Paper

Design of Backward Movement Control for a Truck System with Two Trailers Using Neurocontrollers Evolved by Genetic Algorithms

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In this paper, we propose a design method of neurocontrollers (NCs) evolved by a genetic algorithm (GA) for the backward movement control of a truck system with two trailers. The difficulty and complexity of the backward movement control depend on the number of connected trailers and the angular limitations of the trailer-truck system. In order to search for the best neurocontroller more quickly and effectively, for the two-trailer system which has extremely small angular limitations, we propose a modified GA which adaptively changes the number of offspring and the mutation rate according to the diversity of NC population. The simulation results show that the modified GA significantly improves the search performance. We apply the control method not only to computer simulations but also to experiments of a small-scale real mechanism. The results of both show that the control method is highly effective.

Keywords: backward movement control, trailer-truck system, genetic algorithm, neurocontroller

1. Introduction

Backward movement control of a trailer-truck system is known to be one of the typical nonlinear control problems. Difficulty of control not only causes the dynamics to be nonlinear but we also have to consider inherent physical limitations of the system such as the "jackknife" phenomenon. For the control objects, the soft computing fields of fuzzy control and neuro control have been reported. In these reports, it is shown that fuzzy control exhibits good control performance for the backward movement control of the trailer-truck systems [1][2]. With regard to neuro control, which is said to be well suited for the nonlinear control [3], first Nguyen and Widrow [4] have successfully solved the backward control problem using the back-propagation (BP) algorithm. Second, Jenkins and Yuhas [5] report a small sized neurocontroller (NC). However, on utilizing the BP method it is necessary to compute the partial derivative of the control object which is usually a very complex and mathematically difficult process and sometimes, even the partial derivative cannot be obtained.

Recently, a method of evolutionary computation [6] has been well studied and applied for many industrial problems [7]~[9]. If the evolutionary computation such as genetic algorithm (GA) is applied to the NC training, then the design of the control system becomes more simple. In a previous study, Kinjo *et al.* [10] proposed a control method using NCs evolved by a GA to solve the backward movement control problem. But in ref. (10), the truck is connected to only a single trailer. It is clear that the control problem becomes more difficult when the number of connected trailers increases and when the angular limitation of the trailer-truck system is extremely small. The difficulty and complexity of the problem depends on the the number of control variables and the mechanism of the trailer-truck system. When the truck system has two or more trailers and the physical angular limitations are extremely small, then the method of NCs with GA is not often able to produce a better controller, or the GA process takes too long to obtain the NC that can control the trailer-truck system successfully.

However, for a real trailer-truck system, it is often necessary to connect two or more trailers, and the limitations of the steering angle and of angular differences of the trailers are not designed to be so large. The aim of this study is to construct the NCs with GA more quickly and effectively. We must determine a design method of NCs that has better control performance for the two-trailer system with extremely small angular limitation.

To solve these problems, we propose a modified GA which adaptively changes the number of produced NCs and the mutation rate according to the similarity of NCs. In the GA process, we define index of diversity of the NC population and examine the similarity of NCs using the diversity index. If the diversity is lost then adaptive changing of both the number of offspring and the mutation rate is applied. The simulation results show that the modified GA significantly improves the search

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performance. Finally, we apply the control method to a small-scale real mechanism for verifying the effect of the control method.

The contents of this paper are as follows. In section two, a model of the truck system with two trailers is shown. In section three, the control system is described. In section four, the modified GA is shown and is applied to the NCs evolution. In sections five and six, simulation and experimental results are given. In section seven, the efficiency of the methods is discussed. Section eight contains the conclusions.

2. Model of Trailer-Truck System

Figure 1 shows the model of a truck system with two trailers and its coordinate system. Table 1 shows the parameters of the trailer-truck system.

