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An automated signalized junction controller that learns strategies from a human expert

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A R T I C L E I N F O

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A B S T R A C T

An automated signalized junction control system that can learn strategies from a human expert has been developed. This system applies machine learning techniques based on logistic regression and neural networks to affect a classification of state space using evidence data generated when a human expert controls a simulated junction.

The state space is constructed from a series of bids from agents, which monitor regions of the road network. This builds on earlier work which has developed the High Bid auctioning agent system to control signalized junctions using localization probe data. For reference the performance of the machine learning signal control strategies are compared to that of High Bid and the MOVA system, which uses inductive loop detectors.

Performance is evaluated using simulation experiments on two networks. One is an isolated T-junction and the other is a two junction network modelled on the High Road area of Southampton, UK. The experimental results indicate that machine learning junction control strategies trained by a human expert can outperform High Bid and MOVA both in terms of minimizing average delay and maximizing equitability; where the variance of the distribution over journey times is taken as a quantitative measure of equitability. Further experimental tests indicate that the machine learning control strategies are robust to variation in the positioning accuracy of localization probes and to the fraction of vehicles equipped with probes.

1. Introduction

This paper describes the development of a machine learning junction control system that employs pattern matching techniques including logistic regression and neural network classification to find statistical trends between the signal control decisions made by the human expert and the state of a simulated network as described by simulated localization probe data.

1.1. Background

In the United Kingdom urban signalized road junctions are usually controlled by one of two systems, MOVA (Vincent and Peirce, 1988) for use at isolated junctions and SCOOT (Hunt et al., 1982), which can coordinate multiple adjacent junctions. Both these systems use sensors, including inductive loops (Sreedevi, 2005) and microwave emitter/detectors (Wood et al., 2006), to detect the presence of vehicles at fixed locations on the roads around the junction. The data from these sensors are used as a descriptor of the state of the network by the control algorithms to inform decisions on which colour to set the traffic lights.

Data collected from counts of vehicles at fixed locations are called *census* data. Previous reviews (e.g. Rose, 2006) have suggested that*localization probe* data, that are dynamic position and speed data from on board vehicle sensors, can present a different view of the state of the network. The European Commission has recently invested significant resources in three major studies to look into the benefits of vehicle to infrastructure (V2I) and vehicle to vehicle (V2V) communications (Kompfner, 2008; COOPERS, 2010; SAFESPOT, 2010). Furthermore common European protocols have been set for this type of communication (IEEE 802.11p). This has laid the ground for this technology to become commonplace in Europe in the near future. This technological advance would enable localization probe data to be collected and employed in urban traffic control (UTC) systems.

1.2. Context and motivation

Early work to investigate the scenario of localization probe data in signal control has employed simulation to develop and evaluate control methods. Box and Waterson (2010a) presents an *auctioning agent* control method. This work showed the auctioning agent

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approach outperforming MOVA in simulations on an isolated T-junction. In Waterson and Box (accepted for publication) the auctioning agent system was subjected to a rigorous quantitative stochastic analysis, which characterized the effects of varying the positioning accuracy and the fraction of vehicles equipped with probes.

The simulation test bed used for the work presented in this paper is described in detail in Box and Waterson (2010a), Waterson and Box (accepted for publication). In summary: it uses S-Paramics microsimulation software to model networks and simulate the movement of individual vehicles through junctions. Built around this are a number of bespoke software modules for simulating localization probe data, making control decisions, and implementing control directly in the simulation.

Box et al. (2010) showed that a human interface layer can be connected to the simulation test bed allowing an expert human to control the signals at simulated junctions. Results indicated that an expert human controller can outperform both MOVA *and* the auctioning agent approach from Box and Waterson (2010a) in terms of delay across the junction.

This motivates the development of machine learning junction control systems that can mine the data generated when a human expert controls simulated junctions and emulate human control strategies under automated control. Box et al. (2010) also demonstrated how the auctioning agent method could be adapted, employing the pattern recognition technique of logistic regression, to create a *learning junction agent*.

In this paper both the auctioning agent system and the learning agent are developed further. The principal contributions are as follows:

1. An updated structure for the auctioning agent method introducing the *lane agent*.
2. A new learning junction agent, which employs a two layer neural network with back propagation to learn strategies from a human expert.
3. A comparison between the logistic regression and neural network learning junction agents including variation in the resolution of the training data.
4. Simulation tests carried out on a two junction network, which models the High Road area of Southampton, UK.

