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A two-level urban traffic control for autonomous vehicles to improve network-wide performance

Tamás Tettamanti [a], Arash Mohammadi [b], Houshyar Asadi [b], István Varga [a,*]

[a] *Dept. of Control for Transportation and Vehicle Systems, Budapest University of Technology and Economics, Stoczek u. 2., Budapest, 1111, Hungary*

[b] *Institute for Intelligent Systems Research and Innovation, Deakin University, CISR Drive, Waurn Ponds, Victoria 3216, Australia*

Abstract

In the near future, autonomous vehicles will face with new challenges in several fields. One of the most exciting changes will be represented by the network-wide optimal traffic control. When driverless vehicles take over the road, classical road signalization schemes will become superfluous. Accordingly, the paper's aim is to propose a control design methodology for autonomous vehicles in urban traffic network by considering the network-wide performance. The proposed two-level control strategy solves a tractable optimization problem for a network wide traffic control. On the one hand, a local intersection controller is designed which ensures safe crossings of vehicles and aims to reduce traffic emission in the junction area. On the other hand, the local controllers also optimize the network performance by minimizing the queues in all road links. The traffic is therefore modeled in a two-level fashion. A microscopic dynamics is considered in junctions and macroscopic model is applied for the whole traffic network. The control strategy is tested and evaluated based on microscopic traffic simulation.

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Keywords: driverless vehicle, autonomous intersection, traffic control, nonlinear model predictive control

1. Introduction

Autonomous vehicle technology represents the main innovation trend of automotive industry of our days. Automated cars will totally transform road transportation of the near future (Fagnant and Kockelman, 2015; Tettamanti et al., 2016). However, beside the spectacular features of individual driverless vehicles another important

* Corresponding author. Tel.: +36-1-463-3555,
E-mail address: ivarga@mail.bme.hu

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opportunity appears, i.e. the cooperated control of them. Transportation research of the last decades has mainly focused on the control by using traditional road-side units, i.e. traffic controller and signal heads (Papageorgiou et al., 2003; Tettamanti, 2013). However, the general aims of urban road traffic management are achievable through the cooperated control of connected autonomous cars as well. These are mainly the minimization of delays at intersections and maximization of the network throughput. Accordingly, some major research works have already been published concerning autonomous intersection control, i.e. traffic control without traditional traffic signals which are able to efficiently tackle the junction control problem. Dresner and Stone (2008) proposed a new intersection control mechanism called Autonomous Intersection Management (AIM) and showed that by applying the multiagent perspective, intersection control can be made more efficient compared to traditional control for an isolated intersection. Hausknech et al. (2011) extended the previous study beyond the case of an individual junction and investigated AIM considering a network. Carlino et al. (2013) presented a market-based pricing mechanism for isolated intersection control for driverless cars. These papers clearly showed that by exploiting the control capabilities of autonomous vehicles it is possible to design an intersection control that is more efficient than traditional traffic signals. As a novel contribution to this research field our paper introduces new solutions in terms of a network-wide traffic control with a two-level traffic model and the use of an efficient nonlinear model predictive control scheme. A feasibility study is also carried out to demonstrate the viability of the proposed method by using a validated microscopic traffic simulator. The paper is structured as follows. In Section 2, the two-level urban traffic model is introduced. The elaborated control design is described in Section 3. Section 4 demonstrates the simulation results. The paper ends up with a short conclusion.

2. Model

2.1. Junction traffic model (microscopic)

It is assumed in our work that the automated cars fulfill the requirements defined by the 5th SAE level (SAE International, 2014), i.e. "full-time performance by an automated driving system of all aspects of the dynamic driving task under all roadway and environmental conditions that can be managed by a human driver." Furthermore, as all cars are assumed to be autonomous, they follow a known and predefined trajectory. Therefore, the direction of trajectory $\vec{d}(\vec{S}(t))$, is known based on location $\vec{S}(t)$ which contains (x, y) coordinates. It allows us to obtain the location of vehicles at the next time step $[kT;\ (k+1)T]$ where T denotes the sample time and $k = 0, 1, 2, \ldots$ is the discrete time index:

