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Multi-intersection Signal Control based on Traffic Pattern-Learning

Jinseop Choi
Researcher, Korea Institute of Civil Engineering and Building Technology, Korea

ABSTRACT: *Based on the conversion of IT and traffic area, the intelligent traffic system is spotlighted on urban traffic control fields. To address the inefficiency of fixed traffic signal control method, actuated signal control method is introduced and slightly improves the traffic congestion problem. However, since the current actuated signal method deals with only the single intersection, it has limited applicability in urban downtown environment with severe variation in traffic flow. In this paper, a new traffic signal control method is proposed for the multiple intersections of urban traffic environment. The proposed method is composed of traffic pattern learning, searching for congested areas, and the control of multiple intersections. The interlocked functions of these components alleviate the traffic congestion problem as soon as possible. In particular, as the learning of traffic pattern is accumulated, the optimal signal control in various traffic conditions can be produced. To prove the efficiency of signal traffic methods, the proposed method and other previous signal control methods are evaluated on microscopic simulator.*

KEYWORDS *-Traffic signal control, Intelligent Transport System, Multi-Intersection Control, Reinforcement Learning, Congestion Control.*

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I. INTRODUCTION

Based on the conversion of IT and traffic area, the ITS(Intelligent Traffic System) is spotlighted on urban traffic control fields. The ITS supports various traffic information and control the traffic signal actively, intelligently in the real-time level. However, regardless of the advanced technologies in ITS, a traffic congestion in urban downtown area does not solve until now. The downtown area has multiple intersections with high traffic volume and also composes of traffic network junctions. So, even if a little traffic congestion occurs, its impact reaches out to surrounding link roads [1]. However, the traffic flow in downtown area has regular patterns. In particular, the important patterns have represented in rush hour times.

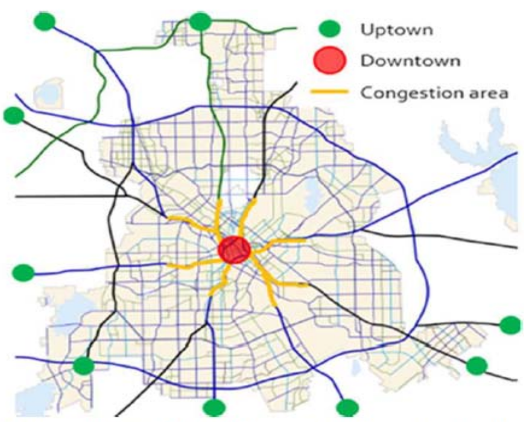

Figure 1. Traffic Patterns in Downtown Areas

The Fig. 1 shows the repetitive traffic patterns in downtown area. From this figure, if the office-going hour and closing hour are excluded, the steady traffic pattern appears. For rush hour times, the traffic flow is from uptown to downtown, or opposite flow direction. These two cases had induced the heavy traffic congestions in the entrance and exit roads of downtown area. So, to support the efficient traffic control in urban area, a new multiple intersection signal control reflected on the repetitive traffic patterns are needed.

In this paper, a new traffic signal control method is proposed for the multiple interconnections in urban traffic environment. The proposed method is composed of traffic pattern learning, searching for congested areas, and the control of multiple interconnections. The interlocked functions of these components can alleviate the traffic congestion problem as soon as possible. In particular, as the results of traffic pattern learning are accumulated, the optimal signal control according to traffic conditions can be provided. To prove the efficiency of signal traffic methods, the proposed method and other previous signal control methods are evaluated on microscopic simulator. In evaluation, when compared to other methods, the proposed method shows the increasing traffic volume and the reduction of average travel time and the decrease of delay time.

II. REINFORCEMENT LEARNING

The reinforcement learning is one of machine learning theories. It performs repeated searching to surrounding environment and decides the best selection based on the saved feedback data. From the repeated searching in uncertainty environment, it can choose the optimal direction to the next action. Since the result of selections accumulates for the future decision, the effect of learning increases as time passes. The reinforcement learning has applied for the effective management to the specific fields requiring the high complexity and dynamic activity [2].

