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Real Time Traffic Signal Learning Control Using BPNN Based on Prediction for Probabilistic Distribution of Standing Vehicles

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Abstract**:** In this paper, a new method to predict the probabilistic distribution of traffic jam at crossroads and a traffic signal learning control system are proposed. First, the Dynamic Bayesian Network is used for build a forecasting model to predict the probabilistic distribution of vehicles for traffic jam during the each period of traffic signal. The adjusting algorithm of traffic signal control is applied to maintain the probability of a lower limit and ceiling of the standing vehicles to get the desired probabilistic distribution of the standing vehicles. In order to achieve the real time control, a learning control system based on the Back Propagation Neural Network is used. Finally, the effectiveness of the new traffic signal control system using the actual traffic data will be shown.

Keywords**:** Traffic signal control, Bayesian Network, BP neural network, probabilistic distribution

Ⅰ INTRODUCTION

In recent years, the traffic congestion has become serious problem. The traffic volume continues to increase and the streets are congested with cars. The traffic signal control is the most-effective method to solve the problem.

In general terms, the traffic signal has three parameters that are cycle time, split, and offset. Traffic signal control method is selected on the complexity from the simple system that uses historical data to determine fixed timing plans, to the adaptive signal control, which optimizes timing plans for a network of signals according to traffic conditions in real time. As the adaptive signal control, the traffic forecasting has been known as a most important part. [1]

In this paper, the historical data and real time traffic flows of the adjacent to crossroads are used to predict the probabilistic distribution of standing vehicles. After that, the traffic signals are adjusted until to get desired probabilistic distribution of the standing vehicles. Finally, the BPNN model to establish the real time traffic signal learning control system is used.

Ⅱ FORECASTING MODEL

The Bayesian network is applied to build a forecasting model of the standing vehicles at crossroads. The Bayesian network is a directed and acyclic graphical model, and each node represents variables of the given problem. The relationship between each variable is evaluated quantitatively using the conditional probability. [2]

2.1 Bayesian network model of standing vehicles

Two crossroads are considered in this paper as shown in Fig.1.

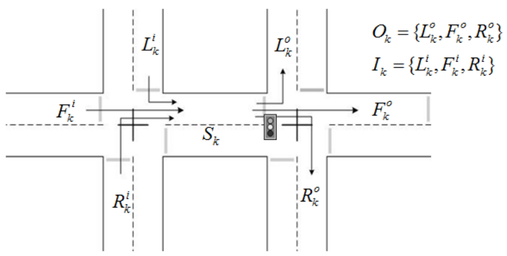

Fig.1 Crossroads

The random variables of the inflows *Ik*, and the outflows *Ok* and the standing vehicles *Sk* between crossroads have relationship as following: *Sk* = *S*(*k*-1)+*Ik*-*Ok*. And then, the Bayesian network model is built up using this relationship, and the random variables of the inflows and the outflows of each direction and the standing vehicles are represented as the nodes. The Bayesian network model is shown in Fig.2.

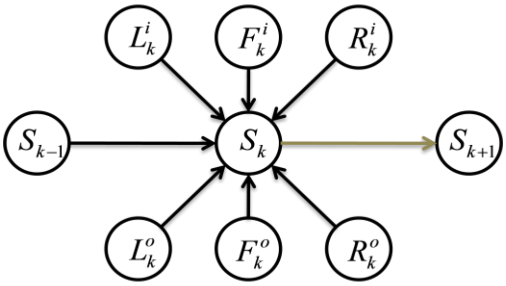

Fig.2 Bayesian network model of standing vehicles

The probabilistic distribution of the standing vehicles at *k th* cycle is obtained by summing over all values of the other variables as following,

$$P(S_k)=\sum_{S_{k-1}}\sum_{F_k^i}\sum_{R_k^i}\sum_{L_k^i}\sum_{F_k^o}\sum_{R_k^o}\sum_{L_k^o}P(S_k,S_{k-1},F_k^i,R_k^i,L_k^i,F_k^o,R_k^o,L_k^o) \qquad (1)$$

With the chain rule, the joint probabilistic distribution is represented as the product of the conditional probability. And then, according to the d-separation, Eq.(1) can be represented as

$$P(S_k)=\sum_{S_{k-1}}\sum_{F_k^i}\sum_{R_k^i}\sum_{L_k^i}\sum_{F_k^o}\sum_{R_k^o}\sum_{L_k^o}P(S_{k-1}) \times P(F_k^i)P(R_k^i)P(L_k^i)P(F_k^o)P(R_k^o)P(L_k^o) \qquad (2)$$

According to Eq.(2), the probabilistic distribution of the standing vehicles is predicted.

