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Applying V2V for operational safety within Cooperative Adaptive Cruise Control

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Abstract

Cooperative Adaptive Cruise Control aims to automate a truck longitudinally for following its predecessor at reduced following distances in order to minimize fuel consumption. Short inter vehicle distances can be realised by the use of Vehicle-To-Vehicle communication (V2V). This application should be operational safe, which means to prevent harm to personnel in hazardous situations in case the system is fully operational: the system should avoid collisions with other road participants and with the leading truck. This paper proposes to use V2V communication in a platoon to share information on surrounding traffic participants in order to predict possible hazardous traffic situations continuously, which could be used to ensure functional safety in case of V2V failure. In case these situations can be predicted in time, actions could be taken to avoid collisions.

Keywords:

CACC, Prediction of (Individual) Traffic Participant Behaviour, V2V, Shared Map, Collision Avoidance, Machine Learning

I Introduction

Cooperative Adaptive Cruise Control (CACC) has a high potential for reducing fuel consumption and consequently reducing CO2 emissions when applied to trucks. CACC automates the following truck longitudinally. By communicating the intended behaviour of the lead truck, shorter inter vehicle distances can be achieved. Shorter inter vehicle distances are beneficial for both fuel consumption and traffic efficiency [1]. In the future the driver of the following truck may no longer have a driving task. Therefore, he or she can no longer be considered as a reliable fallback option in case of a safety-critical situation. CACC should be functional safe as well as operational safe. Functional safety aims to prevent (or minimize) harm to the personnel in case of a hardware or software failure, whereas operational safety relates to safety in hazardous situations in case the system is fully operational. An example of operational safety is collision avoidance with other traffic participants.

Within the field of Advanced Driver Assistance Systems (ADAS), several collision avoidance applications have been developed (e.g. Autonomous Emergency Braking (AEB), [2]). Since these systems are only assisting the driver, false positives are considered to be more severe than a false negative. So, ADAS systems are allowed to miss an activation of braking, but should never activate while no unsafe situation exists. On the other hand, at higher automation levels, where the driver is no longer a backup, the reliability requirements of collision avoidance systems are increasing. Missing an activation of braking is no longer acceptable. Also, the timing of AEB system activation is based on human driving, which may be too conservative for automated truck following which aims for short inter-vehicle distances. As a result, state of the art ADAS systems in the field of collision avoidance cannot be directly applied to the automated driving systems that will be considered throughout this work.

This paper aims to describe the approach how operational safety can be extended towards CACC. A few important use cases for operational safety in combination with CACC is described in Section II. Situations which should be considered are, at least, a cut-in or a braking action of (unequipped) vehicles around the platoon. Since the following truck and the lead truck are assumed to be equipped with on-board sensors they can share information of surrounding traffic with each other. Based on this information, unsafe situations can be predicted and thereby collisions can be prevented, even in situations with hardware failures such as a communication failure. These predictions can also be used for more efficient path planning, or decision making (e.g. when to make a lane change).

II Use cases for operational safety in combination with CACC

For both the lead as well as the following truck operational safety should be considered. In case the lead truck avoids collisions, the following truck is also more likely to avoid collisions. So two parts must be considered:

1. In the lead truck a driver is assumed to be present and therefore currently developed ADAS systems such as AEB could already reduce the risk of a collision for this truck. Also, in case Adaptive Cruise Control (ACC) is active, the probability of driver mistakes can be decreased. However, the safety systems in the lead can be further extended since the following truck can inform the lead truck about a car passing, which could help the lead truck in predicting a cut-in situation (e.g. by allowing a shorter initialization time of its sensors classification). So, the prediction on hazardous traffic situations can be further improved.

   Two use cases can be further specified:

   a. a braking action of a preceding vehicle in front of the lead vehicle
   b. a cut-in of another vehicle, in front of the lead vehicle, possibly followed by a braking action.

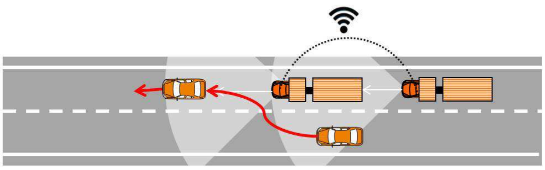

Figure 1: Sharing information of surrounding traffic participants is desired to realize operational safety in combination with CACC.

