TRAFFIC STATE PREDICTION SERVICES FOR AUTOMATED DRIVING AND TRAFFIC MANAGEMENT

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ABSTRACT

The target in the PRYSTINE project is to realize Fail-operational Urban Surround perceptION (FUSION), which is based on sensor fusion, and control functions in order to enable safe automated driving in urban and rural environments. Estimation of the complete current and (near) future traffic conditions ahead, beyond the range of on-board vehicle sensors, provides the automated driving controller with enhanced information to act better and more comfortably in the current situation and to extent road safety. Traffic state prediction is also an important input for pro-active traffic management as identified within TM2.0 (Traffic Management2.0 vision ERTICO). The derivation of a common operational picture for traffic management and mobility service providers, like CAV, enables the collaboration between public and private parties in facilitating traffic. Stimulating and enhancing this collaboration is part of the Dutch innovation program MobilitymoveZ. Significant improvements of quality and availability of data offers the opportunity to provide such information. By combining data science and traffic modelling techniques, an application is developed consisting of current and short term traffic prediction (typically up to 10 minutes ahead) and a virtual patrol detecting congestion and incidents for urban and non-urban networks.

1. INTRODUCTION

Traffic management, traditionally a task of public road authorities, needs accurate and complete information on traffic conditions, especially when non regular traffic conditions occur. Usage of short term predictions would increase possible societal benefits, because it opens the opportunity for pro-active traffic management or at least overcoming the latency in data availability. Traffic Management 2.0, an Innovation Platform established in 2014 by the ERTICO Partnership (Vlemmings et al. 2017), introduced a vision on traffic management enabling interactive traffic management, because of the increase of private parties (i.e. private mobility service providers) involvement and influence on traffic operations. These private parties will increasingly provide new connectivity and information services for vehicles and travelers. This includes developments on bringing ever more information to the vehicle itself providing connected and cooperative ITS services and deployment and operation of autonomous vehicles. Both stakeholders, public road authorities and private mobility service providers, need information on and derived from the current as predicted traffic state to act upon the daily urban system and its spatial and temporal dynamics. Vlemmings et al. (2017) conclude that these parties need to exchange data to be able to cooperate. Furthermore, when these parties have access

to a common operational picture, it becomes easier to determine and (automatically) negotiate deployment of measures balancing individual driver versus collective societal objectives.

1.1   Connected automated vehicles (CAV)

The automation of vehicles ultimately aiming at fully autonomous driving has been identified as one major enabler to master the Grand Societal Challenges 'Individual Mobility' and 'Energy Efficiency'. Highly automated driving functions (ADF) are one major step to be taken. One of the major challenges to successfully realizing highly automated driving is the step from SAE Level-2 (Partial automation) to SAE Levels-3 (Conditional automation) and above. At level-3 the driver remains available as a fall-back option in the event of a failure in the automation chain, or if the ADF reaches its operational boundaries. At higher levels, the driver cannot be relied upon to intervene in a timely and appropriate manner, and consequently, the automation must be capable of handling safety-critical situations on its own. For this, fail-operational behaviour is essential in the sense, plan, and act stages of the automation chain. PRYSTINE's target is to realize Fail-operational Urban Surround perceptION (FUSION), which is based on robust Radar and LiDAR (Light Detection and Ranging) sensor fusion, and control functions in order to enable safe automated driving in urban and rural environments (Prystine, 2018).

While the sensors within the vehicle have a sense range of 100-150m, traffic state prediction is the sensor outside the vehicle to 'see through' surrounding vehicles and to look further ahead. This sensor identifies incidents and classified levels of service of traffic flow downstream the route as inputs to decision making for vehicle control or transition of control operations. For the decision making different levels are distinguished:

Level	Added value of traffic state prediction
Tactical level	Actual traffic speed and volumes next road segments for arbitration changing lane or speed adaption
Tactical level	Information about location tail traffic jam next road segments to reduce speed between vehicle and tail traffic jam
Strategic level	Information about incident or predicted traffic jam downstream for calculation expected delay or alternative route
Strategic level	Predicted traffic states to be used in the route navigation systems for estimating actual arrival time

