Multi-agent traffic light control framework based on direct and indirect coordination

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ABSTRACT
Traffic congestion is a serious problem in urban life causing social problems such as time loss, economical loss, and environmental pollution. Therefore, we propose a multi-agent-based traffic light control framework for intelligent transport systems. For smooth traffic flow, real-time adaptive coordination of traffic lights is necessary, but many conventional approaches are of the centralized control type and do not have this feature. Our multi-agent-based control framework combines both indirect and direct coordination. Reaction to dynamic traffic flow is attained by indirect coordination, and green-wave formation, which is a systematic traffic flow control strategy involving several traffic lights, is attained by direct coordination. We show the detailed mechanism of our framework and verify its effectiveness through comparative evaluation through simulation.

Categories and Subject Descriptors
I.2 [**ARTIFICIAL INTELLIGENCE**]: Distributed Artificial Intelligence

General Terms
Algorithms, Performance

Keywords
ITS, intelligent traffic control, multi-agent coordination

1. INTRODUCTION
Traffic congestion in urban areas causes serious problems in terms of economic loss, time loss, and environmental pollution. Major solutions to eliminate traffic congestion are intelligent car navigation [5][8] and traffic light control. The former technology, such as the Vehicle Information and Communication System (VICS) in Japan, and the Probe-Car Information System, has progressed rapidly. VICS is an innovative information and communication system that enables one to receive real-time road traffic information, This information is edited and processed by the VICS Center and displayed on the navigation screen in text or graphical form. The Probe-Car Information System uses cars as mobile sensors for collecting data, which are sent to a central server to produce new information for avoiding congestion and providing efficient navigation.

Even though computer-based traffic light control systems are based on centralized control, they have disadvantages. Therefore, we focus on improving such traffic light control systems.

The basic steps in the traffic light control design process is deciding on phases and calculating the control parameters. The various traffic flows at an intersection are allowed to move in phases. Each phase of a signal cycle is devoted to only one traffic flow. The control parameters define the timing of switching phases. The major control parameters are "cycle length", "clearance", "split" and "offset" in the traffic light control system.

- Cycle length is the time required for one cycle of traffic light phases (e.g. green -> yellow -> red). Figure 1 shows an example of this.
- Clearance is the time it takes to clear an intersection area.
- Split is the percentage of cycle length allocated to each traffic light phase.
- Offset is the time lag between green indications of adjacent traffic lights. Figure 2 shows an example of offset control (green-wave formation).

Traffic congestion mainly begins at intersections. Traffic flow fluctuates dynamically during morning and evening rush

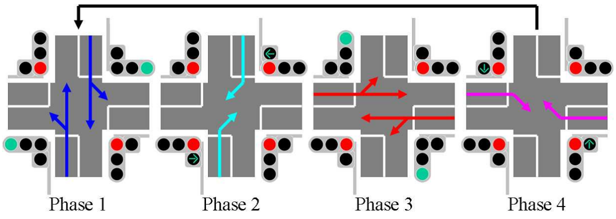

Figure 1: Example of phases and cycle

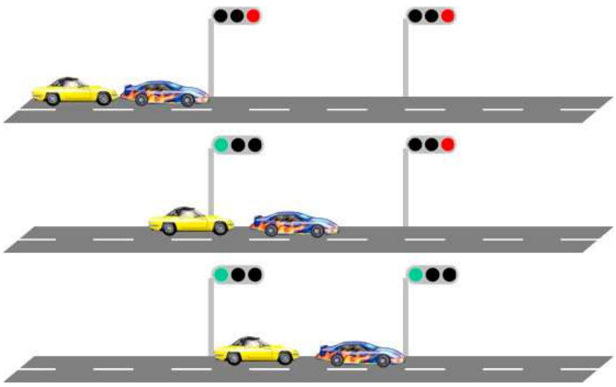

Figure 2: Example of offset control

hours. Moreover, unexpected events, such as road accidents, and unexpected popular events dynamically cause traffic congestion. Therefore, it is important to be able to appropriately align these parameters at any time.

The current traffic light control systems can be classified into two types; static, which use the above parameters calculated beforehand, and dynamic, in which traffic flow is monitored and the values of the parameters are adapted. These parameters are aligned dynamically (as in MODERATO in Japan and OPAC[4] in US). In the static type, several parameter sets are calculated beforehand according to each traffic flow situation during rush hour, daytime or nighttime. While this type is effective in envisioning changes in traffic flow, it cannot deal with unexpected situations. In the dynamic type, traffic flow is detected by sensors installed along roads, and traffic lights are controlled based on this sensor information. However, current systems are of a centralized control type, which is unsuitable for the management of dynamic complex traffic flow.current systems are of a centralized control type

In MODERATO, real-time information is not utilized appropriately. This is mainly due to its algorithm, which selects a favorable parameter set matched to each traffic flow situation from the several parameter sets calculated beforehand by off-line simulation.

