An Intelligent Traffic Light Control Based on Extension Neural Network

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Abstract. This paper presents an intelligent traffic light control method based on extension neural network (ENN) theory for crossroads. First, the number of passing vehicles and passing time of one vehicle within green light time period are measured in the main-line and sub-line of a selected crossroad. Then, the measured data are adopted to construct an estimation method based on ENN for recognizing the traffic flow of a standard crossroad. Some experimental results are made to verify the effectiveness of the proposed intelligent traffic flow control method. The diagnostic results indicate that the proposed estimated method can discriminate the traffic flow of a standard crossroad rapidly and accurately.

Keywords: Extension neural network theory, traffic light system, traffic flow control.

1 Introduction

The conventional traffic light control methods include fix-time control, time-of-day control, vehicle actuated control, semi-actuated control, green wave control, area static control and area dynamic control [1]. However, there is no system meeting the adaptive characteristic. Although some significant artificial intelligence (AI) methods such as fuzzy logic [2,3], neural network [4], evolutionary algorithms [5,6] and reinforcement learning [7,8] have been proposed to tune the cycle length and splits adaptively, the success in timing optimization and convergence rate are still limited. The cycle length and splits could be determined by using the fuzzy control method, and thus that could shorten the queue, and reduce total traffic delay. However, most researchers work at controlling an isolated intersection with the fuzzy control method. Few apply this method to the coordinated control of area traffic because it is a complex large-scale system. There are many interaction factors, and it is difficult to describe the whole system using some qualitative knowledge. This is the limitation of fuzzy control methods. The applying effect of artificial neural network (ANN) depends on its generalization capability. So the samples should be ergodic and the learning process should converge to the global optimal point. In fact, it is hard to meet these conditions for a real application. The evolutionary algorithms such as genetic algorithm, ant algorithm and particle swarm optimization are all biomimetic methods

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for global optimization. Therefore, evolutionary algorithms are not likely to be trapped in local optima because of their characteristics of random search and implicit parallel computing. Also, when meeting a large-scale problem, these methods will spend much time to converge to the optima. It is disadvantageous for on-line optimization of area traffic coordinated control. In addition, the convergence rate is sensitive to parameters selected, which depend on practical problems to be solved. Thus, applying the evolutionary algorithm to area traffic coordinated control is limited. The advantage of reinforcement learning is that it is not necessary to set up the mathematic model for the external environment. However, there is also the disadvantage of converging slowly.

To satisfy the requirements of timing optimization and convergence rate for urban traffic light control, an intelligent control method based on extension neural network theory is proposed in this paper. The proposed traffic signal control method can adjust various traffic signal control parameters adaptively in response to varying traffic demand. The proposed ENN method has the advantages of less learning time, higher accuracy and less memory consumption.

2 Extension Neural Network

Extension neural network [9] uses a combination of neural networks and extension theory. The extension theory [10] provides a novel distance measurement for classification processes, while the neural network can embed the salient features of parallel computation power and learning capability. The schematic structure of the ENN is depicted in Fig. 1. It includes both the input layer and the output layer. The nodes in the input layer receive an input feature pattern and use a set of weighted parameters to generate an image of the input pattern. In this network, there are two connection values (weights) between input nodes and output nodes, one connection represents the lower bound for this classical domain of the features, and the other connection represents the upper bound. The connections between the j-th input node and the k-th output node are W_{kj}^{L} and W_{kj}^{U} . Only one output node in the output layer remains active to indicate a classification of the input pattern.

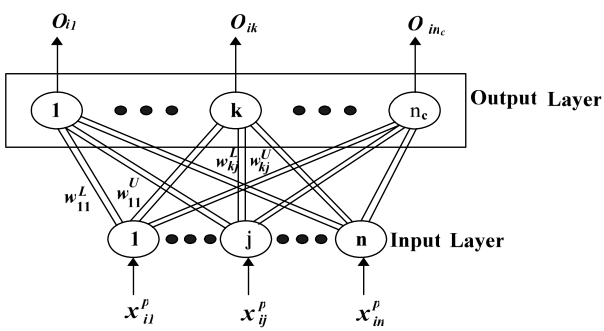

Fig. 1. The structure of extension neural network

2.1 Learning Algorithm of the ENN

The learning of the ENN can be seen as supervised learning, and its purpose is to tune the weights of the ENN to achieve good clustering performance or to minimize the clustering error. Before the learning, several variables have to be defined. Let training pattern set be $X \equiv \{X_1, X_2, ..., X_{N_P}\}$, where N_P is the total number of training patterns. The i-th pattern is $X_i^p \equiv \{x_{i1}^p, x_{i2}^p, ..., x_{in}^p\}$, where n is the total number of the feature of patterns, and the cluster of the i-th pattern is p. To evaluate the clustering performance, the total error number is set as N_m, and the total error rate E_τ is defined below:

$$E_\tau = \frac{N_m}{N_p} \tag{1}$$

The detailed supervised learning algorithm can be described as follows:

