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草地における車両誘導のためのファジィコントローラの提案
A Fuzzy Logic Controller for Vehicle Navigation on Grass Land

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I Introduction

Accurate vehicle guidance system is required for some precision agriculture operations. Many researches on this domain were investigated for the last two decades (Torii, 2000; Keicher & Seufert, 2000; Reid et al., 2000; Wilson, 2000).

In Japan most grass lands are located in hilly areas, where agriculture mobile robots perform various tasks. Due to variations in ground surface profiles, tire-ground friction forces, slope variations, etc, conventional control technologies, e.g. PID control, have limitations in guiding vehicles under such conditions. On the other hand, fuzzy logic has claimed significant promises in situations where the status is imprecise and uncertain and the merely crisp control reaches its limit (Decreton, 2003).

In recent years, more and more works were devoted to fuzzy logic approaches for autonomous vehicle navigation. Numerous applications on fuzzy logic based vehicle guidance have been reported (Saffiotti, 1995; Leyden et al., 1999; Toda et al., 1999; Thongchai et al., 2000; Qiu et al., 2001; Kim et al., 2002; Vellasco et al., 2003; Castro et al., 2003). But most of them were for flat ground. Seraji (2000) proposed a new concept, i.e., fuzzy traversability index, for terrain-based navigation, which guided the robot toward the safest and the most traversable terrain. However, only some simulation studies were presented to demonstrate the capability of the mobile robot to reach the goal safely while avoiding impassable terrains.

This paper presents the development of a two-hierarchy fuzzy logic controller (FLC). The upper level controller utilized the terrain slope and the posture variable derived from the pitch and roll of vehicle to determine the types of procedures; whereas the lower level controller used the offset error and the orientation errors to obtain the optimum steering angle change for autonomous navigation. The fuzzy rules were extracted by optimization with genetic algorithm (GA) based on the neural network (NN) vehicle model. In addition, the path tracking method was specified. Field tests were performed to validate the developed fuzzy controller.

II Fuzzy controller design

1. Path tracking method

A navigation map (Noguchi et al., 2002) was used for autonomous guidance. This map consists of a series of navigation points, which include the latitude and longitude based on the world coordinate system, and the curvature of tracking path at these points. The navigation map can be derived by path recording or manually coding with observation.

Before developing the path-tracking methods, three coordinate systems must first be defined, as shown in Figure1. First, the world coordinate system is defined where the x-axis is along the contour line on the slope, the y-axis points uphill and the z-axis is defined to form a right hand coordinate system. The origin of the world coordinate system o is determined at the location of Total Station.

The vehicle coordinate system is defined where the x-axis is in the forward direction of the vehicle, the y-axis is laterally out the left side of the vehicle and the z-axis is defined to form a right hand coordinate system. The origin of the vehicle coordinate system o_v is defined at the center of gravity of the vehicle, which also serves as control point in autonomous navigation.

Finally, a moving coordinate system is defined where the origin o_r is a waypoint (or navigation point) on the planned path. It supposes that P_i is the closest waypoints away from current vehicle position, i.e., the control point o_v, and the origin o_r is defined at P_i. The coordinates of the point o_v in the moving frame are x_{rov} and y_{rov}, whereas those of P_{i+1} are x_{rpi+1} and y_{rpi+1}. Which waypoint will be selected as the origin o_r is subject to following rules:

The waypoint P_i will be selected as the origin o_r except for the below two conditions, namely, if $x_{rpi+1} - x_{rov} < l$, then P_{i+1} will be selected as the origin o_r; if $x_{rov} < -l$, then P_{i-1} will be selected.

Where, l is the look-ahead distance, which was determined by the experiment.

The x-axis of the moving coordinate system is oriented in the direction from the origin o_r to the next waypoint, the z-axis is upward with respect to the sloping ground and the y-axis is defined to form a right hand coordinate system.

