A Multi-Hop Agent-Based Traffic Signal Timing System for the City of Richardson

Extended Abstract

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ABSTRACT

In this paper, we present a multi-agent Traffic Signal Timing system (TST) where intersection controller agents collaborate with one another across congested areas of the traffic network. The multi-hop agent-based traffic system is based on the TST of the City of Richardson, Texas, and is intended to be deployed with minimal changes to the infrastructure.

ACM Reference Format:

Behnam Torabi, Rym Zalila-Wenkstern and Robert Saylor. 2018. A Multi-Hop Agent-Based Traffic Signal Timing System for the City of Richardson. In *Proc. of the 17th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2018), Stockholm, Sweden, July 10–15, 2018,* IFAAMAS, 3 pages.

1 INTRODUCTION

The application of the agent paradigm to traffic signal timing has been of interest to MAS researchers for some time. Distribution, autonomy and coordination are agent properties that are naturally suited for the traffic domain. In the context of traffic signal timing, researchers have proposed the use of a variety of techniques (e.g., game theory [5, 10], neural networks [9, 19], fuzzy logic [7, 11, 15]), including the commonly used Reinforcement Learning (RL). RL-based-solutions attempt to address two types of traffic signal timing problems: non-coordinated and coordinated. In non-coordinated RL-systems, an agent's goal it to optimize the signal timing at its intersections only [1, 4, 13, 16]. The lack of coordination between agents often leads to a degradation of the overall traffic conditions. On the other hand, in coordinated agent-systems, agents implicitly coordinate with their direct neighbors by sharing their states and intended actions [6, 8, 14, 17, 18]. Given the astronomical number of states and actions that need to be considered for any realistic traffic model, coordinated RL-systems have no option but to overly simplify the traffic model. Other agent-based systems using vehicle-to-vehicle and vehicle-to-infrastructure (V2X) communications have been proposed [12, 21]. Although some these approaches provide impressive simulation results [12], they are based on assumptions that do not have their counterparts in the real world. In addition, V2X communication technologies are still in their infancy and their global deployment is decades away.

Proc. of the 17th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2018), M. Dastani, G. Sukthankar, E. André, S. Koenig (eds.), July 10–15, 2018, Stockholm, Sweden.

In this paper we present a multi-agent Traffic Signal Timing system (TST) where intersection-controller agents collaborate with one another across traffic areas that may be affected by congestion. Our work improves on the state-of-the-art in that it: 1) considers collaboration between controller agents which spans more than one-hop neighbors; 2) It does not make assumptions on the availability of data not readily accessible in the field (e.g., queue length); 3) has been tested on the largest realistic simulated network (1365 road segments and 128 signalized intersection) published in the agent-based TST literature . Our agent-based collaborative model was implemented in MATISSE 2.0, a large-scale multi-agent traffic simulation system [2, 3]. Experimental results show that the agent-based solution outperforms the traditional pre-timed and actuated systems currently in use by the City of Richardson.

2 ALGORITHMS FOR AN AGENT-BASED TST

In this section, we present the algorithms to the main scenarios. A detailed discussion of special cases is given in [20].

2.1 Model Definition

$RD = \{r_{c_1,c_2}, .., r_{c_m,c_n}\}$ is the set of road segments between intersections.

$LN_{r_{c_m,c_n}}$ is the set of lanes for a road segment r_{c_m,c_n}.

$PH_{c_n} = \{ph_{c_n,1}, ..ph_{c_n,k}\}$ is the set of phases for the intersection controlled by c_n. A phase $ph_{c_n,k}$ is defined in terms of γ, the split time, ν, the minimum green time, η, the maximum green time and $LN_{ph_{c_n,k}}$, the set of lanes it applies to.

$p(r_{c_m,c_n}.ln_w, r_{c_n,c_p}.ln_u)$ is the probability that a vehicle exiting lane w in road segment r_{c_m,c_n} enters lane u in road segment r_{c_n,c_p}. This probability is computed by traffic engineers based on historical data.

$p(r_{c_m,c_n}, r_{c_m,c_n}.ln_w)$ is the probability that a vehicle which enters road segment r_{c_m,c_n}, leaves it from lane w. This probability is also computed by traffic engineers based on historical data.

$rateOut(r_{c_m,c_n}.ln_w)$ is the rate of vehicles (per second) that can leave the intersection through lane w of road segment r_{c_m,c_n} within the current split γ.

$rateIn(t_i, r_{c_m,c_n})$ is the rate of vehicles (per second) that enter road segment r_{c_m,c_n} in the evaluation interval τ that ends at time t_i.

$\xi_{t_i,r_{c_m,c_n}.ln_w}$ is the *traffic throughput* for lane $r_{c_m,c_n}.ln_w$, i.e., the ratio of vehicles getting in and leaving the lane. It is defined as

$$\xi_{t_i,r_{c_m,c_n}.ln_w} = \frac{rateIn(t_i, r_{c_m,c_n}) \times p(r_{c_m,c_n}, r_{c_m,c_n}.ln_w)}{rateOut(t_i, r_{c_m,c_n}.ln_w)}$$

2.2 Agent Algorithms

Detecting Congestion Intersection controller c_n continuously evaluates the traffic state to determine if a re-timing operation is necessary. At each t_i, c_n receives $rateIn$ (detected through c_m's induction loops) and determines $rateOut$.