In this paper, Q-learning algorithm is used which is the representative algorithm in reinforcement learning theories [3]. According to choosing which kind of parameters to comparison targets, Q-learning has an advantage applying to many various fields. Otherwise, it has a burden which the starting point and ending point for searching are predetermined. However, since the traffic system can exploit existing traffic information, this shortcoming could be solved in the Q-learning procedure.

$$\mathrm{Q}(S_t, a_t) = R(S_t, a_t) + \gamma maxQ(S_t + 1, a_{t+1}) \qquad (1)$$

The equation (1) is the expression for calculate the Q value in the Q-learning. The Q-learning represents the state and the action of the target system. The notation S means 'state' and the notation a means 'action' in this equation. The notation R denotes the compensation (traffic volume). For example, R(S, a) represents the compensation when the action 'a' (green time) executes on the state 'S' (signal lamp). The notation γ is a learning parameter which is degree of maximum Q value when the action 'a' is applied. The γ has the value between 0 and 1 and it reflects the maximum Q value to the next state of target system.

$$Q_{update}(S_t, a_t) = (1-\alpha)\mathrm{Q}(S_t, a_t) + \alpha[R(S_t, a_t) + \gamma maxQ(S_t + 1, a_{t+1})] \qquad (2)$$

The equation (2) represents the update procedure of Q values calculated from the Q-learning algorithm. The equation (2) includes the equation (1). The Q value is updated by applying fixed rates from the previous Q value and the recently calculated Q value. The notation α means the parameter of learning rate and has the value between 0 and 1. It decides the reflection ratio between the previous Q value and the recent Q value. As a result, the Q-learning algorithm accumulated the Q values every steps and it searches the optimal route as choosing the state with the highest Q value.

III. MLTI INTERSECTION SIGNAL CONTROL BASED ON TRAFFIC PATTERN LEARNING

In this paper, a new traffic signal control method is proposed for the multiple intersections of urban traffic environment. The interlocked functions of these components alleviate the traffic congestion problem as soon as possible. In particular, as the learning of traffic pattern is accumulated, the optimal signal control in various traffic conditions can be produced. Based on the traffic pattern in intersections, the MICTAL (Multiple Intersection Traffic Signal Control based on Traffic Pattern Learning) method is proposed to support the optimal signal control for various traffic conditions. This algorithm requires the real-time monitoring to the crossroads with traffic detection devices.

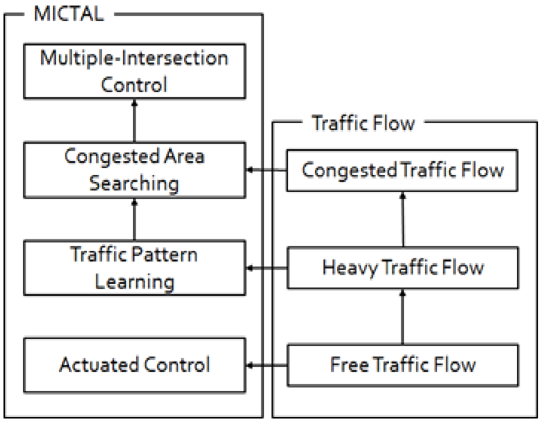

Figure 2. Traffic Monitoring System with MICTAL

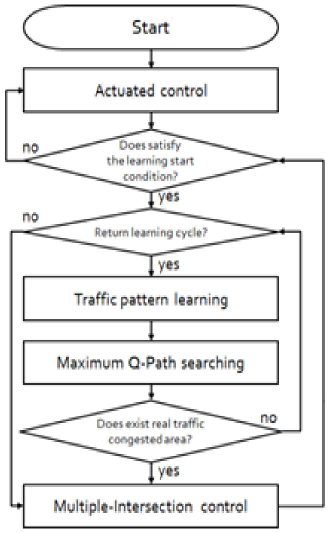

Figure 3. MICTAL Architecture

The Fig. 2 shows the relationship between the MICTAL and real traffic environment. If the free traffic flow is monitored, the MICTAL uses actuated signal control. However, if the heavy traffic flow is detected, the traffic pattern learning is applied. Moreover, if the congested traffic flow is monitored, the MICTAL searches the possible congesting paths based on the current traffic data and pre-learned traffic pattern data. As a result, it begins to control the multiple intersections on the congesting paths.

