Development and validation of the lane-keeping controller using a similarity-type fuzzy reasoning method

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***Abstract*— This paper proposes the Similarity-type Fuzzy Reasoning method based on the calculated overlap coefficient of sensor rules and sensor input data for a lane-keeping controller. Fuzzy control reasoned by a membership function and human-adjusted rules. Those are required to improve the control performance. In this paper, instead of using the membership function, the inference result was calculated by the similarity of the rules and the input data. We try to implement the lane-keeping controller using the similarity-type fuzzy reasoning method, and this method has been succeeded to develop new advance two-stage fuzzy control.**

Keywords— fuzzy control, lane keep, similarity, micro controller

I. Introduction

The fuzzy set theory was proposed by LA Zadeh in 1965[1]. Mamdani's reasoning method [2], functional reasoning method [3], and simplified reasoning method [4] are examples of commonly used fuzzy reasoning. It is widely established in the industrial world as a method of describing knowledge with ambiguous expressions similar to human senses. Generally, these inference methods perform inference using a fuzzy number, which is a convex fuzzy set defined by a set of real numbers. Non-convex fuzzy sets are difficult to handle easily, and when they are used, the non-convex fuzzy sets are converted convex fuzzy sets, but computation is increased [5].

Takimoto and Hoshino worked that fuzzy control has possible to control a line trace car. This fuzzy controller is successful in highspeed control. This control style is smooth and operation time of the steering on the curved course. In this research, Takimoto used multi-stage fuzzy control [6]. Takimoto was proved that the lane-keeping system using fuzzy theory. This control system can perform the line keeping control approximately. In this system, white lines are tracked by 8 photosensors. However, for more precise control, the number of sensors must be increased or a camera sensing device must be utilized. In addition, when the many numbers of the sensor input value are covered from a non-convex fuzzy set. There is a problem that the fuzzy number cannot support by any combinations. Also, a membership can be designed that an increase in the combination of inputs causes. But those membership functions and rules are increased. This is a disadvantage of the fuzzy theory. Adjustments of membership functions were succeeded by using GA and PSO algorithms. Those works are trying as the optimization problem for membership functions [7].

Hoshino has proposed a new reinforcement learning system for the large environment. It's the fuzzy environment evaluation reinforcement learning (FEERL) [8].

The purpose of this study is to realize smooth and fast control, and the controller should be a tracking control using similarity fuzzy inference. Fuzzy inference is applied to nonlinear systems by constructing inference rules. Those rules can be designed by incorporating the human experience. However, to improve accuracy, it is necessary to adjust the rules by humans. This adjustment is necessary for a long time. Furthermore, many input combinations and rule numbers are possible to improve inference accuracy. But those will a problem the huge processing time and a bad affection the control. Therefore, in this study, we propose a method of controlling a line trace car by fuzzy inference using similarity calculation to reduce the tuning time of the membership function. In this paper, the control rules were determined based on the data from the two-stage fuzzy control, and the similarity of control rules and running sensing data was applied to the motor control of the line trace car as the inference result. We compared the motor behavior and the driving reproducibility in the two-stage fuzzy control and similarity type fuzzy control. We compared the motor behavior and the driving reproducibility in the two-stage fuzzy control and similarity-type fuzzy control.

II. System overview

We follow a control system for tracking white lines which adopted the line trace car used in Japan micom car rally, and developed based on it. The system is equipped with a wi-fi module and can log running data (sensor values, motor output values, steering angles, etc.) in real-time.

Fuzzy control that can expect high-speed processing was applied to the control. Fuzzy control enables linguistic processing, and the control is determined mainly by a product-sum operation. Therefore, mounting on a microcontroller was possible, and an inexpensive system was realized. Fig. 1 shows the appearance of the lane-keeping system.

