

INTELLIGENT TRAFFIC LIGHT CONTROL- A REVIEW PAPER

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Abstract:- Vehicular travel is increasing throughout the world, particularly in large urban areas. Therefore the need arises for simulating and optimizing traffic control algorithms to better accommodate this increasing demand. In this paper we study the simulation and optimization of traffic light controllers in a city and present an adaptive optimization algorithm based on reinforcement learning. We have implemented a traffic light simulator, Green Light District that allows us to experiment with different infrastructures and to compare different traffic light controllers. Experimental results indicate that our adaptive traffic light controllers outperform other fixed controllers on all studied infrastructures.

Keywords: *Intelligent Traffic Light Control, Reinforcement Learning*

I INTRODUCTION

Transportation research has the goal to optimize transportation flow of people and goods. As the number of road users constantly increases, and resources provided by current infrastructures are limited, intelligent control of traffic will become a very important issue in the future. However, some limitations to the usage of intelligent traffic control exist. Avoiding traffic jams for example is thought to be beneficial to both environment and economy, but improved traffic-flow may also lead to an increase in demand [Levinson, 2003]. There are several models for traffic simulation. In our research we focus on microscopic models that model the behavior of individual vehicles, and thereby can simulate dynamics of groups of vehicles. Research has shown that such models yield realistic behavior [Nagel and Schreckenberg, 1992, Wahle and Schreckenberg, 2001]. Cars in urban traffic can experience long travel times due to inefficient traffic light control. Optimal control of traffic lights using sophisticated sensors and intelligent optimization algorithms might therefore be

very beneficial. Optimization of traffic light switching increases road capacity and traffic flow, and can prevent traffic congestions. Traffic light control is a complex optimization problem and several intelligent algorithms, such as fuzzy logic, evolutionary algorithms, and reinforcement learning (RL) have already been used in attempts to solve it. In this paper we describe a model-based, multi-agent reinforcement learning algorithm for controlling traffic lights. In our approach, reinforcement learning [Sutton and Barto, 1998, Kaelbling et al., 1996] with road-user-based value functions [Wiering, 2000] is used to determine optimal decisions for each traffic light. The decision is based on a cumulative vote of all road users standing for a traffic junction, where each car votes using its estimated advantage (or gain) of setting its light to green. The gain-value is the difference between the total time it expects to wait during the rest of its trip if the light for which it is currently standing is red, and if it is green. The waiting time until cars arrive at their destination is estimated by monitoring cars flowing through the infrastructure and using reinforcement

learning (RL) based RL method to that of other controllers using the Green Light District simulator (GLD). GLD is a traffic simulator that allows us to design arbitrary infrastructures and traffic patterns, monitor traffic flow statistics such as average waiting times, and test different traffic light controllers. The experimental results show that in crowded traffic, the RL controllers outperform all other tested non-adaptive controllers. We also test the use of the learned average waiting times for choosing routes of cars through the city (co-learning), and show that by using co-learning road users can avoid bottlenecks.

II. MODELLING AND CONTROLLING TRAFFIC

In this section, we focus on the use of information technology in transportation. A lot of ground can be gained in this area, and Intelligent Transportation Systems (ITS) gained interest of several governments and commercial companies [Ten-T expert group on ITS, 2002, White Paper, 2001, EPA98, 1998]. ITS research includes in-car safety systems, simulating effects of infrastructural changes, route planning, optimization of transport, and smart infrastructures. Its main goals are: improving safety, minimizing travel time, and increasing the capacity of infrastructures. Such improvements are beneficial to health, economy, and the environment, and this shows in the allocated budget for ITS. In this paper we are mainly interested in the optimization of traffic flow, thus effectively minimizing average traveling (or waiting) times for cars. A common tool for analyzing traffic is the traffic simulator. In this section we will first describe two techniques commonly used to model traffic. We will then describe how models can be used to obtain real-time traffic information or predict traffic conditions. Afterwards we describe how information can be communicated as a means of controlling traffic, and what the effect of this communication on traffic conditions will be. Finally, we describe research in which all cars are controlled using computers.

III. TRAFFIC LIGHT CONTROL

Traffic light optimization is a complex problem. Even for single junctions there might be no obvious optimal solution. With multiple junctions, the problem becomes even more complex, as the state of one light influences the flow of traffic towards many other lights. Another complication is the fact that flow of traffic constantly changes, depending on the time of day, the day of the week, and the time of year. Roadwork and accidents further influence complexity and performance. In practice most traffic lights are controlled by fixed-cycle controllers. A cycle of configurations is defined in which all traffic gets a green light at some point. The split time determines for how long the lights should stay in each state. Busy roads can get preference by adjusting the split time. The cycle time is the duration of a complete cycle. In crowded traffic, longer cycles lead to better performance. The offset of a cycle defines the starting time of a cycle relative to other traffic lights. Offset can be adjusted to let several lights cooperate, and for example create green waves. Fixed controllers have to be adapted to the specific situation to perform well. Often a table of time-specific settings is used to enable a light to adapt to recurring events like rush hour traffic. Setting the control parameters for fixed controllers is a lot of work, and controllers have to be updated regularly due to changes in traffic situation. Unique events cannot be handled well, since they require a lot of manual changes to the system. Fixed controllers could respond to arriving traffic by starting a cycle only when traffic is present, but such vehicle actuated controllers still require lots of fine-tuning. Most research in traffic light control focuses on adapting the duration or the order of the control cycle. In our approach we do not use cycles, but let the decision depend on the actual traffic situation around a junction, which can lead to much more accurate control. Of course, our approach requests that information about the actual traffic situation can be obtained by using different sensors or communication

systems. We will first describe related work on intelligent traffic light control, and then describe our car-based reinforcement learning algorithm.

III CONCLUSION

In this article we first showed that traffic control is an important research area, and its benefits make investments worthwhile. We described how traffic can be modelled, and showed the practical use of some models. In section 3 we explained reinforcement learning, and showed its use as an optimization algorithm for various control problems. We then described the problem of traffic light control and several intelligent traffic light controllers, before showing how car-based reinforcement learning can be used for the traffic light control problem. In our approach we let cars estimate their gain of setting their lights to green and let all cars vote to generate the traffic light decision. Co-learning is a special feature of our car-based reinforcement learning algorithm that allows drivers to choose the shortest route with lowest expected waiting time.

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