For offset control in current traffic control systems, when one-way traffic flow becomes quite high during the morning rush hour from residential areas to urban areas, green-wave offset control (through-band offset control) is adopted. In green-wave offset control, offset timing of several traffic lights are aligned to allow each car to move without stopping at a traffic light. Ideally, the group of traffic lights that make up the green-wave control should be organized dynamically. However, in the current systems, these groups are pre-defined, and it is impossible to freely construct the green-wave control anywhere.

The essential factor for next generation traffic light control systems are real-time adaptability, to be able to quickly react to the dynamic traffic flows. To achieve this, we believe that a framework in which each traffic light is autonomous and coordinates with others to react to dynamic traffic flow is necessary.

We propose a traffic light control framework based on a multi-agent paradigm to react to dynamic traffic flow, decrease the number of cars stopping at a red light, and adaptively form a green-wave control group. An agent is implemented at each intersection for controlling the several traffic lights that belong to that intersection. Our framework combines indirect and direct coordination. That is, reaction to dynamic traffic flow is attained by indirect coordination using a spring model based on stigmergic dynamics, and green-wave organization is achieved by direct coordination.

In section 2 we discuss related studies and explain the major control parameters of traffic lights in Section 3. In Section 4, we discuss our proposed framework and show the evaluation results. We conclude our discussion in Section 5.

2. RELATED STUDIES

One approach for obtaining optimized parameters is using a genetic algorithm (GA). Takahashi et al. proposed an offset optimization model using a GA [13]. In this model, offset values of traffic lights were used to represent a chromosome. Sánchez et al. proposed another parameter optimization model using a GA [10]. In this study, optimized cycle length, clearance time, split, and offset could be calculated. Mikami et al. proposed a multi-agent-based model in which reinforcement learning is used to optimize the parameters [6]. In this model each agent performs reinforcement learning independently, and each parameter set, which is calculated by each agent, is aggregated to the central control module. Then the central control module uses a GA to find the optimized parameter set. Balaji et al. also proposed a multi-agent-based centralized optimization methodology using a GA [1]. Kosonen et al. proposed a multi-agent real-time traffic light control system using fuzzy inference, and Schmöcker et al. proposed a multi-objective traffic light control method using fuzzy logic [12]. The membership functions of fuzzy logic are optimized using a GA executed in a microscopic traffic simulator. These GA-based approaches are attractive when there are many parameters to be optimized, but require large calculation cost and time until convergence. A more optimized solution can be derived with centralized calculation approaches, but these approaches do not exhibit real-time adaptability.

Another approach is a stochastic control model. Yu et al. achieved traffic light parameter optimization as a decision making problem of a controlled Markov process [14]. They say that the stochastic approach is suitable for the traffic light control problem, especially under the conditions of high volume but not saturated traffic demand. However, when the size of the road network is increased, the dimension number of the proposed control framework increases, and more memory space and computation time become necessary.

On the other hand, there are several related studies based on the distributed approach to achieve real-time adaptability. Nishikawa proposed an offset control algorithm based on the phase oscillator model [9]. In this study, the functions of each traffic light were modeled as oscillators and traffic lights were coordinated through synchronization of each oscillator. Satoh proposed a split control model based on the spring model [11]. In this study, traffic flow was assumed to be the same as the force of a spring. The split ratio was modeled as the force balance of a spring. Coordination between adjacent traffic lights was also modeled as a spring model. Traffic lights were connected with a spring, and the split ratio of traffic light was assumed to be the same as the force of a spring. Oliveira proposed a multi-agent-based split control approach [3]. Each agent calculates the congestion degree independently and controls its split value to decrease the total congestion degree.

These conventional approaches are all attractive, but their performances were evaluated using quite simple and small-scale road environments, and most of them concerned about only a few parameters. Therefore, it is difficult to apply them to more complex and large-scale environments.

3. MULTIAGENT CONTROL

In this chapter, we describe our multi-agent based traffic light control framework, our proposed split control model with spring model by indirect coordination, and our proposed offset control and green-wave formation model by direct coordination. As for agent based approach, useful survey was done in [2].

Generally, indirect coordination exhibits adaptability and low coordination cost but optimality cannot be ensured. On the other hand, direct coordination exhibits optimality but requires high coordination cost and longer convergence time than indirect control. A traffic light control consists of split and offset controls. To quickly reduce the waiting queue of cars at an intersection, control of the split value of each traffic light is necessary. Therefore, real-time adaptability is necessary for split control. On the other hand, to form a green-wave control group with several traffic lights, some deliberate coordination is necessary. Therefore, in our proposed framework, split control is attained using the indirect type of coordination, and offset control is attained using the direct type of coordination.