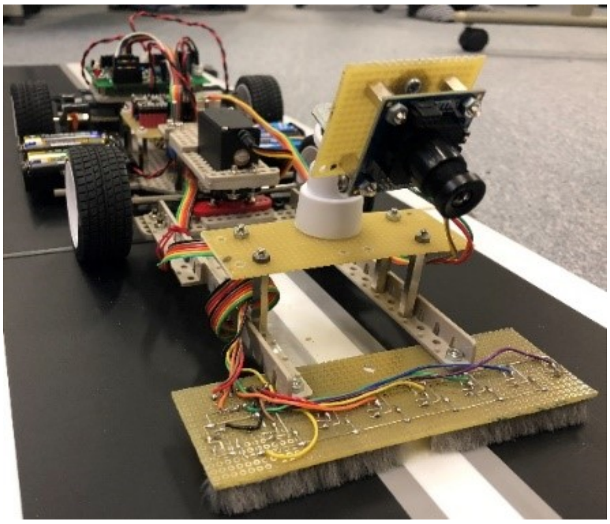


Fig. 1. The lane-keeping control system

III. System Configuration

In this paper, the running performance of two lane-keeping controllers that a two-stage fuzzy inference and a similarity fuzzy inference were developed and compared. The system components used for both controllers were identical and only the control system was modified. Both controllers sense the course information using 8 photo reflectors and perform the identical processing, such as fuzzy operation, using an ESP32-divKitC microcontroller. TableI illustrates the main components of the system.

TABLE I. Item configuration

Item name	Type	Quantity
Micro controller	ESP32-DevKitC	1
Reflective photo sensors	LBR-127HLD	8
Line scan camera	TSL1401	1
Body	M-S226	1

The body used a microcomputer car production kit sold by Hitachi Intermedix Co., Ltd. The developed system is shown below.

A. Two-stage fuzzy control

This controller has a servo motor and a rear wheel motor. Therefore, the control of the rear wheel motor also changes according to the control of the servo motor. It is effective to determine the rear wheel motor control based on the servo motor control results. We have selected a two-stage fuzzy control for which control rules can be easily designed as a comparison target.

Fig. 2 shows an overview about the system configuration of the lane-keeping controller using a two-stage fuzzy inference. In this system, a white line on a course composed of three colors-white, black and gray, is judged by 8 photosensors. First, the fuzzy inference of the steering angle θ is performed from the position of the white line, and the servo motor is controlled from the inference result. Next, the fuzzy inference of the right and left motor-controlled variable is performed based on the fuzzy inference result of the steering angle θ and the right and left motor is controlled from the zinference result. As a result, the lane-keeping control is achieved.

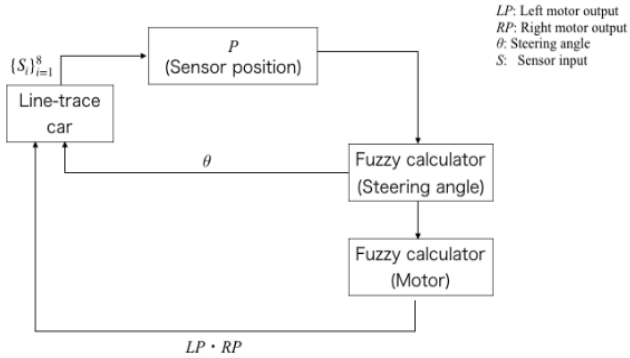


Fig. 2. System configuration of two-stage fuzzy inference white line tracking controller

The function P is the position of the white line determined by the 8 photosensor values. The control variables calculated after converting the 8 photosensor values into P values. As shown in Fig. 3, apply a loads w_i of [-4, -3, -2, -1, 1, 2, 3, 4] to each photosensor.

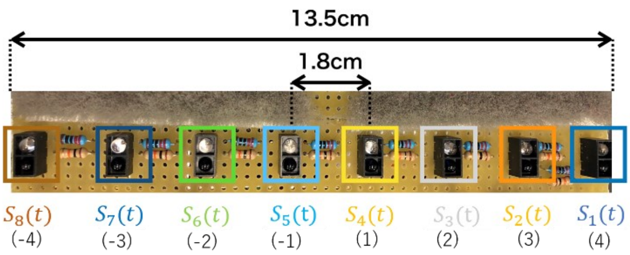


Fig. 3. Sensor weight and number seen from the back

The input value of the photosensor $S_i(t)$ indicates the degree of reflection of the course. The photosensor number are $S_1(t)$, $S_2(t)$ to $S_7(t)$ and $S_8(t)$ from left to right. This sum of the photosensor input value is the reflection degree of the entire course acquired by each sensor at the time *t*. At this time, the value obtained by assigning the sensor weight shown in Fig. 3 to each photosensor input value is defined as the following function:

$$N_i(t) = w_i S_i(t) \tag{1}$$

Therefore, the position of the white line P is obtained by dividing the sum of $N_i(t)$ by the sum of $S_i(t)$. The position of the white line P is as follows:

$$P = \frac{\sum_{i=1}^{8} N_i(t)}{\sum_{i=1}^{8} S_i(t)} \tag{2}$$

This system is a one-input three-output controller that the position of the white line P calculated from the 8 photosensor values and outputs the steering angle θ and the left and right motor output *LP* and *RP*.

