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A NEW LEARNING ALGORITHM FOR DRIVING A MOBILE VEHICLE

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ABSTRACT

The strategy presented in this paper is based on modifying the past patterns and adjusting the content of the driving patterns by a new algorithm. Learning happens during the driving procedure of a mobile vehicle. The purpose of this paper is to solve the problem how to realize the hardware neurocomputer by back propagation (BP) neural network learning on-line.

1. INTRODUCTION

Learning and adaptation especially are essential characteristics of intelligent control systems and, while adaptation does not necessarily require a learning ability for systems to be able to cope with a wide of variety of unexpected changes and environments, learning is invariably required. Though the maximum principle in the framework of optimal control theory can compute time optimal paths with constraint conditions, it is not easy for an arbitrary nonholonomic system to compute a time optimal path by using this principle and only approximate solutions are given in general cases. The strategy presented in this paper is based on modifying the past patterns and adjusting the content of the driving patterns. Learning actions happen during the driving procedure of the mobile vehicle. Our basic idea is to use the human knowledge to make the mobile vehicle be capable of learning, evaluating results of actions and modifying the inputs of the controller itself in order to acquire optimal or near-optimal results.

The training the neural network or neural controller based on human expert experience is sometimes very feasible method, especially for those complex and hardly defined processes. The BP neural network model changes the input-output problem of a set of sample into a nonlinear optimal map[1]. The steepest descent method, one of the common near-optimal algorithms, is applied. The learning and keeping are realized by weight update with recurrent computation in the inner neural network.

The purpose of this paper is to solve the problem how to realize the hardware neurocomputer which a BP neural network is inside as shown in Fig.1 learning on-line on the base of our former researches[2][3][4].

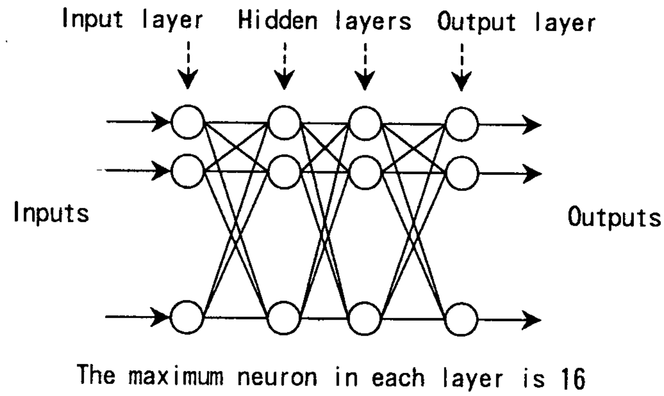

Fig. 1. The neural network in RN-2000

2. PROBLEMS TO BE SOLVED

The on-line control of the mobile vehicle is based on the neural control and applied the new algorithm into the teaching patterns. The key point of this new algorithm is utilize a cost function to evaluate the teaching patterns used in the neurocomputer RN-2000, and then produces new teaching patterns. These new patterns will be used to train the neurocomputer again. This algorithm needs several driving periods till satisfactory driving results are practiced. The control system is shown in Fig. 2. In normal case, the former patterns are used to train the mobile vehicle. If a teaching pattern changes nothing, what the mobile vehicle has learnt will be no change. In order to get more driving knowledge, pattern changes are hopeful. Let us introduce a cost function $J(\mathrm{t})$. The cost function are definited as the difference between the driving position $\mathbf{q}(\mathrm{t})$ and desired position $\mathbf{q_d}(\mathrm{t})$ at the time t, the cost function is also used to operate the logical switch $K1$ and $K2$ to control which patterns are put into use.

