OVERVIEW OF DISTRIBUTED DECISION-MAKING FOR URBAN TRAFFIC CONTROL

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Abstract: The traditional way of controlling urban traffic is using centralised control approaches: There is a single control centre where decisions are made about the traffic control in the whole urban area. Currently, this paradigm is shifting towards more decentralised hierarchical approaches with smaller control centres serving sub-regions of the intersection network in a city. The paper reviews possible directions of future development in this area, which are the use of distributed or multi-agent systems in the form of peer-to-peer networks of decision-makers.

Keywords: Urban traffic control, Distributed decision-making, Game theory, Fuzzy control, Bayesian agents

1. INTRODUCTION

Many current urban traffic control (UTC) strategies make use of *vehicle actuated* signal switching to improve throughput of single intersections. While this method significantly outperforms fixed signal control, the conflicting preferences of particular intersections present a major challenge in case of coordinated control of a larger traffic network. A traditional way of coping with this problem is the use of centralised control strategies where a single macro-controller limits the autonomy of intersection controllers.

A more scalable and flexible scheme is based on distributed control, where intersections are represented by intelligent agents that mutually cooperate in order to reach an optimum traffic state. A first attempt for real-world deployment of agent-based decision-making application was probably the distributed decision support system installed in Barcelona (Ossowski *et al.* 1998). While it provided support for traffic management at urban motorways and at several critical approaches to the city, it was not used for traffic control in the inner city.

Control strategy can be also devised by playing a *distributed stochastic game* between agents (Camponogara and Kraus Jr 2003). This technique makes use of reinforcement learning to find an globally optimal policy which maps observed states to control actions. At least for a simple simulation scenario it gives very promising results.

Most of the presented systems use agents as impersonation for an intersection or even a group of intersections. Some approaches, however, use even finer granularity and place agents at individual signal groups at an intersection (Kosonen 2003). These agents then negotiate optimum signal plan setting for the intersection, given the constrains from other signal group agents at the intersection and constraints imposed by neighbouring intersections.

The most advanced example of an agent coordination strategy based on *distributed evolutionary game* models different variants of traffic control policies and offers them to a traffic manager (Bazzan 2005).

While all the methods presented above address one very important issue of urban traffic control, namely the uncertainty between causes and actions that is present in the system, the communication between agents is closely related to the physical construction of the underlying intersection controllers. A different approach is proposed by the Bayesian Agents (Šmídl and Přikryl 2006) where every agent describes the whole intersection (traffic model, control aims, control actions) in form of probability density functions. In such a way, agents cooperate by exchanging their "wishes" as pdfs and the task of devising an optimum control strategy can be represented by the merging operation.

2. COOPERATION MECHANISMS

We will review three basic cooperation mechanisms used for distributed urban traffic control approaches. Section 2.1 presents an overview of game-theoretic methods in traffic control, the following Section 2.2 shows an interesting signal plan negotiation method using fuzzy agents. The overview ends by presentation of a Bayesian approach to negotiation in Section 2.3.

2.1 Distributed games

Many researchers fell that *game theory* is a powerful means of negotiation between isolated agents. In game-theoretic approaches, game participants learn their optimum strategy by observing the actions of other players, which leads to an equilibrium state where all players receive maximum possible payoffs. In a similar way, an agent will learn its optimum behaviour by observing interactions in which it is involved.

The main problem of the below mentioned methods is that they do not guarantee that a globally optimal equilibrium state will be found. In traffic control, two methods have been used to avoid the non-optimal equilibria:

- Stochastic games (Q-learning)
- Evolutionary games

Let us now look at both approaches in more detail.

Stochastic games (Q-learning) present a reinforcement learning technique which is able to compare the expected utility of actions without requiring a model of the environment. This makes the

The learning process works by estimating the values of state-action pairs. It is governed by function $Q(s_t, a_t)$ which describes the utility of selecting action a_t at time t from a set of possible actions a^*, given the current state s_t,

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \cdot [r_{t+1} + \phi \cdot \max_{a \in a^*} Q(s_{t+1}, a) - Q(s_t, a_t)].$$

Here, r_t is the reward read from the environment, $\alpha \in \langle 0, 1\rangle$ is the learning rate, and $\phi \in \langle 0, 1\rangle$ is the discount rate which specifies if the agent prefers immediate rewards (ϕ closer to zero) or if it considers long-term payoff of its actions (ϕ closer to one).

The traffic control application (Camponogara and Kraus Jr 2003) simulated a simple scenario on two intersections connected over a single arm. The quality of the control was expressed by total waiting time of a vehicle.

Four scenarios were considered:

- Random policy – random selection of a signal at every intersection. The results were used as the ground truth for comparing other methods, which is quite unrealistic (it would be fair to use a fixed control scenario).
- Best effort – a control policy discharging the longest queue. This prefers the directions with maximum traffic intensity and blocks conflicting flows.
- One Q-learning, one random – in this case maximum 18% gain over the random policy was reached.
- Both Q-learning – if both agents devise their strategy using Q-learning, approximately 40% gain over random policy can be reached.