The lateral deviation Δy and the orientation error $\Delta\theta$ of the vehicle are measured based the moving coordinate system. The

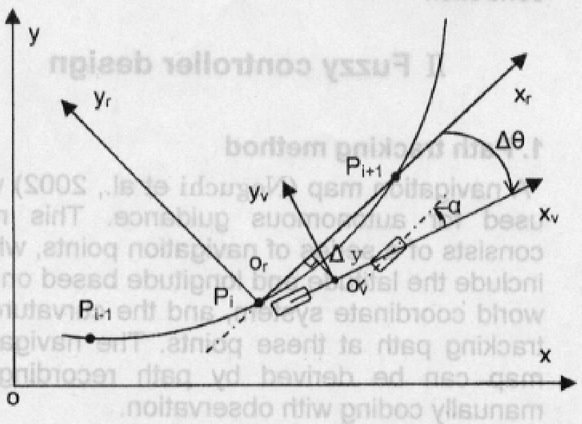

Figure 1. Defined coordinate systems

lateral deviation is the y-coordinate of the control point, and the orientation error is defined as the angle between the current vehicle orientation and the x-axis of the moving coordinate system. The vehicle steering angle is then controlled such that the lateral deviation and orientation error are kept as small as possible. A zero lateral deviation and zero orientation error mean that the vehicle passes the navigation point with the same orientation as that of planned trajectory at this waypoint.

The designed path tracking method is different from common geometric path-tracking methods, such as follow-the-carrot or pure pursuit, which do not use the orientation at the navigation points. Both the location and orientation of the navigation points are employed to determine the current steering angle for vehicle motion. In terms of this path-tracking method, the steering angle is determined with two portions. One part, α_b, in degree, bases on the orientation of the navigation point, which can be obtained from geometry of the vehicle bicycle model (Figure 2). The α_b is calculated to be:

$$\alpha_b = \frac{180}{\pi} \tan^{-1} \frac{L}{\sqrt{\frac{1}{c^2} - L_r^2}} \tag{1}$$

where L is the wheelbase; L_r is the distance between COG (center of gravity) and center of rear axle; c is the path curvature at current navigation point. The other part $\Delta\alpha$ is the steering angle change evaluated by autonomous navigation controller, i.e., the fuzzy controller in this work. Therefore, the desired steering angle, α, was computed as follows,

$$\alpha = \alpha_b + \Delta\alpha \tag{2}$$

2. Architecture of fuzzy controller

A fuzzy system is a static nonlinear mapping between its inputs and outputs (Passino & Uurkovich, 1997). Figure 3 shows a

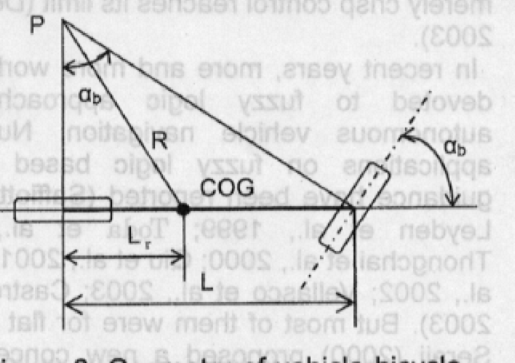

Figure 2. Geometry of vehicle bicycle model

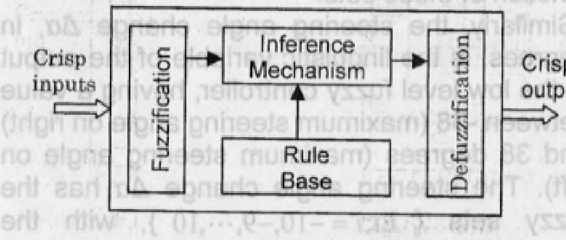

Figure 3. Typical fuzzy system

typical fuzzy system. The inputs and outputs are "crisp"—that is, they are real numbers, not fuzzy sets. The fuzzification block converts the crisp inputs to fuzzy set, the inference mechanism used the fuzzy rules in the rule-base to produce fuzzy conclusions (e.g., the implied fuzzy sets), and the defuzzification block converts these fuzzy conclusions into the crisp outputs.

In this work, a two-hierarchy fuzzy controller was designed, as shown in Figure 4. This fuzzy controller adopts multi-layer architecture to organize the rule sets. Therefore, every sub-rule set has a relevant simple structure, and can be designed easily. The upper level fuzzy controller, according to high-layer rule set, selects the low level controllers. Then the crisp outputs of every low level controller are inferred based on each rule set. Finally these outputs are coordinated to produce the resultant steering angle change desired for vehicle motion.

