limit-cycle-like fluctuation with a digital computer control, which means lineally unstable, is more robust against the disturbance than the lineally stable fluctuation according to the previous experiments[6]-[11], [13]-[19]. The limit cycle was very stable in the sense of nonlinearity, which means it is robust against the disturbance. It was found that the estimated degree of freedom of motion composed of a human operator and a control object increases and the estimated amount of disorder decreases with an increase of trials in the experiment.

Furthermore, it was shown that the neural network controller identified from time series data of each trial of several operators exhibits the human-generated decision-making characteristics with the chaos and a large amount of disorder. It was also confirmed that the estimated degrees of freedom of motion increases and the estimated amount of disorder decreases with an increase of trials or proficiency [20][21].

This paper investigates the identification of 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. Human operators in an experiment were trained so that they were skilled to some extent in stabilizing the pendulum by training, and the data of ten trials per person were successively taken for an analysis.The entropy is estimated from the time series data as a measure of the amount of disorder in a system, and the degrees of freedom of the motion are estimated by the dimensions when curves of the largest Lyapunov exponents are saturated against the embedding dimensions for quantifying the proficiency.

2. Chaos-Entropy Analysis of Human Operator's Skill during Stabilizing Control of an Inverted Pendulum on a Cart

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 the line of a sliding rail of limited length while it is hinged to the cart so that it rotates in one plane. A human operator manipulates the 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 becomes less difficult after the first success of stabilizing.

Human operators in an experiment were trained so that they were skilled to some extent in stabilizing the pendulum by training, and the data of ten trials per person were successively taken for an analysis. The angle that the pendulum makes with the vertical axis and the displacement of the cart were measured, from which the derivatives and the force that moves the cart can be derived.

Fig.1 Stabilizing control of an inverted pendulum.

2.2 Diagnosis of amount of disorder by entropy analysis

In order to stabilize an unstable system such as the inverted pendulum, strict judgment of the situation is required. Accordingly, it can be expected that a human operator exhibits a complex behavior intermittently.

Consider a hypothetical statistical system for which the outcome of a certain measurement must be located on a unit interval. If a 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

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

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 the maximum value. Conversely, if the outcome is known to be in a particular subinterval, then $S = 0$ is 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, and when $S = 0$ no further information is required [(22), (23)]. 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 as the net entropy calculated with Eq.(1) and $S/(\log_e N)$ as the entropy ratio [(10)(17)(18)].

2.3 Diagnosis of Chaotic Dynamics by entropy analysis

It is necessary to analyze time series data for detecting chaotic dynamics and characterizing it quantitatively when the 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 obtain the dynamics from a single time series without reference to other physical variables[(22) - (24)]. This concept was given a rigorous mathematical basis by Takens[(25)] and Mane [(26)].

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 the embedding dimensions and a dimension, that is, the degrees 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.*[(27)]. The Lyapunov exponent can be used to obtain the measure of the sensitivity upon initial conditions. This measure of sensitivity is characteristic of chaotic behavior. If the Lyapunov exponent is positive, nearby trajectories diverge, and so 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 $\boldsymbol{X_i}$:

$$\begin{aligned}
\mathbf{X}_1 &= (x(t_1), x(t_1+\tau), \cdots, x(t_1+(m-1)\tau)) \\
\mathbf{X}_2 &= (x(t_2), x(t_2+\tau), \cdots, x(t_2+(m-1)\tau)) \\
\mathbf{X}_3 &= (x(t_3), x(t_3+\tau), \cdots, x(t_3+(m-1)\tau)) \\
&\vdots \\
\mathbf{X}_i &= (x(t_i), x(t_i+\tau), \cdots, x(t_i+(m-1)\tau)) \\
&\vdots \\
\mathbf{X}_N &= (x(t_N), x(t_N+\tau), \cdots, x(t_N+(m-1)\tau))
\end{aligned} \tag{1}$$

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 is 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 [(22)]. We chose seven times the spacing between the time series points, that is, 7 x 0.0293 [s], as the value of τ because the calculated largest Lyapunov exponents were not too sensitive to τ, and because the curves of the largest Lyapunov exponents against embedding dimensions were smooth within a reasonable range τ, whereas the dominant period of the experimental time series data was 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

$$x_{n+1} = f(x_n) \tag{2}$$

The differentiation of the above equation is approximated as

$$\frac{df(x_j)}{dx_j} = \frac{dx_{j+1}}{dx_j} = \frac{x_{j+1} - x_j}{x_j - x_{j\text{-}1}} = f'(x_j) \qquad (3)$$

Thus, the general expression of the Jacobian matrices and the orthogonal vectors $\boldsymbol{b}_{ij}(i = 1,2,\cdots,m)$ can be obtained [14]. The Lyapunov exponents λ_i against each embedding dimension i are then obtained as [22] [24] - [27] [30]

$$\lambda_i = \frac{1}{t_n - t_0}\sum_{j=1}^{n-1}\log_{\mathrm{e}} \boldsymbol{b}_{ij} \quad (i = 1,2,3,\cdots,m) \qquad (4)$$

The degrees of freedom of the motion are estimated by the dimensions when curves of the largest Lyapunov exponents are saturated against the embedding dimensions.