The agents are isolated, they do not have possibilities to influence each other directly, but as they can observe the full state of the system, the optimum policy is created in an indirect way by converging to a stable strategy for given state s_t. The best effort policy significantly outperforms Q-learning for low traffic intensities where queues can be discharged quickly. As the traffic intensity grows and the system moved towards saturated conditions, the Q-learning process clearly wins.

Evolutionary games are inspired by evolutionary algorithms which are used to find solutions for computationally demanding problems by simulation of reproduction and mutation of small genetic entities. In order to avoid non-optimum equilibria, all players search for an *evolutionary stable strategy*, that is, a strategy of the whole population that cannot be beaten by some other mutation.

In the evolutionary traffic control approach (Bazzan 2005) the play game with the aim to minimise the number of cars on their inputs. The evolutionary stable strategy is constructed through payoff analysis and a particular strategy is chosen by extrapolating moves from the past.

The sketch of the approach is presented in Figure 1. The aim of the methods is to create a "green wave" at an arterial by selecting a unique signal plan from a predesigned set of signal plans a^*. Players are not informed about strategies played in their neighborhood, the convergence follows from the genetic nature of the algorithm. However, as with all genetic algorithms, the convergence is not guaranteed.

The method does not take into account external disturbances (like traffic accidents, or platoons) and these cause problems. Also, the conflicting traffic flows may get delayed quite a lot.

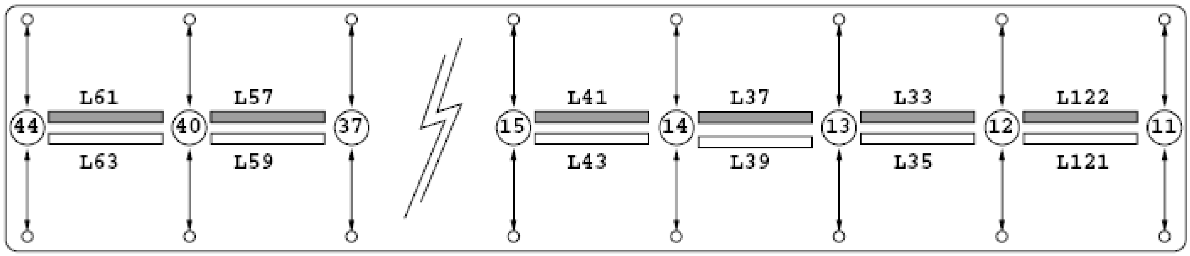

Fig. 1: Signal plan selection at an arterial using distributed game-theoretoc reasoning. Reproduced from Bazzan (2005).

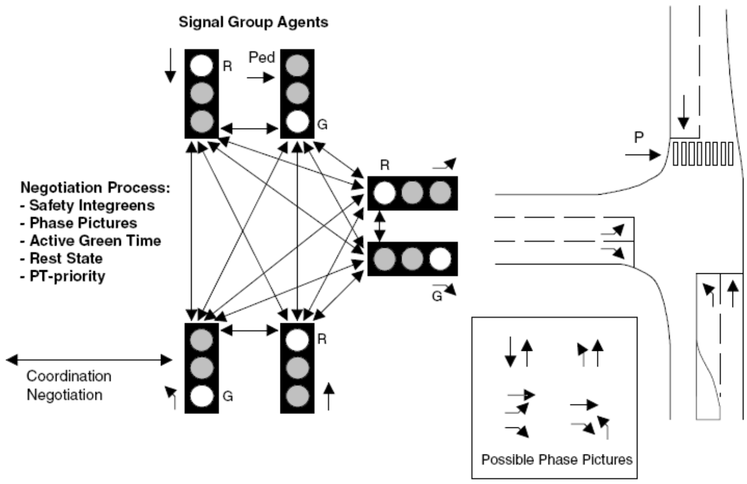

Fig. 2: Signal coordination at a single intersection. Reproduced from Kosonen (2003).

2.2 Fuzzy reasoning

The fuzzy control approach is based on the fact that traffic control has been in general controlled by rules, which makes fuzzy rule-based signal control a plausible choice. Membership functions can be used to define such terms like "short-queue" and "long-queue" by means of fuzzy logic. These functions can be then used to describe the current situation to other agents, hence creating a distributed multi-agent signal controller.

The approach we will discuss here (Kosonen 2003) is slightly different from other distributed traffic control methods as it uses *signal group agents* impersonating particular parts of a signal plan at an intersection that negotiate through fuzzy inference whether to extend or terminate the active green signal and which signal shall be selected next (see Figure 2). The advantage of this approach is that there are no fixed stages, and any reasonable phase picture can be formed as needed. The inherent disadvantage is the difficulty to synchronise neighbouring intersections.

The signal group agents negotiate a control strategy that takes care of several objectives: *safety* (providing plausible inter-green lengths), *equality* (each direction will get a possibility to go green, this is a variant of a phase ring), adequate *timing*, and *transition minimisation* (an optimal rest state of the intersection).