$$\vec{S}(k+1) = \vec{S}(k) + \vec{d}\left(\vec{S}(k)\right) \cdot v(k) \cdot T, \qquad (1)$$

where $v(k)$ is the vehicle velocity. The vehicles are assumed to have a rectangular shape. Model (1) is applied solely for the junction region (see Fig. 1 (a)), i.e. only the vehicles are considered which are in the vicinity of the intersection. Outside of the junction regions the vehicles are moving according to the microscopic car-following model provided by SUMO simulator (see later in Section 4). Fig. 1 (b) shows the time distance between two conflicting cars. To avoid collision, condition $|d_A - d_B| > d_{min}$ must be valid at all times. This constraint is considered later in the control design.

Additionally, vehicle based emission is considered in the control design. Traffic emission mainly consists of CO, NO_x, HC, and CO_2. For microscopic emission the COPERT IV model was adopted (Ntziachristos et al., 2000). In our work, an average emission function is used for the Hungarian fleet composition. For simplicity, a quadratic approximate is applied for the emission factor in the following form (Csikós, 2015):

$$ef(v) = \alpha_2^p v^2 + \alpha_1^p v + \alpha_0^p, \qquad (2)$$

where v is the average speed during the sample time and α_i^p denotes the emission parameters for pollutant p. In our work, only CO_2 is considered with specific coefficients characterizing the national vehicle fleet: $\alpha_0^{CO_2} = 195.33, \alpha_1^{CO_2} = -1.82$, and $\alpha_2^{CO_2} = 0.03$. The emission factor's unit is $[g/km]$.

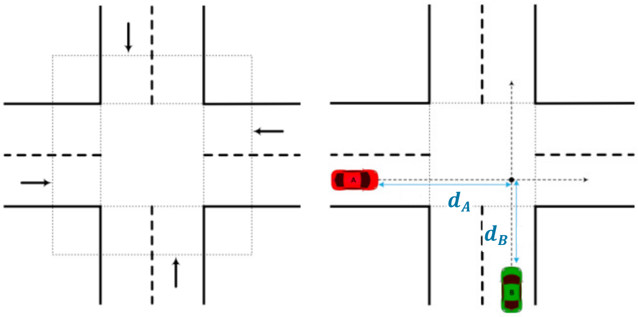

Fig. 1 (a) Junction region; (b) Conflict (collision) point.

2.2. Network traffic model (macroscopic)

The urban traffic network is modeled by using link-based traffic dynamics. A general urban road traffic network (see Fig. 2) can be described by graphs where node $j \in J$ represents the junction and edge $z \in Z$ the road link.

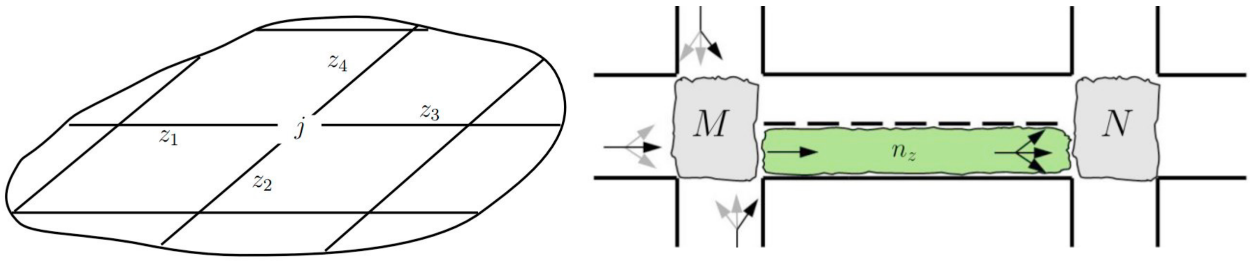

Fig. 2. (a) Traffic network modelling; (b) Traffic flow modelling with the vehicle-conservation law.

