

Intelligent Control Method for Autonomous Vehicle by Fuzzy-Neural Network and Self-position-azimuth Correction

Ryunosuke Takauji¹, Peng Chen², and Mitushi Yamashita³

^{1,2,3}Mie University, Mie 514-8507, Japan
(Tel: 059-231-9592)

¹511m209@m.mie-u.ac.jp, ²chen@bio.mie-u.ac.jp, ³yamasita@bio.mie-u.ac.jp

Abstract: This paper proposes an Intelligent Control Method for Autonomous Vehicle which will roughly-appropriately and automatically recognize and judge the running environment and run along a given orbit without disarray by using Fuzzy-Neural Network (FNN). To realize autonomous running by using FNN, We extracted human's driving knowledge (teaching data for the FNN) from the running data. For acquiring the teaching data for the FNN, the running data are processed and normalized by rough set and defuzzy method. Moreover, we proposes an error correction method called "self-position-azimuth correction" to detect and correct the position and azimuth error between estimated position and actual measured position of the vehicle by using a pole at already-known position. The efficiency of the method has been verified by computer simulations and tests using a model vehicle.

Keywords: Autonomous vehicle, Fuzzy-neural network, Rough set, Self-position-azimuth correction

1 INTRODUCTION

Recently, labor saving in agricultural area is being needed increasingly because of decrease of agricultural workers due to the aging society. The autonomous running for the agricultural vehicle is one of the methods for the labor saving.

The purpose of this research is to construct an intelligent control system by using the fuzzy-neural network (FNN) for an autonomous vehicle which will roughly-appropriately and automatically recognize and judge the running environment and run along a given orbit without disarray.

Though various methods for orbit tracking of the vehicle have been proposed, there are many problems which have not been solved for learning human's driving knowledge and controlling the vehicle quickly as driven by a human driver. To solve these problems, this paper proposes an intelligent control method using fuzzy-neural network and Self-position-azimuth correction.

2 CONSTRUCTION METHOD

2.1 Model vehicle

The model vehicle used for the verification (called RoboCarTM) is shown in fig. 2.1.

The dimensions of the model vehicle are W195.0 mm/D429.0 mm/H212.2 mm.

Speed control and steering angle control can be carried out by the rotary encoder and the servo motor respectively.

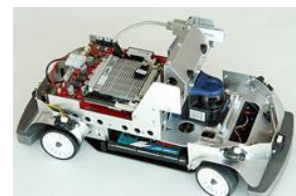


Fig. 2.1. RoboCar

2.2 Setting target orbit

The target orbit is sampled as points expressed by coordinate values which are set with the interval of about 20 cm. The straight line connecting points on the target orbit is regarded as approximate orbit of the target orbit. Also, these points are memorized in the computer of the model vehicle beforehand. The relative distance between the vehicle and point of target orbit are sequentially calculated while running. Then the point with the smallest relative distance is selected as the present target orbit point, the next point of that is regarded as sequential target orbit point. Finally, next point of now target orbit point is next target orbit point.

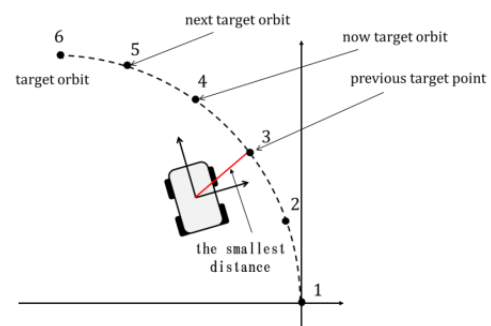


Fig. 2.2. Recognition of target orbit

2.3 Parameters between the vehicle and target orbit

P_a is the relative distance between the center point of the vehicle and the target orbit. P_b and P_c are the relative angle between the direction of the vehicle and the line connected cross point 1 or cross point 2 to the center of the vehicle. Cross point 1 and cross point 2 are the points that the circle centered on the vehicle with the radius 30 cm, 60 cm intersects a target orbit. The vehicle recognizes a relative position by these parameters.

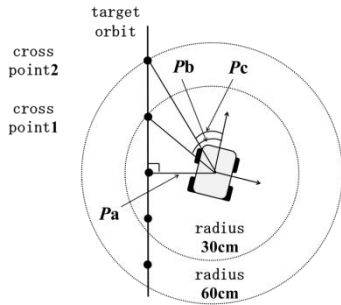


Fig. 2.3. Relative parameters

2.4 Method for extracting driving knowledge

Firstly, the running data is recorded while the vehicle is driven along target orbit by a human driver. P_a , P_b , P_c and steering angle are acquired as the running data. Then, the running data is processed and normalized by rough set and defuzzy method. Human's driving knowledge (teaching data for the FNN) is extracted from the running data.