3. Generation of a Fuzzy Controller from Time Series Data during Stabilizing Control of an Inverted Pendulum by a Human Operator

We choose the pendulum angle θ_t, angular velocity θ'_t, the cart displacement X_t and its velocity X'_t as input 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 [14] - [19]. 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} (Fig.2).

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} (Fig.3).

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.(5).

$$F_{\mathrm{OUT}} = \frac{(-4.4\cdot\mathrm{NB}) + (-2.0\cdot\mathrm{NS}) + (0.0\cdot\mathrm{ZR}) + (2.0\cdot\mathrm{PS}) + (4.4\cdot\mathrm{PB})}{\mathrm{NB} + \mathrm{NS} + \mathrm{ZR} + \mathrm{PS} + \mathrm{PB}} \qquad (5)$$

We can determine the output label by using Fig.4 and construct the operator's control rule for balancing the inverted pendulum as shown Fig.5.

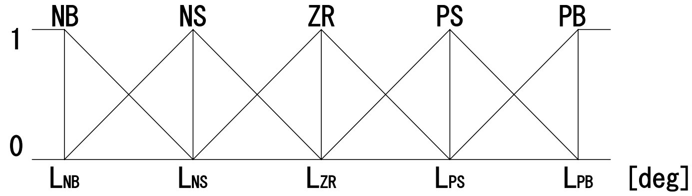

Fig.2 Membership function for input

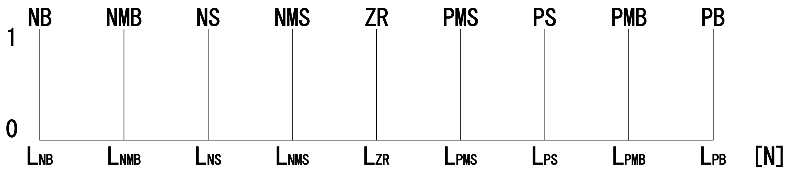

Fig.3 Membership function (Singleton)for output

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

Fig.4 Conformity of output F_{out}

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

Fig.5 Rule for control of a pendulum on a cart (Ist trial NK01 of Human operator NK)

4. Identification of Individual Skill of Human Operator and Generation of Fuzzy Controller

4.1 Identification of individual skill and fuzzy control simulation

Figure 6 shows a model of an inverted pendulum on a cart. The differential equation of motion of this pendulum- cart system would be described as

$$M\ddot{X} - mL\ddot{\theta}\cos\theta + mL\dot{\theta}^2\sin\theta + \mu_x\dot{X} = F \qquad (6)$$

$$I\ddot{\theta} - mL\ddot{X}\cos\theta + \mu_\theta\dot{\theta} = mgL\sin\theta \qquad (7)$$

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, 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 7 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].

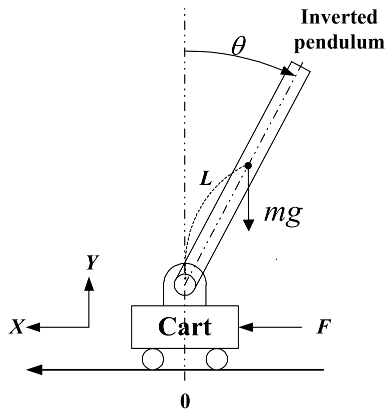

Fig.6 Model of an inverted pendulum on a cart.

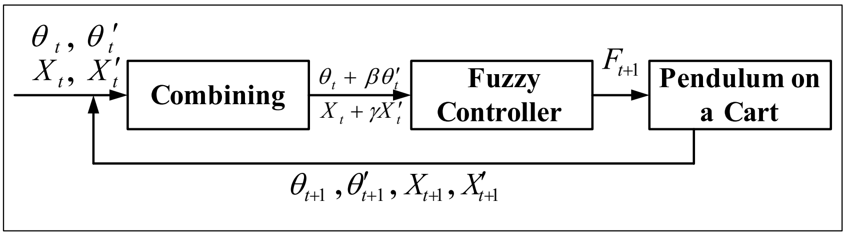

Fig.7 Stabilizing control simulation of the pendulum using the constructed fuzzy controller from human operator's time series data.

4.2 Identification of the skill and the individuality

Figure 8 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 9 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.

Figure 10 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

Figure 11 and Fig.12 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 13 shows the 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.