For split control, each agent calculates the split value autonomously by referring waiting queue of cars at a traffic light it directly controls. Each agent does not interfere with neighbor agents. That is, there is no direct coordination cost; therefore, real-time control can be achieved. On the other hand, functions of each agent indirectly affect its neighbor agents through the change of traffic flow. This indirect coordination is generally called "stigmergy[1]".

For offset control in current traffic control systems (e.g. MODERATO), several groups that may perform green-wave control are pre-defined, so dynamic formation is impossible. On the other hand, in our proposed framework, green-wave control formation can be dynamically established anywhere.

In normal daily traffic flow, each agent functions based on the indirect coordination mode. However, when the traffic flow balance collapses near certain agents, the agents change their coordination mode to direct coordination mode to form a green-wave control formation. Therefore, such direct coordination of an agent group can be seen as interfering with the indirect coordination of agents. However, indirect coordination has an advantage against such interference. The important point is affinity of both coordination types.

Cycle length and clearance were not considered in most related studies. However, both parameters also affect traffic flow; therefore, we focused on both parameters. We adopted the Webster cycle length approximation formula, which is also adopted in MODERATO (details are discussed in Section 5). Clearance length is a constant value.

3.1 Definition of agent

Agent A_i, which controls the traffic lights of $intersection_i$, collects the following information:

- Distance $l_{i,j}$ between $intersection_i$ and its directly connected $intersection_j$.
- Traffic flow (number of cars) per unit time $intersection_i$ to $intersection_j$, which is defined as $p_{(i,j)}$.
- Average velocity of cars heading from $intersection_i$ to $intersection_j$ is defined as $v_{i,j}$.
- C_i is the cycle length, S_i is the split value, and O_i is the offset value of $intersection_i$.
- T_i shows the start time of C_i, and current step count is t_i.
- Total traffic flow into $intersection_i$ is defined as $P_(i) = \sum_j p_{(j,i)}$

Traffic flow p is calculated based on the total traffic flow of the last five cycles that showed the best effect from the results from a pre-exploratory experiment. Each agent calculates and updates these values at the beginning of every cycle.

3.2 Cycle length control

Cycle length is controlled depending on whether each agent performs direct or indirect coordination. When the agent is in indirect coordination mode, cycle length is calculated using Webster's equation.

$$C_o = \frac{1.5L + 5}{1 - \lambda} \tag{1}$$

where C_o is the optimal cycle length, L is the clearance length, and λ is the ratio of p to the saturation traffic flow.

On the other hand, when the organization of green-wave formation, which is formed by several agents, becomes necessary, the coordination mode of these agents becomes direct, and the cycle length of these agents becomes the same.

[1]The term "stigmergy" was introduced by French biologist Pierre-Paul Grass in 1959 to refer to termite behavior.

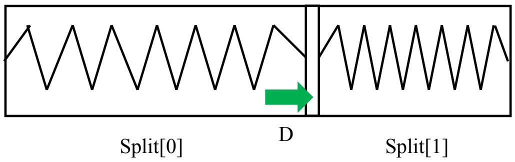

Figure 3: 2 phase spring model

Details of cycle length calculation are discussed in Section 3.4.

3.3 Split control by indirect coordination

Each agent at an intersection observes the traffic flow of each road connected to the intersection during the green phase of each road. The agent then calculates the split ratio based on the proposed spring model so as to equalize the traffic flow of each road. At this point, each agent calculates its split value by using only local information and does not directly interact with others, exhibiting real-time characteristics and low communication cost.

Now, we consider a crossroad and 2-phase traffic light (red and green) in this intersection. The split ratio of one of the two phases $phase_1$ is defined as $split[0]$, and the other phase $phase_2$ is defined as $split[1] = 1 - split[0]$.

Figure 3 shows a diagrammatic illustration of our spring model. Traffic flow is considered as force. The spring equation is defined as.

$$K(C - Csplit[0]) + D = K(C - Csplit[1]), \quad (2)$$

where C is the cycle length, D is the difference in traffic flow between $phase_1$ and $phase_2$, and K is the spring constant, which is defined as the number of cars waiting for the red light phase during one step.

$$split[0] = \frac{(KC + D)}{2KC} \quad (3)$$

Therefore, we can calculate $split[0]$ and then $split[1]$. However, Eq. 3 may give a split value of $split[0] \geq 1$ or $split[1] \geq 1$, where $split \geq 1$ means that the traffic light cannot change the phase. Therefore, we define the maximum value of $split$ as 0.9 and the minimum value as 0.1.

