IS 2010- Scientific Communication
Assignment 1 - B18 L2 S2
Department of Interdisciplinary Studies, Faculty of IT, University of Moratuwa
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Instructions to candidates

Read the given extract from a research paper and write a critical review (a summary) on it. Your summary should include;

1. Title of the paper and the author/s
2. A brief summary of the research/project
3. Positive Comments
4. Negative Comments
5. Your conclusion with justifications

Intelligent Traffic Light Control

Marco Wiering, Jelle van Veenen, Jilles Vreeken, and Arne Koopman

Intelligent Systems Group

Institute of Information and Computing Sciences

Utrecht University

Padualaan 14, 3508TB Utrecht, The Netherlands

email: marco@cs.uu.nl

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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, Multi-Agent Systems (MAS), Smart Infrastructures, Transportation Research

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) algorithms. We compare the performance of our model-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. This paper is organized as follows. Section 2 describes how traffic can be modelled, predicted, and controlled. In section 3 reinforcement learning is explained and some of its applications are shown. Section 4 surveys several previous approaches to traffic light control, and introduces our new algorithm. Section 5 describes the simulator we used for our experiments, and in section 6 our experiments and their results are given. We conclude in section 7.

Conclusions

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.

We performed three series of experiments, using the Green Light District traffic simulator. We described how this simulator works, and which traffic light controllers were tested. The experiments were performed on three different infrastructures. The first experiment, which uses a large grid, shows that reinforcement learning is efficient in controlling traffic, and that the use of co-learning further improves performance. The second experiment shows that using co-learning vehicles avoid crowded intersections. This way, vehicles avoid having to wait, and actively decrease pressure on crowded intersections. The third experiment shows that RL algorithms on more complex and city-like infrastructure again outperform the fixed controllers by reducing waiting time with more than 25%. The third experiment also shows that in some situations a simplified version of the reinforcement learning algorithm performs as well as the complete version, and that co-learning not always increases performance.

Further Research

Although the reinforcement learning algorithm presented here outperforms a number of fixed algorithms, there are several improvements that could be researched. For example, we can use communication between road-lanes to make green waves possible, and let estimated waiting times depend on the amount of traffic on the next road-lane. The co-learning driving policy might be improved as well. The current implementation suffers from saturation and oscillation. Because all drivers on a route choose the optimal lane, this lane might become crowded. Only when the performance of such a lane decreases because of this crowding, drivers will choose another lane. A less greedy form of co-learning might prevent this effect. Although the bucket algorithm works well for the fixed algorithms, it did not work well together with the RL algorithms. We have to study this more carefully, since the bucket algorithm, when designed well, may help in creating green waves in very crowded traffic conditions. The simulator might be refined as well, to allow for comparison with other research. Refinements could include more complex dynamics for the vehicles and other road users, as well as an implementation of fixed-cycle traffic-light controllers.