Cooperative Strategical Decision and Trajectory Planning for Automated Vehicle in Urban Areas

Reza Dariani
Institute of Transportation Systems,
German Aerospace Center (DLR)
Braunschweig, Germany
reza.dariani@dlr.de

Julian Schindler
Institute of Transportation Systems,
German Aerospace Center (DLR)
Braunschweig, Germany
julian.schindler@dlr.de

***Abstract*— Rapid growth of the number of vehicle in Europe in the last two decades requires efficient transportation and mobility, especially in urban areas. Special focus is needed for the bottlenecks of urban areas: the intersections. The European H2020 project MAVEN is working on such concepts. By using new technologies like vehicle automation, communication and interaction with traffic lights, intersections are transformed into communication hubs, where the needs of all traffic participants are aggregated and the most efficient way to proceed is calculated in a hierarchical way. Signal plans are optimized, and hints for smoother travelling (i.e. lane, speed and platoon advices) are given to the vehicles. On the other hand automated vehicles, as future means of transport, communicate not only to infrastructure, but also with each other's. The focus of the paper is on design, implement and prove the functionality of a strategical decision module and a trajectory planner which is aligned with above mentioned requirement.**

Keywords—Cooperative trajectory planning, strategical decision, vehicle automation

I. INTRODUCTION

The statistics show that progress to halve the number of road traffic death by 2020 is far from sufficient [1]. 1.35 million pepole die each year on the world's road. Based on the research done at National Motor Vehicle Crash Causation Survey (NMVCCS) on light vehicles several factors are associated in a crash in which driver error with 94% plays the most important and critical role [2]. For this reason the modern vehicles are equipped with a high number of sensors and Advanced Driver Assistance Systems (ADAS) to inform, warn and even intervene in critical driving situations. As further development of such systems, the partially-automated and automated driving functions aim to take the driver partially or completely out of the driving process.

This paper describes the aspects of vehicle automation for fully-automated vehicles and focuses particularly on a proposed trajectory planning module and strategical decision module, see Fig.1. The strategical decision module deals mostly with cooperation aspects of vehicle automation and it also analyses the road geometry, other road users and information received via communication and defines a strategy for the trajectory planning module. A platooning state machine, called "platoon logic", has been designed as part of this module which deals with platooning vehicle states [3] [4]. The trajectory planner based on the defined strategy from strategical module, plans an optimal trajectory and delivers the vehicle actuators input to the vehicle controller. The vehicle controller consists of several feedback and feedforward controllers to guarantee that the vehicle follows the planned trajectory.

The functionality of the designed algorithms of vehicle automation has been proved in close field tests and tests in public traffic in a complex urban area.

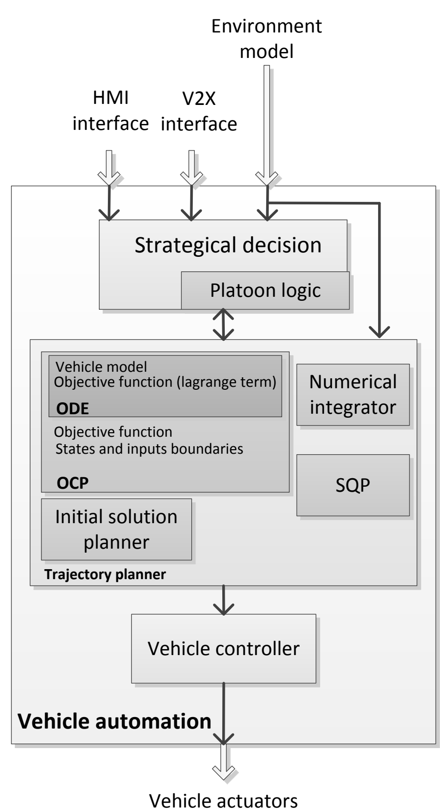

Fig. 1. Vehicle automation

The outline of the paper is as follows; chapter 2 describes the vehicle automation and explains the trajectory planner and strategical decision. Chapter 3 presents some results from closed field and urban experiments.