The kinematic model of the system is governed by the following equations

$$x_0(t+1) = x_0(t) + \frac{v\Delta t}{l}\tan[u(t)] \quad \cdots\cdots\cdots\cdots (1)$$

$$x_1(t) = x_0(t) - x_2(t) \quad \cdots\cdots\cdots\cdots (2)$$

$$x_2(t+1) = x_2(t) + \frac{v\Delta t}{L}\sin[x_1(t)] \quad \cdots\cdots\cdots (3)$$

$$x_3(t) = x_2(t) - x_4(t) \quad \cdots\cdots\cdots\cdots (4)$$

$$x_4(t+1) = x_4(t) + \frac{v\Delta t}{L}\sin[x_3(t)] \quad \cdots\cdots\cdots (5)$$

$$x_5(t+1) = x_5(t) + v\Delta t \cdot \cos[x_3(t)] \times \sin[\frac{x_4(t+1)+x_4(t)}{2}] \quad \cdots\cdots (6)$$

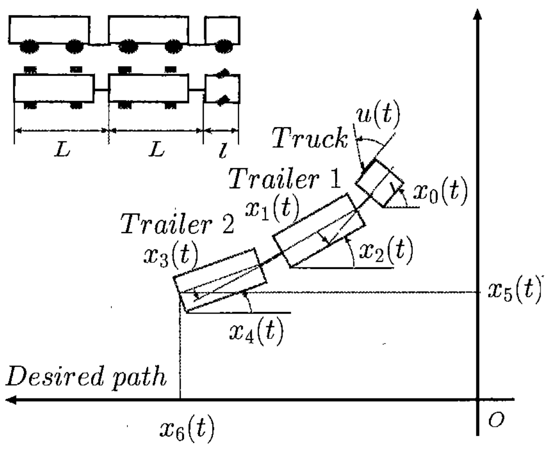


Fig. 1. Model of a truck system with two trailers.

Table 1. Parameters of trailer-truck system.

l	length of truck (=0.129 [m])
L	length of trailer (=0.124 [m])
Δt	sampling time (=1.7 [s])
v	constant speed (=-0.03 [m/s])
$x_0(t)$	angle of truck
$x_1(t)$	angular difference between truck and 1st trailer
$x_2(t)$	angle of 1st trailer
$x_3(t)$	angular difference between 1st trailer and 2nd trailer
$x_4(t)$	angle of 2nd trailer
$x_5(t)$	vertical position of 2nd trailer
$x_6(t)$	horizontal position of 2nd trailer
$u(t)$	steering angle

$$x_6(t+1) = x_6(t) + v\Delta t \cdot \cos[x_3(t)] \times \cos[\frac{x_4(t+1)+x_4(t)}{2}]. \quad \cdots\cdots (7)$$

The control purpose is to back up the trailer-truck system along the straight line ($x_5(t) = 0$) without forward movement. That is

$x_1(t) \to 0,\ x_3(t) \to 0,\ x_4(t) \to 0,\ x_5(t) \to 0.$

For simplicity, the variable $x_6(t)$ is not a control variable in the trajectory control.

3. Control System

Figure 2 shows the control system using NC with GA evolution. In the figure, NC denotes a neurocontroller which receives the error of angles x_1, x_3, x_4 and position x_5 as inputs and outputs steering angle u. The trailer-truck system receives the steering angle u and outputs the state variables of the next step while referring to the present configuration. GA denotes the genetic algorithm procedure.

Figure 3 shows the structure of the NC. The NC is a three-layered feed-forward neural network. In the hidden layer of the NC, the most popular node function, sigmoid function, is used. The node function of the input and output layers is a linear function.

By applying the genetic algorithm to the NC evolution, we obtain the "best individual" from the evolved NCs.

4. Genetic Algorithm

4.1 Evolution of NCs Figure 4 shows the flow chart of the evolution procedure of the NCs. The proce-

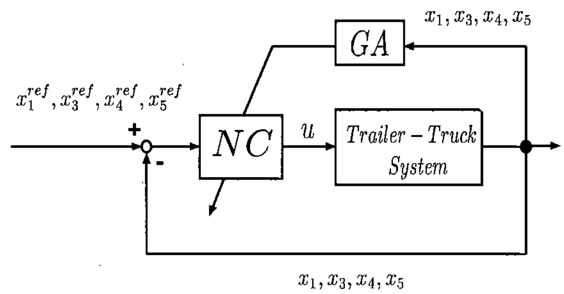


Fig. 2. Control system using NC with GA evolution.

