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Self-organizing urban traffic control based on fuzzy cellular model

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ABSTRACT

The paper introduces a self-organizing traffic signal system for an urban road network. In the presented system, the traffic control decisions are made on the basis of predictions that are obtained from a fuzzy cellular traffic model. The fuzzy cellular model represents traffic streams at the microscopic level. Therefore it can directly map parameters of individual vehicles and the vehicle classes can be taken into account in making the control decisions. Simulation experiments were performed to compare the performance of the self-organizing traffic control for two scenarios: first, when the class of vehicles is taken into account and second, when the information on the vehicle class is unavailable. Results of the simulations allow us to explore the possibility of performance enhancement of the urban traffic control through the utilisation of microscopic traffic models and vehicle classification systems.

KEYWORDS: self-organization, urban traffic control, fuzzy cellular automata

1. Introduction and motivation

The main aim of urban traffic control is to maximize the throughput of a road network by means of real-time actions [8]. This aim is usually pursued by application of adaptive traffic signal control strategies that take into account current traffic estimates and predictions [9] in order to optimize objective functions, such as minimizing travel time, delays or stop counts.

Conventional traffic control methods attempt to optimize traffic signal settings for a road network in a centralized system. However, the global optimization of traffic flow in a road network is known to be an NP-hard problem [8]. Due to the high computational complexity, the optimization algorithms cannot be executed in real-time. Therefore, the conventional centralized traffic control approaches are based on a simplified optimization (adaptation), which concerns only selected parameters (cycle time, splits, offsets) for some pre-calculated signalization schedules [5].

Limitations of the available methods have motivated the recent development of self-organizing traffic signal systems. A system is called self-organizing if its elements interact in order to achieve a global function or behaviour. This function or behaviour is not imposed by a single element, nor determined hierarchically but it emerges dynamically as the elements interact with one another. The interactions of elements produce feedbacks that regulate the system [3].

In the self-organizing traffic control systems, the global coordination of traffic flows in a road network is achieved through a decentralized optimization scheme. According to this method, the traffic control unit at an intersection makes autonomous decisions about optimal signal settings on the basis of local traffic measurements. Additionally, the self-organizing optimization algorithm can utilize traffic data delivered from neighbouring intersections. The local optimization rules lead to emergent coordination patterns such as "green waves" and achieve an efficient, decentralized traffic light control. When applying this control strategy, signal plans are not based on cyclic control schemes determined from average traffic conditions, but they respond instead to actual real-time traffic data. This makes the traffic control more flexible with respect to local demands and more robust to variations in the traffic flows.

The self-organized traffic control algorithms available in the literature were developed using macroscopic traffic models that describe traffic behaviour in terms of traffic volumes, queue lengths and congestion levels. By contrast, the system presented in this paper is based on a microscopic fuzzy cellular traffic model, which considers individual vehicles and thus the vehicle parameters can be taken into account in making control decisions. The parameters of particular vehicles (position, velocity, acceleration, class, etc.) are accessible in modern traffic monitoring platforms [12]. These data cannot be fully utilized when using the existing control methods. Interestingly, in the proposed approach the precision of traffic description is variable and can be adjusted to match the precision of available traffic data.

The rest of the paper is organized as follows.: Related works are reviewed in Section 2. Section 3 describes details of the self-organized traffic control algorithm and presents the microscopic traffic model, which enables on-line simulation of traffic streams for the control purposes. Section 4 contains results of the simulation experiments that were performed in order to examine the dependency between input data precision and performance of the self-organizing traffic control. Finally, conclusions are given in Section 5.

2. Related works

In the literature there is an increasing number of publications dealing with application of the self-organization paradigm in the context of urban traffic control. One of the first papers in this direction [14] introduced a self-organizing control strategy for a signal network described as a system of nonlinear oscillators with the nearest neighbourhood coupling. Another proposal of self-organizing control strategy was based on macroscopic two-dimensional cellular automata, which enables real-time processing of traffic data [15].

