Estimation of Human Reasoning State in Machine Operation Using Fuzzy Linear Regression*

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An estimation method to detect the human reasoning state in machine operation is discussed in terms of a fuzzy linear regression model. Simple experiments of human operation using a computer display show that the change in the human internal state during the reasoning in the operation can be reflected in the system parameters of the fuzzy linear regression model. This model is constructed using fundamental operational data, and fuzziness parameters are calculated by means of traditional linear programming approaches. The characteristics of the human reasoning state are represented by fuzziness parameters, and the advantage of the proposed approach to human reliability is demonstrated by the example of vehicle operation.

Key Words: Reliability Engineering, Human Engineering, Modeling, Fuzzy Reasoning, Fuzzy Linear Regression, State Estimation

1. Introduction

It is important to clarify the fundamental factors of human operational error in man-machine systems, so as to realize good system performance and user-friendly interaction. The basic features of human error and reliability characteristics in man-machine operation have not yet been clarified, in spite of research in human dynamics and ergonomics over many years⁽¹⁾⁻⁽³⁾. In this paper, a concept of the change in the human internal state during reasoning in machine operation is introduced, and an estimation method to detect the human reasoning state during the operation is proposed. It will be shown that the change in the human internal state during reasoning is reflected in the system parameters of the fuzzy linear regression model. The effectiveness of this approach is also discussed. One of the most important features of this approach is that the change in the human internal state during reasoning, which is not easy to detect directly, is derived from the essential data of the machine operation. The fundamental relation

between the change in operational load and human operational error is also discussed from the viewpoint of the effect of the change in operational load to the human internal state. In addition, the advantage of the proposed approach to human reliability analysis is discussed, and a system design concept to reduce the extent of human operational error is also presented.

2. Estimation of the Change in Internal State

In general dynamic systems, the changes in system states are represented by linear or nonlinear dynamical models. The state variables are estimated using advanced filters, such as the Kalman filter, with observation data under the assumption that disturbance and noise signals are represented by white Gaussian signals. However, for the case of the human internal state during reasoning in machine operation, it is quite difficult to use such approaches^{(4),(5)}. In this paper, a state observer is introduced to estimate the human internal state. This observer is constructed using the fuzzy linear regression model that was introduced by Tanaka^{(6),(7)}.

The main feature of this approach is that a new parameter, which is named "fuzziness of the model", is introduced. The fuzziness of the model represents the structural fuzziness of the system construction that is defined by input-output relations. The struc-

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tural fuzziness is derived from the difference between observed values and estimated values of the constructed model. Under the assumption that the structural fuzziness of the system is derived from the parameter fuzziness of the system model, the fuzzy linear regression equation

$$Y_i = A_{i0} + A_{i1}x_{i1} + \cdots + A_{in}x_{in} \quad (1)$$

is derived. The fuzziness parameter is analyzed in terms of the estimated values of the fuzzy numbers A_{i0} - A_{in} of Eq. (1). In this equation, x_{ij} is the normal input value, A_{ij} is the fuzzy parameter with mean value and distribution, and Y_i is the output fuzzy value. The difference between this representation and the traditional linear regression equation is that the difference between the real system and the model is due to the fuzziness of the system structure, not to the probabilistic distribution of the system parameters⁽⁸⁾. The fuzzy numbers Y_i and A_i shown in Eq. (1) are the symmetric L-L fuzzy numbers (as shown in Fig. 1) of the L-R fuzzy numbers⁽⁹⁾.

According to Tanaka⁽⁷⁾, Eq. (1) is defined by the following linear regression problem. Input variables are x_i (x_{ij} ; $j=1, \dots, m$) at the condition i , output fuzzy number is Y_i and the fuzzy parameter vector of the linear regression model is A_i . The mean values of Y_i and A_i are y_i and a_i , and the parameters of their ranges are e_i and c_i , respectively. The reference parameter α is defined such that the probability of the vector set (a_i, c_i) , in which Y_i is equal to $(\sum A_i x_i)$, is greater than or equal to α . Then, the linear regression model is described as follows:

$$\begin{aligned} &\text{minimize } J(c_i) = \sum_{i=1}^n c_i |x_i| \\ &\text{subject to} \\ &-y_i + a_i x_i \leq -L^{-1}(\alpha)e_i + L^{-1}(\alpha)c_i |x_i| \\ &y_i - a_i x_i \leq -L^{-1}(\alpha)e_i + L^{-1}(\alpha)c_i |x_i| \\ &i=1, \dots, n \\ &a_{ij}, c_{ij} \geq 0, x_{ij}; j=0, \dots, m \end{aligned} \quad (2)$$