2.4.1 Normalization

Firstly, we need to normalize P_a , P_b , P_c and steering angle for processing the teaching data by rough set. The range of the normalized relative distance and angle is narrow when the vehicle position is near to the target orbit, else it is wide when the vehicle position is distant from the target orbit. Steering angle is normalized with the interval of 3 degree.

Table 2.1. Range of normalization

Parameters	P_a [cm]	P_b [deg]	P_c [deg]
1	~-30	~-90	~-90
2	-30~-20	-90~-70	-90~-70
3	-20~-10	-70~-55	-70~-55
4	-10~-6	-55~-40	-55~-40
5	-6~-3	-40~-30	-40~-30
6	-3~-1	-30~-20	-30~-20
7	-1~-1	-20~-15	-20~-15
8	1~3	-15~-10	-15~-10
9	3~6	-10~-6	-10~-6
10	6~10	-6~-3	-6~-3
11	10~20	-3~-1	-3~-1
12	20~30	-1~-1	-1~-1
13	30~	1~3	1~3
14		3~6	3~6
15		6~10	6~10
16		10~15	10~15
17		15~20	15~20
18		20~30	20~30
19		30~40	30~40
20		40~55	40~55
21		55~70	55~70
22		70~90	70~90
23		90~	90~

2.4.2 Rough set

In this section, we explain the rough set used this research. As a simple example, the data set is shown in Table. 2.2. P (the set of kinds of parameter) is shown by formula (2.1).

Table 2.2. Before rough set

Data No	Parameters P			S_k
	a	b	c	
X_1	3	2	1	0
X_2	3	4	1	1
X_3	1	7	3	0
X_4	1	4	1	0
X_5	3	4	1	1
X_6	1	4	1	1
X_7	4	6	2	0
X_8	3	2	1	0
X_9	4	6	2	1
X_{10}	1	4	1	1

$$P = \{a, b, c\} \tag{2.1}$$

The i^{th} set of parameter value is shown by formula (2.2).

$$\begin{aligned} {}^1P &= \{3, 2, 1\} \\ {}^2P &= \{3, 4, 1\} \\ &\dots \\ {}^{10}P &= \{1, 4, 1\} \end{aligned} \tag{2.2}$$

Approximation space set A is shown by formula (2.3).

$$\begin{aligned} A &= \{r_1, r_2, r_3, r_4, r_5\} \\ &= \{ \{X_1, X_8\}, \{X_2, X_5\}, \{X_3\}, \{X_4, X_6, X_{10}\}, \{X_7, X_9\} \} \end{aligned} \tag{2.3}$$

Then,

$$\begin{aligned} r_1 &= \{3, 2, 1\}, {}^1S = \{0, 0\} \\ r_2 &= \{3, 4, 1\}, {}^2S = \{1, 1\} \\ r_3 &= \{1, 7, 3\}, {}^3S = \{0\} \\ r_4 &= \{1, 4, 1\}, {}^4S = \{0, 1, 1\} \\ r_5 &= \{4, 6, 2\}, {}^5S = \{0, 1\} \end{aligned} \tag{2.4}$$

By formula (2.4), ${}^S\beta_{r_i}$, uncertainty of measurement to state S of equivalent class r_i , are

$$\begin{aligned} {}^0\beta_{r_1} &= 2/2 = 1:100\% \\ {}^1\beta_{r_1} &= 0/2 = 0:0\% \\ {}^0\beta_{r_2} &= 0/2 = 0:0\% \\ {}^1\beta_{r_2} &= 2/2 = 1:100\% \\ {}^0\beta_{r_3} &= 1/1 = 1:100\% \\ {}^1\beta_{r_3} &= 0/1 = 0:0\% \\ {}^0\beta_{r_4} &= 1/3 = 0.33:33\% \\ {}^1\beta_{r_4} &= 2/3 = 0.67:67\% \\ {}^0\beta_{r_5} &= 1/2 = 0.5:50\% \\ {}^1\beta_{r_5} &= 1/2 = 0.5:50\% \end{aligned} \tag{2.5}$$

Table 2.3. After rough set

rough sets r_i	Probability		Parameters P		
	${}^0\beta_{ri}$	${}^1\beta_{ri}$	a	b	c
0 0 $r_1 = \{X_1, X_8\}$	100%	0%	3	2	1
1 1 $r_2 = \{X_2, X_5\}$	0%	100%	3	4	1
0 $r_3 = \{X_3\}$	100%	0%	1	7	3
0 1 1 $r_4 = \{X_4, X_6, X_{10}\}$	33%	67%	1	4	1
0 1 $r_5 = \{X_7, X_9\}$	50%	50%	4	6	2

2.5 Fuzzy-Neural Network

FNN can control the vehicle automatically and roughly-appropriately recognize and judge the running environment as human driver. Because FNN can output the appropriate results even if the input data have not been learnt beforehand, if we have appropriately made the leaning for the FNN. In this research, the inputs of the FNN are Pa , Pb and Pc , the output of the FNN is steering angle. The construction of the FNN is shown in Fig. 2.4.