In [3] three simple traffic-responsive methods were introduced for traffic signal control that uses the self-organization paradigm. It was demonstrated that with simple rules and no direct communication, traffic lights are able to self-organize and adapt to changing traffic conditions, reducing waiting times, number of stopped cars, and increasing average speeds. These methods were further extended to more complex scenarios employing an hexagonal road network model with multiple-way intersections [4]. As a continuation of this research direction the paper [1] proposed a history-based self-organizing traffic control, which was designed to fit the existing conventional vehicle detection technology.

A control strategy reported in [5] was inspired by an observation of self-organizing oscillations of pedestrian flows at bottlenecks. The approach assumes a priority-based control of traffic lights by the vehicle flows themselves, taking into account short-term predictions of vehicle flows. For the purpose of this strategy the traffic flow predictions were obtained using a macroscopic fluid-dynamic model. This self-organizing traffic control was compared to the currently implemented state-of-the-art adaptive control in a simulation of real-world road network [6]. Results of these experiments showed that the self-organizing control provides a superior performance.

Research reported in [13] was conducted in order to develop a self-organizing traffic signal system that enables utilization of data collected in a vehicular sensor network. Another example of potential future applications is the in-vehicle traffic lights system based on a vehicle to vehicle communication [10].

3. Proposed approach

This section introduces a self-organizing traffic signal system for an urban road network. A traffic control algorithm in this system was developed on the basis of the prioritization and stabilization strategies by Lämmer and Helbing [5]. The main novelty of the proposed method lies in the fact that all control decisions are based on predictions obtained from fuzzy cellular traffic model. The fuzzy cellular model represents traffic streams at the microscopic level and therefore it can directly map parameters of individual vehicles. From the practical point of view, it means that the vehicle classes can be directly taken into account in making control decisions. In comparison with the original self-organizing control method [5], which uses a macroscopic (fluid dynamic) traffic model, the proposed approach enables a better utilization of the microscopic traffic data that can be collected using the available sensing technologies.

3.1. Traffic control algorithm

In the presented algorithm, the decentralized self-organizing strategy [5] was applied to manage the traffic flow in a road network by controlling traffic signals. The self-organizing traffic control is based on an optimization and a stabilization rule. Both rules are executed in parallel for all intersections in the road network in order to adapt the traffic control to local flow conditions.

According to the self-organizing traffic control strategy the consecutive control decisions are made in time steps of one second. A particular control decision determines which traffic stream should get a green signal at an intersection. The decision is made using the following formula:

$$\sigma = \begin{cases} \text{head}\ \Omega & \text{if } \Omega \neq \varnothing \\ \arg\max_i \pi_i & \text{otherwise,} \end{cases} \tag{1}$$

where: σ indicates the traffic stream which will get green signal, Ω is an ordered set containing indices of the traffic streams that have been selected using the stabilization rule, π_i denotes priority of stream i, which is calculated on the basis of the optimization rule.

The aim of stabilization rule is to assure that all traffic streams will be served at least once in T_{max} period. To this end, for each traffic stream a service interval Z_i is predicted as the sum of preceding red time r_i for stream i, intergreen time τ_i^0 before switching the green signal for stream i, and green time G_i required for vehicles in lane i to pass the intersection:

$$Z_i = r_i + \tau_i^0 + G_i \tag{2}$$

The index i of traffic stream joins the set Ω as soon as $Z_i \geq T_{max}$.

Optimisation rule aims for minimizing waiting times by serving the incoming traffic as quickly as possible. According to this rule a traffic stream with the highest priority index π_i gets green signal, provided that the set Ω is empty. The priority index for stream i is defined as

$$\pi_i = \frac{N_i}{\tau_{i,\sigma}^{\text{pen}} + \tau_i + G_i} \tag{3}$$

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where: N_i denotes number of vehicles in lane i that are expected to pass the intersection in time $\tau_i + G_i$, $\tau_{i,\sigma}^{pen}$ is a penalty for switching from stream σ to i, τ_i denotes intergreen time after green signal for stream i and σ is the index of currently served traffic stream.