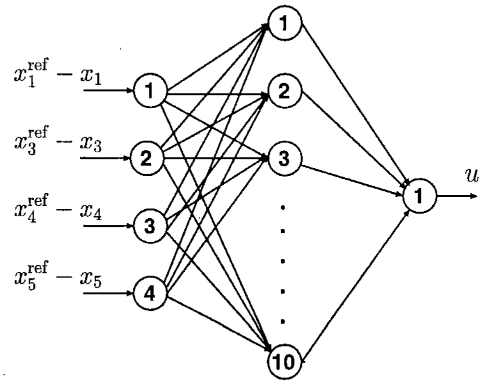


Fig. 3. Structure of NC.

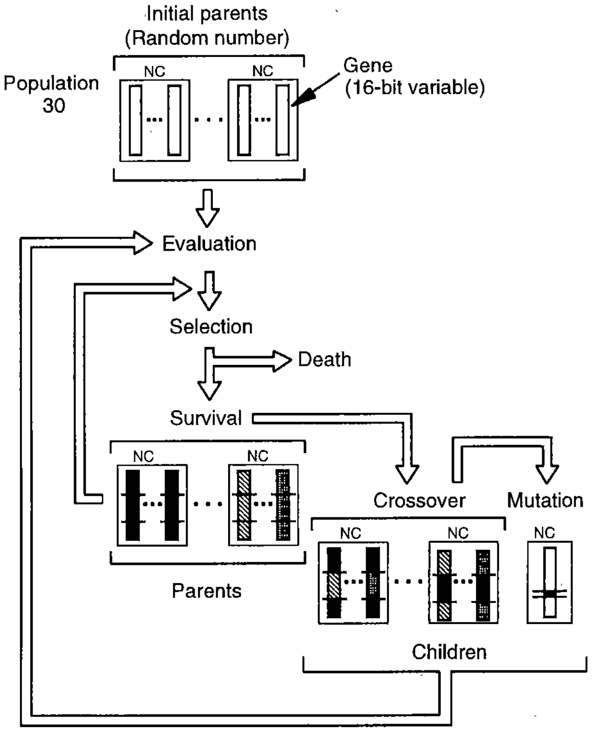


Fig. 4. Flow chart of NC evolution by GA.

dure of adapting NC is as follows. First we produce some NCs, whose connecting weights are chosen initially at random. Each NC has a genetic code which is transformed from the connecting weights. The transform equation $g = [(\frac{w}{N_r} + 1)\frac{65535}{2}]$ is used, where g and w are the genetic code and connecting weight, respectively; the symbol $[\cdot]$ denotes a Gaussian function which transforms decimals to integers; N_r is a coefficient that indicates the range of w.

In the evaluation process, the control performances of NCs are evaluated. The NC evaluation is performed as follows. The trailer-truck system is set to an initial configuration. The truck backs up using the NC, undergoing many individual cycles of backing up, until it stops. The final error of the trailer-truck system is recorded. Next, we place the trailer-truck system in another initial configuration and allow it to back up until it stops. Table 2 shows the initial configurations chosen by us. When control trials starting from the nine configurations are completed, the control performance of the NC is evaluated. All of the NCs in the population are evaluated by the same methods.

After the evaluation process, some pairs of NCs are selected and produce new NCs by a two-point crossover operation and a mutation operation. In a previous study reported in ref. (10), we had confirmed that the two-point crossover is superior than the single-point one in these applications. Therefore, we use the two-point crossover.

After the NC production process, the new NCs go to the evaluation process, and repeat the GA processes until the best individual, with good control performance,

Table 2. Initial configurations for NC evolution.

Pattern No.	x_0, x_2, x_4 [deg]	x_5 [m]
1	0	0.6
2	90	
3	180	
4	0	0.0
5	90	
6	180	
7	0	−0.6
8	−90	
9	−180	

is obtained.