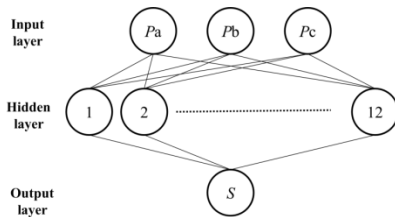


Fig. 2.4. Construction of the FNN

3 POSITION-AZIMUTH CORRECTION

We use the Dead Reckoning Method for the vehicle’s positional presumption. But dead reckoning method has the disadvantage that the cumulative error of the vehicle position becomes a big gradually while running. The error is caused by slipping the wheel, etc. To solve this problem, we adopt self-position-azimuth correction using external information. In the verification, a pole (height is 200 mm; diameter is 65 mm) is set at already-known position on the world coordinate system $\Sigma(x,y)$. Laser-Range-Finder (LRF) installed on the model vehicle measures a relative distance and angle between the vehicle and a pole. The range of detection of LRF is 5m and 240 degree like Fig. 3.1. Principle of Self-Position-azimuth Correction is shown in Fig. 3.2. $\vec{W}_{j'1}$ and $\vec{W}_{j'2}$ are the vector from the center of the vehicle to a pole. Also, the vector \vec{W}_{j2-j1} can be calculated as follows.

$$\vec{W}_{j2-j1} = \vec{W}_{j2} - \vec{W}_{j1} \tag{2.6}$$

$$\theta_{L3} = \theta_{L2} - \theta_{L1} \tag{2.7}$$

$$\theta_{L4} = \sin^{-1} \left(\frac{l_2}{l_3} \times \sin \theta_{L3} \right) \tag{2.8}$$

$$\theta_G = \theta_{L4} - \theta_{L1} \tag{2.9}$$

$$R^{-1} = \begin{bmatrix} \cos \theta_G & \sin \theta_G \\ -\sin \theta_G & \cos \theta_G \end{bmatrix} \tag{3.0}$$

$$\vec{G} = \vec{W}_{j2} - R^{-1} \vec{W}_{j'2} \tag{3.1}$$

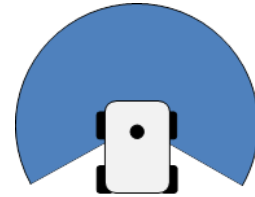


Fig. 3.1. The range of LRF

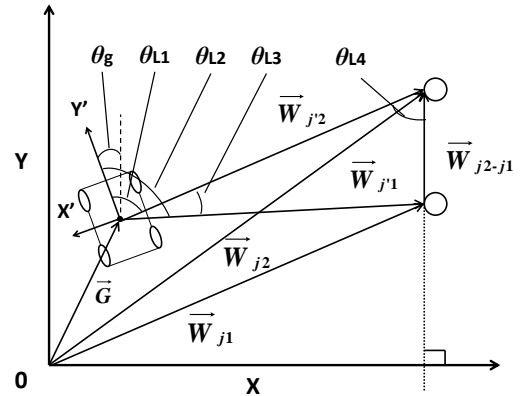


Fig. 3.2. Self-Position-azimuth correction

4. VERIFICATION

4.1 Vehicle communication environment

The model vehicle has Linux and is operated by other PC using access point.

Autonomous running will be operated by installed program.



Fig. 4.1. Communication system

4.2 Method for control of autonomous running

We need to construct the FNN in advance to control the vehicle. For the purpose, the teaching data is acquired by driving the model vehicle by human driver. And the learning for the FNN is done by Back Propagation Algorithm. When autonomous running is executed, the vehicle is controlled by output of the FNN. Output of the FNN is calculated by input Pa , Pb and Pc to the FNN which has learnt the teaching data.

4.3 Acquisition the teaching data

Target orbit are the straight line and half circles with the radius 57.5 cm, 150 cm and 200 cm when we acquire the teaching data for the FNN. The initial positions are shown in Fig. 4.2, Fig. 4.3 when acquiring the teaching data.