3.4 Offset control by direct coordination

The offset is calculated based on the traffic flow between two adjacent intersections. When the condition for constructing the green-wave formation is satisfied for a certain agent, the agent tries to start direct coordination with its adjacent agents by sending them a coordination request message. First, we define three agent modes. Then we explain the offset equations and show the sequence of green-wave formation.

3.4.1 Agent's mode

Each agent consists of three types of modes depending on the condition of its adjacent agents and amount of traffic flow it controls.

- Independent mode: An agent does not interact with the green-wave formation.
- Master mode: An agent in this mode becomes the center of coordination and is called the "master agent". When the construction of the green-wave formation is satisfied for a certain agent, that agent's mode changes from independent to master.
- Fellow mode: When a certain agent accepts the coordination request from the master agent, the mode of this agent changes from independent to fellow.

3.4.2 Offset calculation

The offset is calculated based on the difference between in-bound and out-bound traffic flow on the road between two adjacent intersections. When the difference between in- and out-bound flows reaches a certain value, the offset is calculated to give priority to the more congested direction.

We define p_l as $p_{(i,j)}$ or $p_{(j,i)}$, whichever is the larger, and p_s as $p_{(i,j)}$ or $p_{(j,i)}$, whichever is the smaller. The notations γ and δ are thresholds of traffic flow (γ is bigger than δ). For $\frac{p_l}{p_s} \geq \gamma$, we consider only the more congested direction, and the relative offset value O_r is defined as

$$O_r = \frac{l_{(i,j)}}{v_l}, \quad (4)$$

where v_l is the velocity of the more congested traffic flow. On the other hand, in case of $\gamma > \frac{p_l}{p_s} > \delta \geq 1$, it is necessary to consider both flow directions. Therefore, the relative offset value O_r is defined as

$$O_r = \frac{l_{(i,j)}}{v_l} \frac{(\frac{p_l}{p_s} - \delta)}{(\gamma - \delta)} \quad (5)$$

Finally, when a master agent of intersection A_i sends a coordination request message to an independent agent of its adjacent intersection A_j, the offset value, which is assumed to be A_j, is $O_{(i,j)} = -Or$ ($p_{(i,j)} \geq p_{(j,i)}$) or $O_{(i,j)} = Or$ ($p_{(i,j)} < p_{(j,i)}$). As mentioned above, when A_j accepts this coordination request, its mode changes to fellow.

3.4.3 Direct coordination process

We describe the constructing sequence of green-wave formation through the coordination of agents.

All independent agents have the possibility of becoming a master or fellow agent. The condition for an agent A_i to become a master agent A_{xc} is that A_i is in independent mode and $P_i > \alpha$, or A_i is fellow mode and $P_i >= P_{xc}$. P_{xc} is defined as a master agent A_{xc}'s total traffic flow. The notation α is a threshold of traffic flow per unit of time to become master mode.

Step1 If $p_{(ic,j)} \geq \beta$ or $p_{(j,ic)} \geq \beta$, master agent A_{ic} starts direct coordination to control the offset value with its adjacent agent A_j. Then A_{ic} sends the calculated offset value $O_{(ic,j)}$, total traffic flow P_{ic}, start time of cycle T_{ic}, and distance $d_{(ic,j)}$ between A_{ic} and A_j to A_j. The notation β is another threshold of traffic flow per unit of time.

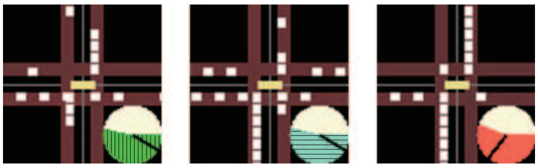

Figure 4: Agent mode
In this simulator, an agent's mode is denoted with three colors. Left is a master agent, Middle is a fellow agent, and Right is an independent agent. When the clock hand points to the colored area, the traffic light's phase is $phase_1$. When the clock hand points to the white area, the phase is $phase_2$.

Step2 If agent A_j is in independent mode, and if $t_j \leq \epsilon C_j$ or $t_j \geq (1-\epsilon)C_j$, it accepts the request from A_{ic}. The notation ϵ is a threshold of time path between the start and the time when A_j will accept the request.

On the other hand, if agent A_j is in the fellow mode with another master agent A_{yc}, the conditions for agent A_j to accept the request from A_{xc} are $t_j \leq \epsilon C_j$, or $t_j \geq (1-\epsilon)C_j$ and $P_{ic} > P_{yc}$, or $P_{ic} = P_{yc}$ and $l_{(ic,j)} > l_{(yc,j)}$.