3. Design of fuzzy controller

3.1 Linguistic variables and Fuzzy sets

There are four linguistic variables as inputs to the fuzzy control system:

(1) Terrain slope, φ, in degree, which is calculated with the pitch (Ψ) and roll (Φ) of vehicle by Equation (3). The universe of discourse of φ is between 0 and 20 degrees.

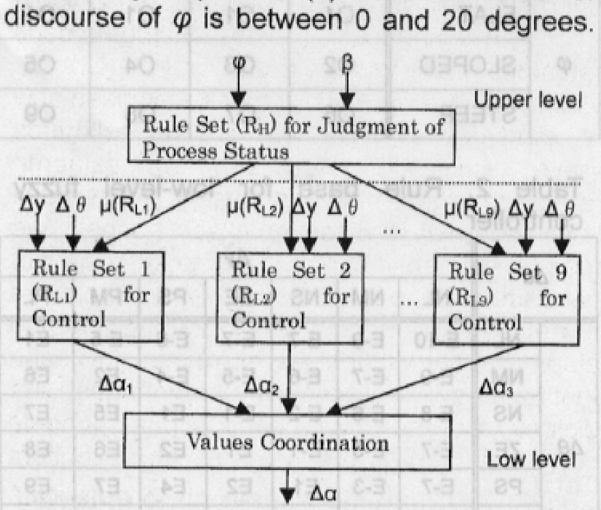

Figure 4. Two-hierarchy fuzzy controller

$$\varphi = 90 - \frac{180}{\pi}\tan^{-1}\frac{\cos\psi\cos\phi}{\sqrt{(\sin\psi\cos\phi)^2 + \sin^2\phi}} \quad (3)$$

The terrain slope φ is represented by three fuzzy sets {FLAT, SLOPED, STEEP}, with the user-defined trapezoidal membership functions shown in Figure 5(a), where the abscissa φ is the magnitude of the terrain slope and the ordinate $\mu(\varphi)$ is the degree of membership.

(2) The vehicle posture β, in degree, which denotes the direction of vehicle's centerline with respect to a predetermined contour line on sloped terrain, and has a value between -180 and 180 degrees. The β is derived from current pitch and roll of vehicle, defined as follows:

$$\beta = \frac{180}{\pi}\tan^{-1}\frac{\sin\phi}{\sin\psi\cos\phi} \quad (4)$$

β values of -90, 0, 90, 180 degrees imply that the vehicle is parallel to contour line (CL), upward (UW), inverted contour line (ICL), and downward (DW), respectively.

The variable β was divided into four fuzzy sets {CL, UW, ICL, DW}. The membership functions of these sets are user-defined trapezoids depicted in Figure 5(b).

(3) Lateral deviation, Δy, in centimeter, is the offset from the control point to the desired path. The lateral deviation Δy is expressed by seven fuzzy sets {NL, NM, NS, ZE, PS, PM, PL}, with the user-defined triangular and trapezoidal membership functions shown in Figure 5(c).

(4) Orientation error, $\Delta\theta$, in degrees, which has a value between -180 and 180 degrees. A

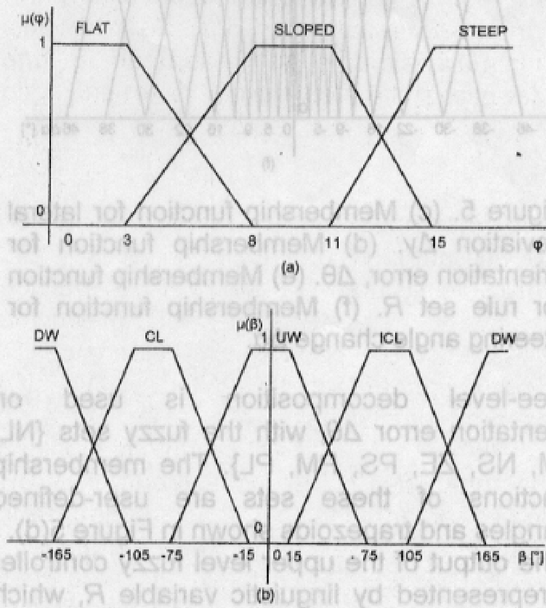

Figure 5. (a) Membership function for terrain slope φ. (b) Membership function for vehicle posture β.