2.2 Procedure of prediction for probabilistic distribution of standing vehicles

In order to get the optimal traffic signals, the prediction of the probabilistic distributions of standing vehicles carried out three cycles before, because future probabilistic distribution of standing vehicles are necessary to adjust the traffic signals.

The procedure of the update for the priori probability and prediction for the probabilistic distribution of standing vehicles are illustrated in Fig.3. Firstly, the priori probability of each variable is updated by the previous data at *(k-1) th* cycle. Then, the probabilistic distribution of standing vehicles at *k th* cycle is predicted using Eq.(2). The future traffic densities are not measured, so the probabilities of the inflows and the outflows at *k th* cycle are assumed to be equal to those at *(k-1) th* cycle based the pre-timed signals. Next, the adjusting algorithm is applied to get the optimal traffic signals and it is used for update the priori probability of the outflows. The adjusting algorithm will be described at next session. Finally, at *k th* cycle the probabilistic distribution of standing vehicles is calculated to predict next cycles. The process of prediction at *(k+1) th* and *(k+2) th* cycles is the same as the *k th* cycle.

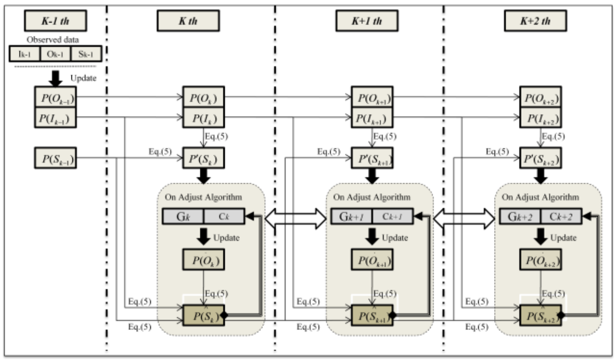

Fig.3 Procedure of prediction for standing vehicles

Ⅲ TRAFFIC SIGNAL CONTROL SYSTEM

The traffic signal control system has two parts: online and offline processing. In the online processing, BPNN is used for calculate the optimal traffic signals based on the result of the forecasting model for the prediction of standing vehicles. And then, the adjusting algorithm is applied to update the weight of BPNN model in offline processing. The Fig.4 shows the procedure of the traffic control system.

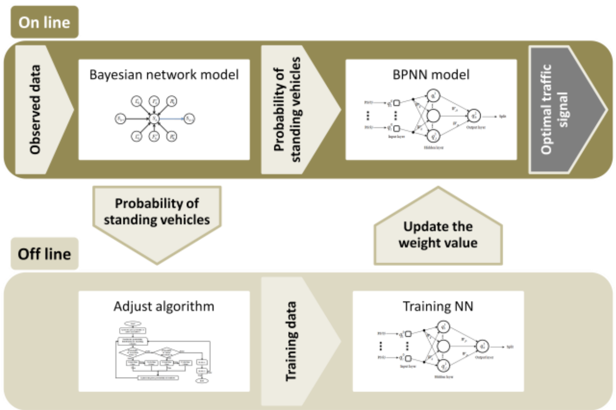

Fig. 4 Procedure of traffic signal control

3.1 Adjusting algorithm of traffic signals

The flowchart of the adjust algorithm is illustrated in Fig.5. The adjust procedure is followed.

Step1: Using observed data of *(k-1) th* cycle, update the priori probabilities of the inflows, the outflows, and the standing vehicles.

Step2: Predict the probabilistic distribution of the standing vehicles at *k th* cycle on pre-timed signal.

Step3: If the probability of over *Smax* of standing vehicles is bigger than a set value *a*, then extend the split or cycle time. And, if the probability of below *Smin* of standing vehicles is bigger than a set value *ß*, then shorten the split or cycle time. The *Smax* and *Smin* are obtained empirically.

Step4: Using new traffic signals, update the priori probability of the outflows.

Step5: Recalculate the probabilistic distribution of standing vehicles of *k t*h cycle.