For more detailed information on the self-organizing strategy see the paper by Lämmer and Helbing [5]. The traffic control algorithm is summarized by the pseudocode in Fig. 1. The capital letters G, N, X and Z in the pseudocode were used to indicate the predicted (estimated) quantities that are represented by fuzzy numbers. The fuzzy variables X describe positions of vehicles. Minimum green time is denoted by e_{min}.

```
for each time step do
  for each lane i = 1 … m do
    if signal i is red then
      r_i = r_i + 1
      if i = σ and min_{k≠i} r_k >= τ_i^0 then
        set signal i green
        r_i = 0
    else
      e_i = e_i + 1
      if i ≠ σ then
        set signal i red
        e_i = 0
    for each vehicle j = 1 … n(i)
      update X_{i,j}
    estimate N_i
    predict G_i
    compute Z_i and Π_i
    if Z_i >= T_max then add i to Ω
  if e_σ >= e_min then
    if Ω is empty then σ = arg max_i Π_i
    else σ = head Ω
```

Fig. 1. Pseudocode of traffic control algorithm

3.2. Traffic model

As it was mentioned at the beginning of this section, all control decisions in the presented system are based on predictions obtained from fuzzy cellular traffic model. The microscopic traffic model is used to estimate the numbers of vehicles approaching an intersection (queue lengths N_i) and to predict the required green times (G_i).

Estimation of queue lengths is based on both the real traffic data acquired from a traffic monitoring system and the results of real-time simulation. During the real-time simulation the traffic model is used to estimate the missing positions of vehicles that cannot be determined by the monitoring system. Besides the data on vehicle positions, the real-time simulation can also take into account the classes of particular vehicles, if such information is available.

Results of the real-time simulation (i.e. data on individual vehicles approaching an intersection) are further used to determine initial conditions for faster than real-time simulation. The task of the faster than real-time simulation is to predict the required green times (G_i) for all lanes at an intersection.

The fuzzy cellular model for traffic simulation was formulated as a hybrid system combining cellular automata and fuzzy calculus. It was based on a cellular automata approach to traffic modelling that ensures the accurate simulation of real traffic phenomena [7]. A characteristic feature of this model is that it uses fuzzy numbers to represent vehicles positions, velocities and other parameters. Moreover, the model transition from one time step to the next is based on arithmetic of the ordered fuzzy numbers. This approach benefits from advantages of the cellular automata models and eliminates their main drawbacks i.e. necessity of multiple Monte Carlo simulations and calibration issues [11].

A traffic lane in the fuzzy cellular model is divided into cells that correspond to the road segments of equal length. Road traffic streams at an intersection are represented by sets of vehicles. A vehicle j in traffic lane i is described by its position $X_{i,j}$ (occupied cell) and velocity $V_{i,j}$ (in cells per time step). The maximum velocity for vehicle j is defined by the parameter $V_{max,i,j}$. This parameter was used in the presented study to distinguish vehicle classes. Velocities and positions of all vehicles are computed simultaneously in discrete time steps of one second. The necessary computations are based on rules of the cellular automata models. More detailed information on the traffic simulation with fuzzy cellular model can be found in [9-11].

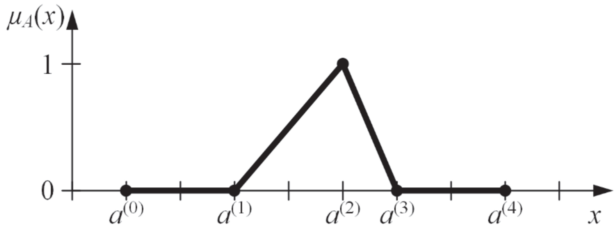

Fig. 2. Membership function of fuzzy number A

It should be noted that all the above mentioned variables in the traffic model are expressed by triangular fuzzy numbers. The fuzzy numbers are defined by 5-tuples of real numbers and the following notation is used:

$$A = (a^{(0)}, a^{(1)}, a^{(2)}, a^{(3)}, a^{(4)}) \tag{4}$$

Membership function of the fuzzy number is shown in Fig. 2. The components $a^{(0)}$ and $a^{(4)}$ determine the allowable range of values $a^{(1)}$, $a^{(2)}$ and $a^{(3)}$.