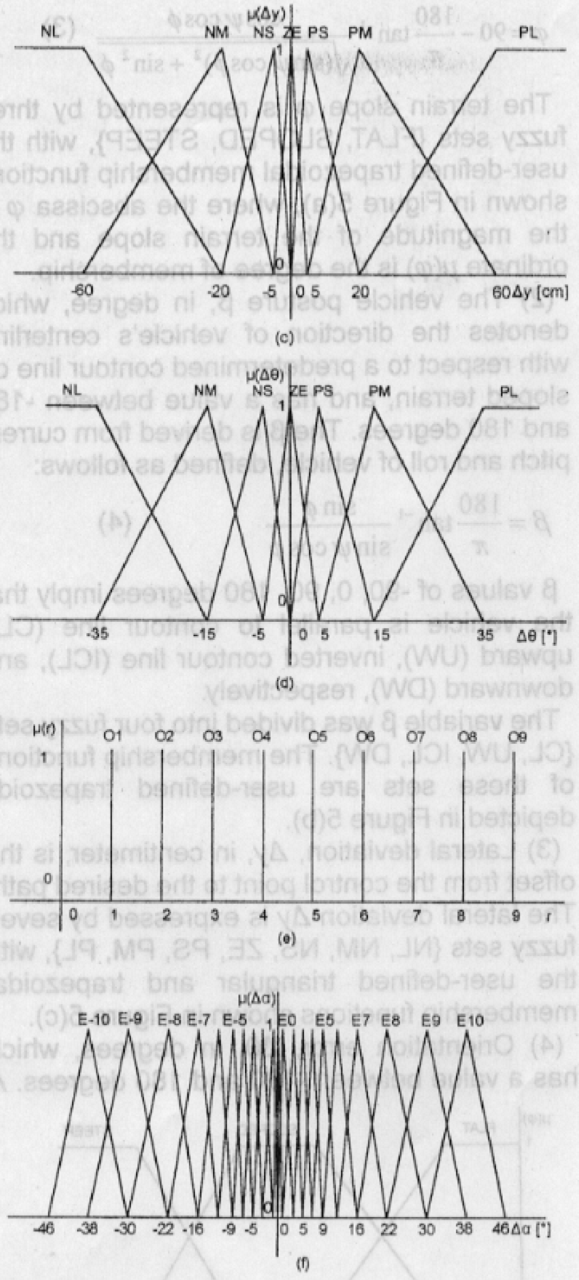

Figure 5. (c) Membership function for lateral deviation Δy. (d) Membership function for orientation error, $\Delta\theta$. (e) Membership function for rule set R. (f) Membership function for steering angle change $\Delta\alpha$.

three-level decomposition is used on orientation error $\Delta\theta$, with the fuzzy sets {NL, NM, NS, ZE, PS, PM, PL}. The membership functions of these sets are user-defined triangles and trapezoids shown in Figure 5(d).

The output of the upper level fuzzy controller is represented by linguistic variable R, which denotes the numbers of activated rule sets in low level rule-base. Singleton fuzzification is applied to variable R, which produces fuzzy sets {O1, O2, O3, O4, O5, O6, O7, O8, O9}. Figure 5(e) shows the singleton membership function of these sets.

Similarly, the steering angle change $\Delta\alpha$, in degrees, is the linguistic variable of the output of the low level fuzzy controller, having a value between -38 (maximum steering angle on right) and 38 degrees (maximum steering angle on left). The steering angle change $\Delta\alpha$ has the fuzzy sets $\{ Ei; i=-10,-9,\cdots,10 \}$, with the user-defined triangular membership functions depicted in Figure 5(f).

3.2 Rule sets

The rule set R is determined by a set of fuzzy relations in terms of the terrain slope φ and the vehicle posture β. With three qualitative levels for terrain slope and four levels for vehicle posture, 12 IF-THEN rules are needed to cover all the possible combinations of variables. The rules in Table 1 were designed based on common-sense criteria.

A fuzzy rule set for steering angle change can be represented by a set of 49 simple fuzzy rules as depicted in Table 2 (for terrain slope is SLOPED, vehicle posture is CL), of the form such as:

IF lateral deviation is NM **and** orientation error is NS **THEN** steering angle change is E-7. GA as an optimization tool was used to capture the expert's knowledge, namely fuzzy rules, based on the vehicle NN model, which was formulated by Zhu et al. (2003).