II. Vehicle automation

An optimal control approach is used to plan a trajectory. Hence the planned trajectory is the solution of a nonlinear optimization problem. One powerful method to solve a sequence of nonlinear Optimal Control Problem OCP is Sequential Quadratic Programming *SQP*. The Newton method or quasi-Newton method finds a point where the gradient of the objective function of *OCP* vanishes. Newton or quasi-Newton method requires a starting point or an initial solution. The quality of the initial solution has high impact on the convergence rate of the optimization problem and consequently on the calculation time. Therefore an initial solution is calculated for a shortest rough path connecting current vehicle position to destination based on the High Definition *HD* map information by inverting a kinematic single-track model.

A strategical level "Strategical Decision" is designed on top of the trajectory planner to define the strategical tasks for the planner. In another hand, due to the complexity of non-linear optimization problem, planning horizon, τ, has its real-time limitation and cannot merge to infinite. The strategical level horizon can be extended to the vehicle perception sensors vision range or even the communication range, which permits the planner to take required actions for events out of the trajectory planner horizon.

A. Trajectory planner

The trajectory planner consists of different components in which non-linear optimal control problem is the core component. And as already mentioned an initial solution as starting point is needed. The initial solution is calculated in initial solution planner. These two components are explained below.

1) Initial solution planner

As the road geometry is precisely defined and known, planning an initial solution can be done based on the information delivered via the HD map. In order to plan an initial trajectory, the environment where the vehicle moves can be defined as a set of connected graphs. There are several methods such as Dijkstra [5]or A* [6] which find the shortest path in this graph. Using the above mentioned algorithm offers the possibility to consider the static or even dynamic objects and plan a collision free path which improves the computational time needed for the optimizer [7] . But in other hand, considering the objects at this level may result in a lane change or an undesired trajectory for the urban scenario. Other road users must be considered in the strategical decision module and the trajectory planner. Therefore without considering any obstacle at this stage, the shortest path is equal to driving on the center line of the road, hence no shortest path algorithm is needed to calculate this path and it can be extracted directly from the HD map as a set of discrete points $\left(x_{sp}, y_{sp}\right)$. Based on the shortest path and a kinematic single-track model, initial control values can be calculated.

2) Optimal Control Problem

The nonlinear optimization problem is defined as (1):

$$\min J(\underline{x}, \underline{u}) \tag{1}$$

with differential equation modelling the vehicles dynamics (2) and nonlinear constraints (3)

$$\dot{\underline{x}} = f(\underline{x}, \underline{u}) \tag{2}$$

$$\underline{g_l} \leq g(\underline{x}, \underline{u}) \leq \underline{g_u} \tag{3}$$

as well as states (4) and inputs boundaries (5)

$$\underline{x_l} \leq \underline{x} \leq \underline{x_u} \tag{4}$$

$$\underline{u_l} \leq \underline{u} \leq \underline{u_u} \tag{5}$$

The optimal control problem non-linearity and also high length of the planning course make the optimal control problem numerically difficult to solve and also it requires high computational time. A possibility to deal with this problem is using Moving-Horizon approach *MHA* [8]. In this approach, the global optimization problem covering the complete driving task is portioned into several local optimal sub-problems of τsecond, or planning horizon, which are comparatively easier to solve. Local optimal control problem structure is similar to global problem just that not the whole driving course is considered. Also in real driving scenario, the driver has limited information about road and knows only about ahead road. Moving-horizon approach also update the optimal control problem by saving the solution for a part of problem, ,named increment as a portion of horizon ξ, and used it as the starting point for the next optimal sub-problem, see Fig.2.

a) Vehicle model

To describe vehicle dynamics the single track model [9] is used. The vehicle is regarded as a rigid body moving in the xy-plane and combines both wheels per axle into one. In the vehicle model roll and pitch angles are neglected and the tire dynamics are approximated by linear tire characteristic with saturation [10]. The vehicle model (1) has the following state vector $\underline{x}$ (6) and control vector $\underline{u}$ (7)

$$\underline{x} = [x\ y\ \varphi\ \dot{\varphi}\ v\ \beta\ \delta\ \dot{\delta}] \tag{6}$$