4.2 **Evaluation Function** During the GA-based training process of NCs, we use an error function E to evaluate the control performance of NC, that is

$$E = \sum_{p=1}^{P}\{q_1(x_1^{\mathrm{ref}} - x_{1p}^{\mathrm{end}})^2 + q_3(x_3^{\mathrm{ref}} - x_{3p}^{\mathrm{end}})^2 + q_4(x_4^{\mathrm{ref}} - x_{4p}^{\mathrm{end}})^2 + q_5(x_5^{\mathrm{ref}} - x_{5p}^{\mathrm{end}})^2\}, \quad (8)$$

where x_p^{end} is the final value of the state vector which starts from any initial configuration of p. For the reference vector x^{ref}, the suffix p is not attached, because the reference value is always zero in every trial. q is the weight factor which adjusts the importance of control variables. In this case, because all values of x_1, x_3, x_4 and x_5 have the same range, we set as $q_1 = q_3 = q_4 = q_5 = 1$. P denotes the number of initial configurations, in this case $P = 9$.

In this study, we consider only the final states of the truck system, as shown in error function E. Sometimes angular differences exceed the physical limitations in control trials in the evaluation process of the GA. However, the NCs that yield the limitation error are eliminated during the GA processes. Setting only the final states in the error function E causes many evolution failures. Therefore, we propose a modified GA that improves the successful evolution of NCs.

4.3 **Improvement of GA** When the number of connecting trailers increases and the physical angular limitations are extremely small, the evolution of NCs becomes difficult and the GA process cannot produce better individuals. This time, all of the NCs in the population are almost all the same individuals and it is considered that diversity in the NCs population is lost. In order to recover the diversity, we propose a modified GA which changes the number of offspring and the mutation rate according to the similarity of NCs in the current population. An index of the diversity in the NC population is defined as the ratio of E_b/E_a, where E_a is an average error of all NCs and E_b is an error of the best individual of the NC population, respectively. If the rate is larger than a certain value (let us call it P_s), we consider that convergence occurs. Then we increase the number of offspring, which are generated from each pair of coupled NCs, that is

$$N = C_N + 2[(\frac{E_b}{E_a} - P_s) \times \frac{S}{1 - P_s}] \cdots\cdots\cdots \quad (9)$$

where the symbol $[\cdot]$ denotes a Gaussian function. S is a scale variable, which controls the total number of offspring generated from each pair of coupled NCs. Also, the mutation rate is adapted as shown by the following equation

$$M = C_M + (\frac{E_b}{E_a} - P_s) \times \frac{0.5C_M}{1 - P_s}. \quad \cdots\cdots\cdots \quad (10)$$

5. Simulation Results

5.1 Evolution Results Table 3 shows the probabilities of successful evolution of classical GA (CGA), modified GA1 (MGA1), modified GA2 (MGA2) and modified GA3 (MGA3). Where, MGA1 uses the varying number of offspring and a constant mutation rate, that is to say, $M = C_M$. MGA2 adopts both the varying number of offspring and the adaptive mutation rate. And MGA3 has a constant number of offspring $N = C_N$ and the adaptive mutation rate.

The number of NCs treated in the GA is set to 30, the probability of crossover is 0.8. We set $N_r = 5$, so that the range of connecting weight w is $[-5, 5]$. Parameter P_s is set to 0.6 in this study. C_N and C_M are constant, and are set to 2 and 0.01, respectively. Parameter C_N is a number of offspring produced by a pair of parent NCs in the classical GA. We consider that a pair of parent NCs produces a pair of offspring NCs. Therefore, we set $C_N = 2$. The other parameters are determined by trial and error. At first, we produce some NCs at random. Then we use these four methods to evolve the NCs. After 1000 generations, we stop the evolution process and choose the best NC. Then, we examine the control performance of the best NC. If the control error E is less than a certain value (in this paper, we use 4×10^{-4}), we consider that the evolution is successful. The threshold value for E is determined with consideration of both control performances and the generalization abilities of NCs by trial and error. We consider that the successful condition of squared error is less than 1×10^{-5} for each variable and each trial. There are four variables and nine trials in the error function E. Thus the successful condition is $E < 4 \times 10^{-4}$. We repeat this process 100 times, then we compute the probabilities of successful evolution. From the Table 3, we can find out that the probabilities of successful evolution decreased when the limit condition of u, x_1, x_3 was more severe. MGA1 obtains a better search performance than CGA. The performances of evolution of MGA3 do not improve for CGA. In this case, applying only an adaptive mutation rate does not affect the evolution performances. We can observe that MGA2 has the best search performance than the other three methods. We observe that MGA2 significantly improves the evolution performance especially when $S = 6$. We also discover that the modified GA is able to obtain a better performance of evolution with the increase of

Table 3. Probabilities of successful evolution.