By considering a macroscopic approach (individual vehicle dynamics is omitted), for link z the number of vehicles can be modelled based on the vehicle-conservation law during the next discrete time step $[kT;\ (k+1)T]$:

$$n_z(k+1) = n_z(k) + T\left[\sum_{w,z} \alpha_{w,z} q_{w,z}(k) - q_z(k)\right]. \tag{3}$$

n_z is the number of vehicles on link z (veh). I_M denotes the set of the incoming links w (depicted by black arrows) at junction M, i.e. $w \in I_M$. $\alpha_{w,z} \in [0,1]$ is the turning rate from link w to link z. $q_{w,z}$ denotes the traffic flow from link w to link z (veh/T). q_z is the traffic outflow from link z (veh/T). Therefore, Eq. (3) represents a link-based traffic model. Indeed, if more than one link is considered, the interconnected links construct a whole traffic network.

A crucial point of Eq. (3) is the dynamics of link outflows. A possible approach to describe traffic outflow in a given network is given by the theory of urban fundamental diagram which was first proposed by Godfrey (1969). This theory is also called Macroscopic Fundamental Diagram (MFD) (a simplified example for MFD can be seen in Fig. 3). The MFD concept has been widely investigated during the past decades, e.g. Mahmassani et al. (1987), Daganzo and Geroliminis (2008), Helbing (2009), Mazloumian et al. (2010), Geroliminis and Daganzo (2008). By using the analogy of the MFD concept, the outflows $q_{w,z}$ and q_z can be defined by restricting the traffic network to link level. This practically means that each link has a dedicated MFD model.

MFD assumes the following fundamental relationship:

$$q(\rho) = \rho \cdot v, \tag{4}$$

where $\rho = n/l$ denotes the traffic density on a given link length (l) and v is the space mean speed on the link. For link z Eq. (4) is recast as

$$q_z(\rho_z) = \rho_z \cdot v_z \,, \tag{5}$$

There are several formulas available in the literature for v (Wang et al., 2009) and thus for q. However, another possibility is to make simulation based measurements in order to create scatter plots. Thus, one is able to fit an appropriate MFD function, e.g. a polynomial link outflow function (Csikós et al., 2015). In this case the outflow can be given as an m^{th} degree polynomial function:

$$q_z(n_z) = a_n \cdot n_z^m + a_{n-1} \cdot n_z^{m-1} + \cdots + a_1 \cdot n_z + a_0, \tag{6}$$

Note that outflow $q_{w,z}$ in Eq. (3) can also be calculated by the formula Eq. (6) but concerning link w.

3. Control

3.1. Low level control in order to avoid collision

The low level control is only applied on cars within a certain distance from the junctions. To reduce the burden of computation, the cars are distributed into separate groups associated with each junction and optimized independently to increase optimization speed. A nonlinear model predictive control (MPC) (Grüne and Pannek, 2011) is applied at each microscopic sampling time. The initial solution used for nonlinear programming solver is the receded value from the previous time step. The optimization objectives are maximization of the total mobility, minimization of acceleration/deceleration, and minimization of vehicle emission.

Another control variable called priority is attached to each vehicle (described in Section 3.2). Priority is determined by macroscopic traffic model as a network-wide control aim. The constraints are to reject solutions which cause collision or breaching a minimum distance between vehicles. In this approach, the controller together with constraints ensure the adequate (accident-free) dynamics for the cars, i.e. no specific car-following model is needed in the zone of the intersections. The nonlinear MPC problem is formulated mathematically as follows:

$$\begin{aligned} \min_{u(k+l-1)} \quad & J(k), \\ subject\ to \quad & u(k+l-1) \in \mathbb{U}, \\ & x(k+l) \in \mathbb{X}, \\ & l = 1,2,\dots,K, \end{aligned} \tag{7}$$

where the control inputs are computed by minimizing cost function $J(k)$ over prediction horizon K. $\mathbb{U}$ and $\mathbb{X}$ denote the constraint sets for control input vector u (desired vehicle speeds) and state vector x (vehicle positions calculated based on Eq. (1)) respectively. $J(k)$ is defined as a quadratic cost function with weighting parameters α, β, γ:

$$J(k) = \sum_{l=1}^{K} \sum_{i=1}^{N_{vehicles}} \left[\alpha[1+p_i]v_i^2(k+l) + \beta[v_i(k+l) - v_i(k+l+1)]^2 + \gamma\, ef_i^2\big(v_i(k+l)\big)\right], \tag{8}$$

