Intelligent Control Strategy of Traffic Light at Urban Intersection

http://dx.doi.org/10.3991/ijoe.v9i3.2681

Qiang Han[1] and Yong Zhou[2]
[1] Shandong University of Finance and Economics, Jinan, China
[2] Institute of Science and Technology Development Strategy of Shandong Province, Jinan, China

***Abstract*—Urban traffic is closely bound up with daily life, and traffic light is set to let vehicles pass an intersection periodically in certain way. With the sprawl of modern city, its traffic system is getting so complex that conventional way can't improve its performance any more. So, based on system control theory, this paper makes traffic light control system optimized in three organic steps: first, adopts circular coloring method to determine the optimal phase number; then assigns proper green light time to each phase by fuzzy control rule; finally, improves current scheme on a 3-layered feedforward neural network. Simulation result demonstrates the effectiveness of this method.**

***Index Terms*—Intelligent Transportation Control System, Coloring Theory, Fuzzy Control, Fuzzy Neural Network**

I. INTRODUCTION

With the increment of motors, it is an important task to lead traffic flow off an intersection smoothly and effectively. To settle this problem, some accurate mathematical models have been constructed as in [1, 2, 3]. However complex and smart the models are, they still stimulate the real life in ideal state, and remain true only in early city without so many motors.

The best way to lead traffic flow out of an intersection is appointing a sophisticated traffic policeman at the intersection. Ref. [4] set up the fuzzy set theory, a powerful tool was applied to traffic control. Since fuzzy control is near human thought, it can describe the realism better. In 1976, Ref. [5] applied fuzzy control into traffic control at a single intersection for the first time, and got good effect. Ref. [6] gave information-fusion method for urban traffic flow based on fuzzy rough set theory to increase accuracy for traffic detecting. Ref. [7] described the application of a specific class of neuro-fuzzy system known as the Pseudo Outer-Product Fuzzy-Neural Network using Truth-Value-Restriction method (POPFNN - TVR) for modeling traffic behavior. Ref. [8] presented a fuzzy method for an isolated signalized intersection. Ref. [9] applied a traffic signal controller with two fuzzy layers for signalizing roundabouts.

Traffic light control may go beyond what have mentioned. A traffic control system should contain the following three functions: (1) determine the optimal phase number according to an intersection; (2) assign proper green light time for each phase; (3) extract better and better time assignment scheme. The first level is to partition the traffic flow by least phase, which is the basic function of a traffic control system; the second level assigns proper time for each phase such that as many cars as possible leave the intersection; the third level optimizes existing rules in the second level. If the second and third level are kept repeating, then the control system can be more and more efficient.

II. DETERMINE THE OPTIMAL PHASE

Traffic flows at an intersection have different directions. The conflict can't be avoided if all the traffic flows leave the intersection at the same time. So, traffic flow in different direction must have different green light. The time in which all the traffic flows pass the intersection once is called a cycle. Each green time is a phase.

Graph is an ideal model to solve this problem. Any notations and terms without special description are derived from [10]. Given traffic flows at an intersection, the corresponding graph $G=(V, E)$ can be constructed as follows: every traffic flow is represented by a vertex, and two vertices are adjacent if the corresponding traffic flows are not compatible. Circular coloring in [11] has an important application in phase optimization.

Let C be a circle of length r. An *r-circular coloring of a graph G* is a mapping c which assigns to each vertex x of G an open unit arc $c(x)$ of C, such that for every edge (x, y) of G, $c(x)\cap c(y)=\Phi$. A graph G is called r-circular colorable if there is an r-circular coloring of G. The *circular chromatic number* of a graph, denoted by $x_c(G)$, is defined as $x_c(G)=\inf\{ r : G \text{ is } r\text{-circular colorable.} \}$

For any limited graph G, $x_c(G)$ is always rational. For any graph G, $x(G)-1< x_c(G) < x(G)$.

Then, the definition of circular coloring has implied the relation between the problem to be solved and the circular coloring: a complete traffic period may be taken as a circle C, and each vertex (i.e., each traffic flow) is assigned an interval of C of unit length, which is the time interval during which the corresponding traffic flow has the green light. Thus adjacent vertices of the graph are assigned to disjoint intervals of C, and our objective is to minimize the total length of the circle C. Also, it is obvious that what should be concentrated is how many time intervals are wanted to partition the traffic flow, so it doesn't matter that every time interval is supposed to be of unit length. So, the optimum phase amount equals to the circular chromatic number of the corresponding graph.