The solutions of this linear regression model are affected by the parameter α ($0 \leq \alpha < 1$). The values of a_i and c_i under the given value of α are determined using a traditional linear programming method. By means of fuzzy linear regression, the fuzzy parameter vectors (a_i, c_i) are derived from the data set of operational output y_i and input variables $x_{i1}, x_{i2}, \dots$,

Fig. 1 L-L fuzzy number and membership function

x_{in} . The change in the internal state of human reasoning is estimated in terms of the change in the vector set of (a_i, c_i) .

3. Observation of Internal State

3.1 Observation method

An experimental observation is made in order to understand the change in internal state during reasoning. For this purpose, the relation between the operational load and human reliability at the operation is examined. In the first step, the problem of balancing a beam is considered. The problem seems rather simple but some reasoning is necessary for the balancing operation. In this experiment, some pictures of the experimental balancing beam are shown on a personal computer display (NEC PC 9801 RX 2), as shown in Fig. 2. The operator can change the weight under the beam and is required to balance the beam. The weight can be changed by moving the scale on the display using a mouse pointer. The operation time is set at eight steps of 3, 4, 5, 6, 7, 8, 9 and 10 sec. In addition to the balancing operation, the operator is required to mentally calculate the last digit in two 4-digit integers. This experiment is repeated 500 times for each operation time, so a total of 4000 observation values are acquired. In each trial, the lengths of the right and left sections of the beam are changed by random operation of the computer software. The operator was 25-year-old male who is an expert at computer operation. The system software is written in the C language and is about 40 KB. The experiments were carried out in a traditional laboratory environment.

3.2 Observed data

In order to evaluate the experimental data, an evaluation value which corresponds to the operational reliability is introduced. It is difficult to represent operational reliability with traditional statistical methods. An evaluation criterion is introduced using fuzziness concept. The criterion is defined as a membership value that represents the state of a beam slope of roughly 0 degrees, because in these experiments, the desired state of the beam is roughly hori-

Fig. 2 Display of the computer during the experiment

zontal. The membership function of the roughly horizontal beam is shown in Fig. 3. The evaluation value is calculated as follows, where x_0 is the operational data value.

$$(\text{Evaluation value}) = \max \{0, (0.2|x_0|)\} \quad (3)$$

Table 1 shows the relation between average value and operational time. Each value in the table is an average of 500 observed data values. In this table, the evaluation value indicates the operational reliability, and the operational time corresponds to the operational load. In this case, operational time increases as operational load decreases. The operational reliability decreases exponentially with increasing load. It is also shown, as known from general experience, that operation under an appropriate load positively affects operational reliability, as shown in the case of operational time of 7 sec.

3.3 Identification of fuzzy linear regression model

The change in the human internal state during the experiments described in section 3.2 is represented by the linear regression model. The input value vector set is

$$\begin{aligned} x_i &= (x_1, x_2, x_3) \\ &= (\text{length of right side, length of left side,} \\ &\quad \text{angle of the beam}), \end{aligned} \quad (4)$$

and the output fuzzy number Y_i is the controlled beam weight. The parameter α , which has an important effect on the solution of the linear programming problem, is determined using the following approach. The linear programming problem is solved under the conditions of changing α within the range of 0-0.98 and with a small interval of 0.02, so as to adapt to the

experimental results. The relation between the average evaluation value and α at operational time of 7 sec is illustrated in Fig. 4. In this case, the value of α is 0.8107, which corresponds to the average evaluation value of 0.746 at the operational time of 7 sec. The fuzzy linear regression model is derived by solving the linear programming problem using the value of α defined above.

$$Y_7 = (0, 2.420\ 0) + (0, 0)x_1 + (0.0157, 0)x_2 + (0.847\ 6, 0)x_3$$

In this calculation, the output fuzzy number Y_i is defuzzified by means of probabilistic execution, in which the membership function calculated with the fuzzy linear regression model is mapped to the grade of (0-1). The fuzzy linear regression model is derived as follows, where the operational time is shown by the parameter $i=3\sim 10$, and the fuzzy parameter set A_i is represented by the set (a_i, c_i) .