where $N_{vehicles}$ is the total number of the considered vehicles at the junction, $ef(.)$ is the emission factor, p_i is the priority parameter concerning the current link of the vehicle, and term $[v_i(k+l) - v_i(k+l+1)]^2$ eliminates too much input oscillation. The applied nonlinear constraint is

$$\min(D) > d_{\min}. \tag{9}$$

$d_{\min}$ is the minimum acceptable vehicle distance and $\min(D)$ refers to the smallest member of matrix D defined as follows

$$D = [d_{il}]_{N_{vehicles} \times K} \,, \tag{10}$$

where d_{il} is the minimum distance of i^{th} vehicle (from ahead and back) at the l^{th} step of the horizon.

3.2. Macroscopic level control

Another layer of optimization is considered for the improvement of link flows. Despite localized control of each junction reduces the computational burden, it should be considered that the performance of junctions depend on each other and without taking the global perspective of the entire network into the account, the traffic control system would function in a suboptimal way. Therefore, a macroscopic layer of optimization is appended to the traffic control in order to optimize the flow of each link. As the traffic lights are removed, new control variables are necessary for the macroscopic level optimization. In this paper, a priority value for each link is used as the control variable to influence the traffic flow of cars based on the link on which they are located. This level of optimization is performed with a lower frequency compared with junction controlling layer as the variation of link density is slower compared with the junctions.

The most important conclusion of the MFD (introduced in Section 2.2) is resulted in n^* which is the critical number of vehicles in the network, i.e. in our case within the link. In the vicinity of n^* the link is operated at its maximum capacity (see Fig. 3). Moreover, n^* splits the fundamental diagram to a stable (left side) and an instable part (right side). The instable part of the MFD represents traffic congestion as network throughput q tends to decrease.

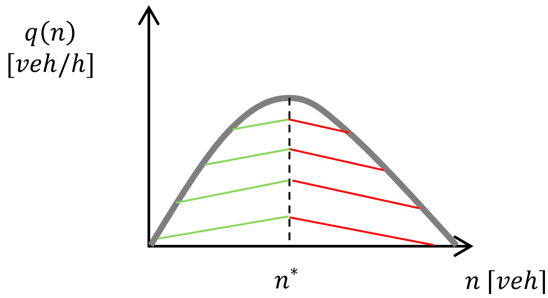

Fig. 3 Macroscopic Fundamental Diagram depicted with the stable (green) and instable (red) parts.

Accordingly, Eq. (3) is used to find appropriate weightings for local controllers (see Section 3.1) based on the link's MFD as follows:

$$p_z = \begin{cases} 0, & n_z \le n_z^* \\ \dfrac{n_z - n_z^*}{n_z^*}, & n_z > n_z^* \end{cases} \tag{11}$$

This means practically that if n_z is equal or smaller than the optimal value n_z^*, no weighting is applied as the system dynamics is still within the stable area. If n_z is higher than the optimal value n_z^* of link z, a proportional weighting p_z is applied for the local control. According to Eq. (11), the high level macroscopic model intends to influence local (junction level) MPC's operation (see Section 3.1), i.e. if vehicle i is traveling on link z, then priority value in the MPC's cost function (see Eq. (8)) becomes $p_i = p_z$.

4. Simulation study

The proposed optimization is implemented by using MATLAB software. For microscopic road traffic simulation SUMO (Simulation of Urban Mobility) software is applied (Krajzewicz et al., 2012). Moreover, a simulation environment is created by TraCI interface for coupling MATLAB and SUMO (Wegener et al., 2008). The test network is depicted by Fig. 4. It consists of 4 junctions and 12 bidirectional roads. The used car-following model was SUMO's default microscopic (Krauss) model with the default parameter settings described here: *http://sumo.dlr.de/wiki/Definition_of_Vehicles,_Vehicle_Types,_and_Routes#Vehicle_Types*.

