

Short Term Prediction of a Vehicle's Velocity Trajectory Using ITS

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ABSTRACT

Modern cars feature a variety of different driving assistance systems, which aim to improve driving comfort and safety as well as fuel consumption. Due to the technical advances and the possibility to consider vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, cooperative adaptive cruise control (CACC) strategies have received significant attention from both research and industrial communities.

The performance of such systems can be enhanced if the future velocity of the surrounding traffic can be predicted. Generally, human driving behavior is a complex process and influenced by several environmental impacts. In this work a stochastic model of the velocity of a preceding vehicle based on the incorporation of available information sources such as V2I, V2V and radar information is presented. The main influences on the velocity prediction considered in this approach are current and previous velocity measurements and traffic light signals. For practical applications a model must capture the driver's reaction on the traffic situation as well as the vehicle dynamics. Here a Bayesian network approach is followed which provides a compact representation of the variable dependencies and allows inferring the mean value and the confidence interval of the prediction. The proposed model is parameterized with real traffic scenarios recorded during road tests. The validation results show that the prediction achieves a high accuracy within a prediction horizon useful for a variety of different driver assistance functions.

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INTRODUCTION

Reduction of fuel consumption is an important goal pursued by the automotive industry. Besides, car manufacturers are challenged to comply the more and more stringent restrictions, for example on CO_2 emissions, shown in [1]. Albeit in the past the focus was primarily on the design and control of fuel-efficient engines and power trains, recent studies revealed that there is still a high saving potential by realizing a fuel-efficient driving behavior. As investigated in [2], simulations had shown that the implementation of a fuel optimal adaptive cruise control could lead to fuel savings of about 15% in case of a FTP-like cycle. In contrast to hybrid vehicles, which conserve kinetic energy through transferring energy from and to a battery, a vehicle with fuel optimal ACC uses a variable spacing policy to conserve kinetic energy. This means that the controlled vehicle has to stay between a velocity dependent minimal and maximal distance to the preceding vehicle. The trajectory of the controlled vehicle is calculated by means of a model predictive control algorithm that minimizes the fuel consumption over a given time horizon. As a result, the controller avoids hard or unnecessary acceleration and braking maneuvers, which would lead to high fuel consumption. Moreover a short-term prediction of a vehicle's velocity could be utilized to improve the performance of vehicles equipped with a start-stop systems or hybrid power trains. However, the fuel savings achieved by such driver assistance functions depend on the quality of the velocity prediction of the preceding vehicle.

Unfortunately, an imprecise prediction could easily lead to additional fuel consumption. As a matter of fact, the predicted velocity trajectory is flawed with uncertainty due to the varying human reactions on the traffic situation. Naturally, the resulting uncertainty should be taken into account to improve the performance and usability. To this end, it is favorable to predict the distribution function of the future velocity instead of a single trajectory.

Modeling and prediction of human driver behavior has been studied in many works. An approach suited for repeatedly driven routes of garbage trucks and city buses is for example to develop a prediction model for the velocity using GPS measurements and a database of prediction profiles. As presented in [3], the prediction is based on previous vehicle operations on the same route that, however, does not take influences of other traffic participants into account. Another work that aims in a similar direction is presented in [4]. Here, the authors investigate a short loading cycle of wheel loader with the aim of calculating a fuel and time optimal trajectory by solving a nonlinear optimization problem. However, these methods are not very practicable in urban traffic because the traffic situation is not necessarily repeatable. Generally, incorporation of V2I and V2V information can improve the velocity prediction significantly. As presented in [5], the additional information provided by these systems is used for identifying nonlinear autoregressive models and led to promising results concerning the estimation performance.

Nevertheless, these models predict the future velocity based on past measurement data and cannot provide an estimation of the uncertainty due to the permanently changing traffic environment.

Finally, [6] presents how a vehicle using CACC can be realized by considering traffic relevant information like digital maps of the traffic environment, V2V data and V2I data. Based on the predicted velocity trajectory a discrete space representation of the possible evolutions of the velocity trajectories is established. Consequently, the optimal velocity trajectory is evaluated through a graph search algorithm. However, in this work only a short-term prediction up to 15s was examined which allows a description with a conditional Gaussian model. An advantage of this modeling strategy is that static Bayesian networks allow more flexibility because the parameters of the prediction nodes are not linked.

The paper is organized as follows: first, a detailed problem description is given. Then the theory of Bayesian networks and conditional Gaussian models is reviewed briefly. In the next step the training data is explained and finally the results are evaluated. A summary of the presented modeling strategy is given in the last section of this work.