In the following truck the prediction of the behaviour of the lead truck is of most importance. System knowledge of the lead truck enables predictions of the lead truck, since it is known how the truck will anticipate. So, in case the inputs to the lead truck are known, such as a braking action of a vehicle in front, the behaviour can be predicted based on the knowledge of a realistic dynamic system model when ACC and/or AEB are active.

Further, an unequipped vehicle could cut-in between the following and lead truck. So, cut-in prediction is needed to increase the time gap in time such that no collision occurs with the (unequipped) vehicle which cuts in and possibly brakes after a cut-in.

Summarized this leads to two use cases:

c. a vehicle brakes in front of the lead truck, which results in a braking response of the lead truck. Consequently, the following truck should respond adequately.

d. a vehicle cuts in between the lead and following truck. The following truck should make a gap (preferably comfortable) to ensure a safe following distance.

This paper will mainly focus on use case 2a. What can be seen an adequately response of the following truck is, is discussed below.

Let us consider two different situations in which a one-lane platoon is driving:

- In situation A, as presented in Figure 2, there's a vehicle at a large distance d_A from the lead vehicle, its relative velocity $\dot{d}_A$ is either small or positive. This situation is not hazardous, and the lead truck is not expected to brake.
- In situation B, as presented in Figure 3, a vehicle is at a close distance d_B to the lead truck, and approaching even closer. The lead truck is likely to perform a braking action in the nearby future.

Figure 2: Situation A

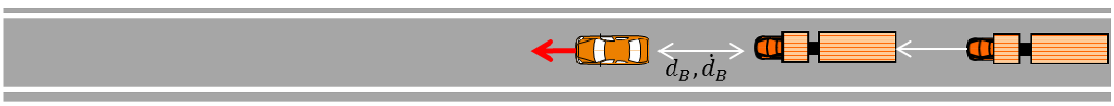

Figure 3: Situation B

If the system in the following truck is fully functional and there are no hardware problems, these situations will both be handled safely by the CACC system, since the intended acceleration of the lead truck is communicated to the following truck. In case of a hardware failure, such as a communication failure, an increase in time gap is required to obtain a safe state. How to reach this safe state is different for the two situations. In situation A the system can increase the time gap smoothly, thereby avoiding unintended braking which could lead to collisions with upcoming traffic and maintaining comfort. In situation B the following truck can better increase its time gap rapidly to avoid a collision with the lead truck. When the behaviour of the preceding car (in front of the lead truck) is known, an improved prediction of the lead truck may become possible. Then, in case of a communication failure, the communicated intended acceleration of the leading truck may be replaced by an estimated intended acceleration.

Let us detail the use case a bit further, using Figure 4. Suppose the lead truck has an ACC (Adaptive Cruise Control K_{ACC}) active and its controller settings and vehicle dynamics (G_1) are known. The lead truck aims to maintain a desired distance to its preceding vehicle (if any, otherwise it will try to realize its desired cruise speed). This desired distance will be controlled by the system, using as inputs the measured the distance d_1, range rate $\dot{d}_1$. Based on these measurements and the current acceleration of the lead, an estimation of the global acceleration of the preceding vehicle can be obtained, e.g. based on a Kalman filter as described in [6]. This global acceleration can serve as a feedforward for the ACC controller running at the lead truck, and the control error can be further regulated towards zero by the feedback part of the ACC controller. This ACC system is further described in [6]. In case the input of the controller is known (distance d_1 and range rate $\dot{d}_1$), the intended acceleration $a_{1,ref}$ of the lead truck can be numerically calculated.

In case of active V2V, the lead truck communicates: its intended acceleration ($a_{1,ref}$), its current measured acceleration, the measured inputs d_1 and $\dot{d}_1$. With these signals, the acceleration of the preceding vehicle, in front of the lead truck, can be estimated. So, it is assumed that an estimation of the acceleration of the preceding vehicle (in front of the lead truck) is available in the following truck when V2V is active. At the moment a communicated package is lost, the history of these acceleration estimations may be used to predict the future behaviour of the lead truck.

Then, the next step is to estimate the intended acceleration $a_{1,ref}$ based on the predicted a_0.