3.3 Inference and defuzzification

A fuzzy inference engine with the MAX-MIN

Table 1. Rule base for upper-level fuzzy controller

R		β			
		CL	UW	ICL	DW
φ	FLAT	O1	O1	O1	O1
	SLOPED	O2	O3	O4	O5
	STEEP	O6	O7	O8	O9

Table 2. Rule base for low-level fuzzy controller

Δα		Δy						
		NL	NM	NS	ZE	PS	PM	PL
Δθ	NL	E-10	E-9	E-7	E-7	E-6	E-5	E1
	NM	E-9	E-7	E-6	E-5	E-4	E2	E6
	NS	E-8	E-6	E-2	E-1	E1	E5	E7
	ZE	E-7	E-5	E-1	E1	E2	E6	E8
	PS	E-7	E-3	E1	E2	E4	E7	E9
	PM	E-5	E1	E4	E6	E7	E8	E9
	PL	E1	E6	E7	E8	E9	E9	E10

inference method was employed to fire the appropriate fuzzy rules being relevant to the current situation, where the minimum operator is used in the IF part of each rule to compute the degree of truth of the antecedent, while maximum operator is used in the THEN part of rules to determine the degrees of truth of each linguistic term of the output linguistic variable. The connective "and" has been implemented using also the MIN operator. As an example, suppose that the input sensor values result in the following pertinence ($\mu(x)$) for the input fuzzy sets: $\mu_{SLOPED}(\varphi)$=1.0; $\mu_{CL}(\beta)$=1.0; $\mu_{NL}(\Delta y)$=1.0; $\mu_{ZE}(\Delta\theta)$=0.4; $\mu_{PS}(\Delta\theta)$=0.6. Using the Table 1, we find that only the rule set O2 is fired. In terms of fuzzy rules listed in Table 2, the rules that are on are the following:

RULE 1: **IF** lateral deviation is NL **and** orientation error is ZE **THEN** steering angle change is E-7;

RULE 2: **IF** lateral deviation is NL **and** orientation error is PS **THEN** steering angle change is E-7;

The aggregations of the RULEs are computed by:

RULE 1: Min(1.0, 0.4)=0.4;

RULE 2: Min(1.0, 0.6)=0.6;

Then the composition of the rules is calculated by:

Max(0.4, 0.6)=0.6.

Thus, the resulting degrees of truth for the linguistic term E-7 for steering angle change is measured with pertinence to 0.6.

The defuzzification process converts the fuzzy set information produced by the inference process (i.e., the implied fuzzy sets) into numeric fuzzy controller output. Center of Area (COA) was used as defuzzification method in this work to get the desired steering angle change in low level fuzzy controller. For this method, the crisp output was calculated by:

$$\Delta\alpha = \frac{\sum_{i=1}^{n} \mu_A(\Delta\alpha_i)\Delta\alpha_i}{\sum_{i=1}^{n} \mu_A(\Delta\alpha)} \quad (5)$$

Where, n is the number of fired rules; $\Delta\alpha_i$ is the i'th domain value; and $\mu(\Delta\alpha_i)$ is the truth membership value for that domain point.

Ⅲ Experiment

1. Mobile robot platform

In this experiment a Mitsubishi MT2501D model tractor was modified and served as a mobile robot to follow the target path automatically. A DC motor was added to actuate the steering wheel when a turning command was triggered. A PC with autonomous guidance system program was installed on the mobile robot. A Leica TCA1105 Total Station (TS) was used for positioning. A gyro provides a relative measure of the altitude of the vehicle. The equipment and sensors used in this experiment are shown in Table 3.

2. Experimental conditions

Field tests on path tracking were conducted in April 2004 on a meadow at the hilly areas of the Iwate University Omyojin Research Farm. The field surface was covered with grass and the soil was slightly moist. Average and standard deviation of terrain slope of the field were 10.9° and 3.0°, respectively. At the foot of the field, the terrain slope was about 9°, whereas on the top of the field it was over 14°.

Throughout the test the 0° heading angle was always set parallel with the contour line. The traveling speed was set constant at 0.5 m/s.

However, the comparative tests were performed on asphalt road in Iwate University campus.