The traffic lights have been removed and the cars' velocities have been optimized over the prediction horizon. The control and sample step time is set to 1 second for simplicity, but will be reduced in future work. The length of prediction and control horizons are adjusted to 20 seconds. At each control step, the cars are checked and the ones within the vicinity of a junction are assigned to the given intersection. The vehicle speeds in the neighborhood of each junction are optimized individually to obtain the best mobility with minimization of speed fluctuation as well as minimization of CO_2 emission without colliding other cars. The MPC problem is converted to a nonlinear programming solved by MATLAB *fmincon* function. A simulation period of 30 minutes is used. The achieved control inputs (by Eq. (7)) were realized in the simulator via TraCI interface by directly setting the vehicle speeds.

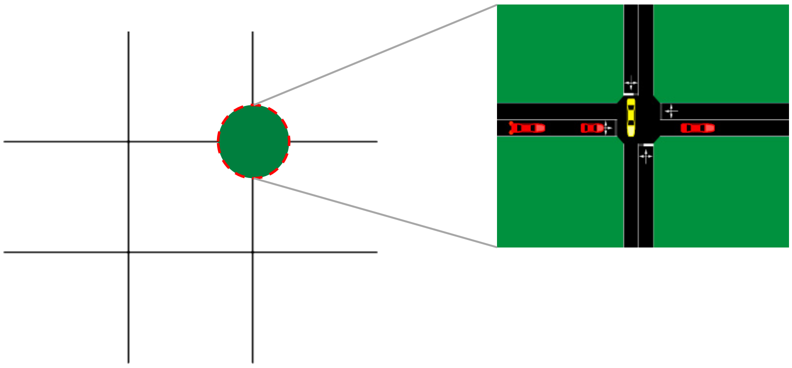

Fig. 4 Test network realized in SUMO road traffic simulator.

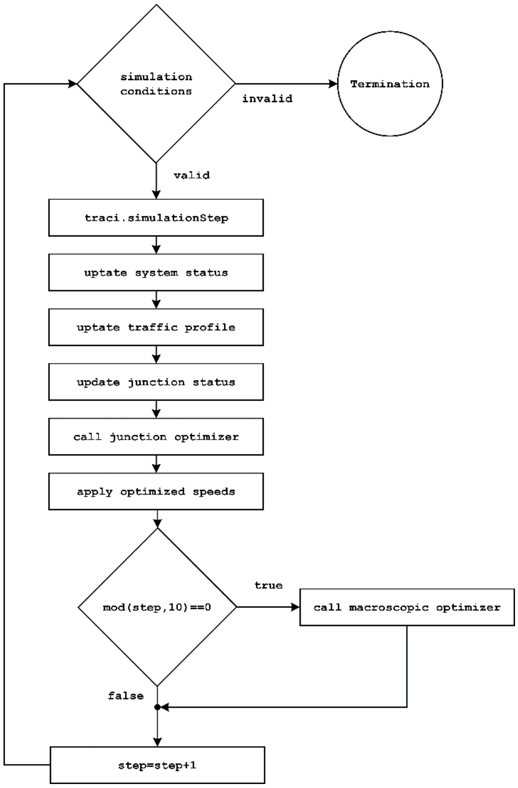

Fig. 5 The implementation flowchart of the proposed two-level urban traffic control.

Another layer of optimization is applied for the improvement of link flows. Hence, a macroscopic traffic problem is optimized to obtain the highest mobility of the entire network by priority parameter of the cars based on the link that they are located or come from. Random trips were generated for the test network in order to create appropriate MFD for macroscopic modeling. To this end, several simulations have been run using the random trips. Finally, an adequate fitting was carried out. Due to the grid network's simplicity, identical MFD can be used for each edge. The following fitting is applied in the control scheme:

$$q_z(n_z) = -0.52 \cdot n_z^2 + 26.92 \cdot n_z \,. \tag{12}$$

The simulation process is as follows. At each sample time, the IDs of all available cars are collected. The vehicle states are recorded and the details of the cars which have left the network are deleted. For each vehicle, the recorded details include the maximum speed of the car (constant), dimensions of the car (constant), the current CO_2 emission, the current travel distance and the past (only one step back) and present information about the link ID, position on the link, angular position, absolute position in x and y coordinate and the velocity. After collecting the status of vehicles, the profile of traffic for the current step is calculated which consists of the total travel distance and the total CO_2 emission. Then, the junction controller is called to solve the problem of speed optimization of the vehicles at the junctions. In the next stage, the calculated optimized speeds are applied to the corresponding vehicles. At each 10 step, the macroscopic optimizer is called to update the link priority values. Hence, the cars based on their links are affected. The flowchart of the implemented code is shown in Fig. 5.