Let J_{max} be the maximum allowing driving difference, if at a time index t, driving difference $J(t) = \|\mathbf{q}(\mathbf{t}) - \mathbf{q_d}(\mathbf{t})\|$

<= J_{max}, switch $K1$ will be in state off and $K2$ in state on, former patterns are not be changed. Otherwise $K1$ will be in the state on and $K2$ in the state off, former patterns will be put into a renewing and reproduction process. To the RN-2000, the teaching patterns must be kept in the form of memo note document, so the results of pattern changes must be represented in one of the memo note document and consist of head mark, pattern number, numbers of input patterns and output patterns, input-teaching patterns and output-teaching patterns. During a driving procedure, the driving result is detected by the cost function J(t), and teaching patterns are adjusted at the same time, the new algorithm reproduces patterns according to the basic patterns which cause of J(t)$\leq J_{max}$, and deleted the patterns which made J(t)$>J_{max}$. And the total patterns are limited in 64 because of the construct of the neurocomputer hardware[2]. The neurocomputer RN-2000 works in the back propagation method[1][4]. An example of real training patterns in a neural controller is presented in Table 1.

3. DESCRIPTION OF THE LEARNING ALGORITHM

The combinatorial optimization problem can be described as foollows:

$$\min_{x} J(x) \tag{1}$$

$$subject\ \ to\ \ x \in X \tag{2}$$

$$X \subset Y \tag{3}$$

where x is possible optimal solution, $J(x)$ is objective function, X is the set of possible optimal solutions and Y is the set of all of solutions. The aim is to search the suitable $\{x\}$ to get $J(x) \leq J_{max}$.
From the teaching patterns shown in Table 1, it can be seen that the input patterns consist of two strings 127 and 0, the driving knowledge is composed by the different arrangement of 16 possible units and an output unit. The new algorithm will change the structure of the neural network in the neurocomputer and the control outputs.

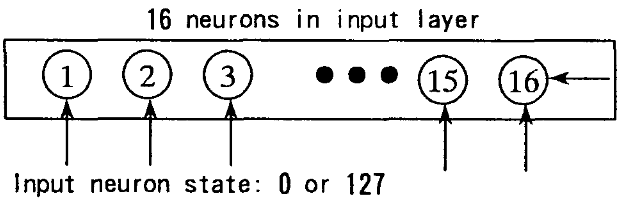

Fig. 2. Input layer of RN-2000

Table 1: Teaching patterns document

Content	Notes	Name
RNC-DAT	head mark	/
7	total patterns	/
1	numberS of BP	/
7 1	I/O neurons	/
127 0 0 0 0 0 0	input pattern	pattern 1
10	output pattern	pattern 1
0 127 0 0 0 0 0	input pattern	pattern 2
20	output pattern	pattern 2
0 0 127 0 0 0 0	input pattern	pattern 3
30	output pattern	pattern 3
0 0 0 127 0 0 0	input pattern	pattern 4
40	output pattern	pattern 4
0 0 0 0 127 0 0	input pattern	pattern 5
50	output pattern	pattern 5
0 0 0 0 0 127 0	input pattern	pattern 6
60	output pattern	pattern 6
0 0 0 0 0 0 127	input pattern	pattern 7
70	output pattern	pattern 7

The principle is illustrated in Fig. 3. Driving patterns are classified into m classes and every class presents a kind of path, for example line, curve and so on. The number of patterns in each class may be equal or not equal. In the case of Fig. 3, two patterns are included in *Class* 1, $j-i$ patterns are in *Class* k, and *class* m has only *pattern* n. *Class* 1 present direct path , *Class* k present urgent curve path and *class* m present curve path. Let the min$\{J11, J12, J13, J14\}$=$J1_{min}$, min$\{Jm1, Jm2, Jm3, Jm4\}$=Jm_{min}. If the $J1_{min}$= $J12$, and Jm_{min}= $Jm1$, respectively, the patterns are formed based on the cost function J12, and Jm1, in *Class* 1 and *Class* m. Here Jl_{min} $(l = 1, 2, \cdots, m)$ is the minimum cost function in the four cost function in a same driving procedure T. The on-line learning needs a certain distance to begin because at least 2 cost function are necessary in a class. There two cases:

Case 1: If Jl_{min}>J_{max}, this is considered that the teaching signal is not good enough and caused a driving difference which does not be allowed. In order to produce more skillful driving knowledge, the past patterns had to be reformed. In the control system of the mobile vehicle, the output-teaching signal is the steering control invariable to the motor driver. If the output-teaching signal is adjusted according to the Jl_{min}(t), then the good propelling results can be expected and after several driving procedure, the x in Eq.(1) to get $Jl_{min}(x) < J_{max}$ is possible. We use the class 1 in Table 1 as an example to illustrated the process. Assume that J_{max}=200mm, and at a time index t $J1_{min}$(t)=min{J11(t), J12(t)}=J12(t)

