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Traffic Signal Control Based on Predicted Distribution of Traffic Jam

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***Abstract*:** In this paper, we propose a new method of a traffic signal control based on the predicted distribution of the traffic jam. First, we built a forecasting model to predict the probability distribution of vehicles for traffic jam during the each period of traffic signal. As the forecasting model, the Dynamic Bayesian Network is used and predicted the probability distribution of the amount of the standing vehicle in traffic jam. According to calculation by the Dynamic Bayesian network, the prediction of probability distribution of the amount of standing vehicles in each time will be obtained, and a control rule to adjust the split and the cycle of the signal to maintain the probability of a lower limit and a ceiling of the standing vehicles is deduced. Through the simulation using the actual traffic data of a city, the effectiveness of our method is shown.

Keywords: Traffic Jam, Traffic Signal Control, Dynamic Bayesian Network, Forecasting model, probabilistic distribution

I. INTRODUTION

In recent years, the traffic congestion has become serious problem, with the number of automobiles increased significantly. The traffic signal control is one of the effective ways to solve the problem.

The traffic forecasting has been known as an important part of the traffic signal control, and the Random walk method, Neuron Network, and Bayesian Network are known as the methods, however these methods do not use the information for neighboring roads.

In this paper, a Dynamic Bayesian networks (DBN) model to predict the probability distribution of standing vehicles is constructed based on the information of the neighboring roads, and the traffic signal control method is proposed.

II. FORECASTING MODEL AND PREDICT PROBABILITY DISTRIBUTION

1. DBN Model

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.

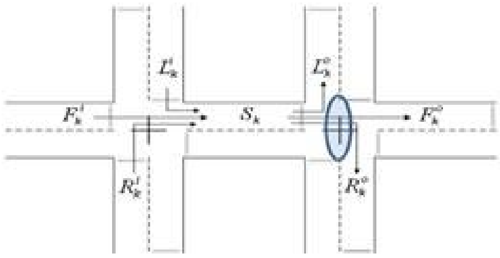


Fig.1 Crossroads and random variables

Here, we consider the two crossroads as shown in Fig.1. The random variables of the inflows and the outflows of the crossroad and the standing vehicles between the two roads are represented as nodes. The Bayesian network model of the standing vehicles is shown in Fig.2.

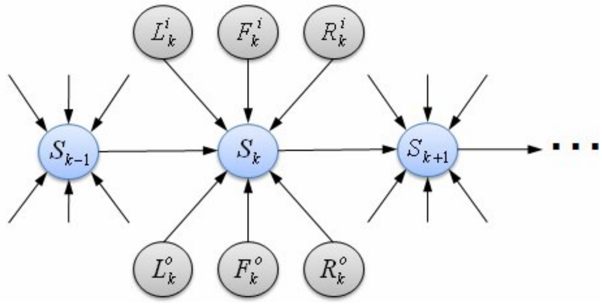


Fig.2 DBN model of standing vehicle

The number of the standing vehicles of k cycle can be calculated as eq.(1).

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

S_k : Standing vehicles of k cycle

S_{k-1} : Standing vehicles of k - 1 cycle

F_k^o : Outflowing straight vehicles of k cycle

L_k^o : Outflowing left turn vehicles of k cycle

R_k^o : Outflowing right turn vehicles of k cycle

F_k^i : Inflowing straight vehicles of k cycle

L_k^i : Inflowing left turn vehicles of k cycle

R_k^i : Inflowing right turn vehicles of k cycle

The probabilistic distribution of the standing vehicles is obtained by summing over all joint probability distribution of the other variables. With the chain rule, the joint probabilistic distribution is represented as the product of conditional probability as following,

$$\begin{aligned} &P(S_k, S_{k-1}, F_k^o, L_k^o, R_k^o, F_k^i, L_k^i, R_k^i) = \\ &P(S_k | S_{k-1}, F_k^o, L_k^o, R_k^o, F_k^i, L_k^i, R_k^i) P(S_{k-1}) \\ &\times P(F_k^o) P(L_k^o) P(R_k^o) P(F_k^i) P(L_k^i) P(R_k^i) \end{aligned} \qquad (2)$$