See Fig 1 for a standard intersection, that is, there are traffic flows along all the directions, including pedestrians and non-motorized vehicles as numbered 1, 5, 9 and 13. Vehicles and pedestrians in each direction have their lanes. The left turn of pedestrians and non-motor vehicles is forbidden. According to the conflict relation between traffic flows, G in Fig. 2 is obtained. If pedestrians and non-motorized vehicles are taken into account temporarily, H in Fig. 3 can be obtained, which is one special graph in a family of B_n when n equals to 8. Then circular chromatic number of Fig. 3 can be computed by the formula $\chi_c(B_n) = n/\lfloor n/3 \rfloor$ in Ref. [12] as follows:

$$\chi_c(H_4) = \chi_c(B_8) = 8/\lfloor 8/3 \rfloor = 8/2 = 4$$

Because H is sub-graph of G, $x_c(G)$ is not less than $x_c(H)$. One most adopted partition scheme of traffic flows is:{1, 3, 9, 11}, {2, 4, 10, 12}, {5, 7, 13, 15}, {6, 8, 14, 16}. So $x_c(G)$ should not be more than 4. Thus $x_c(G) = 4$.

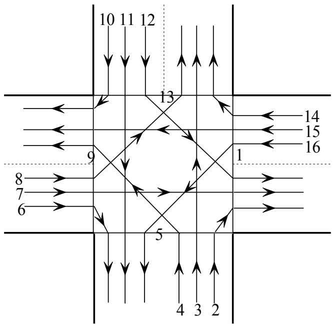

Figure 1. Simplified graph of an intersection

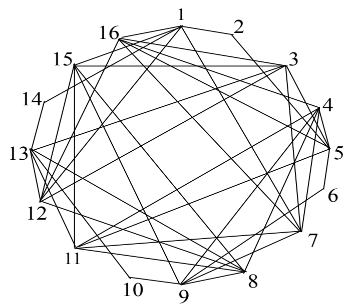

Figure 2. G - Traffic flow relation graph

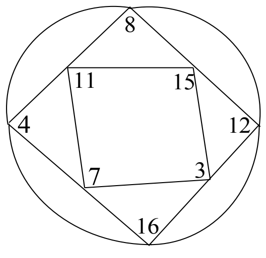

Figure 3. H - Traffic flow relation sub-graph

III. ASSIGN GREEN LIGHT TIME FOR EACH PHASE

Besides taking the queue length as the standard for time extension, this paper will also consider the open green light time, which adds the practicability of the rules. In addition, if there are too much or little traffic flows in all the phases, timed control should be adopted. So, this standard is put forward that if maximum queue length among all the phases is always more than or less than a constant in three continuous cycles, time control should be adopted; if maximum queue length is between two constants in three continuous cycles, then the traffic jam might have gone away, fuzzy control comes back.

Generally, green light time of every phase can't be less than 15s lest that cars off the stop line have no enough time to pass; meanwhile, green light time shouldn't be more than 200s since wait in too long time will affect the driver's mood. Traffic control at a single intersection is that after the determination of optimal phase, certain green light time for each phase should be assigned such that cars can pass the intersection smoothly and the queue length is minimized.

Suppose L_0 is the queue length of current phase, L is that of the next phase; G is the passed green light time, ΔG is the extension of green light time. Let $\Delta L= L_0 - L$. The control algorithm is as follows:

Step 1. If fuzzy control is applied, go to Step2; otherwise, go to Step3;

Step 2. If maximum queue length among all the phases is always more than or less than a constant in three continuous cycles, then fuzzy control presides, and go to Step3; otherwise, keep timed control, and go to Step1;

Step 3. Fuzzy control rule is as follows:

Step 3.1 If maximum queue length is between two constants in three continuous cycles, then resume time control, and go to Step2; otherwise, go to the next step;

Step 3.2 Give green light time ΔG=10s to phase 1;

Step 3.3 Compute ΔL by L_0, L and in ΔG;

Step 3.4 Determine the extension ΔG according to G, L_0, and ΔL. If $G+\Delta G\leq 200$, then extension is ΔG; otherwise, the extension is ΔG=200 - G;

Step 3.5 If the green light time for the current phase has reached 200s, then the next phase has the road light; give initial time ΔG=10s to it, then go to Step3.3;

In application, monitoring data should be transformed into fuzzy quantity first, which produces fuzzy output by fuzzy control rule. Then, according to certain principle, such as maximum membership degree principle, fuzzy output is defuzzified. Every control rule includes three inputs and one single output, which format is as follows: If $G=g_i$ and $L_0=l_j$ and $\Delta L =\Delta L_k$, then $\Delta G = \Delta g_l$.