PROBLEM STATEMENT

As mentioned in the introduction, a typical framework where a velocity prediction of a vehicle is necessary is for example CACC. Here, a short-term prediction of the predecessor's velocity is used to determine the fuel optimal trajectory of the controlled vehicle when driving in a vehicle-following scenario. In an urban traffic environment the future velocity of a vehicle depends mainly on the following factors.

1. Current and past velocity of the vehicle $v_p \in \mathbb{R}^+$ and its predecessor $v_{pp} \in \mathbb{R}^+$
2. Distance of the vehicle to the next traffic light $x_{TL} \in \mathbb{R}^+$
3. Future traffic light signals $TL \in \{\text{red, green}\}$ if the vehicle approaches a set of traffic lights

In this work, the considered traffic conditions on the roads are moderate and non-congested. Lane changes as well as overtaking maneuvers are not considered. In addition, it is assumed that the velocity of the vehicles and their distance to the next traffic light is a positive value. The goal is to predict a vehicle's velocity trajectory up to a prediction horizon of $PH = 15s$ based on actual information provided by ITS and on-board sensors such as radar, camera and GPS systems. Later, this prediction could be utilized for various driver assistance functions.

As it can be observed in measurements, in the first upcoming seconds, the velocity of a vehicle depends mainly on its current velocity and acceleration. That means that for a small prediction horizon the future velocity is mainly influenced by the vehicle's current dynamic state, as shown for example in [5]. For this case an estimation of the velocity using a dynamic system with fixed transitions characteristics between one sampling step and another is conceivable. However, the longer the prediction horizon gets, the

more is the velocity trajectory dominated by the drivers reaction on the future traffic situation, e.g. traffic lights or traffic signs. As a result, a sensible prediction of the future velocity trajectory up to the desired prediction horizon is barely possible without incorporation of V2V and V2I data. The presented modeling strategy that uses for each sampling instance a Gauss distribution for the velocity provides sufficient flexibility to reflect the dynamic behavior and the influence of traffic regulation installations like traffic lights. Moreover, due to the perpetual changing road-users, different vehicle types, traffic volume and weather conditions, the presented prediction model can also be used in an adaptive way. An offline-trained initial model can be used as base model. Then the model can be updated using online measurements of the vehicles radar, V2V and V2I information to address the perpetual changing traffic environment.

Consider a sampling time $T_s = 1s$. As mentioned in the introduction it is beneficial to predict the distribution function of the velocity trajectory because human driving behavior is partial nondeterministic and there are various basically unknown inputs that are affecting the driver. Therefore, it is assumed that the future velocity trajectory can be described using a Gaussian distribution for each sampling instance $i \in \{1, \dots, PH\}$, i.e.

$$v_p(k+i) \sim \mathcal{N}\{\bar{v}_p(k+i), \Sigma_{v_p}(k+i)\}.$$

$\mathcal{N}\{\bar{v}_p, \Sigma_{v_p}\}$ denotes a 1-dimensional Gaussian distribution with mean value $\bar{v}_p$ and standard deviation Σ_{v_p} . In the next step, two possible scenarios that utilize different available traffic information are investigated.

Scenario A

For scenario A it is supposed that there are two vehicles driving in a row. As depicted in [Figure 1](#), the first vehicle (grey) is the controlled vehicle that is following its predecessor also called the second (orange) vehicle. In this scenario it is assumed, that the first vehicle is perfectly equipped with radar, camera and GPS systems to capture the actual traffic situation. Unfortunately, there is no V2V and V2I communication available, hence the upcoming traffic light signals are not known and no information of the predecessor and traffic lights could be transmitted to the first vehicle. However, the current velocity of the predecessor could be measured with the radar system and the distance to the next red traffic light x_{TL} could be evaluated by means of GPS and camera systems. Based on this inputs, the distribution function of future velocity trajectory of v_p is estimated.

Scenario B

As illustrated in [Figure 2](#), in scenario B is supposed that there are three vehicles driving in a row. Again, the controlled vehicle is the first vehicle (grey) in the line and it is assumed that it can establish V2V communication with the second vehicle (orange) and also V2I communication with the next set of traffic lights. In addition, it has been supposed that there is a third vehicle (green) in front of the second vehicle. Its velocity is v_{pp} could be determined by means of the second vehicle's radar sensors and then transmitted over V2V to the first vehicle, even if the third vehicle itself has no V2V system on board. Accordingly, the velocity of the third vehicle v_{pp} could also be provided to the first vehicle by V2V communication.

Based on the aforementioned scenarios, two models have been set up and trained with real traffic data gathered in an urban traffic cycle. All the used input variables for both configurations are summarized in Table 1.