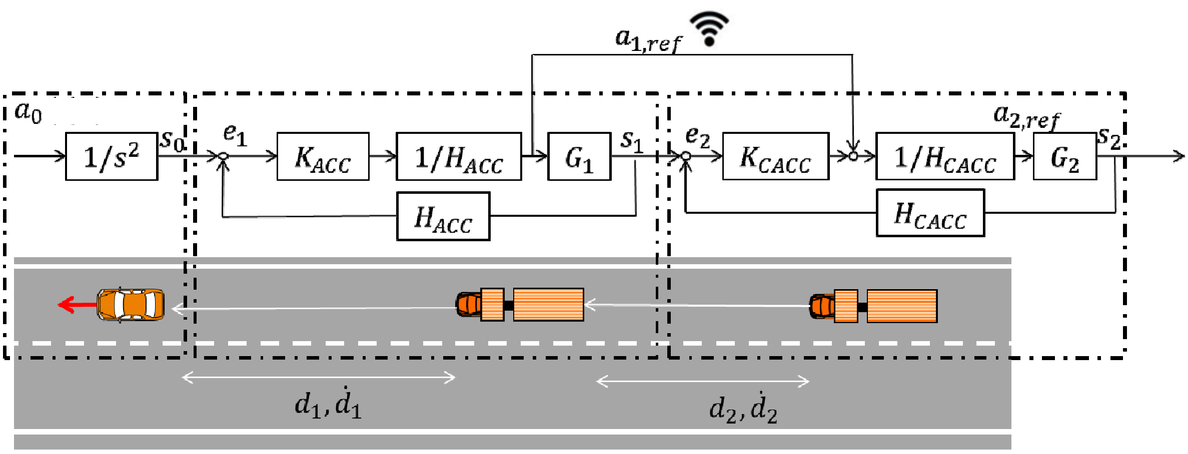

Figure 4: Detailed description of use case 2a. The goal is to estimate $a_{1,ref}$ such that in case the wireless link (temporarily or for a longer period) fails, the estimation can be used as a feedforward for the following truck. When a_0 can be predicted for time interval t, given its history T, $a_{1,ref}$ can be calculated.

III Problem statement

The research question can now be formulated as follows:

- Can we determine $a_0(t|T)$ with $t \in [0, x]$ and $T \in [-y, 0)$? Here x presents the prediction time (in the order of a few seconds) and y is the time in history which must be stored. Or in other words, can the acceleration of the preceding vehicle (in front of the lead truck) be predicted, given the estimated acceleration of a period in history?

The approach and outline of the paper is as follows:

1. The desired prediction horizon is determined in section V. Preferably, this prediction horizon is in the order of a few seconds, such that no aggressive intervention is needed, but a more comfortable action can be taken. However, the reliability of the prediction is likely to decrease by an increase of prediction time.
2. The input variables for the prediction will be presented in section VI.
3. Next, also in section VI, a model will be derived which gives the probability on a certain acceleration, given a set of input variables. This model is build up by using measurement data obtained by 20 volunteers, driving on both highways and rural roads. In total a database of 60 hours of driving is used.
4. The results of a few examples will be presented in section VII
5. Then, the validation of the prediction is also presented in section VII. This is based on the leave-one-out cross validation (LOOCV) method, where the machine learning algorithm creates its model based on all measurements except for one. The prediction of the measurements of one volunteer which is not used for the learning is used for validation. This validation method is applied in this paper for the prediction of the longitudinal acceleration. Furthermore a simple acceleration prediction model of extrapolating of the 2 last data points is used as a reference for the current method.
6. Finally, the conclusions and future work is presented in section VIII.

V Prediction horizon

To analyse the prediction horizon which is needed for comfort a few cases are simulated.
Suppose a lead and following vehicle drive with a velocity of 120 kph and an intervehicle distance of 10 m, and the lead vehicle would starts braking at t=0 s with an instant acceleration of -4 m/s^2. To avoid a collision in a comfortable manner, a jerk of -1 m/s^3 is chosen and it is assumed that a braking action up to -6 m/s^2 is possible for the following vehicle. Now, the required timing for the braking of the following vehicle can be analysed. In case the following vehicle would have started braking 1.3 s before the brake action of the lead vehicle (at t= -1.3 s), a comfortable braking action is possible (resulting in a distance of at least 1.5 m, as is shown in Figure 5 and Figure 6. It can thus be concluded that a prediction in the order of 1.3 s is desired to allow a comfort braking action in the situation described above.