IV. EXTRACT BETTER TIME ASSIGNMENT SCHEME

As to the existing traffic light control system, its rules might not be applicable in the new situation, which then need modifying according to the need.

A. Network Structure

Zero-order Takagi-Sugeno fuzzy model is adopted here, which is often used in time series prediction and parametric estimation, etc. It makes output variables as the function of input variables.

$$y_j(x) = C_j^1 x_1 + C_j^2 x_2 + \cdots + C_j^n x_n + C_j^0$$

Where, $\{x_i\}$ (i= 1, …, n) means n inputs, and $\{y_j\}$ (j= 1, …, m) means m outputs.

General rule of the Takagi-Sugeno model is as follows:

R_k: If x_1 is A_1^k, and x_2 is A_2^k, …, and x_n is A_n^k, then y_1 is b_1^k, …, and y_m is b_m^k, Where, b_j^k is single fuzzy element defined on output variable. Also, membership function of fuzzy set A_i^k is defined from Gaussian:

$$\mu_i^k(x_i) = e^{-(x_i-\omega_i^k)^2 / (\sigma_i^k)^2},$$

where, ω_i^k, σ_i^k are center and width of this normal distribution, respectively. One input $\bar{x}^\circ = (x_1^\circ, x_2^\circ \cdots x_n^\circ)$ produces exact value $\bar{y}^\circ = (y_1^\circ, y_2^\circ \cdots y_m^\circ)$ by

$$y_j^\circ = \sum_{k=1}^{R} \mu^k(\bar{x}^\circ) \cdot b_j^k \Big/ \sum_{k=1}^{R} \mu^k(\bar{x}^\circ),$$

where, $\mu^k(\bar{x}^\circ) = \prod_{i=1}^{n} \mu_i^k(x_i^\circ)$ is satisfaction degree of the kth fuzzy rule and R is the number of rules.

Since fuzzy control system in Part III has three inputs and one output (n = 3, m = 1), 3-layered feedforward neural network can be constructed. See Fig. 4 for its topology, in which one dotted box represents one fuzzy rule, and detailed execution process and meaning of every layer is as follows:

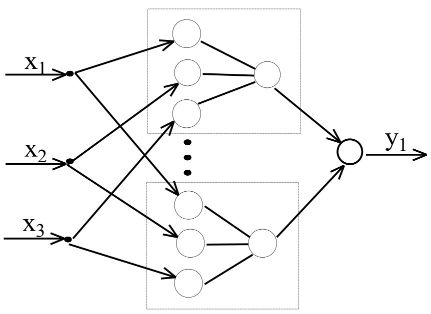

Figure 4. 3-layered neural network

The first layer is system input. Nodes in this layer are divided into R groups, each of which shows condition of one rule. Every group receives exact input (x_1, x_2, …, x_n), judges its validity, computes the degree to which it belongs to fuzzy set A_i^k by

$$f_i^{k(1)}(x_i) = e^{-(x_i-\omega_i^k)/(\sigma_i^k)^2},$$

then produces one number between 0 and 1.

In the second layer, every node means one rule. After receiving the input from the first layer, it outputs

$$f_k^{(2)}(\bar{x}) = \prod_{i=1}^{n} f_i^{k(1)}(x_i).$$

The third layer is system output. Since there is only one output in traffic light control system, this layer has single node (j = 1) and output

$$f_j^{(3)}(\bar{x}) = \sum_{k=1}^{R} f_k^{(2)}(\bar{x}) \cdot b_j^k \Big/ \sum_{k=1}^{R} f_k^{(2)}(\bar{x}).$$

B. Learning Algorithm

The learning algorithm is as follows:

Step 1. Initialize and input training sample set S;

Step 2. Guided learning process;

Step 2.1 Choose one sample $(\bar{x}, \bar{y})$ from S;

Step 2.2 forward: input $\bar{x}$ reduces one output $f_j^{(3)}$, j= 1, …, m;