Angular limits u, x_1, x_3 [deg]	CGA [%]	MGA1 [%]		MGA2 [%]		MGA3 [%]
		$S = 3$	$S = 6$	$S = 3$	$S = 6$	
90	36	39	51	49	57	38
80	39	46	47	43	56	36
70	18	26	36	27	36	22
60	12	15	22	13	27	10

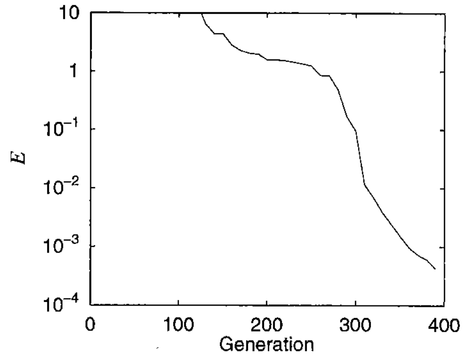
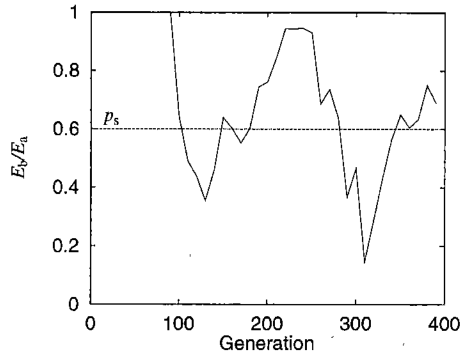
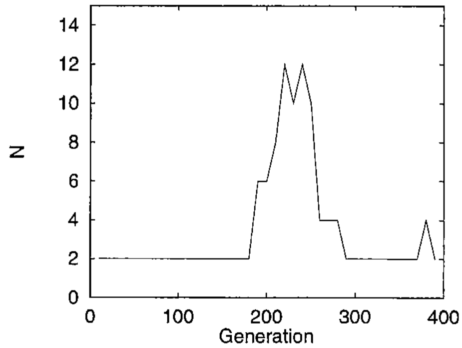


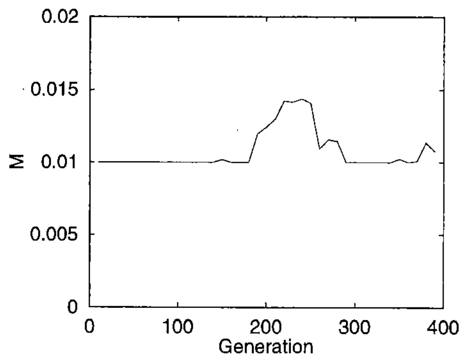
Fig. 5. Evolution results.



(a) Diversity index



(b) Number of offspring



(c) Mutation rate

Fig. 6. Effect of modified GA.

S. We determine the value of S with consideration of both evolution efficiency and computing time.

Figure 5 shows an example of evolution results using MGA2 ($S = 6$). It can be seen that the control error of the best NC decreased rapidly with the evolution of the NC during the GA process.

Figure 6 shows the effect of adaptively changing the number of offspring and the mutation rate. During the initial stage of evolution, the NCs cannot control the backward movement of the trailer-truck system. So all the values of the evaluation function of NCs are equal to the maximum error. In about 100 steps of the GA process, the GA finds some NCs that can control the trailer-truck system, then values of control errors of those NCs become small and the ratio E_b/E_a decreases as the diversity index decreases. Some steps later, the ratio E_b/E_a changes to increase. It is considered that the search converges to a sub-optimal solution because the error of NCs are not so small at that time. While $E_b/E_a > P_s$, the adaptive changing of both the number of offspring and the mutation rate is applied. As a result, the ratio E_b/E_a changes to decrease. Then the diversity of the NC population is recovered and the GA process can be continued to search for the best NC.