$$\underline{u} = [\ddot{\delta}\ \ F_x] \tag{7}$$

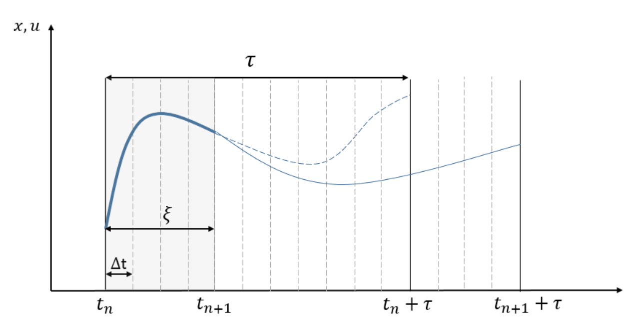

Fig. 2. Moving horizon approach

The states variables are vehicle position in global coordinates $[x, y]$, vehicle yaw angle φ and yaw rate $\dot{\varphi}$, vehicle velocity v, vehicle chassis sideslip angle β, steering angle δ and steering rate $\dot{\delta}$. The control variables are steering angle acceleration $\ddot{\delta}$ to guarantee that the vehicle applied steering angle δ is smooth (two times continuous differentiable) and longitudinal force F_x. For further details about the vehicle models see [7]. The systems differential equation is discretized by applying Runge-Kutta integration of fourth order as numerical integrator, see Fig.1, with step size of Δt and planning horizon of $\tau = N.\Delta t$, where N is the number of integration step, see Fig.2.

b) Objective function

The desired driving behaviour is the result of objective function definition of the optimal control problem. Therefore the planned trajectory, as result of the defined objective function, must be collision free and comfortable for vehicle users. Objective function can be written as (8)

$$J(\underline{x}, \underline{u}) = J_{\mathcal{L}}(\underline{x}, \underline{u}) \tag{8}$$

Index $\mathcal{L}$ stands for Lagrange term, equation (9) which is an additional state inside Ordinary Differential Equation ODE of vehicle model (2). Steering rate $\dot{\delta}$ and steering acceleration $\ddot{\delta}$ are inside the objective function to make the steering behavior smooth and avoid uncomfortable steering wheel impulse. Δv is the difference between desired speed and vehicle current speed. Δd is the vehicle distance to center line. $\ddot{\mathcal{X}}$ and $\dddot{\mathcal{X}}$ are acceleration and jerk in the transverse and longitudinal direction as comfort parameter. The last two terms will not prevent rapid change of direction therefore $\dot{\psi}$ is introduced to attenuates high yaw rates. And $\mathcal{W}$ is a diagonally matrix containing weighting coefficients of each component.

$$J_{\mathcal{L}}(\underline{x}, \underline{u}) = \mathcal{W} \int_{t_n}^{t_{n+\tau}} \mathcal{L}(\dot{\delta}, \ddot{\delta}, \Delta v, \Delta d, \ddot{\mathcal{X}}, \dddot{\mathcal{X}}, \dot{\psi}) dt \tag{9}$$

B. Strategical decision and Platoon logic

Infrastructure plays a crucial rule in MAVEN. It orchestrates the traffic network especially at intersections by sending Lane Advice Messages, *LAM*, and *GLOSA* messages to the automated vehicles. Therefore the vehicle automation must react properly to the messages received from the infrastructure. In addition automated vehicles cooperate with each other, specific in MAVEN are the platoon use cases [3] [4]. Another important point to be mentioned is that, an ideal trajectory planning horizon approaches ∞, but in reality it can be as large as real-time computational time allows. But the strategical decision can be independent from the trajectory planning horizon and can be as large as the vehicle perception sensors vision range or communication range. Fig.3 as an example illustrates a frame from hemispheric camera installed at Tostmannplatz intersection in Braunschweig in which the trajectory planning horizon of DLR automated vehicle, white vehicle left of the figure, is shown in green and in red strategical decision module range is illustrated which is extended to sensor vision range and also communication range, here with traffic light at intersection.

