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傾斜地におけるニューラルネットワーク車両モデルの再構築
Reconstruction of Neural Network Vehicle Model on Sloped Terrain

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I Introduction

Most farm mobile robot systems are not linear time invariant, and can be subject to nonholonomic constraints. Therefore an effective approach must be taken to measure the system's performance. Usually vehicle models are used for this purpose. A kinematic model is usually applicable for slow speed vehicles where effects of side forces can be neglected (Ishida *et al.*, 1998; Cordesses *et al.*, 2000; Roth & Batavia, 2002). However, a dynamic model can take into account the lateral forces at wheels, the mass of the vehicle, the mass moment of inertia of the vehicle, and the location of the center of gravity. So it was widely applied in farm vehicle automatic navigation systems (Miller & Steward, 2002; Kise *et al.*, 2002). In addition, an artificial intelligence (AI) model was also developed by Ishii *et al.* (1998). But most of these models were developed to describe vehicle behavior on the flat land where friction properties were relatively constant.

On sloping ground, many factors influencing tractor dynamics such as sloped terrain, uneven implement load, soil conditions, and so on resulted in developing an available model for sloped terrain. In order to control a tractor along sloped terrain, Bell (2000) introduced a form of bias estimation into his dynamic model. This bias only incorporated the information about implement load and terrain slope, but neglected other factors such as soil conditions and tire configuration. So his model could not precisely respond to inputs when used to investigate the dynamic characteristics of tractor on sloping ground.

Torisu *et al.* (2002) designed a neural network (NN) vehicle model instead of dynamic or kinematic model to express the input-output relationship of vehicle motion on sloping land. But the model could represent only the motion on the specific slope and that the heading angle remains restricted within -60°~60°. By reconstructing a model that is accurate over a wider range, precise expression of the vehicle's dynamic characteristic could be obtained. To attain this task the paper sets out: (1) to reconstruct the NN vehicle model; (2) to train the NN vehicle model with genetic algorithm (GA) and back propagation (BP) algorithm; (3) to validate the model; (4) to conduct field tests on data acquisition and open-loop control on sloped terrain.

II Reconstruction of vehicle model for sloped terrain

1. Structure of vehicle model

In neural networks, as in all modeling problems, we want to use the simplest network that can adequately represent the training set. For a network to be able to successfully generalize what it has learned to the total population, it should have fewer parameters than there are data points in the training set (Hagan *et al.*, 1996). This is the principle for formulating the NN vehicle model.

The architecture of the previous NN model was 6-6-6-3 which had 6 input and 3 output variables together with two hidden layers of 6 neurons each, whereas the reconstructed NN model was 7-6-5-3, as shown in Fig. 1. The input layer, the first hidden layer, the second hidden layer and the output layer had 7, 6, 5, 3 neurons respectively. 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}, namely

$$U_k = (\alpha_k, \Delta\alpha_k)^T \tag{1}$$

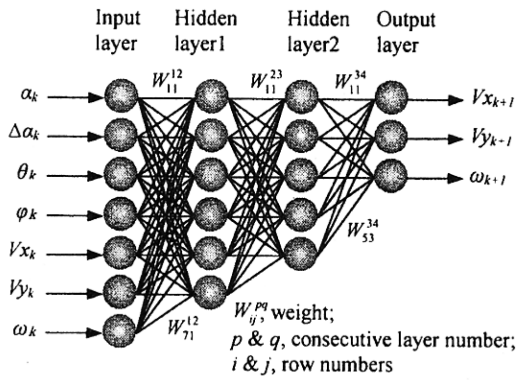


Fig. 1 Architecture of the NN vehicle model on slope terrain

$$Z_k = (Vx_k, Vy_k, \varpi_k, \theta_k, \varphi_k)^T \tag{2}$$

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

where: α_k is the steering angle in °; $\Delta\alpha_k$ is the rate of steering in °/s; Vx_k is the forward velocity of vehicle center of gravity in the vehicle frame in m/s; Vy_k is the lateral velocity of vehicle center of gravity in the vehicle frame in m/s; θ_k: is the heading angle in °; ω_k is the yaw rate of center of gravity in °/s ; φ_k is the slope angle in °; and the subscript k means equally spaced time step (k=1, 2, 3…n) in a discrete system. The output vector ξ_{k+1} represents the vehicle state after each 0.5 seconds. The output is determined by both the current inputs and their previous outputs. The sigmoid transfer function of the model, as shown in the Eq. (4), was used as the threshold function.

$$f(net) = \frac{1}{1+e^{-net}} \tag{4}$$

Comparing with the previous model, the reconstructed one was incorporated with incline information (φ_k), so it could be applicable for different gradients not just for a particular gradient. Although the inputs increased, the adjustable weights and biases decreased from 105 to 99 instead. This lowered the probability of trapping in a local optimum when the model was trained.