These levels are according to the driver task levels earlier distinguished by Michon (1971), although in this case the automatic action patterns of drivers (e.g. shifting gear) are not taken into consideration. Decisions at operational level are not supported by traffic state prediction yet. Besides traffic state prediction also other context aware content should be available, for example weather condition. V2X communication will expand the sight of vehicles including a larger area and possible exceptions in traffic outside of sensors detection range (Figure 1).
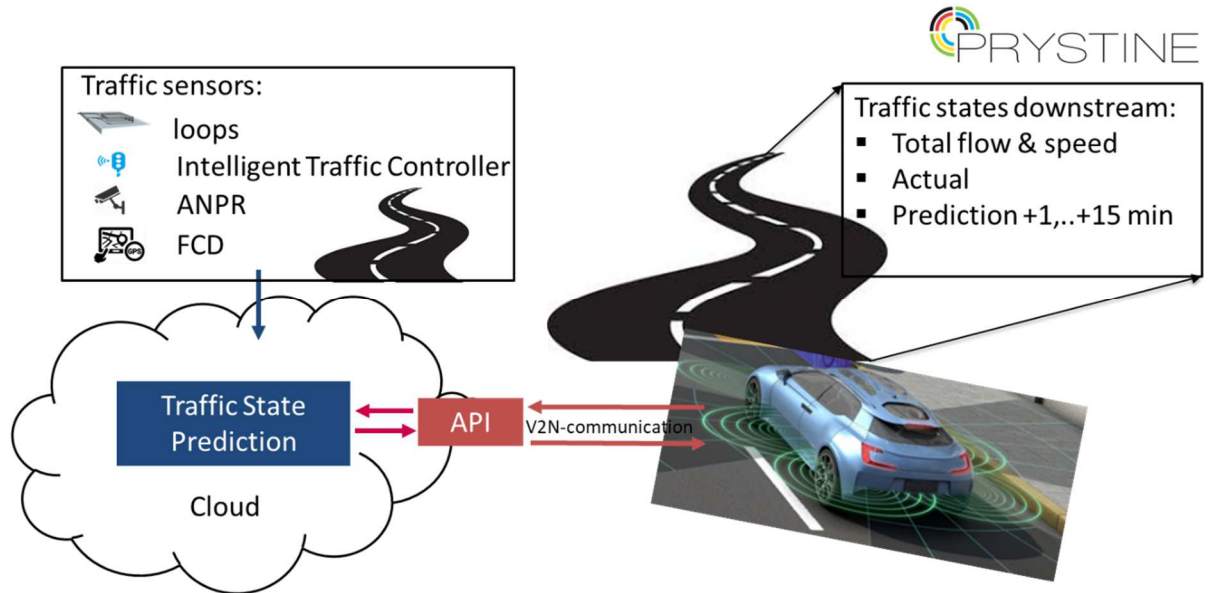
Figure 1 – V2X communication for a wider sensor range

The resulting architectures and reliable FUSION components for autonomous systems will be validated in 22 industrial demonstrators. PRYSTINE's well-balanced, value chain-oriented consortium, is composed of 60 project partners from 14 different European and non-European countries including leading car manufacturers, Tier-1 suppliers, engineering and semiconductor suppliers as well as supply chain partners, technology integrators, universities and research institutes.

1.2 Traffic Management

In the past years there has been a development of local traffic control via corridor control towards regional and network wide traffic management (see Figure 2). However, this has mainly been an instrumental step in terms of realizing the digital infrastructure of connecting local road side measures including its sensing information and traffic management control systems with one regional Network Management System (NMS). The past few years also other real time streaming data sources are being connected with these systems like floating car data, but in most cases these are not fused nor providing a complete traffic state. However, this still does not guarantee coordinated network wide traffic management which requires pro-active management with minimum labour based interventions by traffic operators and (in future years) collaboration between traffic management stakeholder groups (i.e. road authorities and private mobility service providers like CAV).
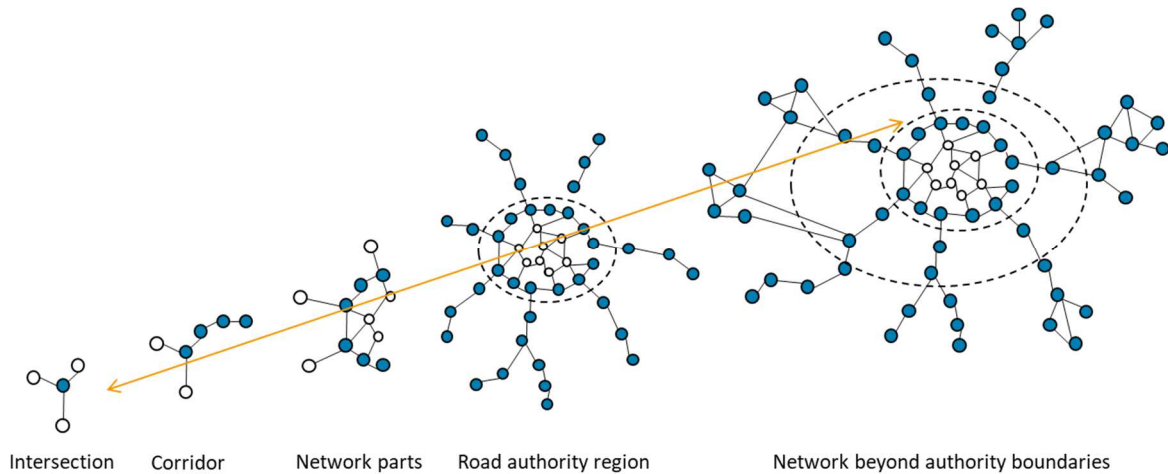
Figure 2 – From local towards network management