Ⅳ Results and discussion

1. Comparison with the controller based lookup table

The developed fuzzy controller was compared with the lookup table controller designed by Torisu et al. (2002). For this purpose, two kinds of tests were performed to evaluate path tracking performance. One is straight path following test; the other is step response. The former measured the accuracy of trackers, by examining how close the tracker stays to predetermined path. Figure 6 shows

Table 3 Specification of instrumentation

Name	Function
DC motor	Power is 82W, used for the steering actuator.
1.0 GHz Pentium PC	Mounted on the tractor, used as the center processing unit.
Potentiometer	Fixed on the front axle, measured the steering angle.
Magnetic sensor	Fixed near the flywheel, measured the engine speed.
Fiber optic gyroscope (FOG)	Model is JG-35FD, used to measure the heading angle with range of ±180°, angular drift is less than ±1.5°/h.
Total Station (TS) and prism	Leica TCA1105 model, 2mm positioning accuracy.
SS wireless modems	Transmit the signals of the tractor position from the TS to the PC.
AD/DA board	Converts the analogue signals to digital (AD) and digital to analogue (DA).
Inclinometer	TCM-2X-90 model, measured the roll and pitch.

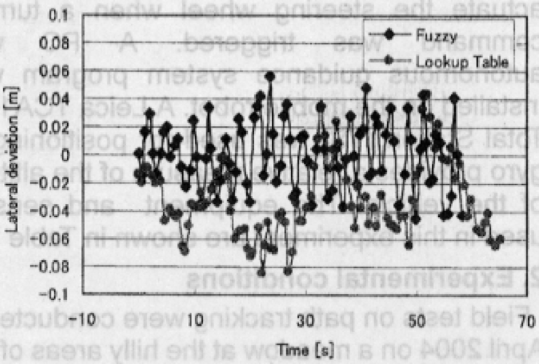

Figure 6. Trajectories of straight line tracking

the trajectories of following the same rectilinear path by two trackers. The mean and standard deviation in tracking straight path by the fuzzy controller were 0.000 m and 0.024 m, respectively; whereas that by the controller based lookup table were -0.032 m and 0.027 m, respectively. The results implied that both controllers had almost the same tracking accuracy when traveling a straight path on flat ground. Controller's response to step change can be used to measure the controller's settling time and stability. In this test the offset was initialized to about 2 m. The time histories of tracking error were depicted in Figure 7. Either controller obviously converged to 0 tracking error after some oscillation. But the fuzzy controller has shorter settling time (20.1 s vs. 30.8 s) and smaller overshoot (10.7% vs. 48.7%) than its counterpart.

2. Rectangular path control

The travel course is composed of four straight paths, namely path *i*, *i*=1, 2, 3, 4, and four curved paths, namely quarter turn *i*, *i*=1, 2, 3, 4. The terrain slope was varied according to each path, with average 9.4° for path 1, and 14.0° for path 3, and a value between these two for other paths. Both straight paths and curved paths were followed by the mobile robot with feedback fuzzy control. The autonomous traveling trajectories are expressed in Figure 8. Table 4 lists the mean lateral deviation and standard deviation of each straight path.

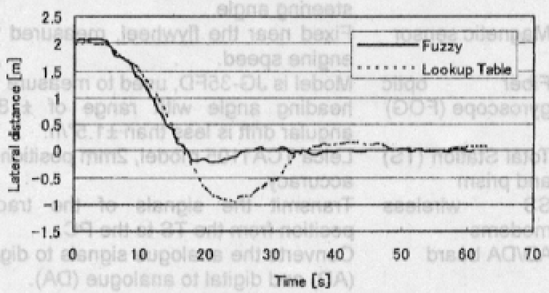

Figure 7. Step response

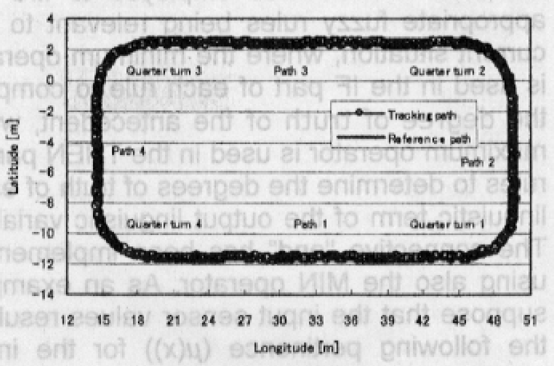

Figure 8. Autonomous traveling trajectories along rectangular path on sloped terrain

Table 4. Autonomous traveling performances for the rectilinear motions of rectangular path

Path No.	Offset error		Orientation error	
	Mean [m]	STDEV [m]	Mean [°]	STDEV [°]
Path 1	-0.003	0.062	1.14	3.34
Path 2	0.012	0.024	1.19	1.44
Path 3	0.007	0.040	-2.35	2.27
Path 4	-0.015	0.034	4.97	2.87
Average	0.000	0.040	1.24	2.48

STDEV: Standard deviation.

The average of the mean and standard deviation of the lateral deviation for the four rectilinear motions were only 0.000m and 0.040m, respectively; and that of the orientation errors were1.24° and 2.48°, respectively. The distribution of the tracking error over all straight segments was also shown in Figure 9. There is 96.4% of the tracking error falling below 10 cm. It is seen that such level of tracking error is quite agreeable with agriculture operation on grass land. Table 5 lists the offset errors and orientation errors at the completion of every turning path. Under about 7 cm max lateral error and about 5° average orientation error allowed the robot to travel to the next working path smoothly. Overall average tracking error is

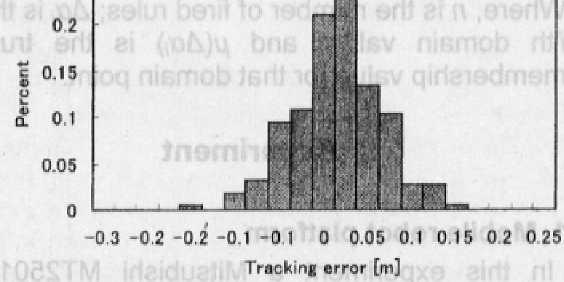

Figure 9. Histogram of tracking errors for straight path

Table 5. Lateral errors at the completion of turning path

Path No.	Lateral deviation [m]	Orientation error [°]
Quarter turn 1	0.002	2.09
Quarter turn 2	0.067	-10.70
Quarter turn 3	-0.051	-3.19
Quarter turn 4	0.070	-6.59
Average	0.022	-4.60

0.043 m, with standard deviation of 0.099 m.

3. Sigmoid path tracking

In order to measure the tracking performance of the controller for responding to variant curvature path, the test along sigmoid path was executed. Figure10 shows the desired and actual autonomous traveling trajectories. It was found that the mean and standard deviation of tracking error were -0.022 m and 0.069 m, respectively; and that of orientation error were 0.47° and 4.49° , respectively. It is seen that the test was successfully completed with the robot following the path precisely.

V Conclusion

A two-hierarchy fuzzy controller was designed for mobile robot autonomous guidance on grass lands. It provided an available approach to realize controlling the robot along a predetermined path, including straight path and curved path.

The path tracking method employed in this work successfully guided the mobile robot along desired path, such as rectangular and sigmoid path, despite of variations in terrain slope, undulant ground and variant path curvature

Optimal control was incorporated into the fuzzy controller since steering angle change in rule-base was acquired by GA. Therefore, the controller is entitled with not only human intuitive understanding of how to best control the process, but also with the capability of optimum inference.

Compared with previously designed controller based lookup table, the fuzzy controller had shorter settling time and better performance.

Field test results indicated that the fuzzy controller tracked straight path precisely, with the mean and standard deviation were 0.000m and 0.040 m, respectively, and with 96.4% of the tracking error falling below 10 cm. For the curved paths, the max lateral deviation and the average orientation error were less than 7 cm and 5° respectively at the completion of these paths.

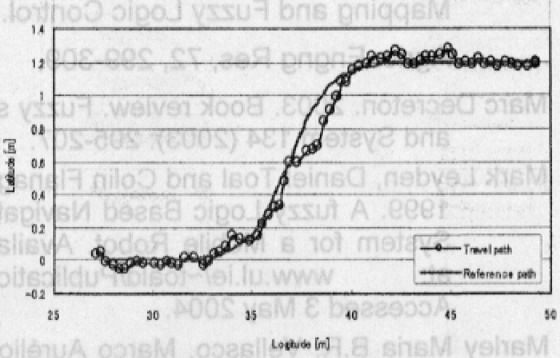

Figure 10. Autonomous traveling trajectories along sigmoid path on sloped terrain

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