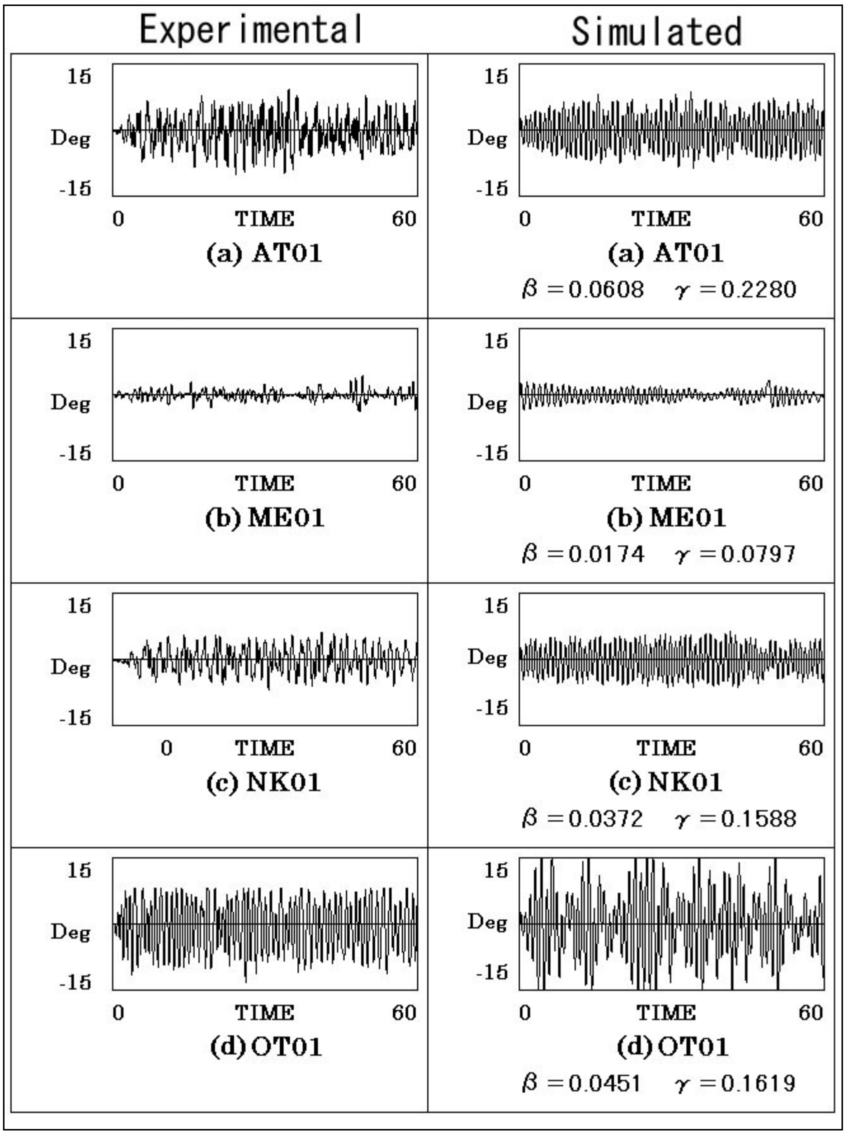

Fig.8 Simulated results using the fuzzy control rules and the membership functions constructed from the experimental time series data, being compared with the experimental results.

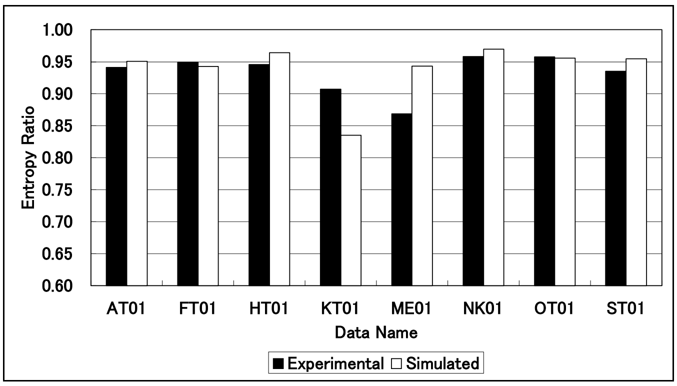

Fig.9 Individual skill of each operator captured in the entropy ratios of the simulation being compared with those of the experiment.