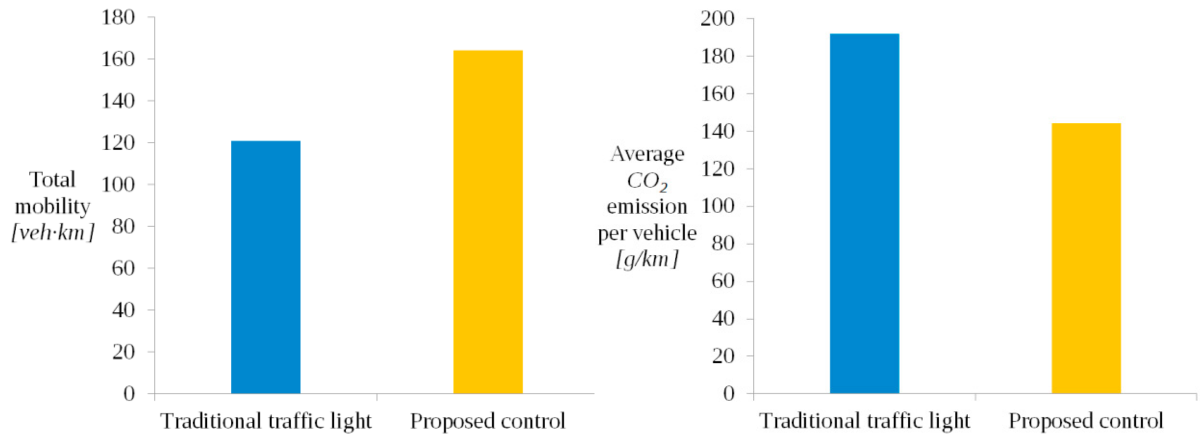

Fig. 6 The comparison of network mobility and CO_2 emission (based on HBEFA v3.1 data) between the traditional and proposed methods.

For comparison, a traditional traffic signal method is applied: the time gap based actuated control which is a built-in tool of SUMO simulator (*http://sumo.dlr.de/wiki/Simulation/Traffic_Lights#Based_on_Time_Gaps*). The simulation results show a significant improvement in the proposed method compared with traditional methods. According to the Fig. 6 the total mobility of the network has increased from 121 $[veh \cdot km]$ in traffic network controlled by traffic lights to 164 $[veh \cdot km]$ in the proposed traffic network with two-level optimization, i.e. 36% gain in total mobility is obtained. This achievement is due to the macroscopic and microscopic optimizations for link prioritization and junction control. In addition, CO_2 emission has also strongly reduced from 192 $[g/km]$ to 144 $[g/km]$ by the proposed method according to Fig. 6. Emission was measured in SUMO by HBEFA v3.1-based emission model (Hausberger et al., 2009). Simulation results demonstrate a significant improvement of traffic network performance by applying the two-layer traffic controller over conventional traffic control in terms of traffic mobility and CO_2 emission.

5. Conclusion

In this paper, a two-layer traffic control is proposed to obtain an efficient traffic flow by removal of traffic light and velocity optimization of each individual vehicle in the vicinity of each junction and prioritizing the links to influence the traffic flow. The link prioritization is used for macroscopic optimization of the system while junction controller is responsible for microscopic optimization of vehicles in a junction region. The main aims of the proposed control system are twofold. On the one hand, overall network mobility is increased through the capability of robo-driver of autonomous cars, i.e. headways can be minimized. On the other hand, environment aspects can also be considered through the reduction of traffic emission. Simulation results have demonstrated the superior performance of the proposed method over traditional traffic control in terms of the abovementioned aims. Future work consists of analyzing the practical applicability and the limits of the method.

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