The application of fuzzy calculus helps to deal with incomplete traffic data and enables straightforward determination of the uncertainty in simulation results [10]. There are two main advantages of the fuzzy cellular model application: firstly, the traffic simulation is computationally efficient due to low complexity of the model; secondly, the uncertainties of the simulation inputs and outputs can be represented by means of fuzzy numbers. An example of simulation results is illustrated in Fig. 3. The gray triangles in this figure represents schematically the fuzzy values of the estimated queue length N_i (simulation input) as well as the predicted green time G_i (simulation output).

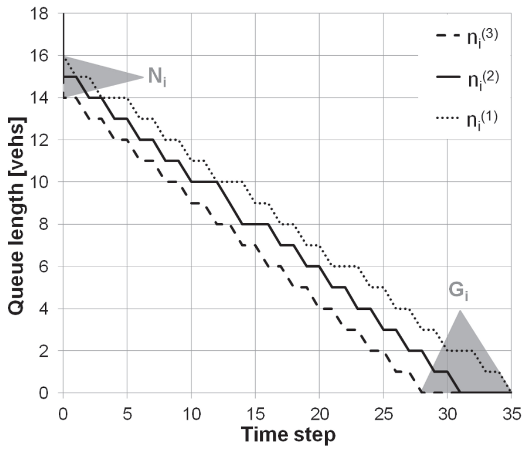

Fig. 3. Example of simulation results

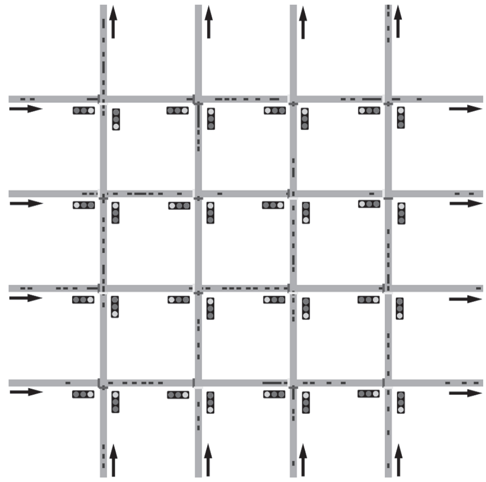

Fig. 4. Simulated road network

4. Experiments

Simulation experiments were performed in order to compare performance of the self-organizing traffic control for two scenarios: first, when the class of vehicles is taken into account and second, when the information on vehicle class is unavailable. Moreover, utilization of two different traffic monitoring systems was considered, i.e. a road-side vehicle detection system and a vehicular sensor network (VSN). For the road-side detection system it was assumed that vehicles can be detected (i.e. their positions can be determined) only when passing intersections or entering the road network. In the case of vehicular sensor network the complete information on vehicles positions is available at each time step of the simulation.

The experiments were performed in a traffic simulator which was developed for this purpose on the basis of Nagel-Schreckenberg (NaSch) stochastic cellular automata [4]. Topology of the simulated network is presented in Fig. 5. Roads are unidirectional, thus each intersection has two incoming traffic streams and two signals. Links between intersections consists of 40 cells that correspond to the distance of 300 m.

A simple modification of the original NaSch model was introduced to take into account two classes of vehicles that differ in their free-flow velocities. The obtained average free-flow velocity was 1.1 cells per time step (30 km/h) for slow vehicles and 1.9 cells per time step (50 km/h) for fast vehicles (the simulation time step is one second).

The self-organizing traffic control was simulated assuming that the intergreen times τ as well as the minimum green times g_{min} are equal to 5 s and the maximum period T_{max} is 120 s. For the purpose of control decision making, traffic streams were mapped using the fuzzy cellular model. In this model, the maximal velocities for particular vehicles were determined by fuzzy numbers on the basis of the class information. If the information on vehicle class is available (scenario 1) then the maximal velocity V_{max} in cells per time step is determined as (1, 1, 1.1, 1.2, 2) for slow vehicles and (1, 1.8, 1.9, 2, 2) for fast vehicles. In opposite situation (scenario 2), the maximal velocity for all vehicles is determined as (1, 1, 1.5, 2, 2).