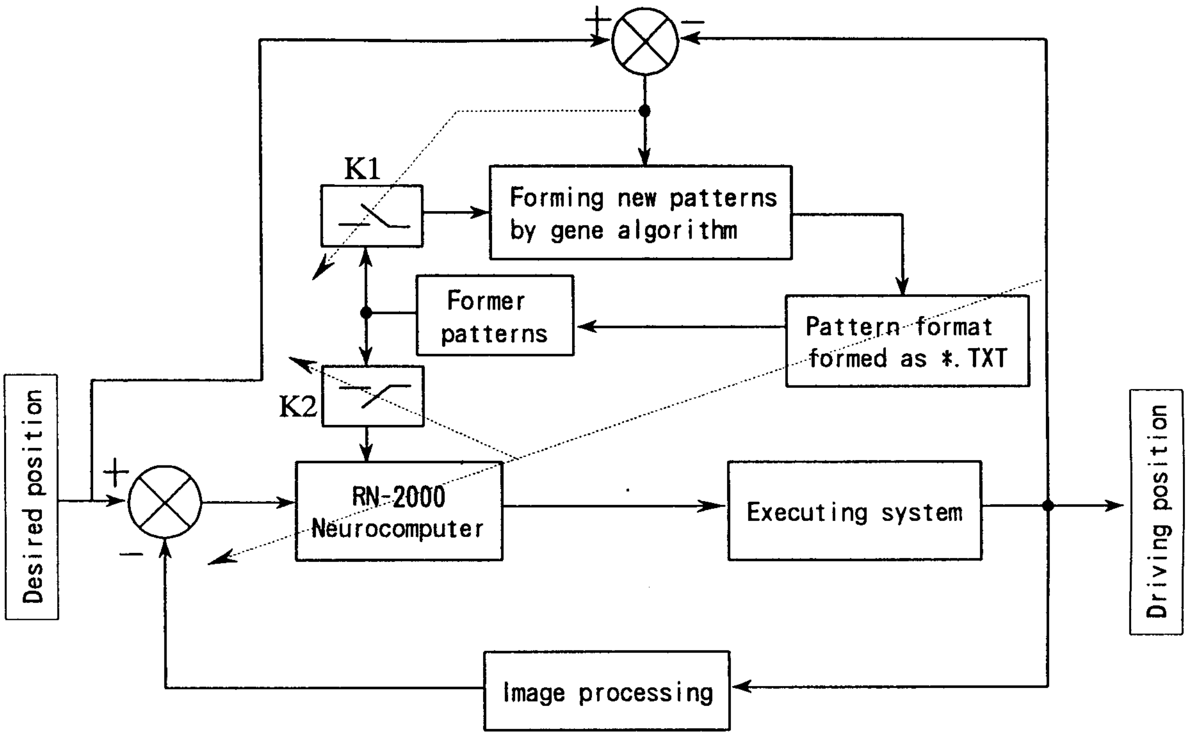

Fig. 3. On-line learning system of the mobile vehicle

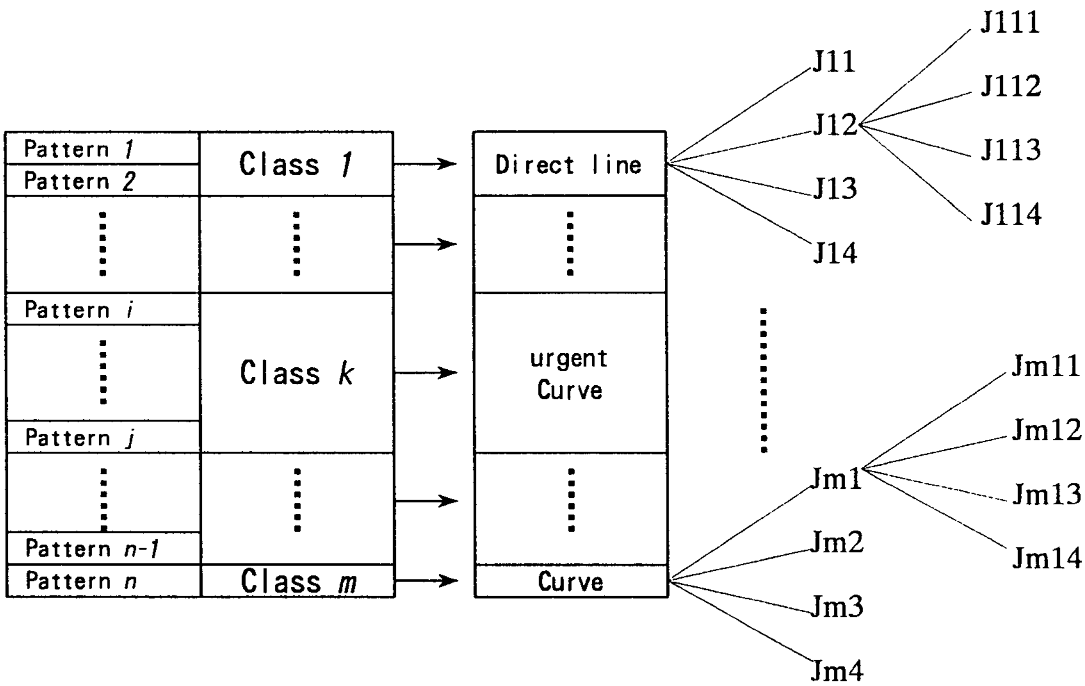

Fig. 4. Classification of driving patterns

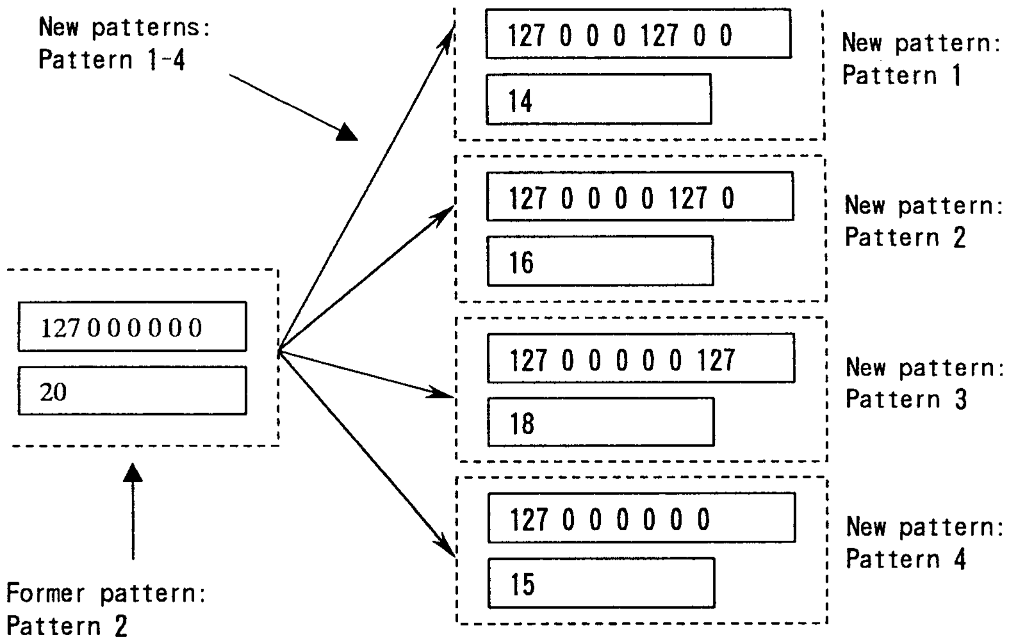

Fig. 5. On-line learning system of the mobile vehicle

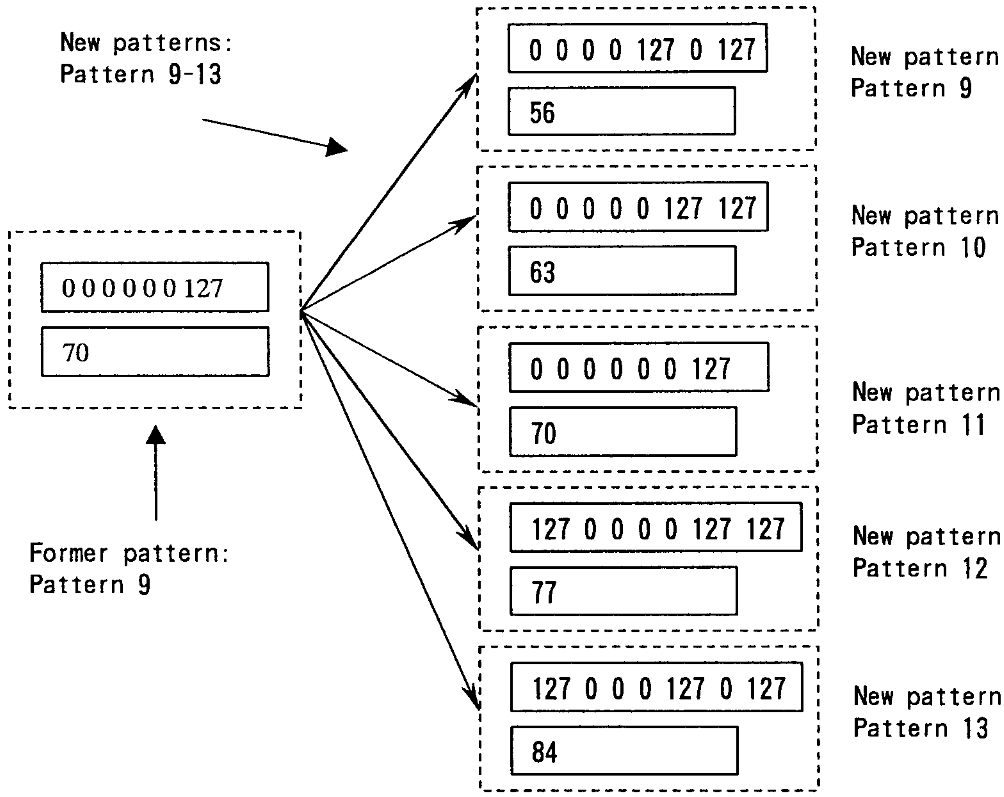

Fig. 6. On-line learning system of the mobile vehicle

Table 2: Teaching patterns document

Content	Notes	Name
RNC-DAT	head mark	/
7	total patterns	/
1	numberS of BP	/
13 1	I/O neurons	/
127 0 0 0 127 0 0	input pattern	pattern 1
14	output pattern	pattern 1
0 127 0 0 0 127 0	input pattern	pattern 2
16	output pattern	pattern 2
127 0 0 0 0 0 127	input pattern	pattern 3
18	output pattern	pattern 3