The Fig. 3 shows the algorithm of MICTAL. The MICTAL controls the traffic signals considering the traffic patterns achieved from this real circumstance. As shown in this figure, the start condition means that traffic volume reaches the heavy traffic flow. In this case, the MICTAL begin to learn the traffic pattern and searches the routes with maximum Q value. Among the detected routes, the MICTAL executes the traffic signal control for the corresponding intersections suffering the traffic congestion. This sequence is repeated periodically.

3.1 Start Condition for Learning

The MICTAL algorithm is begin to execute the checking of start condition. To decide this condition, we use Greenshield's macroscopic stream model. This model is one of traffic flow modeling used in traffic engineering field. It can analyze the relationship among the velocity and the flow and the density of vehicles [4].

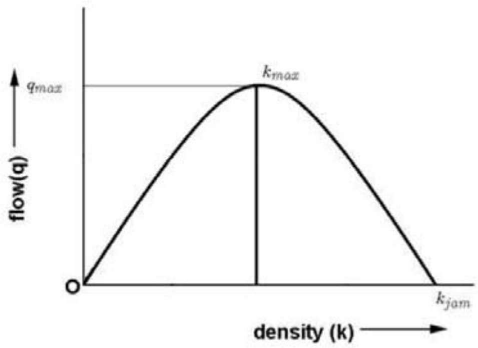

Figure 4. Relation Graph of Traffic Flow and Density

$$k_{max} = \frac{q_{max}}{4} \quad (3) \qquad q_{max} = \frac{v_f \times k_{max}}{4} \quad (4) \qquad v_f = \bar{v} - \mathrm{b} \times \bar{k} \quad (5)$$

$$k_{jam} - \frac{v_f}{|b|} \quad (6) \qquad \mathrm{b} = \frac{\Sigma((k_i-\bar{k})(v_i-\bar{v}))}{\Sigma((v_i-\bar{v})^2)} \quad (7)$$

The equation (3) is the maximum vehicle density. It is driven from the maximum vehicle flow (q_{max}) and the free-flow velocity (v_f). The maximum vehicle flow is calculated in the equation (4), It uses the free-flow velocity (v_f) and the density of congested traffic (k_{jam}). The free-flow velocity calculates in the equation (5). It is driven from the linear equation. and based on the Fig. 4. Otherwise, the traffic congestion density (k_{jam}) of equation (6) is composed of the free-flow velocity and the incline |b| of the Fig. 3. The incline |b| of equation (7) is driven form the combination of the vehicle density and the velocity variance. Based on these equations, finally, the maximum vehicle density of the equation (3) is calculated, which is used as the start condition of MICTAL.

3.2 Learning Period

To reflect real-time traffic condition on traffic control signals, the previous learning results should renew applying the periodical learning process. The most calculation volume of proposed algorithm concentrates on the learning process of traffic patterns. It results in the detection of traffic congestion areas. Based on these results, since the traffic signal is controlled immediately, the suitable period of traffic pattern

$$I_L = \max(T_g) \times N_b \qquad (8)$$

Learning should be decided.

The equation (8) shows the period of traffic pattern learning. To calculate the period of traffic pattern learning, we use the period of green signal light. The learning period (I_L) is calculated by the maximum green time ($\max(T_g)$) and the number of entrance roads in intersections (N_b). If the additional signal time is supplied, this calculated period of equation (8) does not fit in the real environment. However, since the learning is performed on the right time point, we ignore the possibility of this shortcoming.