Step 2.3 backward: compute errors of nodes ($j \in L_3, k \in L_2$ and $i_k = L_1$) in three layers as

$$\delta_j^{(3)} = -\frac{\partial E}{\partial f_j^{(3)}} = y_j - f_j^{(3)},$$

$$\delta_k^{(2)} = -\frac{\partial E}{\partial f_k^{(2)}} = -\sum_{j=1}^{m} \frac{\partial E}{\partial f_j^{(3)}} \frac{\partial f_j^{(3)}}{\partial f_k^{(2)}} = \sum_{j=1}^{m} \delta_j^{(3)} (b_j^k - f_j^{(3)}),$$

$$\delta_i^{k(1)} = -\frac{\partial E}{\partial f_i^{k(1)}} = -\frac{\partial E}{\partial f_j^{(2)}} \frac{\partial f_k^{(2)}}{\partial f_i^{k(1)}} = \delta_k^{(2)} \cdot \frac{\partial f_k^{(2)}}{\partial f_i^{k(1)}};$$

Step 2.4 Modify: revise the weights by the following formulas

$$\Delta b_j^k = \eta \delta_j^{(3)} \cdot f_k^{(2)} \Big/ \sum_{t=1}^{K} f_t^{(2)},$$

$$\Delta \omega_i^k = \eta \delta_i^{k(1)} \left[2(x_i - \omega_i^k) / (\sigma_i^k)^2 \right] f_i^{k(1)},$$

$$\Delta \sigma_i^k = \eta \delta \left[2(x_i - \omega_i^k)^2 / (\sigma_i^k)^3 \right] f_i^{k(1)};$$

Step 2.5 If $E < \varepsilon$, go to Step 2.6, else go to Step 2.1;

Step 2.6 Guided learning process ends and go to Step 3;

Step 3. Improved competitive learning process;

Step 3.1 choose one sample from S, compute

$$d(\bar{x}, \bar{\omega}^k) = n_k \left\| \bar{x} - \bar{\omega}^k \right\| \Big/ \sum_{t=1}^{K} n_t, \text{ for } k = 1, \ldots, K.$$

Here, n_k is the number of winners in the second layer.

Step 3.2 Determine winners and competitors by

$$d(\bar{x}, \bar{\omega}_c) = \min_k \{ d(\bar{x}, \bar{\omega}_k) \} \},$$

$$d(\bar{x}, \bar{\omega}_r) = \min_{k \neq c} \{ d(\bar{x}, \bar{\omega}_k) \};$$

Step 3.3 Update weights by

$$\bar{\omega}_c = \bar{\omega}_c + \alpha_c \left\| \bar{x} - \bar{\omega}_c \right\|,$$

$$\bar{\omega}_r = \bar{\omega}_r - \alpha_r \left\| \bar{x} - \bar{\omega}_r \right\|,$$

where, $0 \le \alpha_r \le \alpha_c \le 1$, are learning ratios.

Step 3.4 If $\frac{1}{K} \sum_{k=1}^{K} \left\| \bar{\omega}_k(t+1) - \bar{\omega}_k(t) \right\| < \varepsilon$, go to Step 3.5, else go to Step 3.1;

Step 3.5 Delete all nodes with n_k=0;

Step 4. End.

During learning, by continuous modification of the parameters, not only membership function can be adjusted automatically, but also importance and validity of the rule can be valued. If the weight is greater than 0, then the corresponding rule reflects true condition. The greater the weight is, more important the rule is. Conversely, if the weight is less than 0, the corresponding rule can't accord with the real condition, then it should be modified and new learning begins. Those rules with the weight near 0

TABLE I.
SIMULATION RESULT OF AVERAGE QUEUE LENGTH IN EACH CYCLE

Average traffic volume of phase 1, 2, 3 and 4 (cars/s)	0.30	0.32	0.34	0.36	0.38	0.30	0.28	0.26
	0.24	0.22	0.20	0.18	0.16	0.18	0.20	0.22
	0.32	0.34	0.36	0.38	0.28	0.32	0.38	0.40
	0.22	0.24	0.26	0.20	0.18	0.20	0.22	0.20
Method in [8]	2.41	3.36	4.56	5.61	3.27	2.03	2.86	3.16
Method in this paper	2.41	3.34	4.52	5.56	3.25	2.03	2.85	3.14

have no much effect on the computation, which can be deleted. Modified rules constitute a new rule database. Adjacency relation can be set newly according to new rules and the network is initialized once again. After several cycles of initialization and modification, we will obtain a network simulating real mapping relation and the simplest rule database in the form of fuzzy language.