5.2 **Control Results** Figure 7 shows the control trajectory of the truck system with two trailers when the angular limitations are set to 60 degrees. In this case, the initial angles are situated between training pattern 2 and pattern 3 in Table 2. From Figure 7, it can be seen that the NC is able to control the trailer-truck system successfully starting from the inside of the training area. Figure 8 shows the steering angle u. It can be seen that the angle u ranges from minus 60 degrees to plus 60 degrees. Figure 9 shows the control result when the trailer-truck system starts from the untrained initial configuration. The initial configuration of the trailer-truck system is shown on the top left in the figure. Although the truck with two trailers starts from an untrained initial position and angle, the NC can still control the backward movement of the trailer-truck system successfully. Figure 10 shows the steering angle.

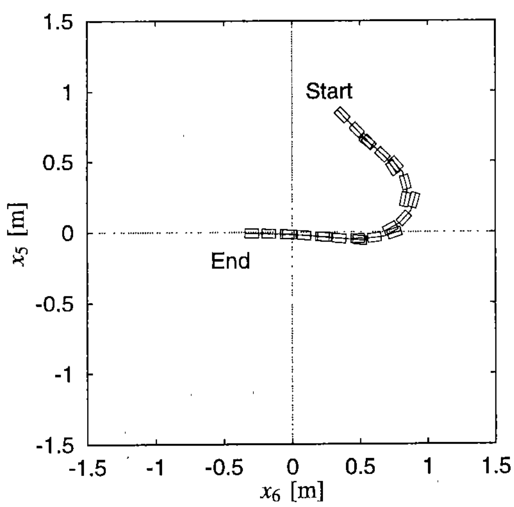


Fig. 7. Trajectory of trailer-truck system in simulation (Initial angle is $x_0 = x_2 = x_4 = 135$ [deg]).

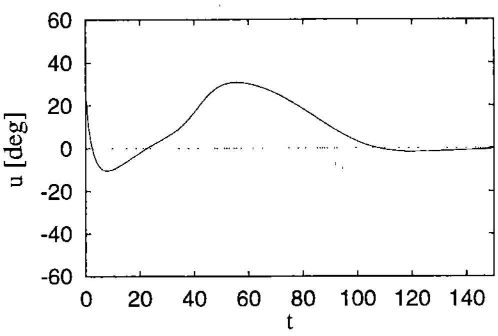


Fig. 8. Steering angle u (Initial angle is $x_0 = x_2 = x_4 = 135$ [deg]).

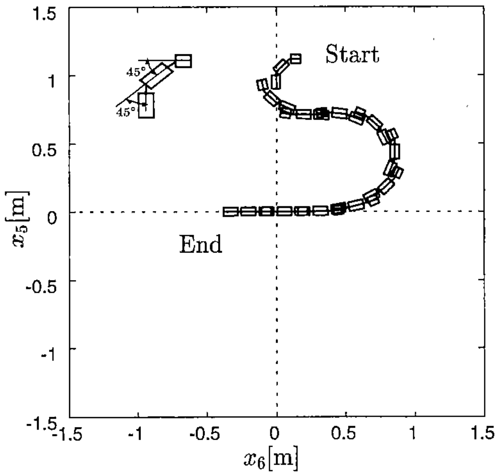


Fig. 9. Trajectory of trailer-truck system in simulation (Initial position is $(x_6, x_5) = (0.0, 0.9)$).

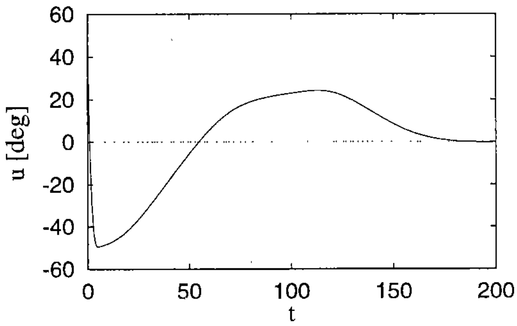


Fig. 10. Steering angle u (Initial position is $(x_6, x_5) = (0.0, 0.9)$).