Results of the simulation experiments in Figs. 5-10 illustrate performance of the self-organizing traffic control for various sets of the traffic data used in making control decisions. The average delays of vehicles were determined from 300 hour traffic simulation. During this experiment, both the traffic flow volume and the fraction (percentage) of slow vehicles were changed in a wide range. The solid lines in diagrams represent average delay for the first scenario (with vehicles classification), the dashed lines correspond with the second scenario (unavailable class information). Figs. 5-7 relate to the case of using road-side detection system to collect the traffic data (information on vehicle position available only at the network entrances and at intersections). Figs. 8-10 shows the results obtained for the case of traffic monitoring by vehicular sensor network (information on vehicle position available in entire road network). The delays in Figs. 5 and 8 were registered for the fraction of slow vehicles equal to 10%. The charts in Figs. 6 and 9 were obtained assuming the traffic flow volume of 540 vehs/h.

The simulation results show that the availability of detailed information on vehicles positions in VSN allows the self-organizing traffic control to reach higher performance for all analyzed traffic flow volumes and all percentages of slow vehicles (compare Fig. 5 with Fig. 8 and Fig. 6 with Fig. 9).

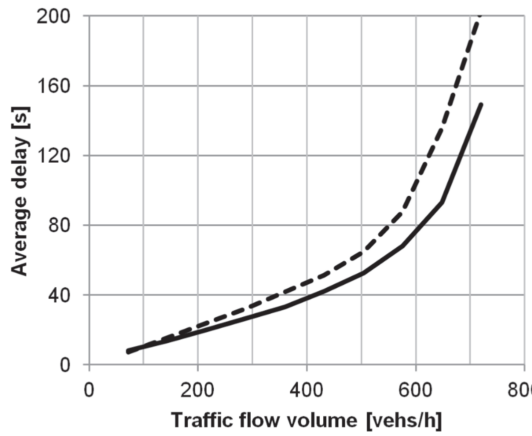

Fig. 5. Average delay vs. flow volume (road-side detection)

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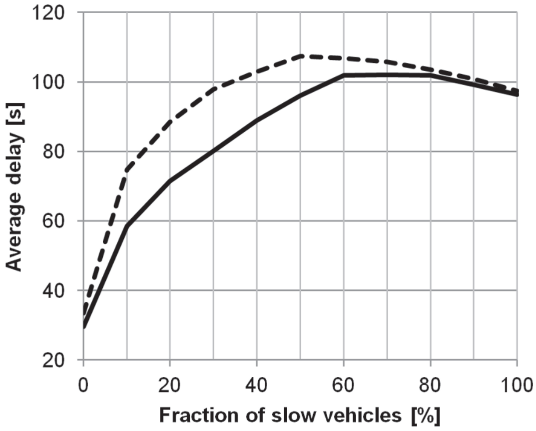

Fig. 6. Average delay vs. fraction of slow vehicles (road-side detection)

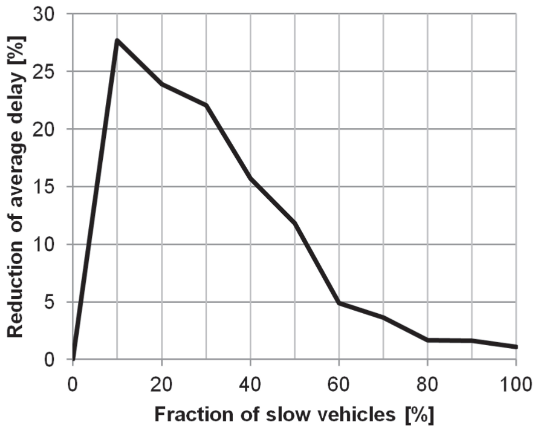

Fig. 7. Delay reduction due to vehicles classification (road-side detection)

If the traffic control algorithm takes into account the information about class of vehicle, then the resulting improvement of the traffic control performance (i.e. delay reduction) grows with the volume of traffic flow (Figs. 5 and 8).