Within our complex and often fragile transport system pro-active management is an essential building block. Repairing revealed traffic problems is multiple times more inefficient and ineffective than avoiding them or at least postponing them. This requires (first condition) pro-activity in which demand is timely redistributed on the available network, the inflow on near saturated links is timely metered or the outflow of this link increased, traffic towards a parking garage is timely redirected, possibly to a less obvious location, etc. Re-active management, i.e. responding on saturated traffic conditions, means that the response is too late, but also the options are limited to solve or mitigate problems.

Minimum manual labour of traffic operators is a second condition for network wide coordinated traffic management. As indicated in Figure 2, the network that needs to be managed is growing. The interaction between certain occurrences, such as bridge control, tunnel closures, road works or even large events, increases as well as the diversification towards specific user groups like pedestrians, bicyclists, passenger cars, trucks and busses. In addition, the network growth is not only spatial focusing on highways only. There is also a growing need for including the increasing options available on urban networks for which there is not always a traffic operator available to deliver twenty-four seven traffic management services. This asks for supporting the traffic operators in further automation of network wide traffic management where possible, focusing their manual intervention on occurrences where it is most needed.

The approach needed should address these two conditions and should provide the option of including the collaboration between the traffic management stakeholder groups, which means both need common information on and derived from the current and predicted traffic state (i.e. a common operational picture) to be able to assess and take appropriate, pro-active actions. Within several initiatives like MobilitymoveZ the further development of such pro-active traffic management and traffic state prediction services is embraced.

2. TRAFFIC STATE PREDICTION
In current practice the focus lies on the upper traffic network (generally highways). Most research on state estimation and prediction is done for highway road networks (Wang et al., 2008, Van Lint and Van Hinsbergen, 2011 and Seo et al., 2017). Intuitively a high quality traffic state estimation and

prediction algorithm has more benefits if applicable on the larger and more detailed urban road network. These urban networks cover besides the upper network also the important primary and secondary urban arterials. This introduces additional challenges compared to highway networks related to data availability, not fully covered by sensor, and urban nature of the traffic network with for example lower traffic volumes, density of junctions and varying junction designs (e.g. traffic signals, roundabouts and priority junctions). Within the research field of traffic state estimation and prediction, a recent shift has occurred altering the scope of research from the relative comfort of freeway segments in highway networks to urban road networks. These urban networks cover besides the upper network also the important primary and secondary urban arterials (Calvert et al., 2015, Nantes et al., 2016 and De Vries et al., 2018). However, in the previous efforts the methods focused on high level state indicators (e.g. travel times), were data drive approaches not well capable in predicting non-regular traffic conditions (Friso et al., 2017), or only applied on synthesized data sets or only one source of data (Nantes et al., 2016). Furthermore, research focusses on either highways or urban roads, although an approach being able to cope with the combination of both is relevant given the needs formulated for traffic management.

2.1   Methodology framework

In our approach we combined parametric and nonparametric methods using traffic flow theory and continuous automated calibration of parameters. These models showed good performance for highway cases (Van Lint and van Hinsbergen 2011 and Seo et al., 2017). This results in a complete and consistent (i.e. in terms of traffic flow theory) estimation of the current state as well as short term prediction. The method is a further development of Vlist et al. (2016).