2. Data acquisition

Although the controller derived from the previous model could guide the tractor along rectilinear path accurately, there was some problem for following quarter-turns under close-loop control. The main reason was the training set had not covered ranges of every variable as wide as possible. Here a lemniscate of Bernoulli path was designed instead of sinusoidal path in the previous model. The path (Fig. 2) was described by:

$$(x^2+y^2)^2 = 2a^2(x^2-y^2) \tag{5}$$

in this paper, a=6.0. The centerline (X axis) is in

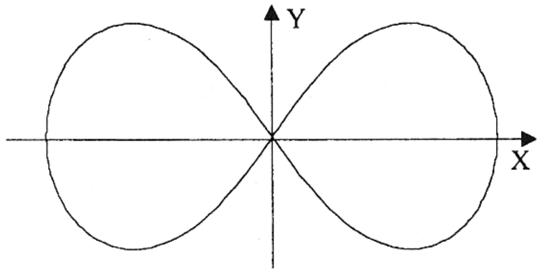


Fig. 2 Lemniscate of Bernoulli path

parallel with the contour line, Y axis is towards the uphill direction.

The training set acquired with this path could be representative of a much large class of possible input/output pairs. The steering angle could not turn beyond roughly ±40°, while the heading angle could involve any angles. However, due to the limit of the threshold function, any value beyond the range [0, 1] could not be used in the NN model. Therefore, all of the input/output variables were normalized by following equation.

$$f(\lambda)=\frac{\lambda+\lambda_{\max}}{2\lambda_{\max}} \tag{6}$$

3. Training of the NN model

A supervised training method, called BP algorithm, together with GA were used to train the NN model. The learning rule of BP is provided with a set of examples (the training set) of proper network behavior:

$$\{p_1,t_1\},\{p_2,p_2\},\ldots,\{p_Q,t_Q\}$$

where, p_Q is an input to the network and t_Q is the corresponding correct (target) output. As the inputs are applied to the network, the network outputs are compared to the targets. The learning rule is then used to adjust the weights and biases of the network in order to move the network outputs closer to the targets.

Although BP algorithm has strong ability for local searching, it easily traps in a local optimum if the multilayer network has many local minima (Hagan *et al.*, 1996). For this problem, GA offers a preferable means of solution. GA offers the attraction that all parts of the feasible space are potentially available for exploration, so the global minimum should be attained if premature convergence can be avoided (Chambers, 1995). On the other hand the GA is often slow for local optimization. Therefore, a combination of GA and BP algorithm was applied to train the NN model. Fig. 3 shows the flowchart of the training procedure. The GA procedure was composed of the steps in the dashed rectangle.