Moreover, if agent A_j itself is a master A_{jc}, the condition for A_{jc} to accept the request from master agent A_{ic} are $P_{jc} < P_{ic}$ and $t_j \leq \epsilon C_j$ or $t_j \geq (1-\epsilon)C_j$. If A_j accepts the request from A_{ic}, A_j becomes a fellow agent of A_{ic}. Then, T_j is changed to T_{ic}, and O_j is changed to $O_{ic} + O_{(ic,j)}$.

Step3 Then fellow agent A_j checks the traffic flow $p_{(j,k)}$ and $p_{(k,j)}$, where k is the intersection adjacent to intersection j. Then if $p_{(j,k)} \geq \beta$ or $p_{(k,j)} \geq \beta$, A_j sends the coordination request to agent A_k, which is the adjacent agent to A_j, similar to a bucket brigade. Agent A_j sends the calculated offset value $O_{(j,k)}$, total traffic flow P_{ic}, start time of cycle $T_k = T_j = T_{ic}$, and distance $d_{(ic,k)} = d_{(ic,j)} + d_{(j,k)}$ to A_k.

Step4 If A_k accepts the request from A_j, the mode of A_k is changed from independent to fellow.

Step5 When the bucket brigade process terminates, the green-wave formation consisting of one master agent and several follow agents begins coordinated offset control.

4. EXPERIMENTS AND RESULTS

4.1 Traffic Simulator

We verified our traffic light control framework through simulation to confirm its effectiveness. The movement of cars is expressed with the Nagel-Schreckenberg (NS) model using cellular automaton rule 184[2] [7]. In the simulator, the unit of time is called "step(= 0.3 sec)" and the unit of distance is "cell". Each car flows into the simulator from the cell on the edge of the simulator according to an inflow probability. The simulator consisted of roads (edges) and intersections

[2]Rule 184 can be used as a simple cellular automaton model for traffic flow in a single lane of a road. In this model, cars can move in a single direction, stopping and starting depending on the cars in front of them.