The model vehicle's speed is at 10 cm/s. The initial directions are 0, 30 and -30 degrees when the vehicle run along a half circle with the radius 150 cm.

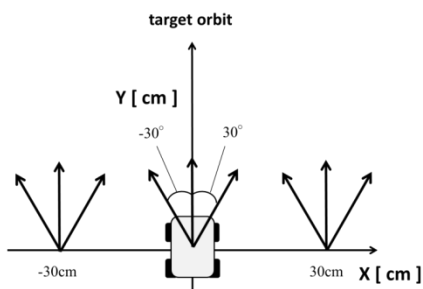


Fig. 4.2. The initial position of the vehicle when the target orbit is straight line

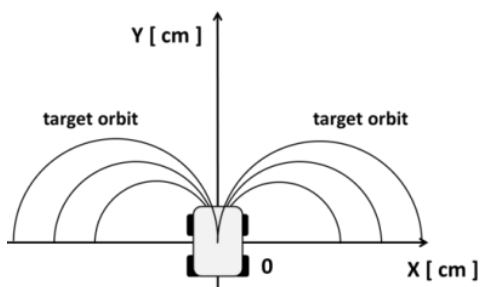


Fig. 4.3. The initial position of the vehicle when the target orbit is a circle

4.4 Running experiment

4.4.1 Verification by simulation

We did the autonomous running simulation using the FNN. The model vehicle's speed was 10 cm/s. The result of the autonomous running simulation is shown in Fig. 4.4, and by the result, the vehicle successfully returned to the straight orbit from the initial position which the FNN has not learnt.

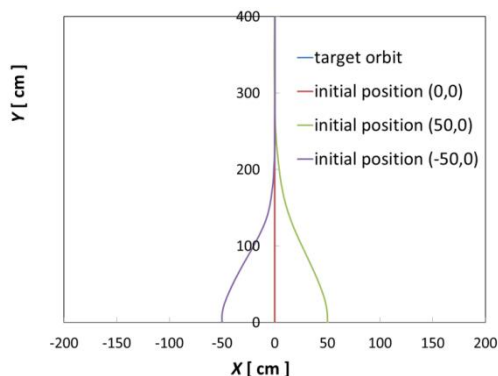


Fig. 4.4. The result of simulation

4.4.2 Verification by the model vehicle

The compound track orbit was set as the target orbit. The vertical straightway section of the target orbit is about 46.2 m, the crosswise straightway section is about 61.9 m, the curve section is a quarter of a circle with the radius 1 m.

Also, two poles are set with about 4m intervals. We did the running experiment of the model vehicle. The vehicle's speed was 0.1 m/s, the initial position was (0,0) on the world coordinate system $\Sigma(x,y)$ and the initial direction was 0 degree. The result of running experiment is shown Fig.4.5. The vehicle tended to go to the left side. But the vehicle recognized the position and direction error between the estimated position and actual measured position by Self-position-azimuth correction and returned to the target orbit again. So, the model vehicle can run longer distance than previous experiment results.

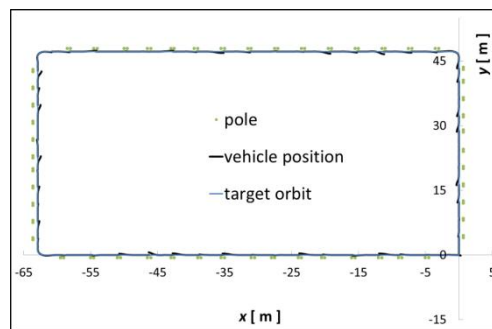


Fig. 4.5. The result of running experiment

5 CONCLUSION

It can be done efficiently to learn the teaching data for the FNN by acquiring the human's driving knowledge from the running data and by processing normalized rough set and defuzzy method even if there is only a small amount of teaching data. It is proved by the verifications that the FNN constructed by these methods can control the vehicle to run along the target orbit while roughly recognize and judge the running environment when the vehicle is in a condition which has not been learnt by the FNN in the vehicle. Also, it is proved that the Self-position-azimuth correction is useful for long distance running. The following problems are considered as the future subjects.

- To install a gyro sensor in the model vehicle and to run automatically in a condition with few poles
- To run automatically at a higher speed than ever
- To establish effective method for avoiding obstacles

REFERENCE

[1] Mukaidono M (1989), Talk of fuzzy (in Japanese). Nikkankougousinbunsha Co., Ltd.
 [2] Yana K, Suzuki Y (1992), Neuro information process technology kaibundousyuppan Co., Ltd. Pp.73-85
 [3] Okishio A (1995), Study on the fuzzy navigation of a mobile robot for outdoor works (in Japanese).