The fuzzy control has been also applied by the same author to area control. In that case a microsimulator is used to predict traffic states and the fuzzy control is used just to negotiate

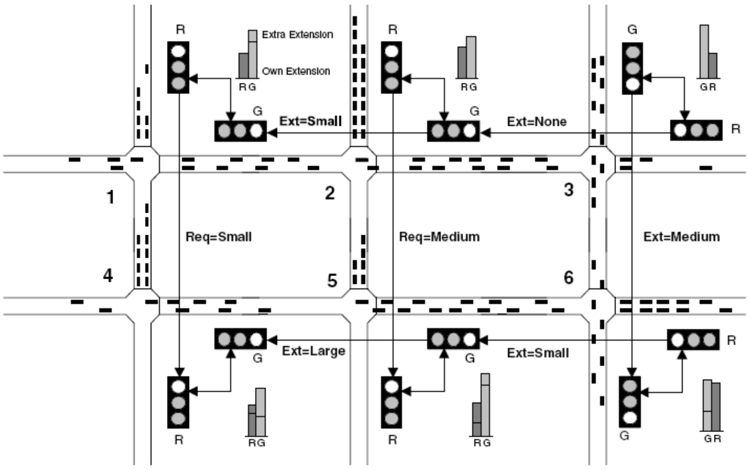

Fig. 3: Signal coordiation of a microregion. Reproduced from Kosonen (2003).

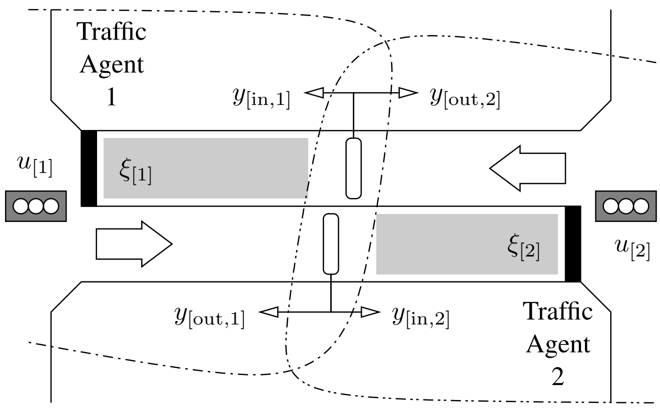

Fig. 4: Signal coordination between a pair of Bayesian traffic agents. Reproduced from Šmídl and Přikryl (2005).

downlink green extension (see Figure 3). The main problem of the approach is the need to resolve conflicts caused by conflicting traffic flows. The method also does not provide the possibility of an intersection to shorten the uplink green signals in case of a traffic jam.

2.3 Bayesian agents

Surface traffic in dense urban areas is a typical example of a system with both strong presence of uncertainty, and the need for decentralized controllers. It has been shown by Šmídl and Přikryl (2006) that Bayesian distributed control can be used to address this problem using an existing model of traffic flow.

The traffic flow is modelled using a particle flow model, where the state θ_t consists of the queue lengths ξ_t and some extra entries. The probabilistic version of the model can be written as:

$$\begin{aligned} f(\Theta_t|\Theta_{t-1}, u_{t-1}, y_{[\text{in}],t-1}) &= t\mathcal{N}\left(A_t\Theta_{t-1} + B_t u_{t-1}, Q_t, \langle 0, \Theta_{\max}\rangle\right), \\ f(y_{[\text{out}],t}|\Theta_t, u_t, y_{[\text{in}],t-1}) &= t\mathcal{N}\left(C_t\Theta_t + D_t u_t, R_t, \langle 0, y_{\max}\rangle\right). \end{aligned}$$

where $t\mathcal{N}(\mu, V, \langle x_{\min}, x_{\max}\rangle)$ is the truncated Gaussian distribution.

The global aim of this traffic control approach is to minimize the total time spend by cars in the network by minimization of the waiting queues ξ_t while maximizing the output intensities $I_{[\mathrm{out}],t}$. This gives the following ideal distributions on queue length and outputs, that every traffic agent aims for:

$$\begin{aligned} {}^{I}f(\xi_t) &= t\mathcal{N}\left(0, V_\xi, \langle 0, \xi_{\max}\rangle\right), \\ {}^{I}f(I_{[\mathrm{out}],t}|\xi_t) &= t\mathcal{N}\left(I_{[\mathrm{out}],\max}, V_{I[\mathrm{out}]}, \left\langle 0, I_{[\mathrm{out}],\max}\right\rangle\right) \end{aligned}$$

Since the maximization of outgoing intensities may be counterproductive if the neighbouring agent is facing a congestion, each agent also formulates its ideal pdf on its incoming intensities, $I_{[\mathrm{in}],t}$ and negotiates it with its negihbours:

$$ {}^{I}f(I_{[\mathrm{in}],t}|\xi_t) = t\mathcal{N}\left(I_{\mathrm{w}}\left(\xi_t\right), V_{I[\mathrm{in}]}, \left\langle 0, I_{[\mathrm{in}],\max}\right\rangle\right)$$

The negotiation process is implemented as the classical algorithm of probability density function merging.

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