6. Experimental Results

As known, the GA process takes a long time to evolve the NCs until obtaining the best individual. Thus, it is unrealistic to train the NC on-line. It is obvious that the NC obtained from off-line training inevitably contains an error when it is applied in experiments. But because of the generalization ability of neural networks we think that we are able to achieve backward movement control of a truck with two trailers even though the control performance might be worse than the results of the

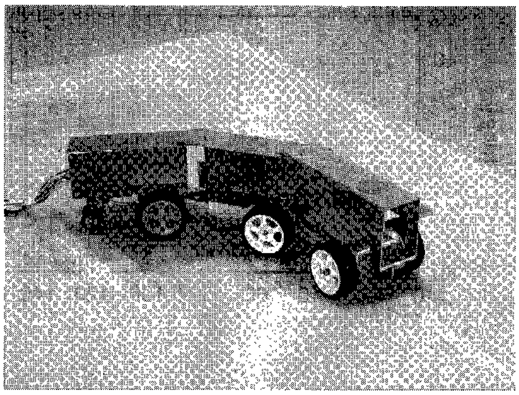


Fig. 11. Photograph of truck with two trailers.

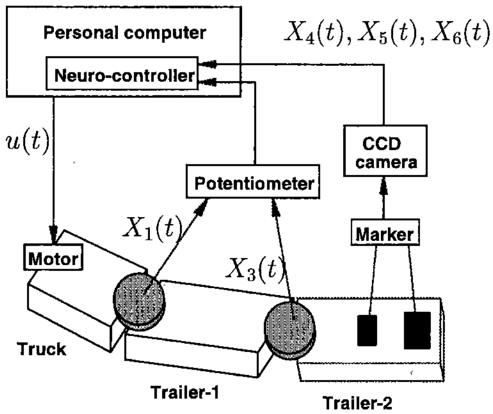


Fig. 12. Experimental system.

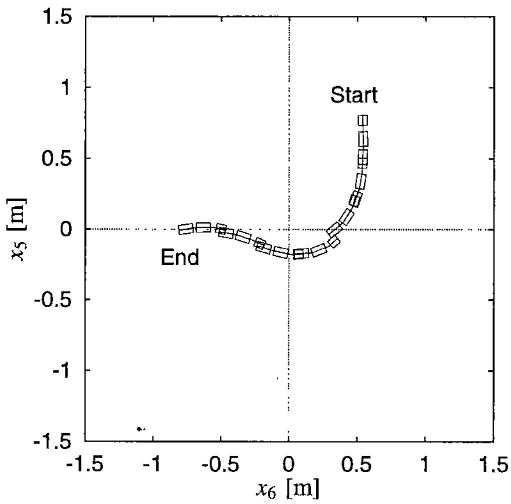


Fig. 13. Trajectory of trailer-truck system in experiment.

simulation. Figure 11 shows the truck system with two trailers used in this experiment. The physical angular limitations of u, x_1 and x_3 are set to 60 [deg].

The experimental system of backward movement control is shown in Figure 12.

Figure 13 shows the control trajectory when the initial angles are $x_0 = 91.62$ [deg], $x_2 = 91.17$ [deg],

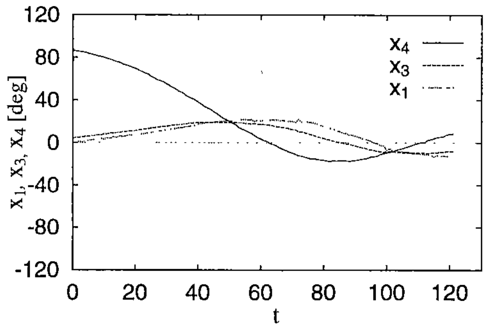


Fig. 14. Angles x_1, x_3 and x_4 in experiment.

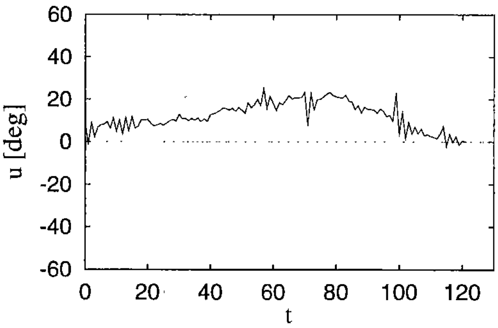


Fig. 15. Steering angle u in experiment.

$x_4 = 87.03$ [deg] and the initial position is set as $(x_6, x_5) = (0.536, 0.459)$. From the figure, it can be seen that although the control result is not accurate enough, it is still possible to achieve the desired control purpose.