$$Y_3 = (0, 1.938\ 4) + (0, 0)x_1 + (0.032\ 8, 0)x_2 + (0.447\ 0, 0)x_3 \quad (5)$$

$$Y_4 = (0, 8.422\ 2) + (0, 0)x_1 + (0.035\ 8, 0)x_2 + (0.481\ 3, 0)x_3 \quad (6)$$

$$Y_5 = (0, 3.762\ 2) + (0, 0)x_1 + (0.035\ 2, 0)x_2 + (0.487\ 8, 0)x_3 \quad (7)$$

$$Y_6 = (0, 2.501\ 4) + (0, 0)x_1 + (0.035\ 2, 0)x_2 + (0.488\ 2, 0)x_3 \quad (8)$$

$$Y_7 = (0, 2.420\ 0) + (0, 0)x_1 + (0.015\ 7, 0)x_2 + (0.847\ 6, 0)x_3 \quad (9)$$

$$Y_8 = (0, 1.938\ 4) + (0, 0)x_1 + (0.031\ 6, 0)x_2 + (0.582\ 5, 0)x_3 \quad (10)$$

$$Y_9 = (0, 2.742\ 3) + (0, 0)x_1 + (0.015\ 8, 0)x_2 + (0.845\ 6, 0)x_3 \quad (11)$$

$$Y_{10} = (0, 2.455\ 2) + (0, 0)x_1 + (0.015\ 9, 0)x_2 + (0.844\ 8, 0)x_3 \quad (12)$$

3.4 Adequacy of identified result

Computer simulations corresponding to the experiments were carried out by means of Eqs. (5)-(12). For each operation time, 500 simulations were performed and a total of 4 000 calculations were made. The relation between the average evaluation value and the

Table 1 Evaluation value and calculation error

OPERATION TIME [sec]	EVALUATION VALUE	CALCULATION ERROR [%]
3.0	0.239	61.8
4.0	0.526	30.2
5.0	0.604	10.2
6.0	0.610	6.4
7.0	0.746	3.0
8.0	0.631	5.0
9.0	0.722	2.8
10.0	0.715	2.4

Fig. 3 Membership function and evaluation value of "roughly level beam"

Fig. 4 Parameter α and evaluation value (operational time 7 sec)

operation time is also derived under the same criterion as described before. A comparison of the experimental results and the simulations is shown in Fig. 5. The deviation between the experiments and the simulations is 7% at most, as shown in Table 2. The shapes of the curves in Fig. 5 are similar. It is thus shown that the identified model described by Eqs. (5)-(12) is an appropriate representation of the change in the human internal state during operation.

3.5 Estimation of the change in internal state

The fuzzy parameters in the fuzzy linear regression model are a_i and c_i , where a_i is related to the central value of output fuzzy number Y_i and c_i is related to the range of Y_i . In our case, meaningful parameters of a_i and c_i are a_{i2} , a_{i3} and c_{i0} .

3.5.1 Characteristics of the parameter c_{i0}

The parameter c_{i0} , which reflects the range of Y , determines the fuzziness factor of the model. The relation between c_i and operation time is shown in Fig. 6. The fuzziness factor of the model represents the fuzziness of the change in the internal state. Thus, Fig. 6 shows the change in fuzziness of the internal state under changing operational load. The larger the operational load, the greater the fuzziness of the reasoning. In conclusion, the relation between the reliability of the operation and the operational load is characterized by the fuzziness factor in the operation.

3.5.2 Characteristics of the parameters a_{i2} and a_{i3}

The relation of the parameters a_{i2} and a_{i3} to

the operational load is illustrated in Fig. 7. The parameter a_i represents the central value of the output fuzzy number Y_i . Therefore, a_i shows the accuracy of the operation. As shown in Fig. 7, the results at the operational times 3-6 sec, 8 sec, 7 sec and 9-10 sec are almost the same values. These results show whether each operation is inaccurate or accurate.

3.5.3 Factors affecting operational reliability

The operational reliability is derived from both the fuzziness factor of the change in internal state and the operational accuracy, as shown in Fig. 8. From these results, we can obtain the following conclusions.

(1) The operational reliability is affected by both the fuzziness factor of the internal state and the operational accuracy.

(2) The fuzziness factor of the human internal state of reasoning changes with the operational load. The larger the operational load, the greater the fuzziness factor.