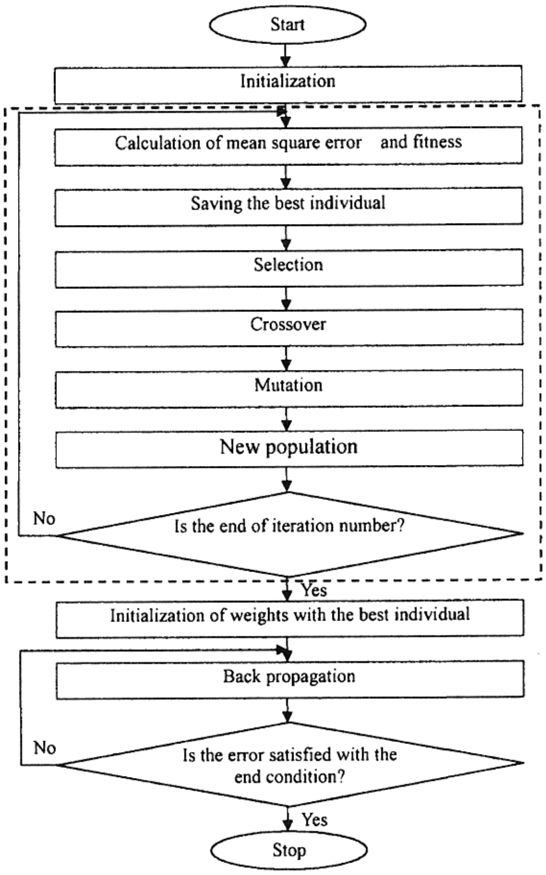


Fig. 3 Flowchart of training the NN vehicle model

In order to prevent premature convergence, keeping the population diversity, some measures were taken. During selection, some individuals whose fitness was better than the average fitness were discarded and replaced with random numbers. And the mutation rate was increased when the iteration number increased.

The trajectories of mean squared errors are shown in Fig. 4. After about 60,000 iterations, the changes

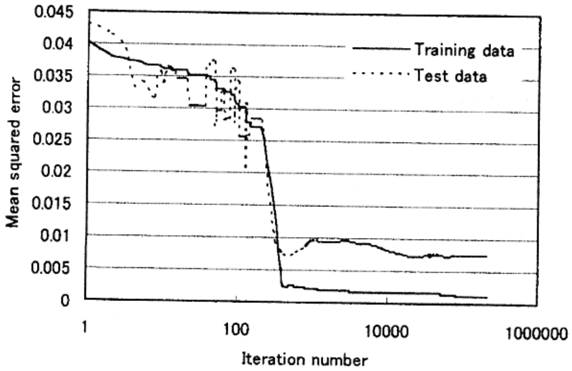


Fig. 4 Trajectories of mean squared error

of the errors tended to be stable. Although the error of the training set continued to decrease, that of the test set had increased. So the weights obtained at that time were selected as the final result.

4. Model validation

To validate the NN model, the vehicle was operated under field conditions, and the experimental results were compared to simulations using the NN model. In the simulation, since steering angle was the only control-input, the derivative ($\Delta\alpha$) of the same steering angle recorded during the data acquisition test was used as the control input. Initial values of the simulation were as same as those in the test, where the rest of the values were calculated. For every step of calculation, the output values were used as the input values in the next step.

Another measure was also taken to further verify the NN model, that is, to compare the open-loop performance of the experiments and simulations. They included rectilinear motions and circular motions on sloped terrain.

During simulation, the slope angle and the interval were initialized to the corresponding averages of them in the test respectively. Other variables were set only at the beginning of simulation, and their values were as same as the first data acquired in the field test.

III Experiment

1. The test tractor and instrumentation

The specification of the test tractor is shown in Table 1. The equipment and sensors used in this experiment are shown in Table 2.

Table 1 Specifications of the test tractor

Type	Mitsubishi MT2501D
Length × Width [m]	2.71 x 1.31
Wheelbase [m]	1.595
Weight [kg]	1125
Rated Power [kW]	18
Drive Mode	4WD
Tire Type	High lug

Table 2 Specification of instrumentation

DC motor	Its power is 82W, being used for the steering actuator.
1.0 GHz Pentium PC	The PC was mounted on the tractor, being used as the center processing unit.
Potentiometer	It was fixed on the front axle and to measure the steering angle.
Magnetic sensor	It was fixed near the flywheel and to measure the engine speed.
Fiber optic gyroscope (FOG)	Its model is JG-35FD, being used to measure the heading angle with range of ±180°. Its angular drift is less than ±5°/10 min.
Total Station (TS) and prism	With Leica TCA 1105 model, it has 2mm positioning accuracy.
SS wireless modems	They transmit the signals of the tractor position from the TS to the PC.
AD/DA board	It converts the analogue signals to digital (AD) and digital to analogue (DA).
Sprayer	It Marks the vehicle locations by spraying color ink.
Inclinometer	With TCM-2X-90 model, it is used to measure the roll and pitch.

2. Experimental conditions

Field tests on data acquisition and open-loop control were conducted in November 2003 on a meadow at the hilly areas of the Iwate University Omyojin Research Farm. Average land inclination, standard deviation and variance of the test course were 9.96°, 1.57°, and 2.46° respectively. Throughout the test the 0° heading angle was always set to parallel with the contour line. The tractor velocity was 0.5 m/s.