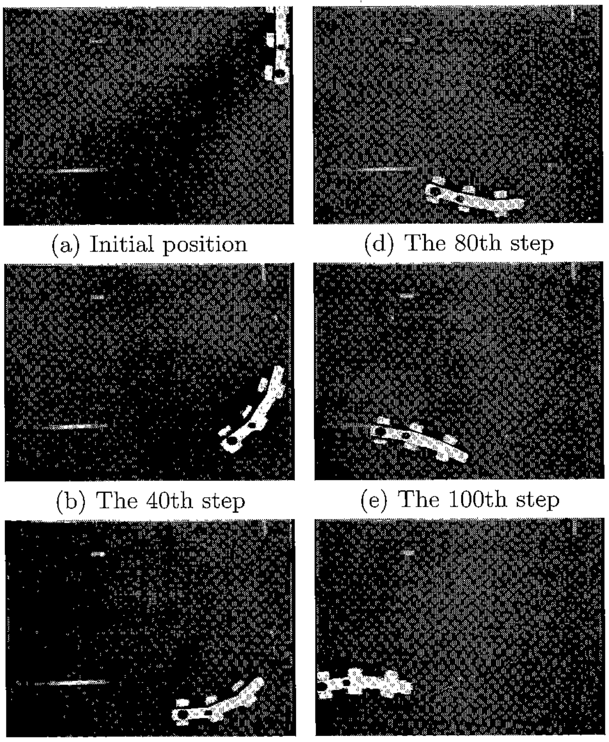
Figure 14 shows the control results for angles x_1, x_3 and x_4. Figure 15 shows the variation of the steering angle u.

Figure 16 shows the photographs taken during the control process by a CCD camera. We choose six typical images from 122 successive images. From the figure, we can see that the proposed control method can enable the trailer-truck system to back up to the desired state.

7. Discussion

From Table 3, it is observed that NCs designed with a GA easily perform the search for the optimal solutions when the angular limitation of the trailer-truck system is large. Large angles limit (*e.g.* 90 degrees) means that we have more freedom to choose good NCs. However, when the angular limitations are extremely small, the successful evolution of NCs decreases, and the difficulty and complexity of the controller design are increased. In the classical GA which uses a constant number of offspring and constant mutation rate, many evolving NCs are trapped in a sub-optimal solution. In the case of the proposed modified GA, which uses an adaptive number of offspring and mutation rate, it is possible to avoid the sub-optimal solution and to reach more suitable solutions.

From the simulation results, we can determine the evolved NC that can successfully control the backward movement of the trailer-truck system even if the trailer-truck system is starting from some untrained positions



(a) Initial position (d) The 80th step

(b) The 40th step (e) The 100th step

(c) The 60th step (f) Final position

Fig. 16. Trailer-truck system movement controlled by NC.

and untrained initial angles. During the self-learning process, the NC with GA not only grasps the knowledge we want to train but also gains rich experience of how to achieve the desired path from the passed trajectory. Moreover, the generalization ability of the neural network also makes the backward control possible.

From Figures 8, 10 and 15, we can observe that the steering angle u oscillates within the angular limitations in the results of both the simulation and experiment. During the selection process in the GA, the inferior NCs that exceed the angular limitations are eliminated and superior NCs survive.

8. Conclusion

In this paper, we propose a method of backward movement control for a truck system with two trailers using neurocontrollers evolved by a genetic algorithm. When the truck is connected to two or more trailers and the angular limitations of the trailer-truck are extremely small, the design method of neurocontrollers using GA would not perform well. In order to search for the best neurocontroller more quickly and effectively, we proposed a modified GA which adaptively changes the number of offspring and the mutation rate according to the diversity of the NC population. The simulation results show that the modified GA significantly improves the search performance. We apply the control method not only to computer simulations but also to experiments of a small-scale real mechanism. The results of both show that the control method is highly effective. In this paper, we discussed the backward movement of a truck system with two trailers as a nonlinear control object. We assert that the control method is suitable for solving problems associated with nonlinear complex kinematic systems.

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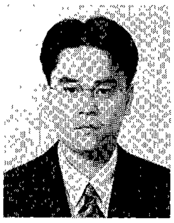

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