Step 1: Set the connection weights between input nodes and output nodes. The range of classical domains can be either directly obtained from the previous requirement, or determined from training data as follows:

$$w_{kj}^L = \min_{i \in N}\{x_{kj}^k\} \tag{2}$$

$$w_{kj}^U = \max_{i \in N}\{x_{kj}^k\} \tag{3}$$

Step 2: Calculate the initial cluster center of every cluster.

$$Z_k = \{z_{k1}, z_{k2}, ..., z_{kn}\} \tag{4}$$

$$z_{kj} = \left(w_{kj}^L + w_{kj}^U\right)/2, \quad \text{for } k = 1, 2 ... n_c \text{ ; } j = 1, 2, ... n \tag{5}$$

Step 3: Read the i-th training pattern and its cluster number p.

$$X_i^p = \{x_{i1}^p, x_{i2}^p, ..., x_{in}^p\} \text{ , } p \in n_c \tag{6}$$

Step 4: Use the proposed extension distance (ED) to calculate the distance between the training pattern X_i^p and the k-th cluster, as follows:

$$ED_{ik} = \sum_{j=1}^{n}\left[\frac{\left|x_{ij}^p - z_{kj}\right|}{\left|\left(w_{kj}^U - w_{kj}^L\right)/2\right|} + 1\right] \text{ , } k = 1, 2, ..., n_c \tag{7}$$

The proposed distance is a modification of extension distance [9], and it can be graphically presented as in Fig. 2. It can describe the distance between the x and a range $\left\langle w^L, w^U \right\rangle$.

Step 5: Find the k^*, such that $ED_{ik^*} = \min\{ED_{ik}\}$, If $k^* = p$ then go to Step 7, otherwise Step 6.

Step 6: Update the weights of the p-th and the $k*$-th clusters as follows:
(a) Update the centers of the p-th and the $k*$-th clusters.

$$z_{pj}^{new} = z_{pj}^{old} + \eta\left(x_{ij}^{p} - z_{pj}^{old}\right) \tag{8}$$

$$z_{k^*j}^{new} = z_{k^*j}^{old} - \eta\left(x_{ij}^{p} - z_{k^*j}^{old}\right) \tag{9}$$

(b) Update the weights of the p-th and the $k*$-th clusters.

$$\begin{cases} w_{pj}^{L(new)} = w_{pj}^{L(old)} + \eta(x_{ij}^{p} - z_{pj}^{old}) \\ w_{pj}^{U(new)} = w_{pj}^{U(old)} + \eta(x_{ij}^{p} - z_{pj}^{old}) \end{cases} \tag{10}$$

$$\begin{cases} w_{k^*j}^{L(new)} = w_{k^*j}^{L(old)} - \eta(x_{ij}^{p} - z_{k^*j}^{old}) \\ w_{k^*j}^{U(new)} = w_{k^*j}^{U(old)} - \eta(x_{ij}^{p} - z_{k^*j}^{old}) \end{cases} \tag{11}$$

where η is a learning rate. The result of tuning two clusters' weights shown in Fig. 3, which clearly indicates the change of ED_A and ED_B. The cluster of pattern x_{ij} is changed from cluster A to B because $ED_A > ED_B$. From this step, we can clearly see that the learning process is only to adjust the weights of the p-th and the k^*-th clusters. Therefore, the proposed method has a rapid speed advantage over other supervised learning algorithms and can quickly adapt to new and important information.

Step 7: Repeat Step 3 to Step 6, and if all patterns have been classified then a learning epoch is finished.

Step 8: Stop if the clustering process has converged or the total error rate E_τ has arrived at a preset value; otherwise, return to Step 3.