And according to the d-separation, eq.(2) can be represented as

$$\begin{aligned} P(S_k) = &\sum_{S_{k-1}} \sum_{F_k^o} \sum_{L_k^o} \sum_{R_k^o} \sum_{F_k^i} \sum_{L_k^i} \sum_{R_k^i} \\ &P(S_{k-1}) P(F_k^o) P(L_k^o) P(R_k^o) P(F_k^i) P(L_k^i) P(R_k^i) \end{aligned} \qquad (3)$$

According to above equation, the probabilistic distribution of the standing vehicle is calculated.

2. Predicted Probabilistic Distribution of Standing Vehicle

The priori probability of each variable is calculated from previous data firstly. And the probabilistic distribution of the standing vehicle at k cycle is calculated using the standing vehicle in proceeding cycle and the observed inflows and outflows of each direction. Next, the probabilistic distributions of the inflows, the outflows, and the standing vehicles at the cycle k+1, k+2,…, are predicted.

The splits and cycle of the traffic signal will be changed by the adjust rule which will be described at next session.

First, the passage ratio is calculated using the split and the cycle time at k cycle as

Passage ratio=traffic flow / (split*cycle time)

and, the future traffic flow is calculated using the fixed cycle and split. Then the probabilistic distributions of the future standing vehicle are predicted.

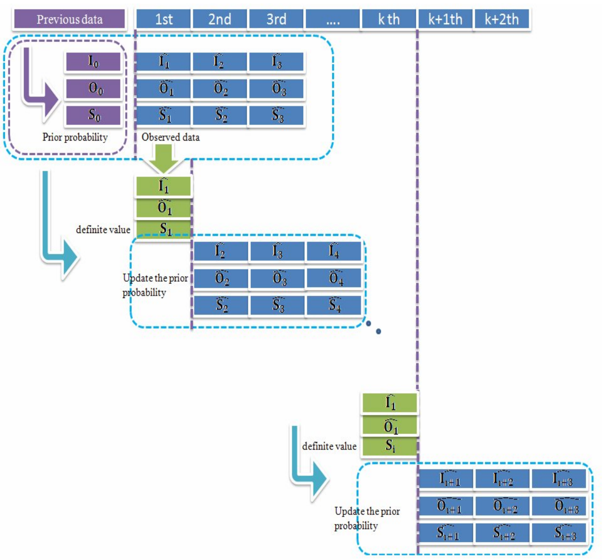


Fig.3 Flowchart of prior probability update

III. TRAFFIC SINGNAL CONTROL

1. Adjust Algorithm of Traffic Signal Control

According to the DBN model the probabilistic distribution of the standing vehicle is obtained. The split and cycle time of the traffic signal are controlled using the predicted probabilistic distribution of the standing vehicles. The control procedure is followed as that:

Step1: Predict the probabilistic distribution of the standing vehicles using the Dynamic Bayesian model to the 3rd cycle.

Step2: Calculate the probabilities Smax or above and Smin or below of the standing vehicles.

Step3: Compare these probabilities with the desired values.

Step4: Adjust the split and the cycle time until the probabilities for Smax and Smin satisfy the desired values.

The flowchart of the procedure for the traffic signal control is shown in Fig.4.

The probabilistic distribution will be change by the increase and decrease of the procedure. The two patters are considered.