B. Simirarity-type control system

Fig. 4 shows the system configuration that similarity-type fuzzy inference lane-keeping controller.

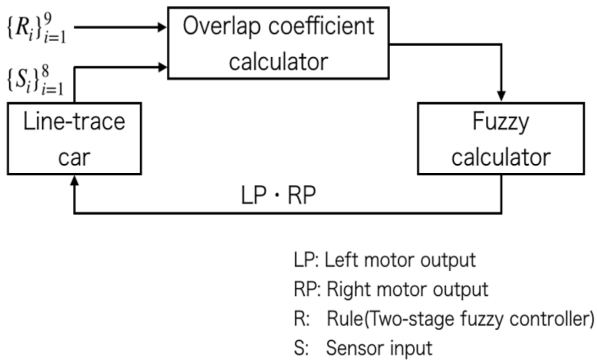


Fig. 4. System configuration of the similarity-type fuzzy inference lane-keeping controller

In this system, a white line on a course composed of three colors, white, black, and gray, is determined by 8 photosensors the same as chapter III(A). The similarity is calculated based on the overlap coefficient between the photosensor input value and the created control rule. The overlap coefficient is mainly used when calculating similarity in a set. Fuzzy inference of right and left motor is performed from the calculation result of similarity, and the lane-keeping control is performed by control the right and left motor.

Here the similarity is calculated by the sensor rules *SR* and motor output rules *MR*, the right and left motors are respectively denoted as *RMR* and *LMR*. These variables are determined using past running data of the two-stage fuzzy control method control system indicated by chapter III, section A. The right and left motor output are determined by similarity-type fuzzy inference, and Table II shows the control rules for the 9 patterns. The control rules in Table II categorized the values on the course that the position of the white line gathered on the left, center, and right, and configured 3 control rules at each average position.

Only the control of the steering angle is a classifier system and outputs the steering angle control rules *AR* of the sensor rule *SR* having the highest similarity with the photosensor input values *S*.

IV. FUZZY INFERENCE

This section describes the designed fuzzy inference for the lane-keeping controller.

A. Two-stage fuzzy control

In this study, we used the simplified inference method [9] proposed by Maeda et al. To simplify and speed up fuzzy inference, the consequent part of the Mamdani-type inference method [8] is given by a constant. Due to the power source of this lane-keeping controller is a battery, a simplified inference method is applied to reduce the computation load. The steering angle control rules are as follows:

$$R_1^1\text{: if } P \text{ is } A_1^1 \text{ then } \theta \text{ is } B_1^1$$
$$R_2^1\text{: if } P \text{ is } A_2^1 \text{ then } \theta \text{ is } B_2^1$$
$$R_3^1\text{: if } P \text{ is } A_3^1 \text{ then } \theta \text{ is } B_3^1$$
$$R_4^1\text{: if } P \text{ is } A_4^1 \text{ then } \theta \text{ is } B_4^1$$
$$R_5^1\text{: if } P \text{ is } A_5^1 \text{ then } \theta \text{ is } B_5^1$$

The steering angle θ in the consequent parts indicates the direction in which the servomotor is controlled. A_1^1, A_2^1, A_3^1, A_4^1, A_5^1 of the antecedent part are given by real number values. The antecedent part adopted a triangular membership function. The variables of the antecedent part and the consequent part were selected based on past running experiments. The steering angle θ of this system take of value -22 ° to 22 °. The diagram of the steering angle control membership function and singleton was designed as shown in Fig. 5.

TABLE II. Sensor input value, steering angle, motor output rule (TR)

		Sensor input value								Output value		
		sensor1 (0 (black) - 1(white))	sensor2 (0 (black) - 1(white))	sensor3 (0 (black) - 1(white))	sensor4 (0 (black) - 1(white))	sensor5 (0 (black) - 1(white))	sensor6 (0 (black) - 1(white))	sensor7 (0 (black) - 1(white))	sensor8 (0 (black) - 1(white))	steering angle(°) (-90 - 90)	lp(leftmotor) (0 - 1023)	rp(rightmotor) (0 - 1023)
Rule	1	1	0.5	0	0	0	0	0	1	-12.06	200	1023
	2	1	1	0	0	0	0	0	0	-10.83	214	1021
	3	0	1	1	0.5	0	0	0	0	-7.78	250	990
	4	0	0	1	1	0.5	0	0	0	-3.16	478	902
	5	0	0	0	1	1	0	0	0	0	727	727
	6	0	0	0	0	1	1	0	0	3.84	885	519
	7	0	0	0	0	0	1	1	0	7.44	930	385
	8	0	0	0	0	0	0	1	1	12.64	1010	228
	9	1	0	0	0	0	0	0.5	1	13.07	1023	220