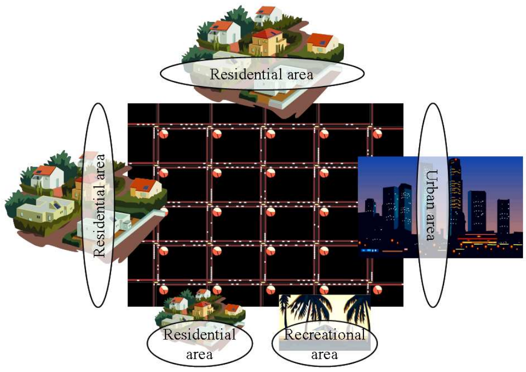

Figure 5: Experiment 3: Road Network

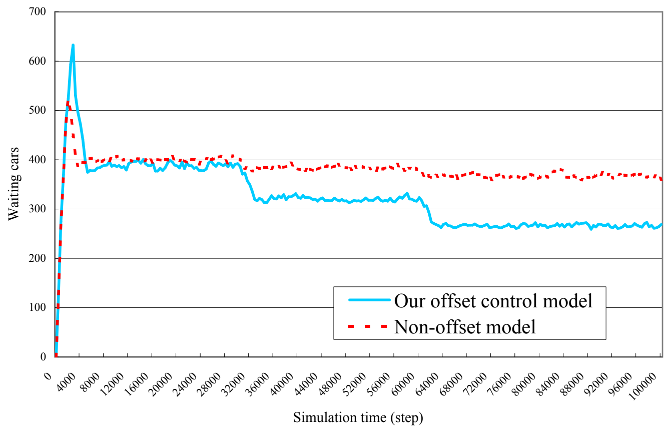

Figure 6: Experiment 1: Transition of Waiting Cars

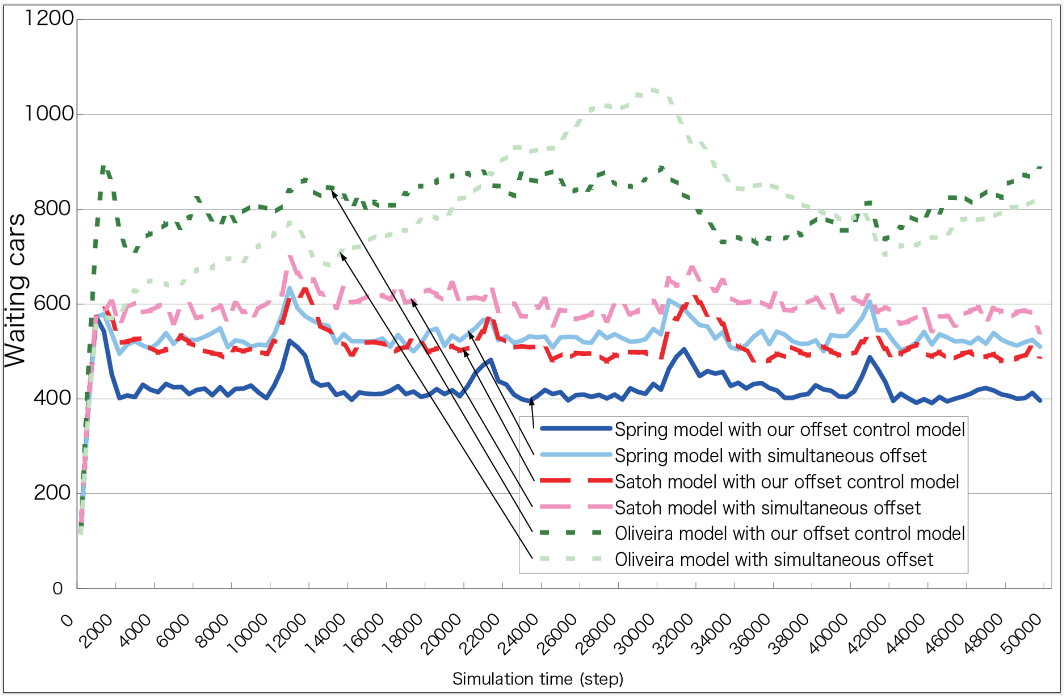

Figure 7: Experiment 2: Transition of Waiting Cars

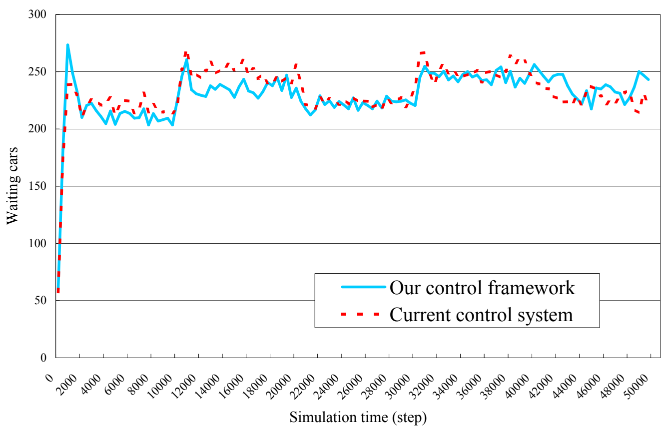

Figure 8: Experiment 3: Transition of Waiting Cars

(nodes). The road network was a grid-type network. Each intersection had the coordinate (x, y). We prepared 1×20 (20 intersections) and 10×10 (100 intersections) networks. The distance between adjacent intersections was 50 cells. The velocity of cars was 1 cell per step. We set each threshold value, which is the best value, based on pre-exploratory experiments as follows: α=0.25, β=0.125, γ=1.5, δ=1.1, ϵ=0.2. The simulation environment was Intel Core 2 Duo 2.40-GHz CPU and 2.00-GB RAM.

4.2 Experiments

Experiment 1

To confirm the effectiveness of green-wave control, we prepared a 1×20 straight road network. Cars enter the network from cells at both the east and west edges. Both initial in-

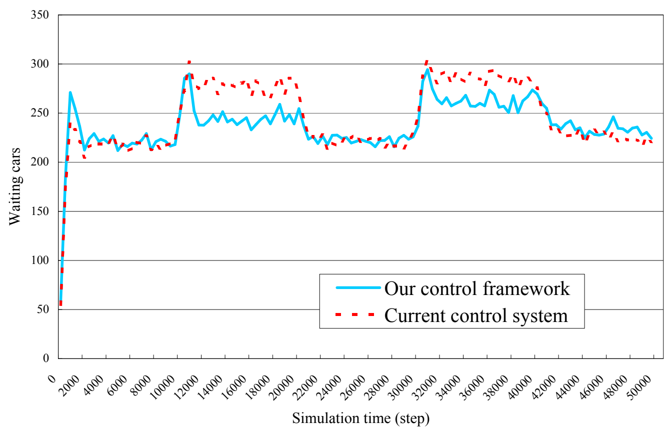

Figure 9: Experiment 4: Transition of Waiting Cars

flow probabilities were 22.5%. We then decreased the inflow probability from the east edge by 5% after 30000 steps, and decreased it an additional 5% after 60000 steps. We fixed the cycle length (400 time steps = 2 min) and split value ($split[0] = split[1] = 0.5$). We compared our offset control model with a non-offset model (all traffic lights control each phase at the same time).