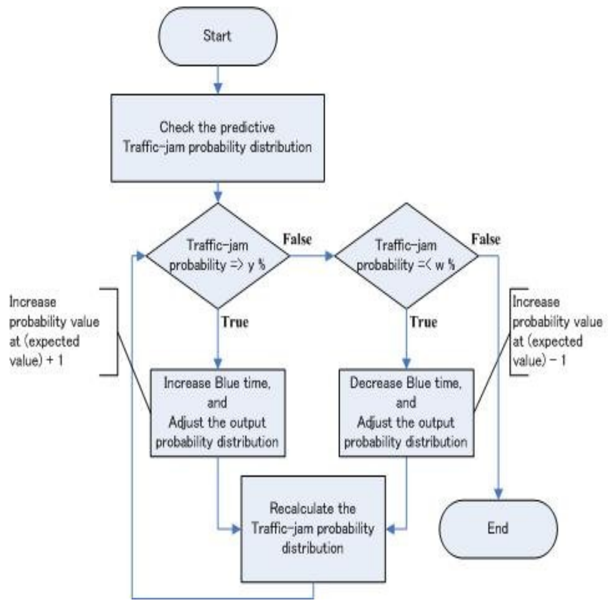


Fig.4 Flowchart of algorithm

2. Updated Patterns of Outflows Probability Distribution

The altered traffic signals will change the probabilities of the outflowing vehicles. To treat this situation, two patterns are considered here. As shown in Fig.5, the pattern 1 is to shift the probability distribution according to change of green time. The pattern 2 is to shift probability distribution as pattern 1, and increase probability of neighboring expectation and reduces others. In the simulation, pattern 2 to change the probabilistic distribution of the outflows is adopted.

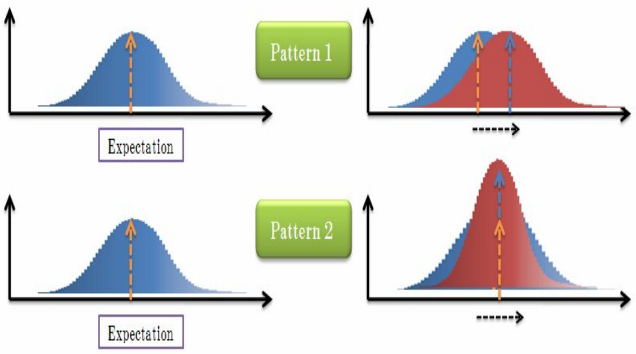
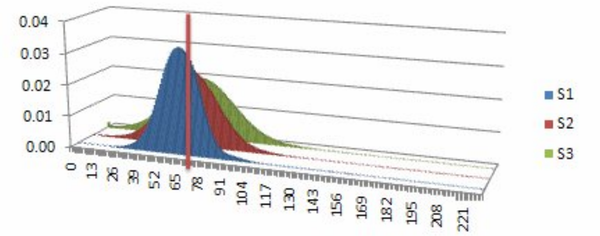


Fig.5 Update patterns

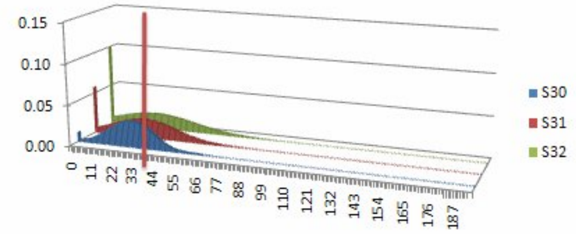
IV. SIMULATION

To prove the effective of the proposed method, a simulation was carried out based on the actual data at Tutuyimati, Kitakyushu on January 17th. 2007.

The parameters of the simulation are as: cycle length: 60-150[s]; split: 50-70%; Smax=75, Smi=35, α=0.1, β=0.1



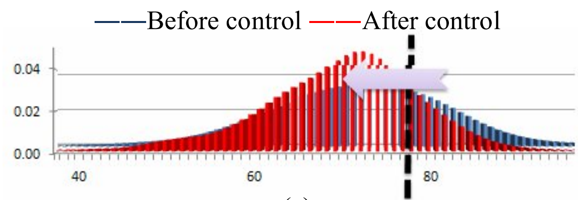
(a)



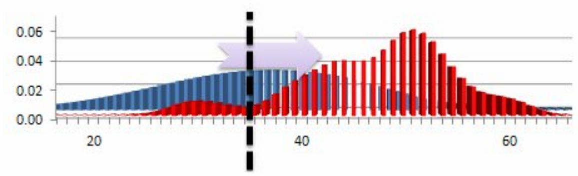
(b)

Fig.6 Predictive probabilistic distribution

Fig.6 shows the predicted probabilistic distribution of the number of standing vehicles from the cycle 1 to 3 and 30 to 32. We can see that probability of more than Smax is bigger than α in Fig.6(a), and the probability of less than Smin is bigger than β in Fig.6(b) .