3.3 Traffic Pattern Learning

In the traffic pattern learning, MICTAL collects the traffic data as real-time and performs the pattern learning using the Q-learning algorithm.

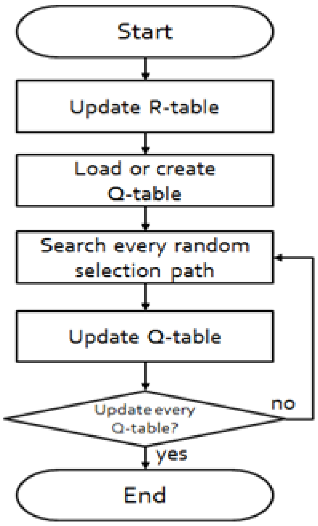

Figure 5. The flow chart for the traffic pattern learning

The Fig. 5 shows the flow chart for the traffic pattern learning. In the first step, the MICTAL updates the R-table(Reward table) as using the real collected traffic data such as the number of waiting vehicles.. In the second step, the Q-table achieved from the previous traffic data is loaded to enhance the accuracy of pattern learning. If there are no previous traffic data, the new Q-table should be created. The Q-tables create for all cases from the start position to the finishing position of learning. For all Q-tables, the random-selection method applies to search the routes and also the Q values in Q-table update repeatedly. As a result, from the Q-table updated every period, the route with the maximum Q value is detected from the start position to the finishing position. The R-table updates every time with new real traffic data and the Q values also update as applying the equation (2). As the traffic pattern learning is repeated, the routes with the frequent traffic congestion problem have the high Q values. These routes are controlled to get the better traffic flow.

3.4 Searching the route with Maximum Q

The maximum Q rout searching is based on the stored Q-tables. After it compares all Q values from the start position and the finishing position, the route with maximum Q value is selected. However, this route is decided according to the Q values calculated from the current traffic pattern learning. Thus, the traffic volumes by Q values are represented as the relative values among all routes. So, the Q values do not reflect on the quantitative traffic volume in real road environment. To solve this problem, to find the quantitative traffic volume, the searching for real traffic congestion areas should be proceeded in the next step.

3.5 Searching Real Traffic Congested Areas

As mentioned the above section, the route with maximum Q value is relative traffic volume. It is not good approach that the control of multiple intersections applies to the route with maximum Q values. So, to find the real congested areas, we filter the firstly searched route as using the threshold value of the areas the traffic congestion doubted. The threshold uses the start condition parameters and examines the searched routs by sections. If the vehicle density satisfies the start condition of algorithm, it is regarded as the traffic congestion area. Throughout these procedures, we can find the traffic congestion areas in real traffic road environment.

3.6 Multiple Intersection Control

Typically, there are two methods in multiple intersection signal control. The first is that the green signal lights toward the route of interconnected intersections are turned on sequentially. However, this method induces low safety in traffic environment because the signal changing is irregular in the aspect of single intersection. The second is that the order of signal control lights is fixed and the time length of green signal is controlled. This method can give the maximum timing of green light to multiple intersections. Also, since this method supplies an additional signal time, it can use for the single intersection.

The proposed algorithm uses the second method. The additional green signal time provides for the congested areas. In the opposite case, the minimum green signal times are provided. As the green light timings in congested areas are linked with each other sequentially, the congestion problem of multiple intersections can be solved. The additional green light time is decided flexibly according to the degree of traffic congestion. The fixed additional time does not apply because it cause unnecessary green light period. In this paper, the green signal time depends on the number of waiting vehicles on the road when the additional time should be applied.

$$T_{jam} = \max(T_g) \times \frac{Current\ Queue\ length}{MAX\ Queue\ length} \qquad (9)$$

The equation (9) is the expression to calculate the green signal time. The signal time for congestion route (T_{jam}) is driven from the maximum green light time ($\max(T_g)$) and a degree of saturation of vehicles on roads. As a result, as the vehicle saturation degree is high, the green light time reaches the maximum green light time.