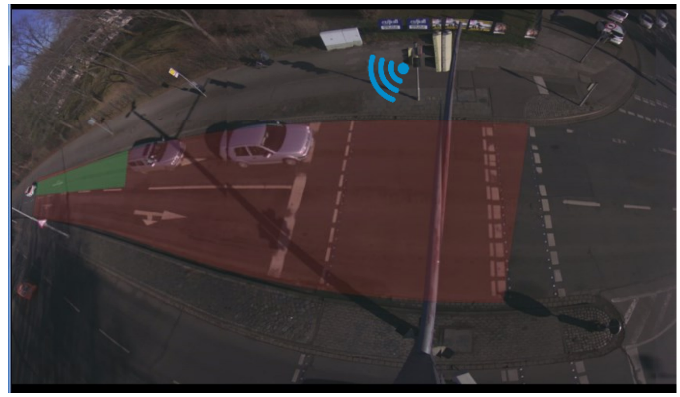

Fig. 3. Trajectory planner horizon (green) vs. strategical decision horizon (red)

1) Lane change

As already mentioned, lane change can be triggered from the infrastructure by sending a Lane Advice Message *LAM*. In processing this, the strategical decision module is analysing possible gaps by using information about the objects on the requested lane. Based on the speed, distance, time headway and detection confidence of the following and preceding vehicle of each gap, a cost value is assigned to each gap. Then the gap with minimum cost is selected and proper action to change the lane such as acceleration to reach the gap in front, deceleration to reach the gap behind and also adaptation of the velocity based on the new lane dynamics are sent to the trajectory planner. Gap analysis due to its dynamics and its independency to ego planning, is not a convex problem, therefore the best gap selection is done not only by gap cost, but also by gap consistency.

2) GLOSA

The vehicle automation receives *GLOSA* messages via *V2I* communication at MAVEN intersections. In these messages several dynamic zones and a velocities assigned to each of these zones are defined [11]. The strategical decision module estimates the advice zone the vehicle is currently driving in and sends the velocity of that zone as desired velocity v_{des} to the trajectory planner, updated each iteration.

3) Intelligent driver model and adaptive driving strategy

Driving in urban area and highway is mostly following the current lane. Therefore an Intelligent Driver Model *IDM* is integrated in the strategical level in which at each iteration based on the front man information, a suitable acceleration value and velocity which does not violate comfortable deceleration and keeps the desired time gap with front man is suggested [12]. The strategical decision also analyses the environment and based on the current traffic situation parametrized the *IDM*, see [13] .

4) Platooning

MAVEN automated vehicles are able to build and drive in platoons. The platoon logic is designed and developed as a unique module used in MAVEN automated vehicles. A brief explanation of the platoon logic is given here. The complete description of each platoon state machine and transition between states (assigned capital letters on each array) can be found in [3] [4].

Fig.4 illustrates the four platoon state machines. The "platooning state machine" represents the overall state of the vehicle, so it describes whether the automated vehicle is currently not able to drive in a platoon, has the wish to create or join a platoon, is currently driving in a platoon or currently leaving one. The "forming state machine" is responsible for the platoon forming procedure. It is used to reflect the state of platoon forming with other vehicles.

The "message state machine" is responsible for defining the content of the messages sent by the vehicles. This state machine is always active. The "distance state machine" is responsible for managing the distance to the vehicle ahead and for opening up gaps in front in order to allow merging of other (manually driven or not MAVEN-automated) vehicles to the own lane. Therefore, this state machine is active independent of the current platoon state machine as it can change the behaviour of single automated vehicles, too.

The strategical decision serves, together with the ego vehicle information as input to the platoon logic and based on the platooning states reformulates the optimal control problem.

III. Tests and Implementation

As already mentioned, the functionality of the trajectory planner and strategical module is approved in closed field tests and tests in public traffic in a complex urban area. The focus of this chapter is on the lane change after receiving a *LAM* from infrastructure in a close test track and urban area, and platooning of two automated driving car in an urban area.