Step6: If the adjustment of *k th* cycle is finished, go to next cycle.

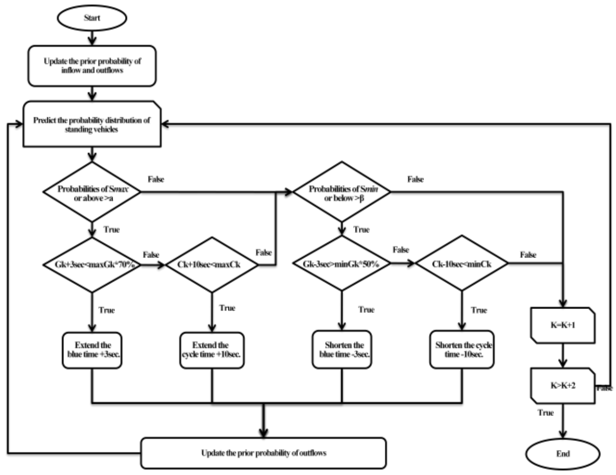

Fig.5 Flowchart of adjust algorithm

For the update of the prior probability for the outflows, the expected and it nearby values are increase and decrease the others.

3.2 Real time control system by BPNN model

The new traffic signal learning control by BPNN model is proposed for the real time control. The traffic signals are adjusted based the predicted and improved probabilistic distribution of the standing vehicles, which satisfy the condition of the probabilities for over Smax and over Smin. So that, the optimal traffic signals can be deduce using the pattern of its desirable probabilistic distribution of standing vehicles.

The BPNN model is powerful learning system, and it can be applied to pattern recognition. The BPNN is a multi-layers network that consists of the input layer, the hidden layer, and the output layer. And then, the BP algorithm can train a given feed-forward multilayer neural network for a given set of input patterns.

The BPNN model of the traffic signal control system is shown in Fig.6. The input values are the probabilities of standing vehicles, which probabilities are predicted by the Bayesian network model, and the output value are traffic signals.

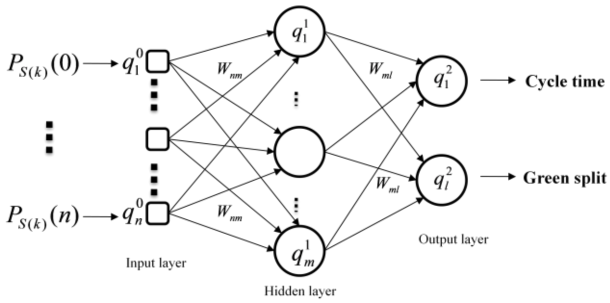

Fig.6 Structure of the BPNN

In this model, the number of the neurons are determined by the number of the input layer. The traffic signal is consisted of two parameters in this paper, green split and cycle time. So, 2 neuron in the output layer are set up. The number of the hidden layer can be calculated by empirical formula as following Eq.(3).

$$m = \sqrt{n \times l} \tag{3}$$

n= number of the neuron in the input layer

m =umber of the neuron in the hidden layer

l=number of the neuron in the output layer

Ⅳ SIMULATION

To prove the effectiveness of the proposed system, a simulation was carried out based on the actual data at Kitakyushu of Japan. The traffic signals of this crossroads have been adjusted by the pre-timed control: the cycle time is 150sec and split is 64% (green time is 96sec). There are 48 cycles actual data altogether, and 1*st* to 24*th* cycles are used as calculation of the initial priori probability of the inflows and the outflows, and the others are used to simulation.

4.1 Result of Adjusting algorithm

In the simulation, the set values of adjusting algorithm are shown in table1.

Tabel 1 Set value of adjusting algorithm

Cycle time	60-150 sec	Split	50-70%
Smax	75	*Smin*	40
a	20%	*ß*	15%

The result of traffic signals by the adjusting algorithm is shown in Fig.7. The new traffic signals obtained by the proposed method are compared with the pre-timed signals.

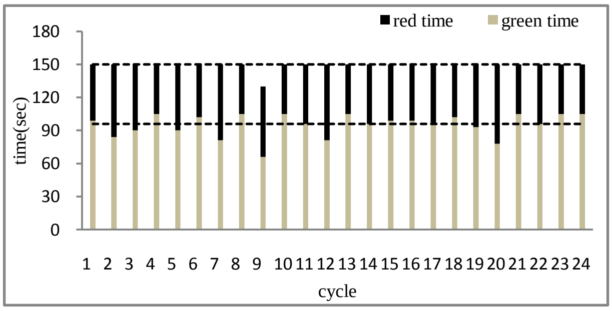

Fig.7 Adjusted Traffic signals

Fig.7 and Fig.8 show the result of standing vehicle at ecach cycle by the adjusted and pre-timed control in main road and mior road respectively.