3. Experiment methods

(1) Data acquisition experiments

Data acquisition test of training pairs for the NN model was conducted on the sloped meadow. A skilled human operator operated the test tractor along predetermined lemniscate of Bernoulli path, which were traced on the ground by means of ropes. All information but vehicle position was continuously recorded in the control computer at 0.5 second regular intervals. The vehicle position was marked by color ink, later measured by TS.

Except for lemniscate of Bernoulli path, a sinusoidal path was also applied for data acquisition. But the data obtained in this test were only used for test set and to invalidate the NN model.

(2) Model validation experiments

Two other types of field test were conducted with the prototype tractor: rectilinear motion and steady-state turn test.

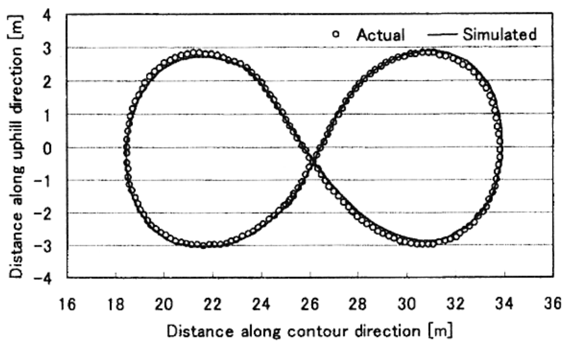
Instead of human operator, a tractor mounted PC and other equipment were used to operate the tractor in the test. For each test the PC generated the designed steering-actuation signals and accordingly the DC motor rotated the steering wheel.

Ⅳ Results and discussion

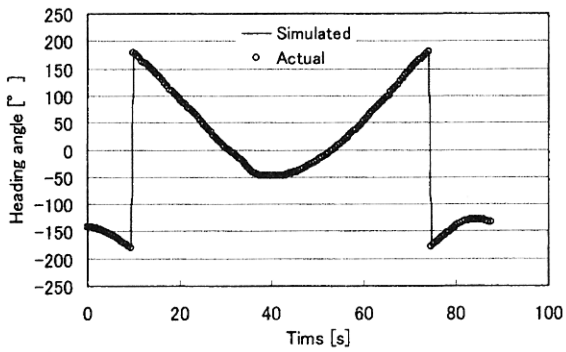
1. The NN model validation

A comparison between the actual and simulated trajectories of vehicle motion along the lemniscate of Bernoulli path on about 10° sloped terrain is shown in Fig. 5 (a). From this figure, it is found that these two trajectories are almost the same. Figure 5 (b) shows that heading angles of simulation and experiment were almost similar.

For checking the generalization of the developed NN model, the test with sinusoidal path was also performed on the same field. The trajectories of experiment and simulation are shown in Fig. 6. Apparently the NN model could produce outputs near from the true responses. So the NN model generalized well.



(a) Vehicle trajectories along the lemniscate of Bernoulli path



(b) Time histories of heading angle

Fig. 5 Comparison of the motions of actual and trained NN vehicle model

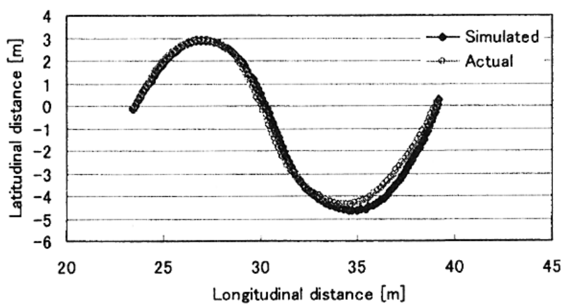
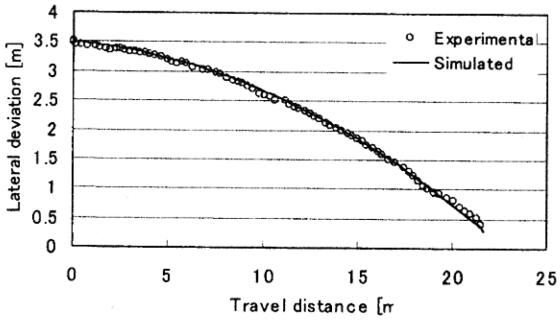