Experiment 2

We verified the effect of our spring model-based split control algorithm. We selected two already proposed related split control models, the Satoh and Oliveira models, for comparison. Because our spring model is based on indirect coordination, each agent does not receive all the information and does not directly interact with other agents. The Satoh model is a direct coordination-type model. Each agent also does not receive all the information but it directly interacts with other agents. The Oliveira model is a direct coordination-type model. Each agent interacts with other agents, but it does not receive all the information.

In addition to these comparative experiments, we also verified the affinity of these three split control models and our offset control model. We prepared a 10×10 road network. We also prepared one input cell having 20% inflow probability, two input cells having 15% inflow probability, and three input cells having 10% inflow probability (total six cells). All other cells had 2.5% inflow probability. For verification of the real-time adaptability of our framework, we replaced these six cells and the other six cells having 2.5% inflow probability after every 10,000 steps. In this experiment, we used Webster's cycle length control.

Experiment 3

We compared our traffic light control framework with the current operating traffic control system model and confirmed its effectiveness.

We assumed this road network had four residential areas, one urban area, and one recreational area, as shown figure 5. We prepared the following traffic scenarios:

scenario 1 Traffic flow just before morning rush hour: Car flow is generally not so heavy, but the flow to the urban area is little heavier.

scenario 2 Traffic flow during morning rush hour: Many cars congregate on main roads heading into the urban area.

scenario 3 Traffic flow after morning rush hour: Car flow to recreational area becomes high.

scenario 4 Traffic flow during daytime: Car flow is not so heavy.

scenario 5 Traffic flow during evening rush hour: Many cars from urban area head to the residential areas.

We changed the traffic flow according to the above scenarios after every 10,000 steps. We evaluated a current operating traffic control system as a comparison. It prepared some traffic light control parameters beforehand and changed them according to a pre-defined time schedule. To prepare these traffic light control parameters beforehand, we conducted the simulation for each scenario with our framework and obtained five parameter sets for each.

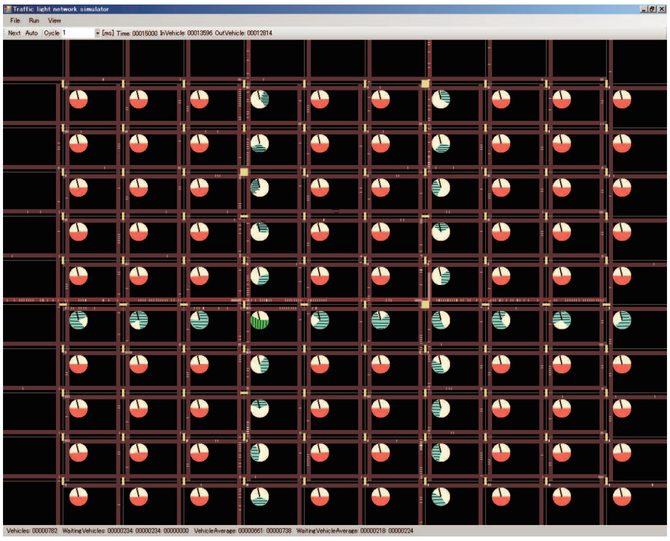

Figure 10: Experiment 3: Screenshot of Simulator during Simulation

Experiment 4

We verified the real-time adaptability of our framework against sudden changes in traffic flow. We modified scenarios 2 and 4 of experiment 3 as follows:

New scenario 2 The road between intersections (6,5) and (7,5) was suddenly closed. Therefore, cars had to go the urban area by bypassing this section.

New scenario 4 The road between intersections (6,5) and (6,7) was suddenly closed. Therefore, cars had to return to the residential areas from the recreational area by bypassing this section. Moreover, we assumed that the recreational area was crowded more than usual.

We changed the traffic flow according to the above scenario (scenario 1 -> new 2 -> 3 -> new 4 -> 5) after every 10,000 steps. We compared our traffic light control framework with a current operating control system, as in experiment 3.

4.3 Results

Figure 6 shows the evaluation results of experiment 1. The average total waiting queue of cars from simulation start to end was 382 with the non-offset model, and 318 cars with our offset control model. This result shows that the green-wave formation can make traffic flow more smoothly. This formation is more effective when the difference in both traffic flows increases.