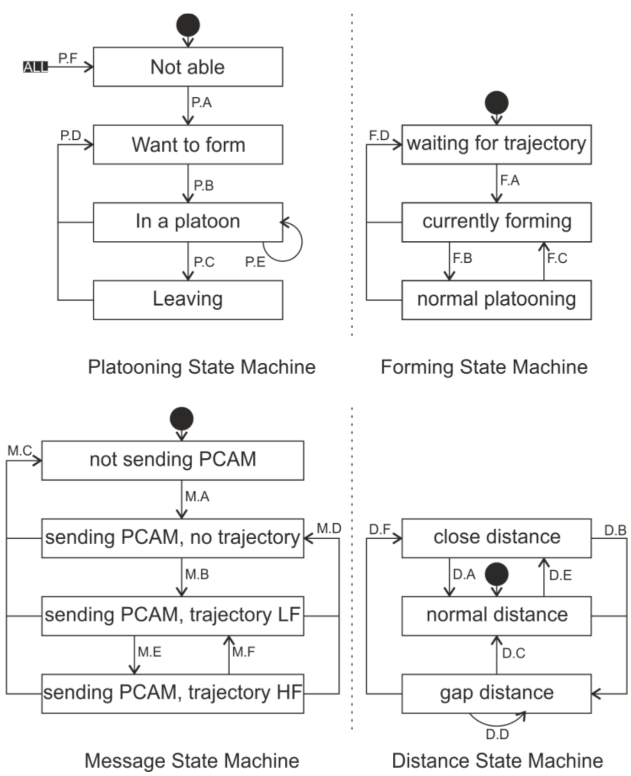

Fig. 4. Platoon state machines

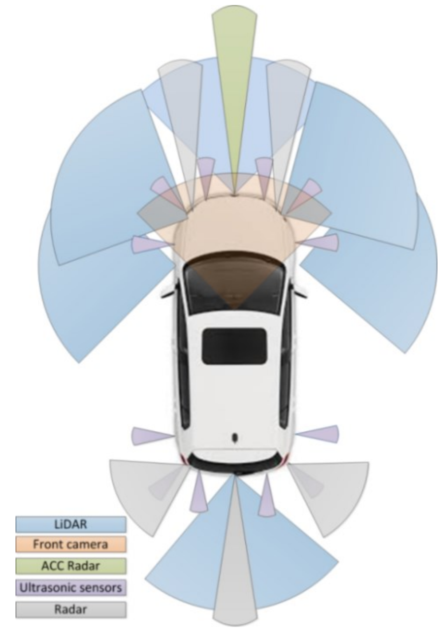

Fig. 5. DLR vehicle perception sensors setup

DLR automated vehicles FASCarE and ViewCar2 have been used for the tests. Both cars have a similar sensors setup. Fig.5 shows the perception sensor equipment of DLR automated vehicles. In addition both cars are equipped with V2X communication modules. More information about DLR test vehicles can be found in [14].

1) Lane change

Fig.6 shows the DLR automated vehicle on the closed test field. A DLR mobile traffic light is equipped with communication module to send the *LAM* messages if needed. Fig.7 illustrates a lane changing scenario in a closed filed test track in four frames. At first FASCarE is driving (white car on the left) and ViewCar2 is stopped behind the red traffic light (grey car on the right). While approaching, second frame, the traffic light detects lighter traffic (i.e. no vehicles) on the left lane and sends a LAM message to FASCarE as it is supposed to be the more efficient lane for the vehicle. At the third frame FASCarE begins lane changing and as it is explained before a gap analysis is done in the strategical module. After changing the lane GLOSA messages are also received. Therefore a velocity adaptation is also done at this stage which results in reaching the intersection at the start of the green phase, fourth frame.

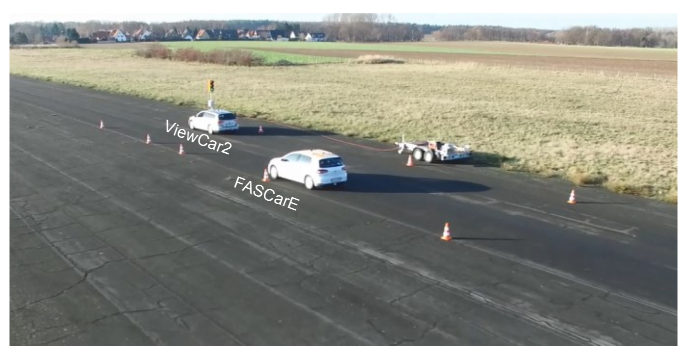

Fig. 6. DLR test vehicles FASCarE and ViewCar2 and closed test field

Fig. 7. Lane changing scenario triggered from traffic light via LAM

The same scenario has been also repeated in a complex urban scenario at Braunschweig-Germany Tostmannplatz (52°17'45.8"N 10°32'26.8"E). As it is shown in Fig.8 the automated vehicle drives from south to north. The red lines on the HD map are the rear axle GPS positions of the automated vehicle. The traffic light sent LAM messages advising to the left lane to the DLR automated vehicle. After detecting and analysing the gaps on the desired lane, a lane change is effectuated.