At time t_i, controller c_n computes $Cong_{t_i,ph_{c_n,k}}$ as the average throughput for the set of lanes controlled by $ph_{c_n,k}$.

$$Cong_{t_i,ph_{c_n,k}} = \sum_{r_{c_m,c_n}.ln_w \in LN_{ph_{c_n,k}}} \xi_{t_i,r_{c_m,c_n}.ln_w}$$

If $Cong_{t_i,ph_{c_n,k}}$ is greater than threshold a, then c_n considers that there is an *instant congestion* and assigns the value of 1 to $InstantCongestion$.

$$InstantCongestion_{t_i,ph_{c_n,k}} = \begin{cases} 1 & Cong_{t_i,ph_{c_n,k}} \geq a \\ 0 & Cong_{t_i,ph_{c_n,k}} < a \end{cases}$$

It proceeds by considering the past b evaluation cycles to determine the percentage of evaluation cycles in which the phase was congested. This is defined as

$$PercentCong_{t_i,ph_{c_n,k}} = \frac{\sum_{j=i-b}^{i} InstantCongestion_{t_j,ph_{c_n,k}}}{b} \times 100$$

If $PercentCong_{t_i,ph_{c_n,k}} > d$ then c_n considers the road lanes controlled by $ph_{c_n,k}$ as congested.

Generate New Plan c_n deliberates to determine the value of a new split that will alleviate congestion on $ph_{c_n,k}$. The value of the new split is calculated as:

$$plan_{new}.phase.\gamma = plan_{cur}.phase.\gamma * (e + \frac{\sum_{j=i-v}^{i} Cong_{t_j,ph_{c_n,k}}}{v} * f)$$

where e and f are coefficients that regulate the influence of the traffic throughput and the current split time. If $plan_{new}.phase.\gamma$ is greater than the maximum allowed split time γ_{MAX}, then its value is set to $ph_{c_n,k}.\gamma_{MAX}$.

Request For Evaluation c_n determines the impact of executing the new plan on its neighboring intersections in terms of κ, the increment in vehicle rate. $\kappa_{r_{c_m,c_n}.ln_w}$ is calculated for road lane $r_{c_m,c_n}.ln_w$ as:

$$\kappa_{r_{c_m,c_n}.ln_w} = \frac{rateOut(t_i, r_{c_m,c_n}.ln_w) \times (plan_{new}.phase.\gamma - plan_{cur}.phase.\gamma)}{plan_{new}.phase.\gamma}$$

$\kappa_{ph_{c_n,k}}$ for a phase $ph_{c_n,k}$ is defined as the sum of $\kappa_{r_{c_m,c_n}.ln_w}$ for the set of lanes controlled by the phase. In the same way, $\kappa_{r_{c_n,c_p}}$ for a road segment r_{c_n,c_p}, is the sum of $\kappa_{r_{c_n,c_p}.ln_w}$. Controller c_n proceeds by sending $plan_{new}$, $\kappa_{r_{c_n,c_p}}$ and $\kappa_{ph_{c_n,k}}$ to each adjacent controller c_p for evaluation.

Compute Level Of Agreement Upon receipt of a new plan, c_n's neighboring controller c_p computes $\kappa_{r_{c_p,c_q}}$ for each of its neighbor c_q and request that they in turn evaluate the plan. The process propagates until at a given intersection, either the value of κ is smaller than threshold g or the plan reaches the road network boundaries. Following this step and recursively, each controller sends back its level of agreement in terms of a real number Ψ, to the controller from which it has received the request. A c_p, calculates Ψ_{c_p} based on the existing traffic throughput, its priority ω and the ratio of the received additional vehicle throughput. After receiving the level of agreement from all involved neighbors, c_p combines them with its own level of agreement Ψ_{c_p} and sends the value back to c_n. The final decision is made based on the value of Ψ_{c_n} representing the feedback of all involved controllers.

3 EXPERIMENTAL RESULTS

The experiments discussed in this section were implemented in MATISSE 2.0 [2, 3] and run on a multicore PC (Intel Core i7 X980 CPU (3.33GHz), 6.00 GB, 64-bit Windows 7). A simulated model of the City of Richardson's traffic network including 1365 road segments and 128 signalized intersections was created. Two simulation settings were run for 86,400 simulation cycles representing a 24-hour time period. We compare the efficiency of pre-timed, fully-actuated and the proposed agent-based model with respect to delay and queue length. Demos are available at *mavs.utdallas.edu/its*

Experiment 1

In this experiment, the number of vehicles during the simulation remains constant but new vehicles are added randomly when others randomly exit the traffic network. This experiment is intended to illustrate random traffic patterns that may not be necessarily captured by the predefined timing plans used by the pre-timed and fully-actuated operating modes. The experiment was run with 100, 250, 500, 1000, 2000 and 3000 vehicles. As expected, the results show that the average traffic throughput for the agent-based model is 10.37 percent lower than the pre-timed and actuated modes. The average queue lengths are also reduced by 12.85 percent by controller agents.

Experiment 2

In this experiment, we make use of traffic data provided by the City of Richardson to determine the number of vehicles in the traffic network at any given time, as well as their distribution in the network. The results show that, between the times of 00:30am and 5:30am, all models perform at the same level with respect to throughput. This is due to the fact that during that time period traffic is very light and therefore the agent-based model operates similarly to the pre-timed and actuated models. As we progress during the day (i.e., 6:30 am to 8:30 am) the average traffic throughput increases, indicating congestion. The agent-based model naturally adapts by dynamically defining and implementing timing plans. This results in a 22.12 percent improvement in the average traffic throughput and a 13.82 percent improvement in the average queue lengths during rush hours.

4 CONCLUSION

In this paper we presented a multi-hop, collaborative agent-based (TST) and its application for the City of Richardson's traffic network. This work is a first step towards the implementation of the agent-based solution for the city. Future work includes the development of a hybrid simulation and the assessment of agent-to-agent communication costs.

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