Figure 7 shows the evaluation results of experiment 2. When we executed our offset control model, the average total waiting queue of cars from simulation start to end was 419 with our spring model, 507 with the Satoh model, and 797 with

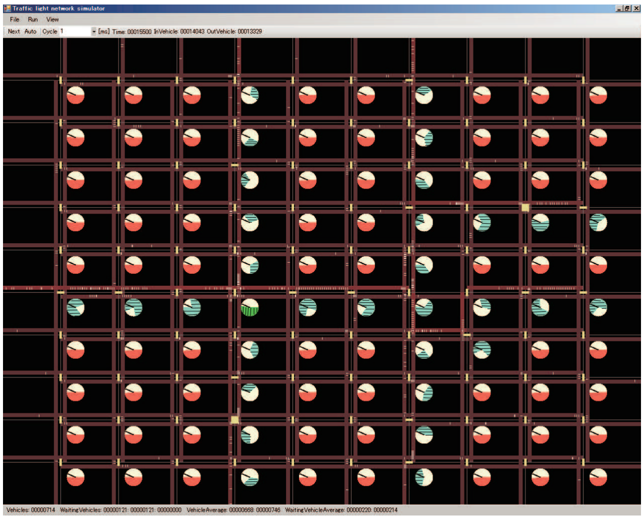

Figure 11: Screenshot of simulator of experiment 4 (New green-wave formation is constructed according to change in traffic flow)

the Oliveira model. When we did not use our offset model, the average total waiting queue of cars was 524 with our spring model, 590 with the Satoh model, and 786 with the Oliveira model.

In the Oliveira model, since the split value is fixed and does not flexibly change, the waiting queue of cars becomes longer. Moreover, This model could not attain smooth traffic flow, even if it was combined with our offset control model. On the other hand, with our spring model and the Satoh model, the waiting queue of cars did not become long. In addition, the length of the queue decreased when these models were combined with our offset control model, making traffic flow more smoothly.

Finally, when our offset control model was combined with our spring model the total waiting queue of cars decreased 20% compared with only our split control model. On the other hand, with the Satoh model, the queue length decreased by 16%. As mentioned above, our spring model is an indirect coordination-type model, and the Satoh model is a direct coordination-type model. Therefore, this result shows that when the split control model is combined with the offset control model using direct type coordination as the upper layer, indirect-type coordination is a more desirable approach for the split control model as the lower layer.

Figure 8 shows the evaluation results of experiment 3. The total average waiting queue of cars from simulation start to end was 228 with our control framework and 231 with the current operating control system. Figure 10 shows a screenshot of the simulator during the simulation of experiment 3. The green, aqua and orange sectors describe an agent's mode (see Figure 4). Agents coordinated with others and formed a subarea and a green-wave formation suitable for traffic flow: many cars congregated on main roads heading to the urban area.

Figure 9 shows the results of experiment 4. The total average waiting queue of cars from simulation start to end was 236 with our control framework and 244 cars with the current operating control system. Figure 11 shows a screenshot of the simulator during the simulation of experiment 4. Agents coordinated with others and formed a subarea and a green-wave formation for changed traffic flow. We could observe that agents on bypasses threw in the coordination, and several agents that had coordinated dissolved the coordination. From 10,000 to 20,000 steps, the queue length was 246 cars with our control framework and 276 cars with the current operating control system, and from 30,000 to 40,000 steps, the queue length was 263 cars with our control framework and 285 cars with the current operating control system.

When traffic flow was normal (situation in experiment 3), there was not much difference between our control framework and the current operating control system having several parameter sets beforehand because there was no unexpected event in this experiment. However, when an unexpected event occurs, such as a traffic accident, the difference in the waiting queue of cars between both our framework and the current system becomes quite large, as observed in new scenarios 2 and 4 in experiment 4. This is because in our framework, green-wave formation can be organized anywhere. This result shows that our control framework can deal with sudden change in traffic flow in contrast to the current operating control system.

With this simulation, we believe that we could show the fundamental effectiveness of our traffic control framework based on a multi-agent paradigm. Several parameters used in the simulation were optimized to the simulation environment. Therefore, to apply our framework to a real traffic system, a pre-experiment to find the appropriate parameter values is necessary. For example, in the current operating control system, MODERATO, many parameters are also necessary and they are set empirically and corrected through actual field observation. Therefore, we believe that a similar approach can also be applied to our framework.

5. CONCLUSIONS

We proposed a multi-agent-based traffic light control framework. To construct dynamic complex distributed systems, top down control and bottom up control are both necessary. In the proposed framework, we combined direct coordination as top-down control, and indirect coordination as bottom-up control. The important point is affinity of both coordination types. By comparative evaluation through simulation, we could verify the basic effectiveness of our framework. In our framework, direct coordination can be seen as interfering with indirect coordination. Mitigating this interference was our strategy. However, another strategy for making both coordination methodologies interact efficiently may be possible. Therefore, we will consider this in the future. Finally, the current simulated road network is a simple lattice structure, so we will perform more evaluations with large-scale and various road networks in the future.

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