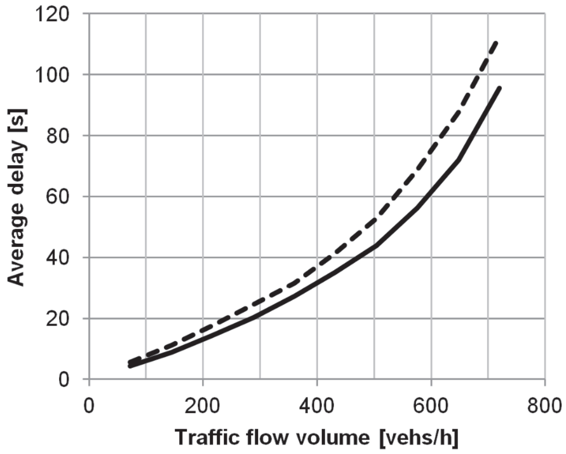

Fig. 8. Average delay vs. flow volume (VSN)

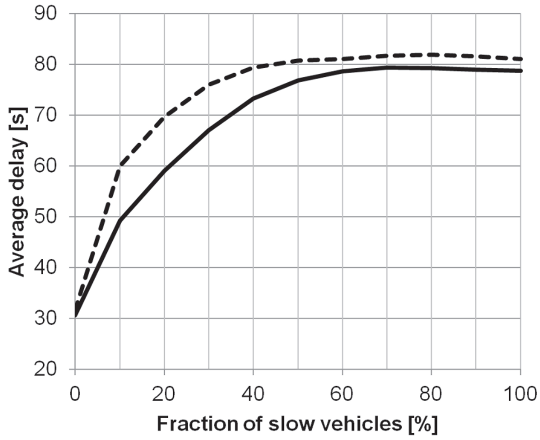

Fig. 9. Average delay vs. fraction of slow vehicles (VSN)

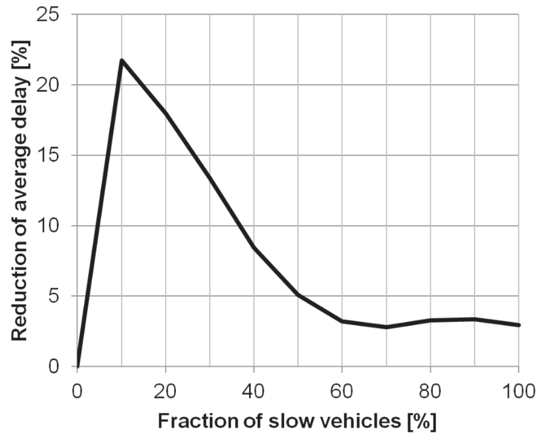

Fig. 10. Delay reduction due to vehicles classification (VSN)

Utilization of the class information enables reduction in the average delay, especially for the percentage of slow vehicles in range between 10% and 50% (Figs. 6 and 9). The highest relative reduction of the average delay was observed for the percentage of slow vehicles equal to 10% (Figs. 7 and 10).

5. Conclusion and future works

In this paper the self-organizing traffic control strategy was integrated with the microscopic fuzzy cellular traffic model. The proposed approach allows the traffic control system to utilize input data that describe parameters of particular vehicles. Such microscopic traffic data can be collected in traffic monitoring systems that are based on new telematics technologies, e.g. video-detection or vehicular networks.

Traffic control decisions in the proposed system are made on the basis of input data that describe traffic streams at the level of individual vehicles. Processing of the large input data sets is performed by using fuzzy cellular traffic model, which enables a fast prediction of queue lengths at intersections. Due to the application of fuzzy calculus, the model is suitable for processing incomplete input data sets that are obtained when some of the data on vehicle parameters are unavailable or ignored. Therefore, the fuzzy cellular model can be used to compare the performance of traffic control for different sets of the input data.

Evaluation of the proposed traffic control strategy were performed in a simulation environment. The experiments aimed at investigating the effect of input data precision on performance of the traffic control. To this end, average delay of vehicles was analysed for a traffic control in a road network. The analysis covered utilization of detailed data describing positions and classes of individual vehicles. Results of the simulations shows that the performance of urban traffic control can be enhanced through utilization of microscopic traffic data.

The obtained results provide a strong motivation for further research on applications of both the self-organization paradigm and the microscopic models in adaptive urban traffic control. An important issue for future studies is the validation of the proposed approach in real-traffic conditions. The experiments should also take into consideration various measures of traffic performance (e.g. travel times, queue lengths, stop counts) and potential sources of errors, i.e. detection accuracy and quality of communication channels.

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