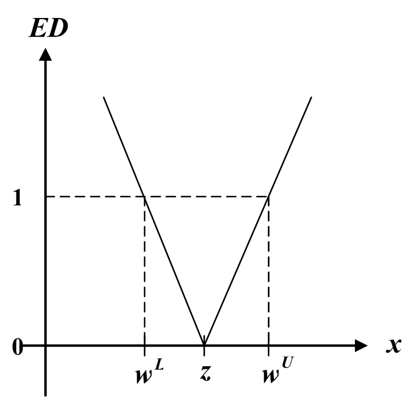

Fig. 2. The proposed extension distance

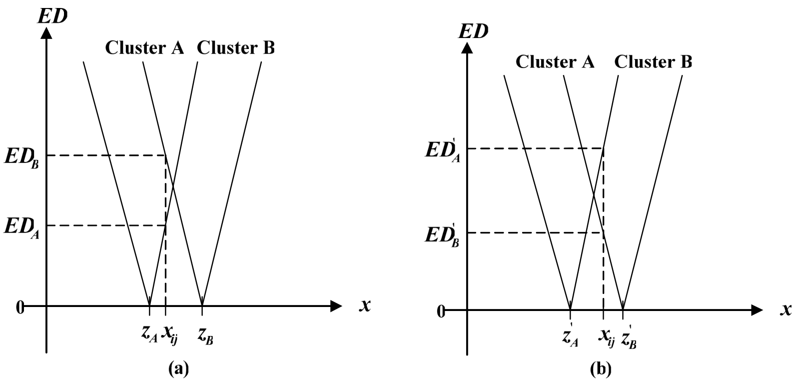

Fig. 3. The results of tuning cluster weights: (a) original condition; (b) after Tuning

It should be noted that the proposed ENN can take input from human expertise before the learning, and it can also produce meaningful output after the learning, because the classified boundaries of the features are clearly determined.

2.2 Operation Process of ENN

There can be recognition or sorting the cluster clearly when the ENN completes a learning procedure and its operation procedure is summarized as follows:

Step 1: Read the weighting matrix of ENN.

Step 2: Calculate the initial cluster centers of every cluster by using equation (4) and equation (5).

Step 3: Read the test pattern.

$$X_t = \{x_{t1}, x_{t2}, \ldots, x_{tn}\} \tag{12}$$

Step 4: Use the proposed extension distance (ED) to calculate the distance between the tested pattern and every existing cluster by equation (7).

Step 5: Find the k^*, such that $ED_{ik^*} = \min\{ED_{ik}\}$, and set the $O_{ik^*} = 1$ to indicate the cluster of the tested pattern.

Step 6: Stop, if all the test patterns have been classified, otherwise go to Step 3.

3 The Proposed Traffic Light Control Method

We can divide traffic flow into nine categories according to the number of passing vehicles and the passing time of vehicles during a green light time period. The represented symbols of these categories are described below:

- TF_1: High traffic flow in main-line and high traffic flow in sub-line.
- TF_2: High traffic flow in main-line and medium traffic flow in sub-line.
- TF_3: High traffic flow in main-line and low traffic flow in sub-line.

- TF_4: Medium traffic flow in main-line and high traffic flow in sub-line.
- TF_5: Medium traffic flow in main-line and medium traffic flow in sub-line.
- TF_6: Medium traffic flow in main-line and low traffic flow in sub-line.
- TF_7: Low traffic flow in main-line and high traffic flow in sub-line.
- TF_8: Low traffic flow in main-line and medium traffic flow in sub-line.
- TF_9: Low traffic flow in main-line and low traffic flow in sub-line.

The actual measured 900 data of different flows at certain crossroads are used to train the ENN proposed in the previous section. To obtain higher and precise convergence rate, the learning rate η and total error rate E_τ are set to be 0.2 and 0.1%, respectively. After the training procedure, one can find that the total error rate is 0% and only learning times 16 is needed.

The proposed ENN method can calculate the distance with respect to each cluster, and accordingly the traffic flow cluster and green light time in next period can be determined. To increase the sensitivity and adaptive capability, the green light time G_{time}^* of next period in each line is determined as follows:

$$G_{time}^* = G_{time,r} + (G_{time,n} - G_{time,r}) \times \frac{ED_r}{(ED_r + ED_n)} \tag{13}$$

Where $G_{time,r}$ and ED_r are the nominal green light time and extended distance of the judged traffic flow cluster. Whereas $G_{time,n}$ and ED_n are the nominal green light time and extended distance next to the judged traffic flow cluster. The nominal green light time of high, medium, and low traffic flow are indicated as GH_n, GM_n and GL_n, respectively.

4 Experimental Results

To prove the effectiveness of the ENN traffic light control method, the traffic flow records at certain crossroads are first selected to test. Table 1 lists the 18 tested data selected arbitrarily from the traffic flow records. The passing time among the vehicles passing through the main-line (c_1) and sub-line (c_3) within the green light time period of one traffic light cycle can be calculated by using the infra-red timer. The number of passing vehicles in the main-line (c_2) and sub-line (c_4) within the green light time period of one traffic light cycle can be counted by using the infra-red counter. Table 2 shows the identified results of the proposed method. Compared to the test data listed in Table 1, it shows the proposed method can correctly recognize the traffic flow cluster. For instance, in tested number 3, the ED_{TF2} (2.02) is the minimum value for the traffic flow cluster TF_2. It signals the crossroad is now toward high traffic flow in the main-line and medium traffic flow in the sub-line. Besides, the ED of other traffic flow cluster are all above 2.02, which means the possibility of the other traffic flow cluster is much lower than the traffic flow cluster TF_2. Letting $GH_n = 25\sec$, $GM_n = 15\sec$, and $GL_n = 8\sec$, the green light time period G_{time}^* of main-line and sub-line found from (13) are 24sec and 18sec, respectively.