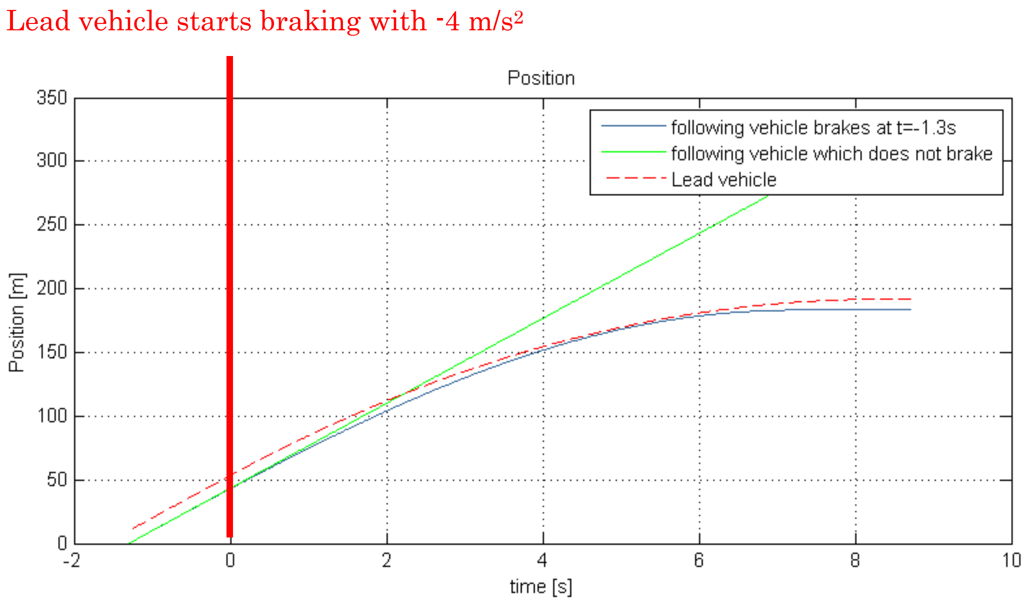

Figure 5: Position of lead and following vehicle for 2 situations: following vehicle does not brake and following vehicle brakes at 1.3s before the braking action of the lead vehicle.

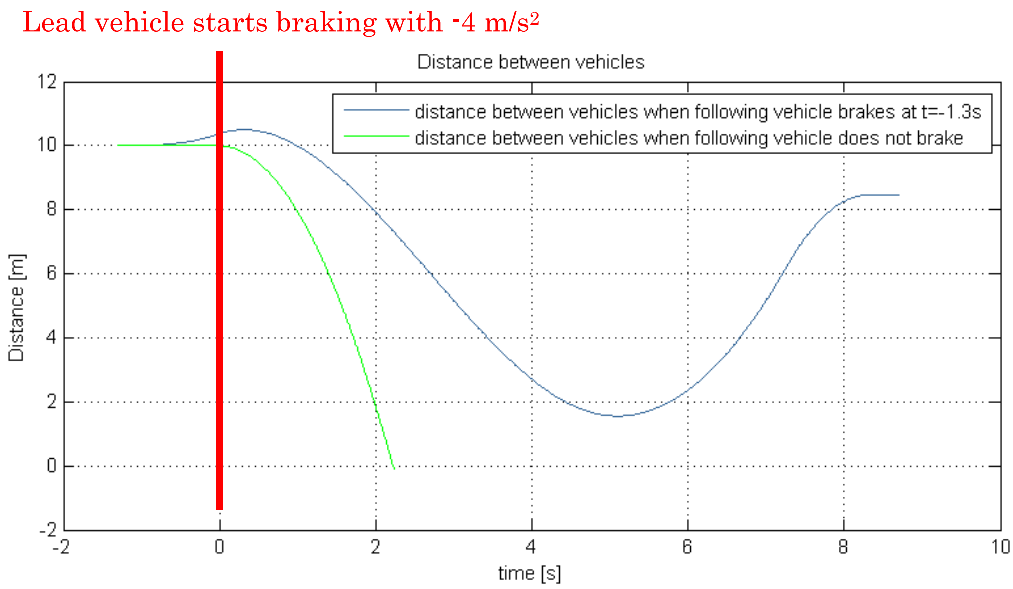

Figure 6: Distance between lead and following vehicle for 2 situations: following vehicle does not brake and following vehicle brakes at 1.3s before the braking action of the lead vehicle.

VI Input variables and prediction model

A prediction of a future time sequence can be based on the recursive prediction of next time steps, as is done when using a first order Markov model. The goal is to estimate the acceleration on a next time step *k+1*, given the current time step *k*. Variables which contribute to this prediction are:

- Current Acceleration (a_k): this variable is discretized with a bin width of 0.01 m/s^2. In total N_a bins are defined. The acceleration at time instant k is element of bin b_j^a will be notated as $a_k \in b_j^a$ with $j \in [1, N_a]$. