

AUTOMATION OF FARM-TRACTOR FOR SLOPE TERRAINS

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ABSTRACT

This paper deals with the development of a tractor-like robot for slope terrain. A neural network vehicle model was developed to represent the input-output relationship of the vehicle motion. A cost function was designed to optimize the control variable, and genetic algorithms were used to seek the optimal control values for different ranges of vehicle deviations. Reference table was prepared with the optimal control values. To obtain the online navigation of the vehicle, a neural network based steering controller was developed from the reference tables. An autonomous travel test was conducted along a 30×15 m rectangular path on a sloping land. The inclination of one longitudinal path was 10° and that of the other path was 20°. The mean vehicle offsets along the paths of 10° and 20° slopes were 0.027 m and 0.05 m respectively, and the mean heading deviations were 3.09° and 2.69° respectively. These insignificant deviations indicate that the developed guidance system is competent to precisely navigate an autonomous tractor on sloped terrains.

Keywords: Vehicle automation, Neural network, Genetic algorithms, Optimum control, Slope terrain.

1. INTRODUCTION

Most of the grasslands of Japan and other countries are in hilly areas where farm tractors perform various task. However, working on hilly terrain can cause discomfort to the operator, due to the effects on body alignment. This also increases the fatigue of the operator and thereby decreases the work efficiency with time. Although much research has been conducted on automatic guidance system for the farm tractor, most is concerned with flatland [1], [2], [3], [4]. Bell [5] devised an automatic tractor guidance system using a kinematic model. A biased estimation method was incorporated into the control software to compensate the effect of slope on the vehicle motion [6]. This study proposed a new approach of automatic tractor guidance system for the navigation along rectangular path on sloped terrain. The objective of this paper is to design and to develop an autonomous tractor that can precisely travel along the rectangular path on sloped terrain. Emphasis is given on the: 1) formulation of vehicle model for sloped terrain, and 2) development of a navigation planner for the rectangular path.

2. FORMULATION OF THE VEHICLE MODEL FOR SLOPE TERRAIN

2.1 Structure of Vehicle Model

A bicycle model of tractor with slope influence is shown in Fig. 1. Whenever an agricultural wheeled-vehicle runs on sloping land, external disturbances such as gravitation force pull it to the

downhill direction, which is strongly nonlinear in the vehicle dynamics. Consequently it is very difficult to formulate a mathematics based vehicle model to express the vehicle motion on sloped terrain. Recently there has been an increase in the number of applications of neural network (NN) in various engineering and biological problems [7], [8]. Therefore, a NN vehicle model is designed to express the input-output relationship of vehicle motion on sloping land. The adjusted interconnecting weights of the neurons in NN can include all of the effective elements such as slippage due to gravity, uneven condition of slope and other external disturbances.

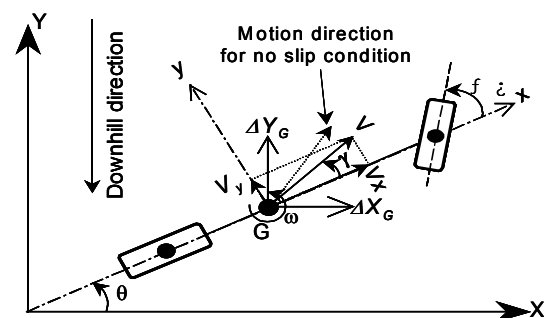


Fig. 1 A vehicle bicycle model with dynamic motions on sloped terrain

The architecture of the neurons (later denoted as units) of this model is 6-6-6-3, which has 6 input and 3 output variables together with two hidden layers of 6

units each (Fig. 2). The input vector is a combination of the control vector U_k , and state vector Z_k , and the output vector is ξ_{k+1} , which is also known as target vector. where,

$$U_k = (\alpha_k, \Delta\alpha_k)^T \quad (1)$$

$$Z_k = (Vx_k, Vy_k, \omega_k, \theta_k)^T \quad (2)$$

$$\xi_{k+1} = (Vx_{k+1}, Vy_{k+1}, \omega_{k+1})^T \quad (3)$$

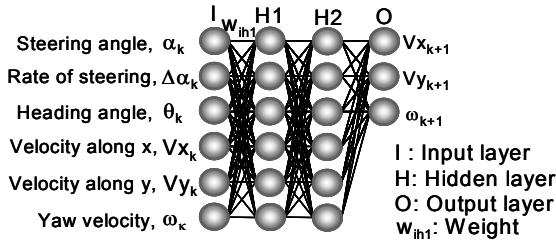


Fig. 2. Architecture of the NN vehicle model on sloped terrain

The control vector U_k is a function of steering angle α and rate of steering $\Delta\alpha_k$. The coordinate XY (Fig. 1) is the earth fixed coordinate system and xy is the vehicle body coordinate system. The elements of vector Z_k are Vx_k , Vy_k , θ_k and ω_k . The output vector represents the vehicle state after each 0.5 seconds (Δt). The output is determined by both the current inputs and their previous outputs. For this reason the network exhibits properties very similar to short-term memory in humans.

2.2 Data Acquisition Test of Training Pairs for the NN Model

Data acquisition test for the NN model was conducted on 0° , 5° , 10° and 15° sloped terrains. For each sloping land a skilled human operator operated the test tractor along a predetermined sinusoidal path, which was traced on the ground by means of a rope and pegs (Fig. 3). The directions of the sinusoidal paths were along the contour lines. The vehicle forward velocity was 0.5 m/s. After every 0.5 sec interval, the position of vehicle center of gravity, heading angle, steering angle and engine speed were recorded by different sensors.

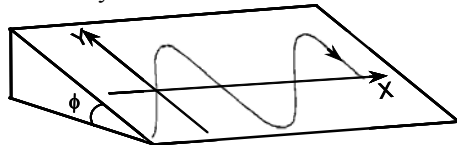


Fig. 3. Sinusoidal path on contour line to prepare training pairs

Due to the limit of threshold function [9], any value beyond the range $0 \sim 1$ cannot be used in the NN model. Therefore, all the variable values were normalized to the range between 0 and 1 to make them usable for the network.

2.3 Training of NN Model by BP Algorithm

To train up the NN vehicle model, pairing of each input vector with a target vector representing the desired output is essential, which are called training pair [9]. The

model was trained by back propagation (BP) algorithm. A set of 90 training pairs was used for this purpose. The training was accomplished by sequentially applying the input vector. In each iteration step of the training process, errors were calculated from the difference of desired output. Accordingly the values of the network's weight coefficients were recalculated using the delta rule [9] and were fed back to the whole network. The training process continued until the error for the entire training set was at an acceptably low level. The steepest decent algorithm was used to minimize the errors. There is no assurance that the model will be properly trained at each low level of error. Therefore, after the end of each trial of training, a simulation was done with the trained model in order to check the accuracy of training achieved. Then the simulated sinusoidal trajectory obtained from the output of trained model was compared with the actual trajectory. The training and checking procedure continued until the difference between the actual and simulated trajectories reached to a reasonable level of accuracy.

3 RECTANGULAR PATH PLANNING

When a tractor runs from path 1 to 2 (Fig. 4), the longitudinal axis of the tractor body rotates 90 degree from the x-axis. Therefore, to develop a navigation planner for rectangular path, it is necessary to transform

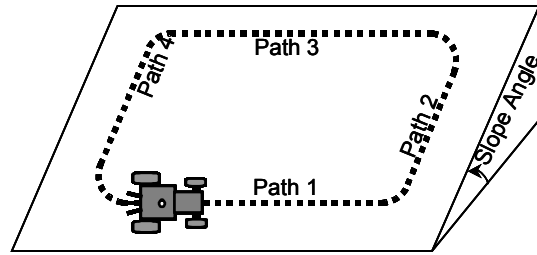


Fig. 4. Rectangular path on sloped terrain

the coordinate according to the change of path directions. Figure 5 shows the rotation of the coordinate axis. An arbitrary point was chosen as the origin O and the vehicle-positioning sensor 'Total Station' is set at another point S . The line connecting these two points S and O

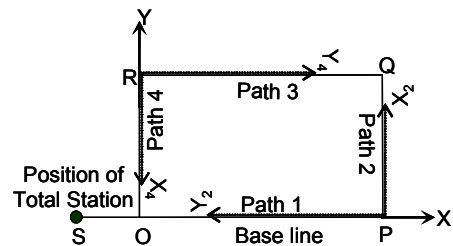


Fig. 5. Rotation of the coordinate axis

was set as the X -axis and considered as a baseline. Then the heading angle of the tractor was initialized to zero along the baseline. The rotational coordinate for the adjacent path i and $i+1$ can be expressed as:

$$\begin{bmatrix} X_i \\ Y_i \end{bmatrix} = \begin{bmatrix} \cos\left\{(i-1)\frac{\pi}{2}\right\} & \sin\left\{(i-1)\frac{\pi}{2}\right\} \\ -\sin\left\{(i-1)\frac{\pi}{2}\right\} & \cos\left\{(i-1)\frac{\pi}{2}\right\} \end{bmatrix} \begin{bmatrix} X \\ Y \end{bmatrix} + \begin{bmatrix} \hat{x}_i \\ \hat{y}_i \end{bmatrix} \quad (4)$$

where X, Y are the earth-fixed coordinate; i is the path number ($i = 1, 2, 3, 4$); and X_i, Y_i are the new coordinates of path i . Here the right most term of Eq. (4) is a vector and is defined as follows:

$(\hat{x}_1, \hat{y}_1)^T = (0, 0)^T, (\hat{x}_2, \hat{y}_2)^T = (0, L)^T, (\hat{x}_3, \hat{y}_3)^T = (L, W)^T, (\hat{x}_4, \hat{y}_4)^T = (W, 0)^T$
 where, L is the length and W is the width of the rectangular path.

4 NAVIGATION PLANNER

4.1 Feedback Control for Rectilinear Motion

When a human operator drives a vehicle, for each lateral and heading deviation from the desired path, he makes necessary correction of the steering angle and velocity (control values). The accuracy of the correction depends on the skill ness of the operator. In the same way, it is therefore, important for an autonomous vehicle to design a control rule, which can make online decision about the appropriate control values like a skill human operator. For this purpose the optimal control rule is designed. Mathematical statements of the optimal control problem consists of: (1) the system to be controlled, which is described by the NN vehicle model; (2) system constraints and possible alternatives, which are described with steering angle α and state variables; (3) the task to be accomplished is to run along the contour line on the slope; (4) the criterion for judging the optimal performance is a quadratic form cost function J , which is defined in Eq. (5). The control input u and state vector X , which are defined in Eqs. (6) and (7) respectively.

$$J = \sum_{k=0}^N (X(k)^T Q X(k) + u^T(k) R u(k)) \quad (5)$$

$$u(k) = \alpha(k) \quad (6)$$

$$X(k) = (\theta(k), X_G(k), Y_G(k))^T \quad (7)$$

$$R = k_4 \quad (8)$$

$$Q = \begin{bmatrix} k_1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & k_3 \end{bmatrix} \quad (9)$$

where k_1, k_3 and k_4 are weights, whose values were determined by simulation.

4.2 Searching Optimum Control Input by GA

Genetic Algorithm (GA) was applied to search the optimum steering angle for each specific range of deviations. In the optimization process, for a specific slope, steering angle α depends on lateral displacement (offset) Y_G and heading angle deviation θ , which can be shown by Eq. (10):

$$\alpha_\phi = f(Y_G, \theta) \quad (10)$$

The subscript ϕ indicates the degree of slope for which the steering will be optimized. The number of individuals or strings of the population used in this searching algorithm was 50. In optimization each set of 0.03 m lateral deviation and 3° heading errors were considered as a feature (gene) of the individual, and different steering angles, within the range of $\pm 20^\circ$, were directly coded as the feature value (allele) for each feature.. Total number of features was 24. Initially the feature values were randomly selected for all 24 features. Crossover and mutation rates were 0.6 and 0.05 respectively.

A 20 m long contour line was considered as the target linear path to follow in the optimization process. In each step, for one set of offset and heading deviation, GA was used to find the optimum steering angle. The flowchart of

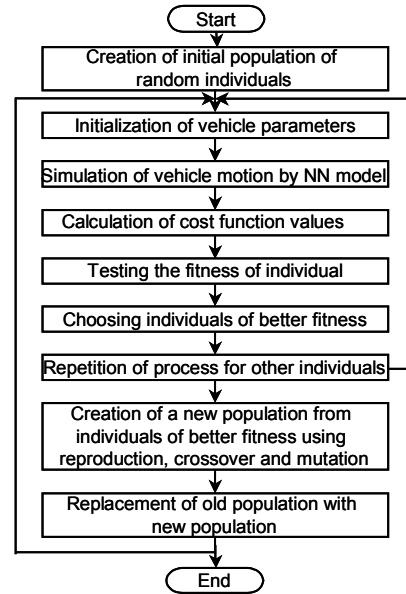


Fig. 6 Flowchart of steering optimization by GA

steering optimization by GA is shown in Fig. 6. Equation (11) was used to determine the fitness of individuals.

$$f = (J + P)^{-1} \quad (11)$$

where, P is a safety factor to avoid infinity when the value of J will be 0.

The optimal steering values were arranged in a matrix form table, introduced as reference table. A sample reference table for 15° sloping ground is shown in Table 1. Similar tables were also prepared for $0^\circ, 5^\circ$ and 10° sloped terrains.

Table 1. A sample reference table for 15° sloped terrain

Steering angle \ Heading (θ°)		Offset (ϵ), (cm)					
		9 ~ 6	6 ~ 3	3 ~ 0	0 ~ -3	-3 ~ -6	-6 ~ -9
Heading (θ°)	6 ~ 3	-7	-5	-3	0	0	4
	3 ~ 0	-3	-1	1	2	5	6
	0 ~ -3	-1	2	4	6	7	9
	-3 ~ -6	5	5	6	9	11	11

4.3 Neural Network based Steering Controller

The reference tables directly can be used to navigate the vehicle on sloping ground, but it has some extent of limitation. For certain range of offset and heading deviation on each specific slope, only one steering value is used in the reference table. In reality optimal steering value varies for slight variation in either of the offset or heading deviation. Another limitation is that each reference table can provide optimal control value for those specific inclinations, on which the vehicle model was trained, like $0^\circ, 5^\circ, 10^\circ$ and 15° sloped terrains. There is no steering information about the intermediate slopes. Therefore, a generalization of the optimal steering is devised using neural network. The multi-layer

neural-network steering controller has three input and one output variables as shown in Fig. 7. The training pairs were prepared from the reference tables 0° , 5° , 10°

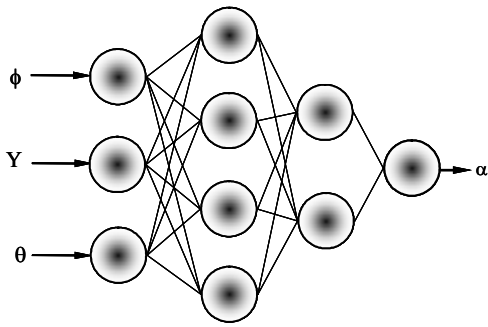


Fig. 7. NN steering controller for vehicle navigation on slope

and 15° sloped terrains. Back-propagation algorithm was used to train the network. For online navigation of the vehicle, appropriate optimal steering value α can be obtained from this network output on the basis of input vales, like degree of slope ϕ , vehicle offset Y , and heading deviation θ . A block diagram of the closed-loop control system is shown in Fig. 8.

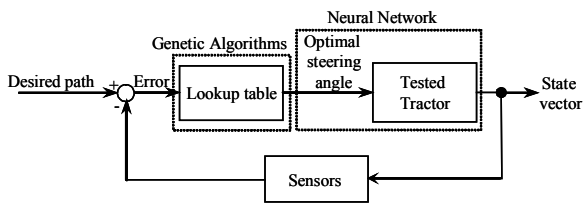


Fig. 8. block diagram for rectilinear motion control

When the vehicle travels along the contour line, uphill steering effort is larger than that of the downhill steering as the gravitational force pulls the tires towards the downhill. Hence it was assumed that for the vehicle motion along uphill and downhill the vehicle offset and heading deviation in left and right side of the path are symmetrical. Therefore, the optimal steering angles for flat land (0° slope) were used to guide the tractor along uphill and downhill.

4.3 Feedforward Control for the Turning Motion

It is quite difficult to accomplish the feedback control method in the guidance of a vehicle along curved path on slope. Therefore, feedforward control method was applied to guide the tractor along four quarter-turns of the rectangular path. The turning process of the vehicle is shown in Fig. 9. Two parameters determine the switching

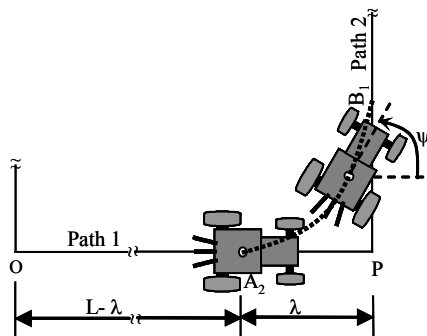


Fig.9. Schematic diagram of the turning process

from feedback to feedforward control. The distance λ determines the initial time τ_1 and the heading angle ψ determines the final time τ_2 in the feedforward control. The values of λ and ψ were determined by trial and error method during supplementary field test. When the tractor reaches the predetermined point $(X_G(\tau_1), Y_G(\tau_1))$ as shown in Fig. 9, the control method switches over from feedback to feedforward. The state vector at this initial time and final time can be expressed by Eq. (12) and (13).