3.7 Parameters in MICTAL

3.7.1 Green Signal Time

The signal control in intersections has affected on the traffic flow in real road environment. The next paragraph describes the methods to decide the green signal time. In the fixed signal control method, the normal green signal time is used, which is explained in the above section. On the other hand, in the actuated signal control, the pedestrian crossing time is used as the minimum green signal time and the maximum time is equal to that of fixed signal control method [5].

The equation (10) shows the pedestrian crossing time used in Korea real local road. The pedestrian

$$T_c = T_e + L_c \times \frac{1}{0.8} + T_g \qquad (10)$$

crossing time (T_c) is composed of the entrance time of pedestrian (T_e: 7 seconds) and the width of crossing walk (L_c x 1 second / 0.8 m) and the postpone time to protect the pedestrian. This calculated pedestrian crossing time is used as the minimum green signal time in proposed algorithm, MICTAL.

3.7.2 Q-Learning Parameters

The proposed method uses the Q-algorithm, which requires several parameters for applying to the specific target systems. The first parameter is the R value of learning finishing position, which is a basic parameter to decide the size of Q value. Since the Q-learning algorithm is a kind of route searching algorithm, it needs criteria for route searching. However, in the initial stage of learning, it is not possible to execute the complete learning procedure because the R values achieved from real roads are not enough. In this paper, to address this limitation, we set the R values in finishing position to more than the maximum value of R value achieved from the real roads and the calculation for Q value is applied. So, the corresponding road reflects on the proximity degree to target position. Even if the reward table is created, the R value of the learning finishing position always has the maximum value and it does not change. So, the Q value also sustains the maximum value.

The second parameter γ decides the Q value such as the finish position R value. According to the equation (1), it decides the reflection ratio of the maximum Q value of next state.

IV. PERFORMANCE EVALUATION

4.1 Experimental Environment

To simulate the traffic environment on urban traffic environment, we used a VSSIM simulator supported by PTV Corporation [6]. The VSSIM is a microscope simulator, which can be implemented and tested for various road environments. In particular, various traffic patterns are experienced by changing the random seed in simulation.

Figure 6. Simulated Road Environment

The Fig. 6 shows experimental environment. It is composed of two-lane each and 16 intersections. The green or red arrows represent the vehicle's direction. As shown in the figure, all intersections have vehicle detection devices and measure the traffic flow. The width of road is 10meter and the distance between intersections is 190meters. So, the maximum number of waiting vehicles is 47(average vehicle length is considered). This number is the maximum R value. The vehicle entrance rate changes by a time zone. For the first 1 hour, it is set to 120(veh/h). For next 30 minutes, 90(veh/h) is assumed and 30(veh/h) is set for the last 30 minutes.

4.2 Parameters

For the decision of parameters in MICTAL algorithm, the fixed signal control method is used in simulated road environment and to collect the traffic data. The Table 1 shows the vehicle density and velocity changing by the hour, which is used to decide the start condition of MITCAL. Based on these data, the equations mentioned in above sections are executed and the results are recorded in the bottom of the Table 1.

The incline |b| of Fig. 4 is -0.15 and the density of congested vehicle density is 259.3(veh/h) and the velocity of free-flow is 38.9(km/h). The maximum vehicle flow is 2571.1(veh/h) and the maximum vehicle density is 64.8(veh/km). When the connecting road length of simulation environment is applied, the maximum vehicle density is calculated as 12 vehicles. So, if 12 vehicles are existed on the connecting road of intersections, the MICTAL algorithm begins to execute.