127 0 0 0 0 0 0	input pattern	pattern 4
15	output pattern	pattern 4
0 0 127 0 0 0 0	input pattern	pattern 5
30	output pattern	pattern 5
0 0 0 127 0 0 0	input pattern	pattern 6
40	output pattern	pattern 6
0 0 0 0 127 0 0	input pattern	pattern 7
50	output pattern	pattern 7
0 0 0 0 0 127 0	input pattern	pattern 8
60	output pattern	pattern 8
0 0 0 0 127 0 127	input pattern	pattern 9
56	output pattern	pattern 9
0 0 0 0 0 127 127	input pattern	pattern 10
63	output pattern	pattern 10
0 0 0 0 0 0 127	input pattern	pattern 11
70	output pattern	pattern 11
127 0 0 0 0 127 127	input pattern	pattern 12
77	output pattern	pattern 12
127 0 0 0 127 0 127	input pattern	pattern 13
84	output pattern	pattern 13

=min{400, 300}=300mm, and pattern 2(former pattern) in Fig. 5 is corresponding to the pattern 2 in Table 1 and the output-teaching signal is 20. That 10 and 20 in *class* 1 caused $\|J1_{min}(t) - J_{max}\|$=100 driving difference. So the 10 is regard as bad one, four new patterns are formed according to the pattern 2 and are illustrated in Fig. 5. Fig. 5 gives the former pattern and new patterns. In Fig. 5 the output teaching patterns are calculated by: pattern 4: (20+10)/2=15, pattern 3: 20×90%=18, pattern 2: 20× 80%=16, pattern 1: 20×70%=14, Finally, the data is wrote into the former memo note and start the new learning process. If necessary, the class can be divided into more detail as shown in Fig. 4.