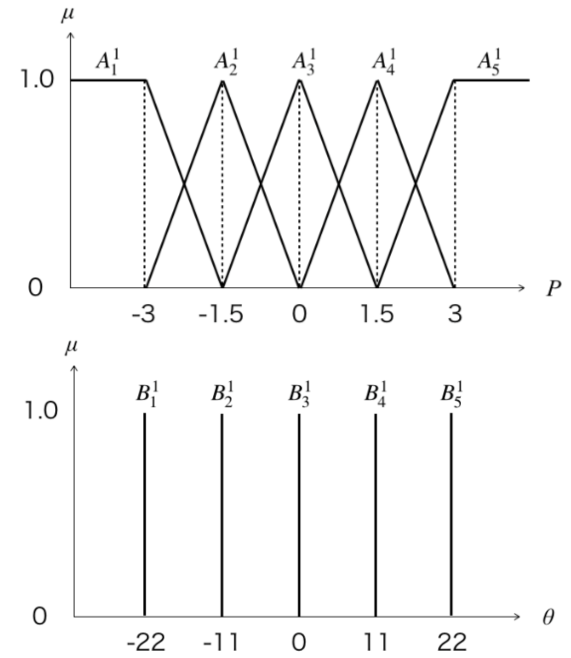


Fig. 5. The membership function and singleton of the steering angle control

Next, the right and left motor-controlled variable is inferred based on the steering angle fuzzy inference result. The right and left motor control rules are given as follows:

【Right motor control rules】

R_1^2: if P is B_1^2 then RP is M_1^1
R_2^2: if P is B_2^2 then RP is M_2^1
R_3^2: if P is B_3^2 then RP is M_3^1
R_4^2: if P is B_4^2 then RP is M_4^1
R_5^2: if P is B_5^2 then RP is M_5^1

【Left motor control rules】

R_1^3: if P is B_1^3 then LP is M_1^2
R_2^3: if P is B_2^3 then LP is M_2^2
R_3^3: if P is B_3^3 then LP is M_3^2
R_4^3: if P is B_4^3 then LP is M_4^2
R_5^3: if P is B_5^3 then LP is M_5^2

The variables *LP* and *RP* are left and right motor-controlled variable. The antecedent part adopted a triangular membership function. The steering angle θ of the inference result is applied to variable *P*. Thus, the value range of the steering angle θ takes of value -22° to 22°. The variables of the antecedent part and the consequent part were selected based on past running experiments. The variables *LP* and *RP* are in [0, 1023]. The membership functions and singletons for left and right motor control are designed as shown in Fig. 6 and Fig. 7.