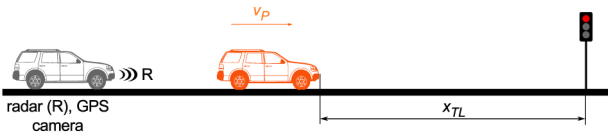


Figure 1. Scenario A: the first vehicle is the controlled vehicle; its predecessor is the second vehicle whose future velocity trajectory is in demand

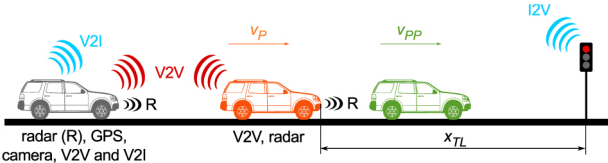


Figure 2. Scenario B: the velocity of the third vehicle v_{pp} is transmitted via V2V communication of the second vehicle to the first vehicle. Again, the future velocity trajectory of the second vehicle is in demand.

Table 1. Input configuration of the CG models

	Scenario A	Scenario B
Used inputs	$v_p(k), v_p(k - 1), v_p(k - 2)$ $x_{TL}(k), x_{TL}(k - 1), x_{TL}(k - 2)$	$v_p(k), v_p(k - 1)$ $v_{pp}(k), v_{pp}(k - 1)$ $x_{TL}(k), x_{TL}(k - 1)$ $TL(k + 1), \dots, TL(k + PH)$

BAYESIAN NETWORK APPROACH

Graphical models such as Bayesian Networks (BN) are used in many applications. Special variants were developed independently by many different communities, as for example in speech recognition (Hidden Markov Models), trajectory tracking (Kalman Filtering) and also in medical diagnostics as for example in [7]. Graphical modeling provides a broad variety of modeling schemes in a single framework and modeling is intuitively conceivable due to the graphical notation. Moreover there is a high number of learning and inference techniques for BN provided in literature. A detailed introduction into graphical models, especially representation, inference and learning can be found in [8] or [9]

A BN is basically a directed acyclic graph in which nodes represent random variables and arcs represent conditional dependence assumptions. For modeling the future velocity of the preceding vehicle a graph structure called conditional linear Gaussian model (CG) is used which enables to take into account discrete and continuous-valued variables. The output of such a model is a multivariate Gaussian distribution conditioned on all discrete variables. An example of this modeling method with a detailed explanation can be found in [10] where the emissions of a waste incinerator are determined by means of a conditional Gaussian model.

By incorporation of a discrete switching variable, namely the future traffic lights in this case, it is possible to split the system into parts of different system behavior. This approach is suitable to the velocity prediction in an urban traffic environment where the dynamics of the system is time varying and dependent on the upcoming traffic light signals.

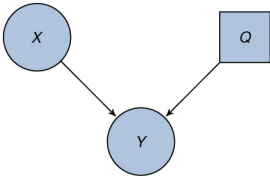


Figure 3. Conditional Gauss model with continuous-valued parent X and discrete-valued parent Q . The distribution of Y is then linear conditional Gauss.

As mentioned in the introduction, it is assumed that the future velocity of a traffic participant can be described with conditional Gaussian distributions with mean value μ and covariance matrix Σ in every sampling step. Figure 3 shows the basic structure of a CG model. Node Y is a continuous-valued node with a linear conditional Gauss distribution. It has a continuous-valued parent X and a discrete-valued parent Q . The conditional probability distribution of Y is then defined as follows

$$p(y|x, Q = j)) = c|\Sigma_j|^{-\frac{1}{2}}e^{-\frac{1}{2}(y-B_jx-\mu_j)^T\Sigma_j^{-1}(y-B_jx-\mu_j)} \tag{1}$$

where $c = (2\pi)^{-\frac{d}{2}}$ is a constant and d is the size of the node Y . The matrix B_j is called regression matrix and its rows are the regression vectors of y when $Q = j$. The components of the regression matrix are estimated by means of a maximum likelihood algorithm. The complete-data log-likelihood with N independent and identically distributed training cases $\{e_i\}$ is then

$$L = \log \prod_{t=1}^N \prod_{j=1}^{|Q|} [\text{Pr}(y_t|Q_t = j, e_t)]^{q_t^j} \tag{2}$$

where $q_t^i = 1$ if Q has the value i in the t^{th} case, and 0 otherwise. There are several algorithms for estimation of the parameters of a CG model with the maximum likelihood method available. However, a detailed treatment of these computations is beyond the scope of this paper. For further details and derivations the reader is referred to [11], [12] or [13].

Dependency Graph of Prediction Model

The first step in creation of a BN is to specify the structure of the directed acyclic graph that defines the causal relationships between the velocity prediction nodes and the nodes of the input variables. To this end every future velocity sample is described through a linear conditional Gaussian distribution as stated in Equation (1). The current and past velocity values v_p , v_{pp} and the distance to the next red traffic x_{TL} are modeled with continuous-valued root-nodes because they are measured input variables and it is assumed that they