Table 1. The tested traffic flow data selected from the records at certain crossroad

Test no.	c_1	c_2	c_3	c_4
1(TF_1)	5.74132	0.775133	5.99438	1.66561
2(TF_1)	4.20955	0.648859	6.3288	2.28554
3(TF_2)	4.068	2.79041	2.80516	0.44863
4(TF_2)	5.76158	2.20405	1.95535	0.488244
5(TF_3)	3.25161	1.77464	1.15812	0.007883
6(TF_3)	5.55277	1.87215	1.12699	0.008835
7(TF_4)	1.67236	0.301306	4.58024	1.55529
8(TF_4)	3.49254	0.274962	4.14906	1.28237
9(TF_5)	1.91049	0.371855	1.69464	0.208063
10(TF_5)	2.76221	0.41706	1.50794	0.152139
11(TF_6)	3.4022	0.467625	1.65596	0.076918
12(TF_6)	1.86082	0.29613	0.022523	0.009581
13(TF_7)	0.427486	0.024916	5.85175	2.09693
14(TF_7)	1.475	0.039962	4.19514	2.90234
15(TF_8)	0.5038	0.091482	1.8569	0.111365
16(TF_8)	1.122	0.061527	2.73535	0.383965
17(TF_9)	1.24789	0.033883	0.519273	0.006247
18(TF_9)	0.435039	0.076354	1.2066	0.020695

Table 2. The identified results of the proposed traffic flow control method

Test no.	The distance between i-th tested pattern and k-th cluster									Judged cluster	Green Light time period	
	ED_{TF1}	ED_{TF2}	ED_{TF3}	ED_{TF4}	ED_{TF5}	ED_{TF6}	ED_{TF7}	ED_{TF8}	ED_{TF9}		Main -line (sec.)	Sub-line (sec.)
1	1.91	8.20	35.63	4.96	12.95	39.48	18.86	30.47	62.69	TF_1	22	23
2	2.66	11.93	47.10	3.62	14.30	49.04	14.50	29.31	71.49	TF_1	21	23
3	5.03	2.02	11.10	16.23	12.66	23.04	53.96	61.24	71.52	TF_2	24	18
4	4.11	1.41	9.93	14.73	12.24	21.05	46.22	52.26	61.62	TF_2	24	18
5	6.23	4.39	2.20	11.93	9.55	9.03	36.51	41.35	40.00	TF_3	23	10
6	4.90	3.12	1.19	13.78	11.81	11.32	41.01	46.38	45.10	TF_3	23	10
7	4.68	9.31	34.22	1.36	8.22	32.51	5.71	13.68	43.20	TF_4	17	24
8	4.09	6.94	27.90	1.79	5.85	26.62	7.91	13.77	38.86	TF_4	18	23
9	7.55	4.98	7.29	4.35	2.73	4.91	9.93	9.22	12.76	TF_5	19	19
10	7.16	4.85	5.54	4.41	2.67	3.24	11.89	11.70	13.43	TF_5	19	12
11	6.68	4.69	3.99	5.00	3.12	2.49	13.53	13.84	13.96	TF_6	19	11
12	8.93	7.00	4.59	5.18	4.69	2.81	9.64	9.96	8.38	TF_6	19	11
13	5.32	13.29	46.09	3.04	13.84	46.12	2.09	12.90	50.84	TF_7	11	24
14	5.03	15.02	57.30	3.26	15.31	57.54	2.00	15.61	65.81	TF_7	11	24
15	8.61	6.23	6.91	5.70	4.67	5.54	4.80	2.89	3.96	TF_8	11	12
16	7.43	4.23	12.32	4.75	3.07	11.11	3.06	0.98	10.45	TF_8	10	17
17	9.18	7.21	4.63	6.48	5.90	4.11	5.24	4.63	2.25	TF_9	10	10
18	9.18	7.09	5.13	6.29	5.73	4.55	5.06	3.66	2.19	TF_9	10	11

5 Conclusions

In this paper, an intelligent traffic flow estimation method based on the extension neural network theory for a standard crossroad was proposed. The experimental results show the proposed traffic flow diagnosis method can easily recognize the main traffic flow cluster and determine the green light time period of main-line and sub-line in next cycle. The good features of the proposed traffic flow diagnosis method include less learning time, higher accuracy and less memory consumption. When the traffic flow of the selected crossroad changes, only a fractional amount of the data should be adjusted, thus the update interval may be much reduced. Therefore, the proposed traffic light control method will be easy to implement in a real-time traffic flow detecting device or a portable instrument. It is also has good economic benefits to apply the proposed traffic light control method to the coordinated control of area traffic.

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