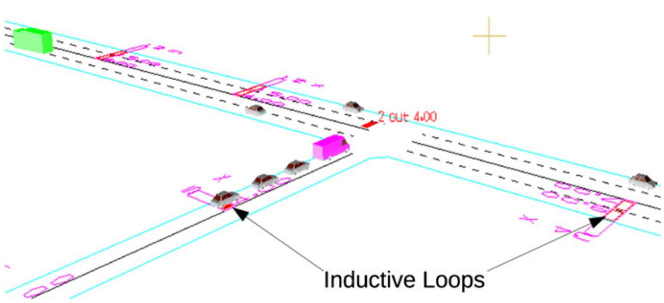

Fig. 1. S-Paramics screenshot of the Simple T-junction simulation model used in simulation tests. Inductive loop locations are marked by arrows.

Other important works where pattern recognition and machine learning techniques have been applied to junction control include (Choy et al., 2003; Mikami and Kakazu, 1993; Chen and Heydecker, 2009). This work has shown how to use neural networks and other techniques to optimize certain parameters in signal control strategies or to select pre-defined strategies. In the work presented here, machine learning techniques are used to select signal control decisions by directly classifying state space using evidence data generated by a human expert (Section 3).

2. Signal control strategies overview

Simulation tests were carried out on two network models. Fig. 1 shows a view of the first, the Simple T-junction. This is an isolated junction with three signal stages. Fig. 2 shows a view of the second, the High Road junction. This is a model of the High Rd area of Southampton, UK. It consists of two signalized junctions a short distance apart. The westerly junction has four signal stages and the easterly junction has three.

This section presents an overview of the junction control strategies that were investigated using simulations on these junctions. These are MOVA, auctioning agents using the High Bid method and auctioning agents using the learning junction agent.

2.1. MOVA

The MOVA control strategy (Vincent and Peirce, 1988) is a common strategy that is employed on many isolated junctions in the real world, therefore it is used as a baseline for junction control performance in these tests. The MOVA control strategy was tested on the Simple T-junction only. The S-Paramics simulation models 11 inductive loop detectors (examples are marked in Fig. 1), which measure counts of vehicles passing over. The signals from these detectors serve as inputs to the MOVA algorithm. In fact the Simple T-junction model was designed by The Transportation Research Laboratory (TRL) as an exemplar for MOVA

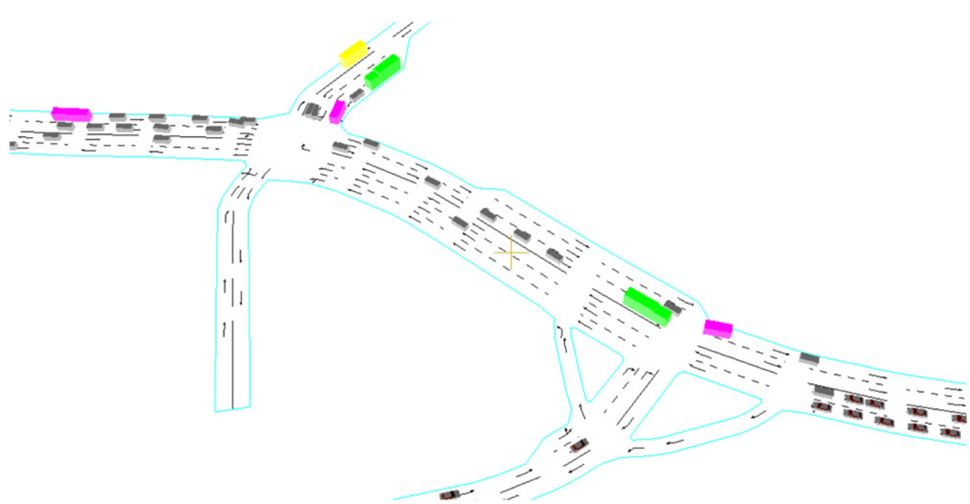

Fig. 2. S-Paramics screenshot of the High Road junction simulation model used in simulation tests.