Table 1. Vehicle Density and Velocity data by hour

Time(min.)	k(density)	v(velocity)	$(k_i - \bar{k})$	$(v_i - \bar{v})$	$(k_i - \bar{k})(v_i - \bar{v})$	$(k_i - \bar{k})^2$
20	22	36.0	-3.17	1.23	-11.25	84.03
40	31	34.9	2.83	0.00	-0.01	8.03
60	41	33.1	12.83	-1.79	-23.00	164.69
80	36	35.8	7.83	0.88	6.89	61.36
100	27	31.9	-1.17	-2.94	3.43	1.36
120	9	34.9	-19.17	-0.03	0.51	367.36

b	-0.15	k_{jam}	259.3 veh/km	v_f	38.9 km/h	q_{max}	257.1 veh/h

k_{max}	64.8 veh/km

In the simulation, we decide the green signal time as 60 seconds because the signal time of two-lane road is usually set to 90 seconds in urban environment [5]. The minimum green signal time is calculated as 25 seconds by the equation (10) when the width of road is 10 meters. When the minimum green signal time 25 seconds applies to 4 ways, the period of traffic pattern learning is 100 seconds.

4.3Performance

To evaluate the performance of MICTAL, we perform two experiments. The first is that fixed signal control, actuated signal control and MICTAL method are simulated on the same working environment. From this experiment, average travel time and the delay vehicles are measured for compared with each other.

The second is aimed to evaluate the effect of traffic pattern learning, which is accumulated on every process. The result of current learning reflects on the next decision to solve the traffic congestion. The effect is confirmed as the reduction of average travel time.

The Fig. 7 shows the average travel times for three methods. The MICTAL has the best performance. When compared to the fixed signal control and the flexible signal control, the MICTAL shows the reduction of 67% and 51 % in the travel time. The Fig. 8 represents the delay times for three methods. The MICTAL shows the reduction of the delay time compared to other methods. The degree of reduced delay times is 63.7 % and 49.8% compared to fixed and flexible signal control methods.

Figure 7. Average Travel Time

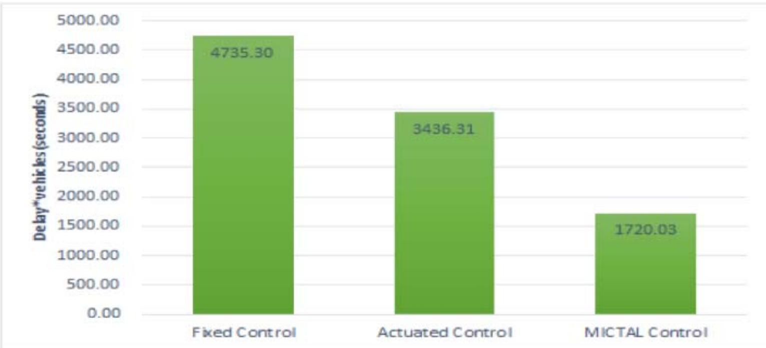

Figure 8. Delay Vehicles

Figure 9. Variations of Average Travel Times

The Fig. 9 shows the variations of average travel times according to use the traffic pattern learning results. Even if the degrees of travel time decrease are not constant, the average travel times have been reduced greatly as more and more learning results are accumulated.

From these experiment results, the MICTAL shows distinguishing performances in urban traffic environment, compare to fixed and actuated signal control methods. In particular, the effect increases as the learning results are accumulated in the next steps.

V. CONCLUSION AND FUTURE WORKS

In this paper, the effective traffic signal control method was proposed. The proposed method called as MITCAL used the Q-algorithm as the traffic pattern learning algorithm. The Q-learning requires the parameters to decide the learning rate. These parameters represent the ratio of the past Q values and new Q values.

In experiments, the fixed, actuated, and MITCAL methods were evaluated in the metrics of average travel time and delay. The MICTAL method represented the best performances in all metrics. It provided the reduction of travel time and the decrease of delay in multiple intersections. In particular, the effect of the MICTAL method had enhanced more and more as the traffic pattern learning was performed repeatedly. Finally, the MICTAL can reduce the traffic congestion in current urban traffic environment.

The performance of traffic pattern learning is affected by the parameters of Q-learning. However, it is difficult to decide the priority between past and new traffic data. In our future work, the rules to get the parameter ratios of learning will be studied for non-experienced working environments.

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