First a network must be made available within a macroscopic dynamic traffic model. For these developments we have chosen to make use of the state-of-art Dynamic Traffic Assignment (DTA) model Streamline, part of our OmniTRANS transport planning software package (Raadsen et al, 2010). Within the model the complete network for which the application has to operate, is included. Subsequently a data processing submodule processes raw real time data. Real time data are extracted from its sources, fused with other data sources and mapped on the available network. This processed data are input for the model environment in which demand and supply are calibrated and traffic state predictions are generated. The real time data can be of various sources, for example loop detector data, floating car data and traffic signal data. Figure 3 displays a general overview of the modules and their relations.
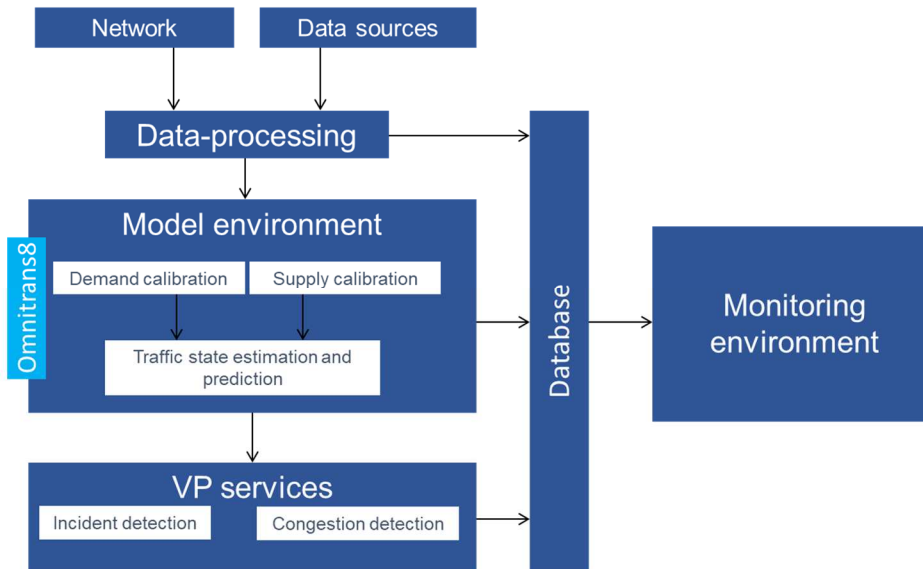
Figure 3 – Framework

2.2 Data fusion and prediction

Fusion of data contains two steps. Within the data processing step the data is map matched (in space and time) filtered and fused if there are two sources providing the same information (e.g. speed at a certain location and time period). The second fusion step is performed within the model environment where all available data is fused over time, space and units, consistent with traffic flow theory. The basic component for this are demand calibration, supply calibration and a continuously running simulation model adapted based on the measurement (via both calibrations).

Demand Calibration
This fused measurement data connected with the model network is used for calibration of the model demand. Flow measurements are used to scale historic origin-destination(OD) matrices in such way that traffic demand fits the demand profiles on predefined locations (typically locations on the borders of the network).

Supply Calibration
The measured traffic data are used to continuously calibrate the fundamental diagrams for each link in the model environment reflecting directly influences of the dynamics in traffic due to the amount of freight traffic, traffic management and weather conditions. Links are logically clustered to be able to update fundamental diagram parameters of unmeasured links as well.

Simulation model
Within the model environment StreamLine::Madam is used for traffic estimation and prediction. StreamLine::Madam is a macroscopic dynamic traffic assignment model that translates traffic demand on OD-level over time into traffic flows, speeds and densities on a link level for each time period (Figure 4).
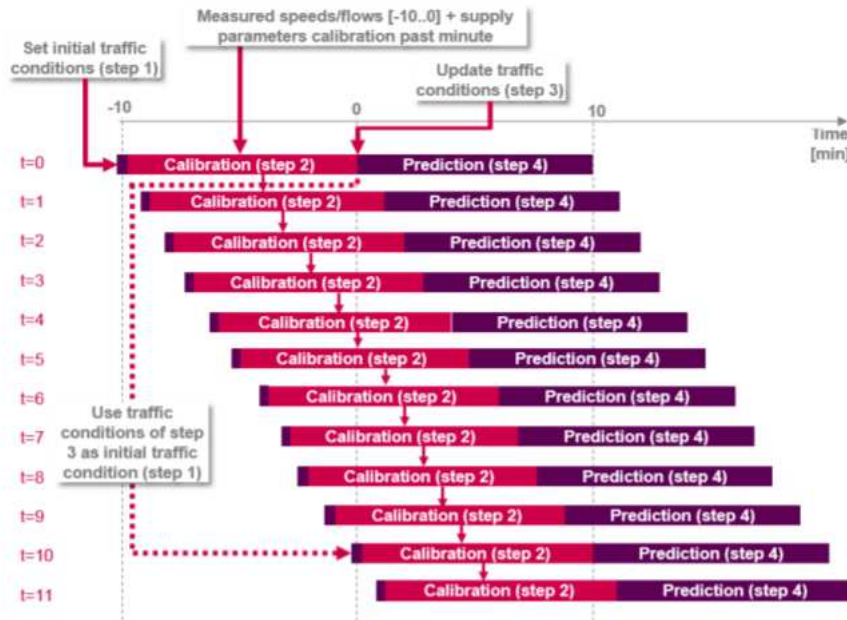
Figure 4 – The process of traffic state estimation and prediction