$$\begin{bmatrix} \theta \\ x \\ y \end{bmatrix} = \begin{bmatrix} \theta(\tau_1) \\ X_G(\tau_1) \\ Y_G(\tau_1) \end{bmatrix} = \begin{bmatrix} \theta(\tau_1) \\ L - \lambda \\ Y_G(\tau_1) \end{bmatrix} \quad (12)$$

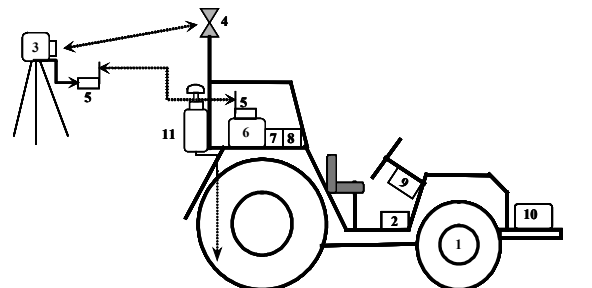
$$\begin{bmatrix} \theta \\ x \\ y \end{bmatrix} = \begin{bmatrix} \theta(\tau_2) \\ X_G(\tau_2) \\ Y_G(\tau_2) \end{bmatrix} = \begin{bmatrix} \psi \\ X_G(\tau_2) \\ Y_G(\tau_2) \end{bmatrix} \quad (13)$$

The steering angle $\alpha(\tau_1)$ begins to increase and when it reaches the maximum (α_{max}), it remains constant until the heading angle of the tractor reaches a predetermined turning angle ψ at time τ_2 . Just after reaching this turning limit, the feedforward control switches over to the feedback control for the next path. Therefore, the final condition of the feedforward control in the quarter-turn becomes the initial condition of feedback control for the next linear path.

5 INSTRUMENTATION AND FIELD TEST

5.1 Instrumentation

The test tractor used in this experiment was a 4WD 18 kW four-wheel drive Mitsubishi MT2501D model. Total mass of the tractor was 1125 kg, wheelbase was 1.595 m and axle was 1.31 m. High lug tire was used for the test. The tractor was equipped with a 100 MHz Pentium PC as the sensor-signal processor and steering control unit. It was also equipped with a DC motor as the steering actuator, a potentiometer to measure the steering angles and a fiber optic gyroscope (FOG) to measure the heading angles. The tested tractor and instrumentation is shown in Fig. 10. The equipment used to measure the vehicle positions was a Total Station of Leica TCA1105 model. A prism, as a pair of Total Station, was mounted on the tractor rear. Two SS wireless modems were used to transmit the signals of the tractor-position from the Total Station to the PC. To get precise-control on the vehicle, 0.5 sec was decided as the data transfer time interval.



1: Potentiometer 4: Prism 7: AD/DA board 10: AC generator
2: FOG 5: Modem 8: Strain amplifier 11: Liquid sprayer
3: Total Station 6: PC 9: DC motor

Fig. 10. Hardware settings in the Tested Tractor

5.2 Test Field and Experimental Conditions

Field test on automatic tractor guidance system was conducted on a meadow at the hilly areas of the Iwate University Omyojin Research Farm. The surface of the meadow was undulating and covered with grass. The test run was performed along a 30x15 m rectangular path. The travel direction of the rectilinear path 1 was along a contour line of 10° average slope and that of the path 3 was along a contour line of 20° average slope (Fig. 4). The tractor velocity was 0.5 m/s throughout the test.