Fig.9 illustrates the velocity profile for the same scenario, as it is shown, when the automated vehicle is approaching the traffic light. At a given time, it receives the LAM message, shown with violet line. Therefore the strategical module analyses the gaps and the required action to merge to the selected gap is reducing velocity. The vehicle merges to the gap and increases its velocity. Then the vehicle reaches the stop zone defined by GLOSA, shown with the red line in the figure, and therefore it reduces its velocity till reaching a stand-still behind the stop line. When the traffic light turns to green, shown with the green line, the vehicle accelerates and crosses the intersection.

2) Platooning

A platooning scenario has been done at Braunschweig in which two automated vehicles driving from south to north and crossing Tostmannplatz intersection. Fig.10 illustrates the result of platooning scenario of the platoon follower vehicle. The vertical red lines show the start and end of fully automated driving phase.

The first sub-figure is the platoon state that for this given scenario has two states, *N* for normal driving or "normal distance" and *P* for in platoon or "close distance".

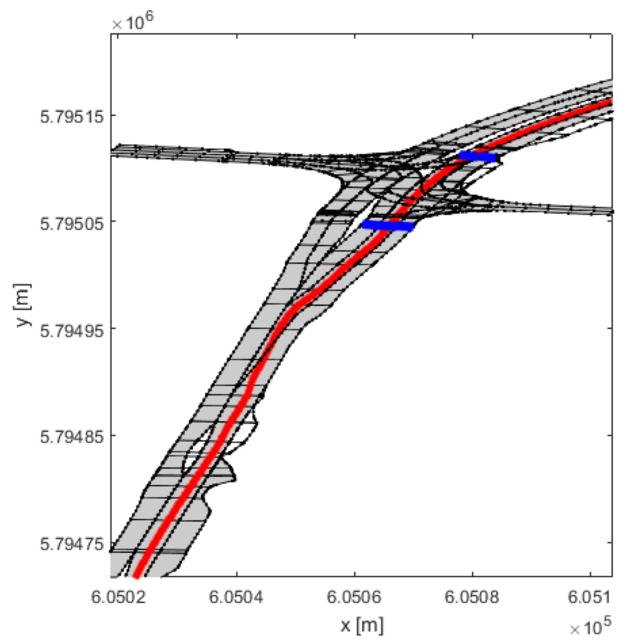

Fig. 8. Vehicle position of lane change scenario triggered from traffic light via LAM

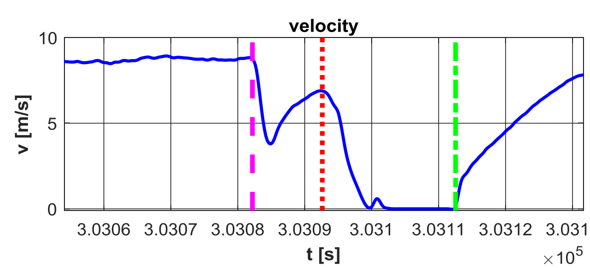

Fig. 9. Velocity profile of lane change scenario triggered from traffic light via LAM