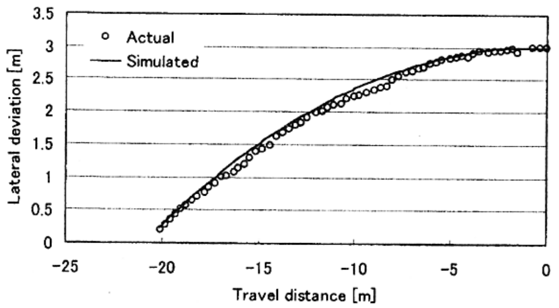
Fig. 6 Trajectories along the sinusoidal path

2. The characteristics of open-loop control

Fig. 7 shows the trajectories of the rectilinear vehicle motion on 10°slope. In Fig. 7 (a), both the experimental and the simulated case were initialized with same conditions. Here the steering angle was fixed at 0°, and the heading angle was initialized to 0°. In Fig. 7 (b), the steering angle was also fixed at 0°, but the heading angle was initialized to -180°. These figures indicate that the reconstructed NN model could represent the actual vehicle motion on the slope.



(a) Travel along contour line



(b) Travel along inverted contour line

Fig. 7 Trajectories of rectilinear motion on the slope

Fig. 8 shows the trajectories of the anticlockwise steady-state circular turn on sloped terrain, where the average inclination was 10.4°, and varied in the range of 7.2°~14.5°. The steering angle was fixed at 30° throughout the test.

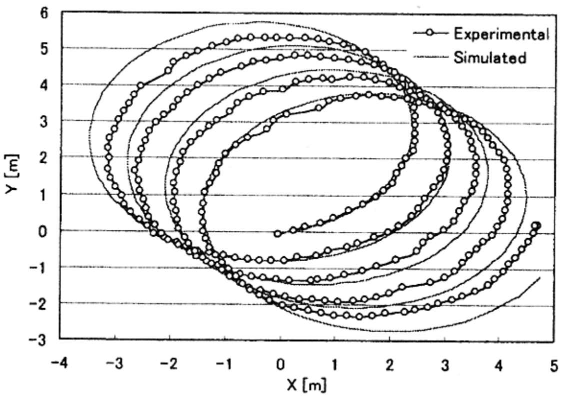


Fig. 8 Trajectories of the steady-state circular turn on 10.4°slope

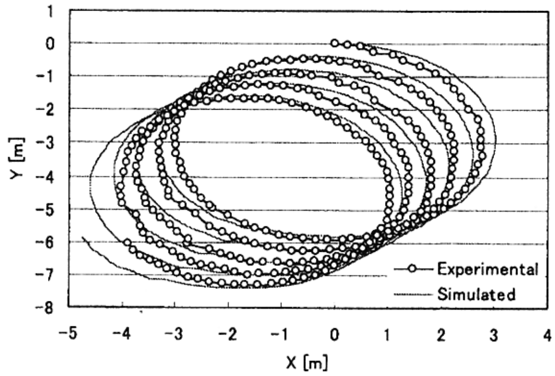


Fig. 9 Trajectories of the steady-state circular turn on 9°slope

Fig. 9 shows the clockwise circular turn for the same place, but at the bottom of the test field, where the average slope inclination was 9°, and varied in the range of 7.5°~ 10.4°. The steering angle was fixed at -30°.

From above two figures, one important fact becomes clear that in steady-state circular turn the vehicle deviation on slope-land is not directly downward, which was unintuitive prior to this test, rather it will be towards the diagonal of the contour line and downhill direction. The results show that the deviation tendencies of being simulated with this model are almost similar to those in the experimental test.

It was noticed that there were slight errors at the top and bottom of the test field. These were due to variant slope angle on the field. At the top the inclination was bigger than the average one, the experimental deviation tended toward downhill direction; On the contrary, at the bottom it was smaller than the average one, the experimental deviation tended to move towards uphill.

Conclusion

A reconstructed NN vehicle model was formulated and trained by GA and BP algorithm. Data acquisition test with lemniscate of Bernoulli path guaranteed that the NN model was accurate over a wider range. The NN model was invalidated with both training set (lemniscate of Bernoulli path) and test set (sinusoidal path). The results show the NN model is available and generalized well. From the comparative study of the experimental and simulation vehicle motion it is clear that NN model was sufficient enough to represent the input-output relationship of the vehicle motion on slope-land environment. The open-loop characteristics of vehicle motion on sloped terrain were also investigated. All of them indicate that the reconstructed model could represent the actual vehicle motion on slope.

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