It calculates the actual traffic situation (combined with the previously described calibration processes) and predicts traffic states for the short term which is typically 1 to 60 minutes depending of purpose. Because of the possibility to intervene real time in all characteristics via so-called controls, calibration on the basis of data and also the calculation of measures is very well facilitated.

Besides a traffic state prediction the application does also assess predictions and measurement data in order to derive relevant decision information for the purpose at hand. This module can be seen as a virtual patrol continuously analysing the estimations and predictions. Within the PRYSTINE project the virtual patrol will be extended for example with information on the level of service of road segments or the location of the tail of a traffic jam downstream the route. For traffic management purposes this can be the detection of congestion and incidents, derivation of travel times between predefined locations or delays (current and future states).

3. DEMONSTRATION

The advancements achieved during the PRYSTINE project will be showcased by dedicated demonstrators. The Traffic State Prediction module will be demonstrated in two highway and urban decision making use cases. The PRYSTINE's FUSION technologies will be deployed in order to develop and achieve a 'co-driver', a model that is able to assist the driver not only during manual control periods, but also when charged to drive autonomously. Therefore, this supply chain will develop a decision making system for a new generation of automated vehicles, where the control can be effectively shared between the ADF and the driver. A demonstrator vehicle will be set up: it will have multiple FUSION components, such as sensors (Radar, LiDAR and Camera), a strong computational unit (for the sensor fusion and decision making) and a communication unit to communicate through internet to provide the traffic estimation with input and report back the estimated traffic.

A test site in the region of North-Brabant (NL) including both highway as well as urban roads will be provided to organize both demonstrations in cooperation with MobilitymoveZ.NL (MobilityMovez, 2018). This demonstration also aims to investigate the added value of the developed traffic state prediction services for pro-active traffic management in the North-Brabant region as well.

This demonstrator approach allows a scalable setup of the decision making algorithm. A test-site consisting of both urban roads as highways is used for both of the use cases:
- • A highway use case is seen as a first step for the decision making as its environment is less complex than the urban use case. A typical scenario is the decision to perform an overtaking manoeuvre.
- • The highway use case is then extended to an urban setting. Hence the speed is reduced but other traffic participants and situations are included: cyclists and crossings. Here a lane change or take-over may be induced by a close by cyclist.

4. Conclusions

The automation of vehicles has been identified as one major enabler to master the Grand Societal Challenges 'Individual Mobility' and 'Energy Efficiency'. Highly automated driving functions are one major step to be taken. While sensors as Radar, LiDAR and vision within the vehicle have a sense range of 100-150m, traffic state prediction is the sensor outside the vehicle to look further ahead. This sensor identifies incidents and classified levels of service of traffic flow downstream the route as inputs to decision making for vehicle control or transition of control operations. The added values of this sensor outside the vehicle are:
- • Actual traffic speed and volumes next road segment for arbitration changing lane or speed adaption.
- • Information about incidents or predicted traffic jams downstream to reduce speed between vehicle and location incident or tail traffic jam.
- • Predicted traffic states to be used in the route navigation systems (actual arrival time, rerouting when unexpected incidents occur).

Additionally the demonstration aims to investigate the added value of the traffic stated predictive services, as well as the completed current traffic conditions providing the common operational picture, for pro-active traffic management.

Within the PRYSTINE and MobilitymoveZ project these added values will be evaluated from different perspectives.

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