(a)

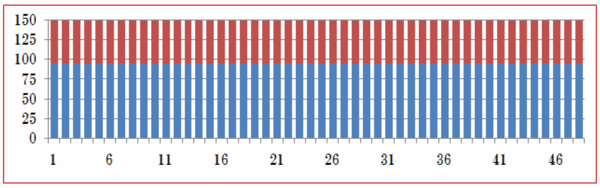


(b)

Fig.7 Probabilistic distribution of before and after control

Fig.7 is the probabilistic distribution of the standing vehicles before and after control at the cycle 1 and 30. By the extension of the green time, the probabilities of the more than Smax and less than Smin are updated to be small.

Before control



After control

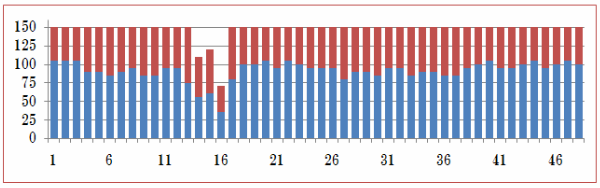
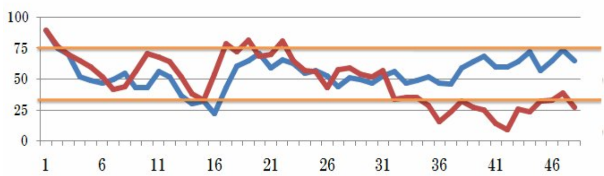


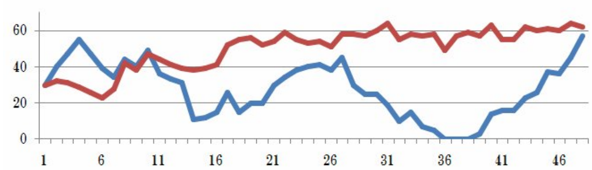
Fig.8 Split and Cycle time before and after control

The result of the splits and cycle time of the traffic signal by the control procedure is illustrated in Fig.8. The numbers of the standing vehicles on the main and minor roads before and after control are shown in Fig.9. In the main road, the numbers of the standing vehicles are within the desired numbers from 35 to 70.

——Before control ——After control



Main road



Minor road

Fig.9 Standing vehicles of main road and minor road

The sum of the main and minor roads is compared before and after control in Fig.10. The number of standing vehicles by the proposed traffic signal control is decreased by 16% compared with the fixed traffic signal.

——Before control ——After control

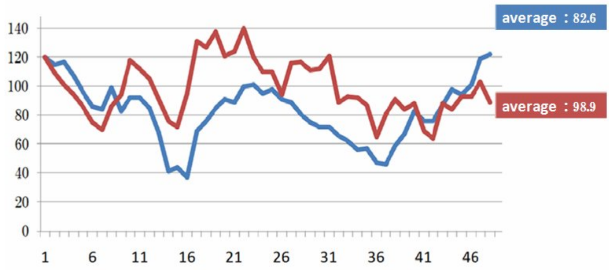


Fig.10 Standing vehicles of before and after control

V. CONCLUSIONS

In this paper, DBN model to predict the probabilistic distribution of the standing vehicles was built. And the adjust algorithm to control the cycle and the split of the traffic signal is proposed. Through the simulation using the actual data, the effectiveness of the new method is shown.

For the future research, the processing time of the adjusting algorithm will be reduced to achieve real-time control.

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