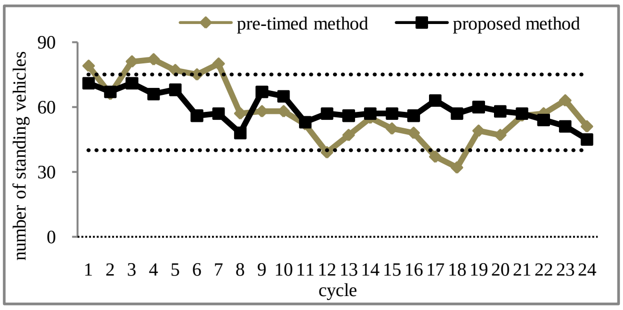

Fig.8 Number of standing vehicles in main road

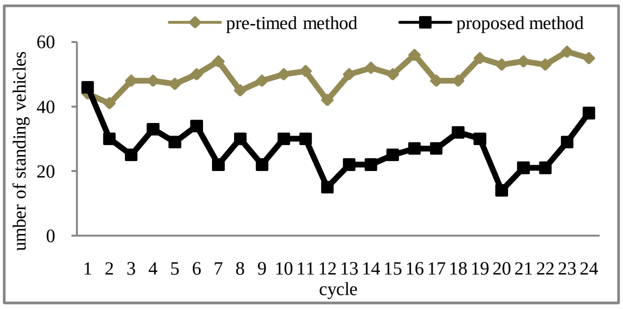

Fig.9 Number of standing vehicles in minor road

These figures show that the numbers of the standing vehicles are within the desired numbers from 40 to75 in main road, and the number of one is reduced markedly in minor road. The total number of the standing vehicles of the main and minor roads is shown in table 2. By the proposed adjusting algorithm the total number of the standing vehicles is decreased about 20% compared whit the pre-timed.

Table 2 Average number of standing vehicles

	Pre-timed method	Proposed method
Main road	58.2	59.0
Mior road	50.0	27.3
Total	108.2	86.3

4.2 Result of BPNN model

According to the Bayesian network model, the probabilities of standing vehicles over 100 are very small, so the number of neuron in the input layer is set up to 100 neurons, and the number of neuron in the hidden layer is set up to 14. The probabilistic distribution of standing vehicles from *1st* to *12th* cycles are used for tanning input pattern, and the result by the adjusting algorithm is used for target data, and then, *13th* to *24th* cycle are applied to obtain the new traffic signals.

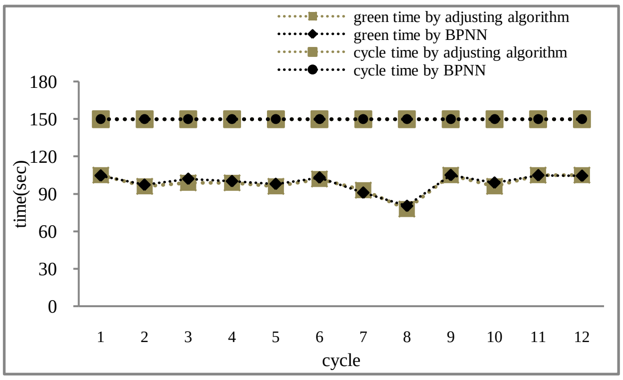

Fig.10 Traffic signals by adjust algorithm and BPNN

Fig.10 shows the traffic signals by BPNN model and by the adjusting algorithm. The result shows that the traffic signals by BPNN are close to the result by the adjusting algorithm and the average error of green time and cycle time is 1.3 sec and 0.1 sec respectively.

V CONCLUSIONS

In this paper, the real time learning traffic signal control system by BPNN based on the Bayesian network is proposed. Through the simulation using actual data, the effectiveness of the new signal control system is shown. The adjusting algorithm effectively calculates the optimal traffic signal to maintain the standing vehicles at main road, and then, the standing vehicles of minor road were also reduced.

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