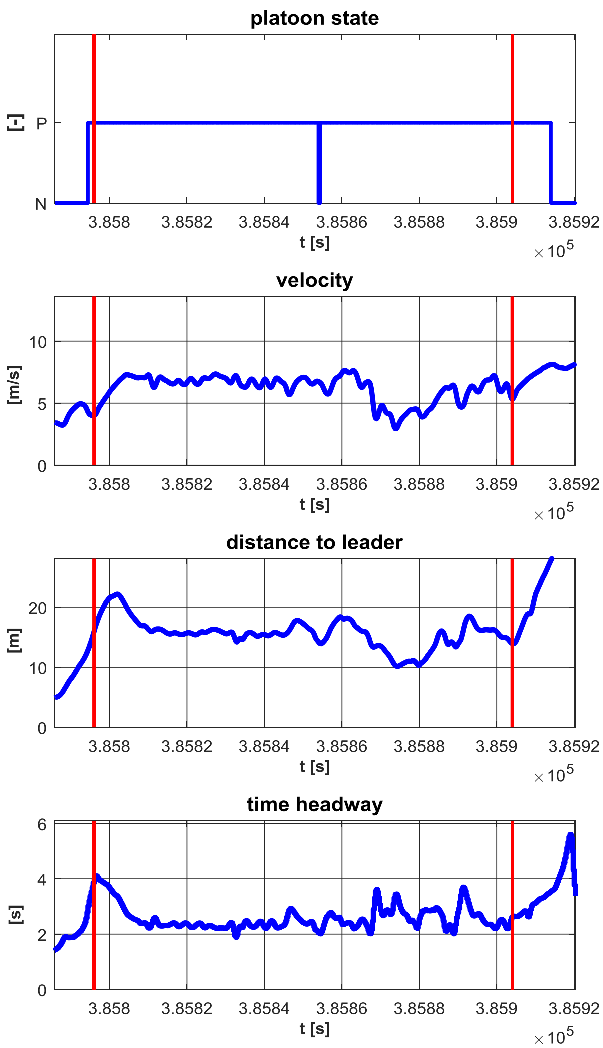

Fig. 10. Follower states during a platoon of two automated vehicles

As it is shown, when the platoon logic switches from “normal distance” to “close distance” and when the vehicle drive automatically, the follower trajectory planner increases the velocity, second sub-figure, in order to have close gap with leader, third sub-figure, which results in decreasing time headway, fourth sub-figure. The platoon time headway was set to 2.5 [s] due to safety reason and as it is shown, while platooning the follower speed was adjusted in order keep the given time headway. As the test was done in public traffic, leader needed to adjust its velocity based on the traffic situation which resulted speed adaptation of follower in order to keep the time headway constant.

ACKNOWLEDGEMENT

This paper was prepared thanks to project MAVEN (www.maven-its.eu).

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under the Grant Agreement No. 690727.

REFERENCES

[1] "Global status report on road safety 2018: summary," World Health Organization (WHO/NMH/NVI/18.20), Geneva, 2018.

[2] “Critical reasons for crashes investigated in the national motor vehicle crash causation survey,” U.S. Department of Transportation, March 2018.

[3] J. Schindler, R. Dariani and T. W. Michele Rondinone, “Dynamic and flexible platooning in urban areas,” in *AAET*, Braunschweig- Germany, 2018.

[4] J. Schindler, R. Dariani, M. Rondinone and T. Walter, “Implementation and testing of dynamic and flexible platoons in urban areas,” in *AAET*, Braunschweig- Germany, 2019.

[5] E. W. Dijkstra, “A note on two problems in connexion with graphs,” *Numerische Mathematik,* pp. 269-271, 1959.

[6] P. E. Hart, N. J. Nilsson and B. Raphael, “A Formal Basis for the Heuristic Determination of Minimum Cost Paths,” *IEEE Transactions on Systems Science and Cybernetics ,* pp. 100-107, July 1968.

[7] R. Dariani, “Hierarchical concept of optimization based path planning for autonomous driving,” Otto-von-Guericke University of Magdeburg, Magdeburg, 2016.

[8] M. Gerdts, “A moving horizon technique for the simulation of automobile test drives,” *Journal of applied mathematics and mechanics,* pp. 147-162, 25 February 2003.

[9] R. Mayr, “Verfahren zur Bahnfolgeregelung für ein autonom geführtes Fahrzeug,” University of Dortmund, Dortmund, 1991.

[10] H. B. Pacejka, Tire and vehicle dynamics, SAE International and Butterworth Heinemann, 2012.

[11] MAVEN Deliverable 5.1, "V2X communications for infrastructure-assisted automated driving", Feb 2018.

[12] M. Treiber, A. Hennecke and D. Helbing, “Congested traffic states in empirical observations and microscopic simulations,” *American Physical Society,* pp. 1805-1824, August 2000.

[13] A. Kesting, M. Treiber, M. Schoenhof and D. Helbing, “Adaptive cruise control design for active congestion avoidance,” *Transportation research,* pp. 668-683, 2008.

[14] “MAVEN Deliverable 6.1. "Integration of basic hardware into test vehicles",” 2017.