V. SIMULATION RESULT

After continuous learning, error between real output of the above artificial neural network and expected output can be less than 10^{-3}. Simulation computer program has been developed for artificial neural network after off-line learning by MATLAB. Traffic flow is simulated by binomial distribution. Average traffic volume is under control to be the same as [8]. We can see from Table 1 that after a period of learning, our method can realize the effect of [8], and superior to it partly.

VI. CONCLUSIONS

In this paper, intelligent control of traffic light is realized from such three levels that phase design, real time control and self-learning with the help of circular coloring, fuzzy control and artificial neural network. It perfects function of traffic light more than traditional method of emphasizing particularly on certain level. The work to be done includes computing the optimal phase number of other intersections and designing the phase assignment scheme practically, which makes optimal phase number usable.

REFERENCES

[1] M. Castro-Neto, Y. Jeong, M. Jeong and L. D. Han, "Online-SVR for short-term traffic flow prediction under typical and atypical traffic conditions," *Expert Systems with Applications,* vol. 36, no. 3, pp. 6164–6173, April 2009. http://dx.doi.org/10.1016/j.eswa.2008.07.069

[2] R. YU, G. Wang, J. Zheng and H. Wang, "Urban road traffic condition pattern recognition based on support vector machine," *Journal of Transportation Systems Engineering and Information Technology*, vol. 13, no. 1, pp. 130–136, February 2013. http://dx.doi.org/10.1016/S1570-6672(13)60097-5

[3] R. C. Carlson, I. Papamichail, M. Papageorgiou and A. Messmer, "Optimal motorway traffic flow control involving variable speed limits and ramp metering," *Transportation Science*, vol. 44, no. 2, pp. 238-253, May 2010. http://dx.doi.org/10.1287/trsc.1090.0314

[4] L. A. Zadeh, "Outline of a new approach to the analysis of complexity systems and decision process," *IEEE Trans on Systems, Man, and Cybernetics*, SMC-3, pp. 28-44, 1973. http://dx.doi.org/10.1109/TSMC.1973.5408575

[5] C. P. Pappis and E. H. Mamdani, "A fuzzy logic controller for a traffic junction," *IEEE Trans on Systems, Man, and Cybernetics*, SMC-7(10), pp. 707-717, 1977. http://dx.doi.org/10.1109/TSMC.1977.4309605

[6] N. Chen and X. Xu, "Information-fusion method for urban traffic flow based on evidence theory combining with fuzzy rough set," *Journal of Theoretical and Applied Information Technology*, vol. 49, no. 2, pp. 560-566, March 2013.

[7] C. Quek, M. Pasquier and B. Lim, "A novel self-organizing fuzzy rule-based system for modeling traffic flow behavior," *Expert Systems with Applications*, vol. 36, no. 10, pp. 12167–12178, December 2009.

[8] Q. Pu, "Application of fuzzy method in signal control at intersection," *Transportation Standardization*, no.19, pp. 125-129, 2011.

[9] Y. Gong and J. Zhang, "Real-time traffic signal control for roundabouts by using a PSO-based fuzzy controller," *IEEE Congress on Evolutionary Computation (CEC)*, pp. 1–8, 2012.

[10] R Balakrishnan and K Ranganathan, "A textbook of graph theory (second edition)," *Springer New York Heidelberg Dordrencht London*, 2012.

[11] J. Nešetřil, P. Mendez and D. Wood, "Characterisations and examples of graph classes with bounded expansion," *European Journal of Combinatorics*, vol. 33, no. 3, pp. 350–373, April 2012.

[12] X. Yan and G. Liu, "Circular chromatic number of one special planar graph," *Journal of Shandong University (Natural Edition)*, vol. 38, no. 3, pp. 43-48, 2003.

AUTHORS

Qiang Han is with the School of Management Science and Engineering, Shandong University of Finance and Economics, Jinan, Shandong Province 250014 China (e-mail: hanqiang18@sina.com).

Yong Zhou is with the Institute of Science and Technology Development Strategy of Shandong Province, Jinan, Shandong Province 250014 China (e-mail: bft@qq.com).

This work was supported partly by the National Natural Science Fund of PRC (71201093) and Shandong Province Soft Science Project of PRC (2010RKMA1001). Manuscript received 15 April 2013. Published as resubmitted by the authors 12 June 2013.