6 RESULTS AND DISCUSSION

Figures 11 and 12 show the trajectory of the autonomous travel along the rectangular path on sloped terrain in 2-D and 3-D respectively. Path 1 and 3 were

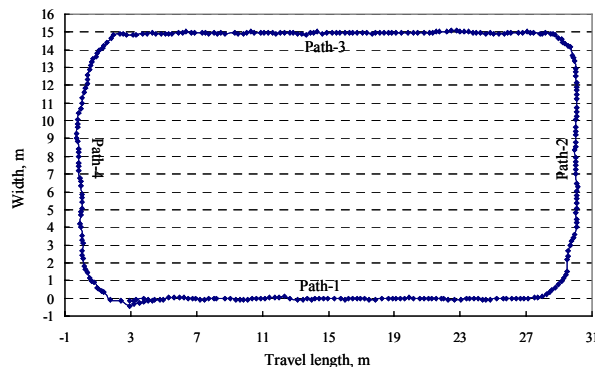


Fig. 11. Autonomous travel trajectory for the tractor-navigation in 2D

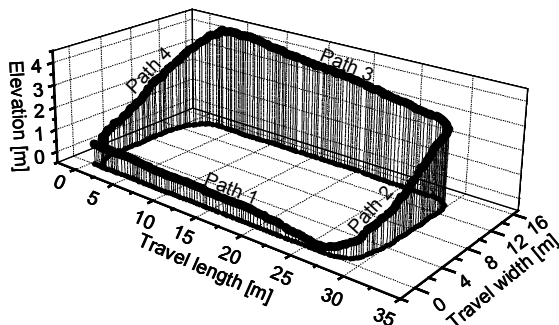


Fig. 12. Autonomous travel trajectory with field topography in 3D

assumed as the contour lines. From Fig. 12 the elevation at the starting point of path 1 was 0.427 m, and at the endpoint was -0.297 m. The elevation at the starting point of path 3 was 2.67 m, and at the endpoint was 4.22 m. The average land-inclination at path 1 was 10° and at path 3 was 20°. Figure 11 shows that in spite of the variable land inclination, the autonomous travel trajectory formed nearly a smooth rectangular path. As shown in Table 2, the mean and standard deviation of the lateral displacement for these two paths were very close to each other (within 0.023 m). But due to the effect of the gravitational force, the mean and standard deviation of the heading angle for downhill motion were a bit more (within 2.73°) than that of for uphill motion.

Table 2 also shows that the average of the mean and standard deviations of the offset for the four rectilinear motions were only 0.044 m and 0.049 m, and that of the

heading angles were 3.053° and 2.47° respectively, which validates the success of the guidance system. Figure 11 also shows that the convergence of the quarter turns was fairly good.

Table 2. Autonomous traveling performances for the rectilinear motions of rectangular path

	Mean Lateral deviation [m]	Standard deviation of lateral deviation [m]	Mean heading angle [°]	Standard deviation of heading angle [°]
Path 1	0.027	0.035	3.09	1.25
Path 2	0.034	0.052	1.85	2.86
Path 3	0.050	0.049	2.69	1.84
Path 4	0.065	0.054	4.58	3.94
Average	0.044	0.049	3.053	2.47

7 CONCLUSION

An automatic tractor guidance system was developed to navigate the tractor along rectangular path on sloped terrain. A NN vehicle model was formulated to express the input-output relationship of the vehicle dynamics for sloping environment. An optimal control law was designed and developed. Using GA with the help of control rule optimal control value (steering angle) for each specific range of lateral deviation and heading errors was determined. A NN based steering controller was finally devised for online navigation of the vehicle. The controller was successfully applied for guiding the tractor along rectilinear contour paths and also along uphill and downhill. A feedforward steering controller was developed for the tractor-motion in quarter-turn. Two control methods were compounded to navigate the tractor along the turns and rectilinear portions of the rectangular path. Despite the variations in land-inclination, the developed guidance system was successful to guide the tractor along the rectangular path on sloped terrain.

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NOMENCLATURE

Symbol	Meaning	Unit
θ	Heading angle	(deg)
ω	Rate of change of heading angle	(deg/sec)
ξ	Output vector	-
λ	Distance	(m)
τ	Time	(sec)
ψ	Predetermined turning angle	(deg)
ϕ	Slope angle	(deg)
i	Path number	-
J	Cost function	-
L	Length of rectangular path	(m)
P	Safety factor	-
U	Control vector	-
V_x	Velocity component of along longitudinal axis of tractor body	(m/s)
V_y	Velocity component perpendicular to tractor body	(m/s)
W	Width of rectangular path	(m)
X	X-axis of earth fixed coordinate	(m)
x	x-axis, along vehicle body	(m)
Y	Y-axis of earth fixed coordinate	(m)
y	y-axis, perpendicular to vehicle body	(m)
Z	State vector	-
α	Steering angle	(deg)