Fig. 6 Relation between c_0 and operation time

Fig. 7 Relation between a_2 , a_3 and operational load

Fig. 5 Comparison of the experimental results and simulation

Fig. 8 Operational reliability and operational load

4. Application of the Estimation of Internal State

4.1 Application to vehicle driving

Vehicle operation is taken as a practical engineering example. In this example, the relation between the operational load and the fuzziness of reasoning is considered. We can confirm the finding that the larger the operational load, the larger the fuzziness factor which is introduced by the change in internal state. In this example, we used the driving simulator shown in Fig. 9. The experiments entailed a changing driving course. As an additional load, the same type of mental arithmetic described in section 3.1 was assigned. The experiments were carried out at 50 km/h vehicle speed either with or without mental arithmetic.

Twenty experiments were carried out for each condition, so that 40 data values were acquired. The evaluation of the drivers is as follows:

good driving 2 "drivers"
 fairly good 5 "drivers"
 not very good (distracted by mental arithmetic) 11 "drivers"
 poor driving 2 "drivers"

The percentages of correct answers to the mental arithmetic were maximum 80%, minimum 60%, and average 72%. These results show that driving while calculating mental arithmetic is a fairly heavy load for the operator.

4.2 Identification of model

We select the input variables as driving distance, deviation from the center line of the course, yaw angle, yaw angular velocity of the vehicle, and vehicle speed. The fuzzy output variable is the turning angle

Fig. 9 Driving simulator

of the steering wheel. The fuzzy regression model is derived for each interval of the course, as shown in Fig. 11. The driving course is divided into nine sections, shown as A to I in Fig. 11. Data for the steering wheel angle from both experiments and calculation with the present model are shown in Figs. 10(a) and 10(b) for driving with and without mental arithmetic, respectively. The characteristics of the time responses are quite similar. It is shown that the fuzzy linear regression model is appropriate for these dynamics.

4.3 Estimation of internal state

We will now analyze the fuzziness factor of the model with and without mental arithmetic. The fuzziness factor change with driving interval is shown in Fig. 11. Both with and without mental arithmetic, at the time of changing vehicle direction, the parameters of the fuzziness factor become large. On the other hand, at the time of no steering wheel movement, the parameters become small. It is considered that the change in operational load with steering wheel action reflects the change in human internal state during the operation. The average values of the fuzziness factor

Fig. 10 Angle of the steering wheel (experiment)

Fig. 11 Fuzziness factor during driving

Fig. 12 Average factor of the model during driving

Fig. 13 Example system

of the model during the entire course A to I in Fig. 11 are represented in Fig. 12, where $\circ$ represents during without mental arithmetic and $\bullet$ is that with mental arithmetic. The results for driving with mental arithmetic are larger than those for driving without mental arithmetic. In general, the average value for driving with mental arithmetic is 47% larger than that for driving without arithmetic. In these results, the fuzziness factor becomes large with heavy operational load. It is confirmed that we can estimate the change in internal state using the fuzziness factor of the present operational model, which can be constructed from fundamental operational data.

4.4 Suggestions for application

We can introduce the concept that the characteristics of human operational error are illustrated in terms of the fuzziness factor. Thus, the relation between the reliability of human operation and the operational load can be analyzed in terms of the fuzziness factor. When considering the possibility of human operational error, it is useful to detect the fuzziness of the internal state during reasoning. An example of this approach is illustrated in Fig. 13. The objective of the system is to reduce the human operational error. It is useful to construct a system which has a function to alarm the operator when the fuzziness factor of the internal state become large. It

would be advantageous to install these systems in vehicles and machine systems involving complex operation and reasoning. In the application of this approach, the most important feature is that no special parameters but only the fundamental and essential data are necessary in order to obtain the fuzziness factor of the human internal state.

5. Conclusions

In this paper, we described an approach to obtain a model for estimation of the change in the human internal state during reasoning by means of the fuzzy linear regression model. Simple experiments show the feasibility of this approach. The human internal state is the parameter most affecting the reliability of human operation. The change in the internal state of the human operator is represented in terms of the fuzzy set of parameters of the linear regression model. The experimental results show that the fuzziness of the internal state becomes large when the operational load increases. The larger the fuzziness factor, the lower the reliability of human operation. In addition, an application to fault detection systems is discussed. The main feature of this approach is that no special parameters but only the fundamental and essential operation data are necessary to obtain the fuzziness factor of the internal state during the operation.

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