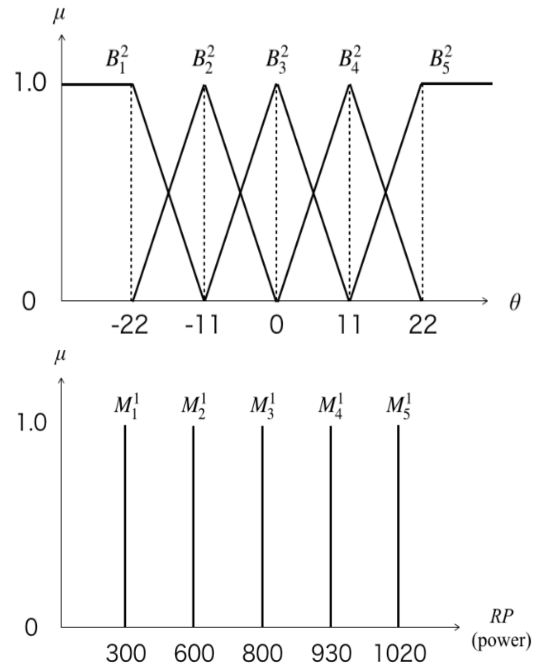


Fig. 6. Right motor control membership function and singleton

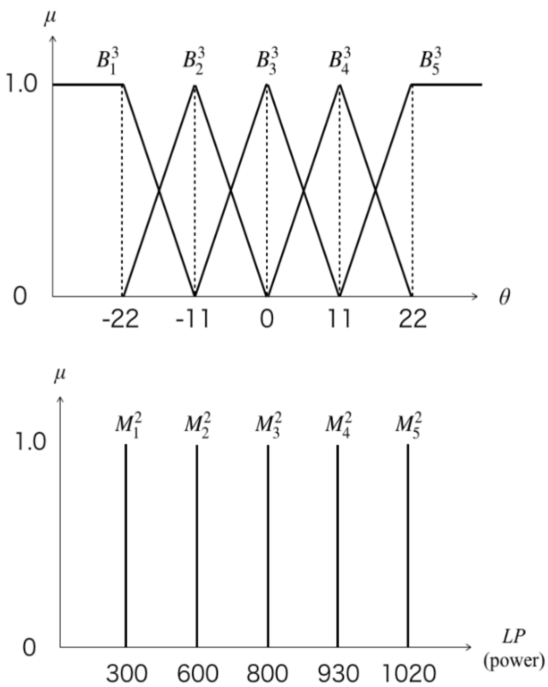


Fig. 7. Left motor control membership function and singleton

B. Simirarity-type control system

In ordinary fuzzy inference, the result μ is obtained from the inference rule and the membership function. In this study, the result μ is obtained without the membership function by substituting similarity. To get the similarity value, this system calculates the overlap coefficient between the photosensor input value *s* and the sensor control rule *SR*. The control rules for right and left motor control are as follows:

$\{R_i\}_{i=1}^{9}$: If s is $\{SR\}_{i=1}^{9}$ Then LP and RP is $\{\mu_i\}_{i=1}^{9}$

As a result, this system obtained inference result μ. The inference result μ is as follows:

$$\mu_i = \frac{\sum_{i=1}^{9} |\{SR_i\}_{a=1}^{8} \cap \{s\}_{a=1}^{8}|}{\sum_{i=1}^{9} \min\{|\{SR_i\}_{a=1}^{8}|, |\{s\}_{a=1}^{8}|\}} \quad (3)$$

Fig. 8 shows an illustrative example how the denominator is calculated. The gray part is a product-set operation of the control rules and photosensor input values and applied for the operation.

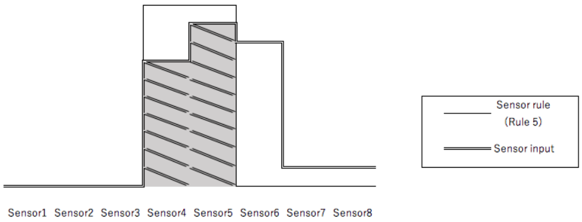


Fig. 8. Derivation diagram of SR∩s

In order to quantify the motor output from the inference result μ, defuzzification was performed using the center of gravity method. The left and right motor control variable calculation are as follows:

$$LP = \frac{\sum_{i=1}^{9} \mu_i \ LMR_i}{\sum_{i=1}^{9} \mu_i} \quad (4.1)$$

$$RP = \frac{\sum_{i=1}^{9} \mu_i \ RMR_i}{\sum_{i=1}^{9} \mu_i} \quad (4.2)$$

V. Experiments

In this experiment, we compare the running behavior of the lane-keeping controller with similarity-type fuzzy inference and two-stage fuzzy control. The running course was 10m long and in accordance with the Japan Micom Car Rally regulations. The running course is shown in Fig. 9. We compared the results of running two lap on the course.

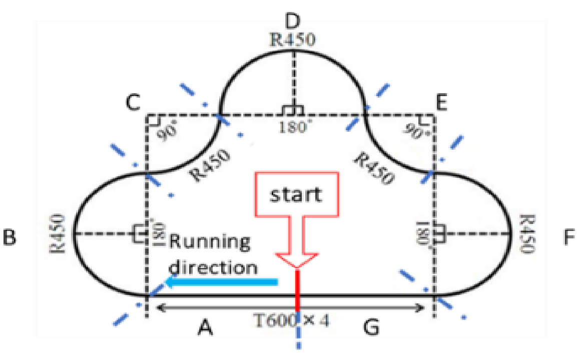


Fig. 9. Running course

We get the running data that photosensor input values, left and right motor-controlled variable and steering angle.

VI. Result

Fig. 10 (a) shows the obtained motor output value during running using two-stage fuzzy inference, and Fig. 10 (b) shows the obtained motor output value during running using similarity fuzzy inference. Comparing the graphs in Fig. 10, it can be seen that the running under two-stage fuzzy control could be reproduced by similarity fuzzy inference without tuning. However, the fluctuation of the motor behavior can be confirmed. This is because the steering angle control is a classifier system, and as a result, the fluctuation of the steering control affected the motor behavior. Also, Fig. 11 shows a comparison of the processing speed and memory usage.