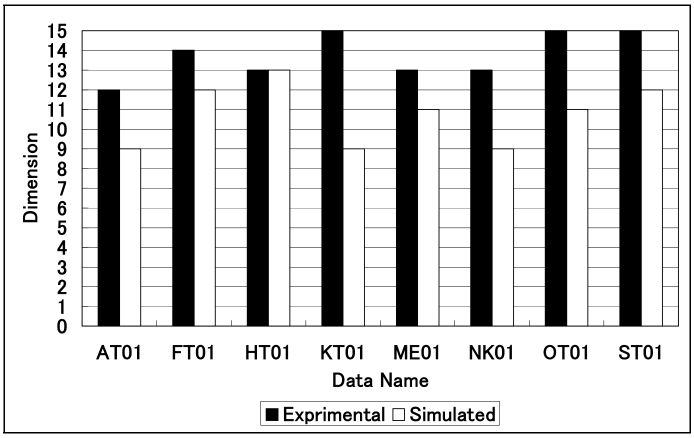

Fig.10 Individual skill of each operator captured in the estimated dimension i.e. the degree of freedom of the system behavior of the simulation being compared with those of the experiment.

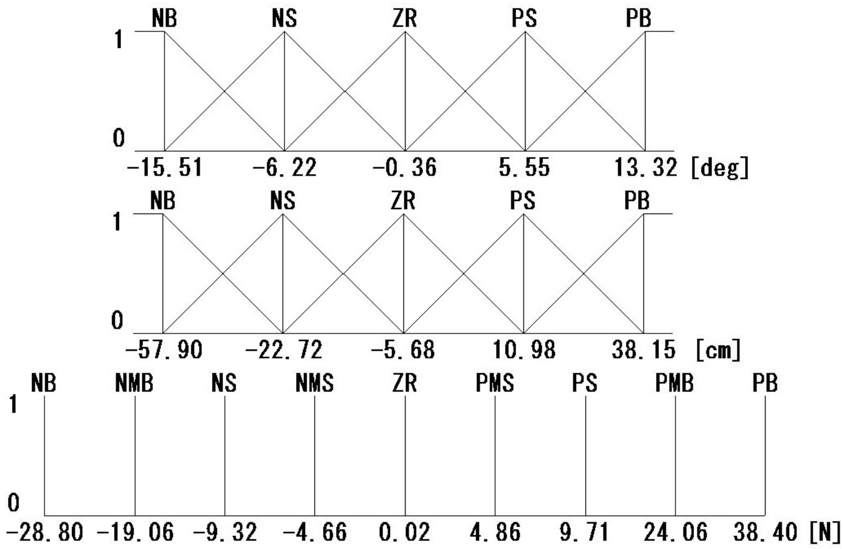

Fig.11 Identified membership function (operator OT01)

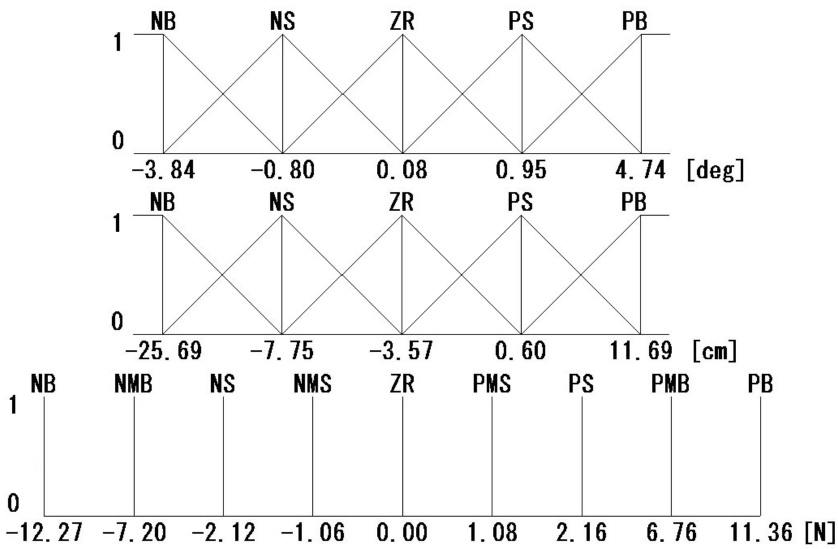

Fig.12 Identified membership function (operator ME01)

$X+\gamma X'$ \ $\theta+\beta\theta'$	NB	NS	ZR	PS	PB
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 AT01
β=0.0608, γ=0.2280

$X+\gamma X'$ \ $\theta+\beta\theta'$	NB	NS	ZR	PS	PB
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 OT01
β=0.0451, γ=0.1619

$X+\gamma X'$ \ $\theta+\beta\theta'$	NB	NS	ZR	PS	PB
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 ME01
β=0.0174, γ=0.0797

$X+\gamma X'$ \ $\theta+\beta\theta'$	NB	NS	ZR	PS	PB
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 ST01
β=0.0595, γ=0.6806

Fig.13 Individual skill of each operator captured in fuzzy rules constructed from the experimental time series data

5. Conclusions

This paper investigated the identification of the individual difference of human operator's behavior from time series data and acquired 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 motion of the system 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.

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