Case 2: If $Jl_{min}<J_{max}$, it is regarded as good teaching patterns, then the all of teaching patterns will be renewed according to this good pattern. We take the pattern 7 in Table 1 as example. The pattern 7(former pattern) in Fig. 6 is corresponding to the pattern 7 in Table 1. Assume that J_{max}=200mm, and at a time index t $J7_{min}$(t)=J71(t)=90mm(here, m=7). A complete teaching document is illustrated in Fig. 7.

4. EXPERIMENTS AND DISSCUSIONS

From Table 2 we can see that the new patterns more details classification than the human knowledge, and the knowledge increase gradually. The new patterns in Fig.8 is used to train the neurocomputer. Compared the results of the teaching patterns in Table.1 and in Table 2, new patterns contribute obvious good features to the mobile vehicle control system. The results are shown in Fig. 7. The input unit is millimeter, and output unit is pixel distance. One pixel distance is about 10mm. More near-optimal teaching patterns show better results than the former one. This can be understood easily because the mobile vehicle has gotten more driving knowledge after learning on-line and is capable of running good paths.

5. CONCLUSIONS

Teaching signal is necessary for BP neural network to learn human knowledge. In normal ways, human has to make these teaching signals. In the mobile vehicle control system, a neurocomputer, which BP neural network is inside, is not only applied to control the driving action, but also realized the learning on-line. In order to get better results learning on-line is one of important method, though it is difficult. The strategies shown in this paper pay attention into those output-teaching patterns and utilize a new algorithm to realize the combinatorial near-optimization method. This idea not only suitable to improve the learning way of the neurocomputer RN-2000, but also helpful to this kind of BP neural network.

6. REFERENCES

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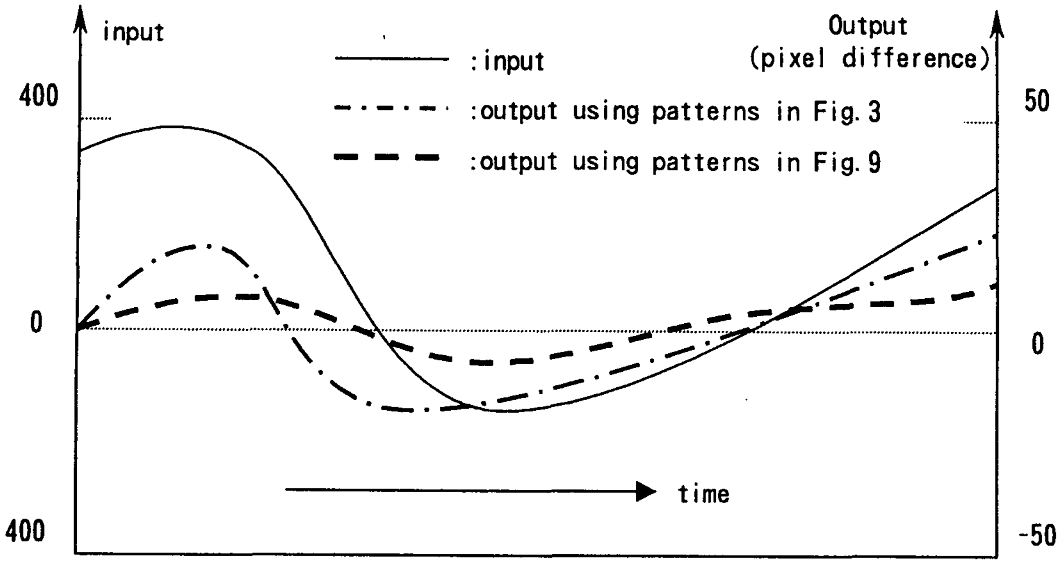

Fig. 7 Comparison of the two teaching results