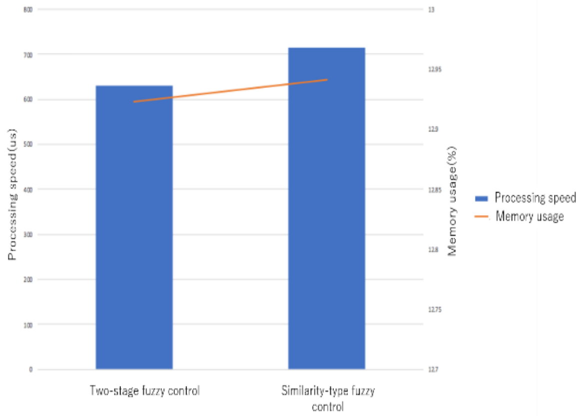


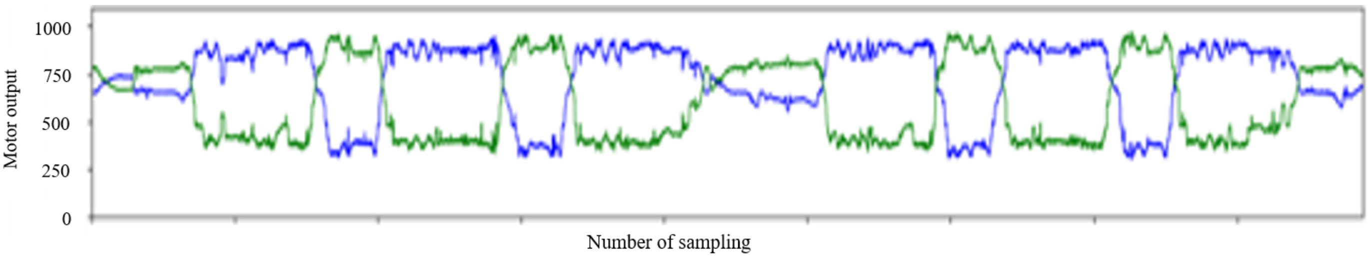
Fig. 11 Comparison processing speed and memory usage

The similarity-type fuzzy control increased processing speed and memory usage compared to two-stage fuzzy control. This is considered that similarity fuzzy inference has more rules than the two-stage fuzzy inference. Therefore, the amount of calculation increased, and the processing speed and memory usage increased.

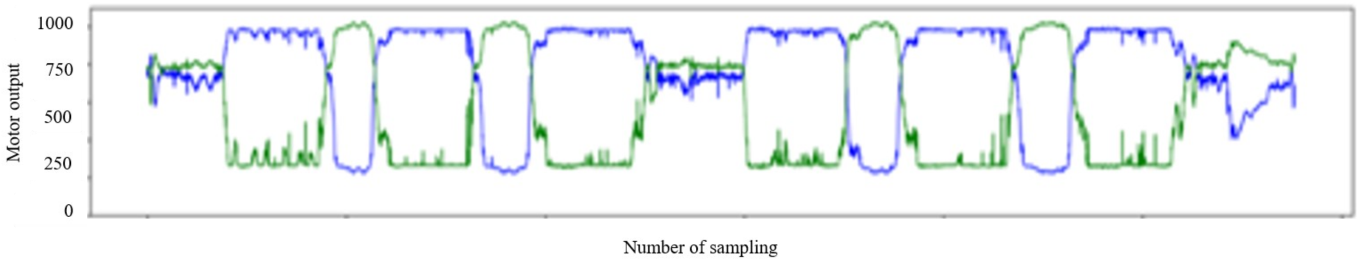
VII. Conclusion

In this paper, we have showed that the running behavior by two-stage fuzzy control could be reproduced by similarity fuzzy inference without tuning. But, it was confirmed that the fluctuation of the steering angle affects the motor output behavior when the similarity fuzzy inference using the photosensor is adapted. In the future, after realizing two-stage fuzzy inference using similarity, we will develop a line trace car that realizes high-speed processing even if the number of inputs increases by applying similarity fuzzy inference to the line camera.

Also, if control is possible by implementing similarity fuzzy inference on a line camera, the control can be determined by the similarity between the ruled image and the input image, so it may be applicable to courses without lines.



(a) Running behavior during two-stage fuzzy control



(b) Driving behavior when fuzzy inference is applied

Fig. 10. Motor output result by running experience

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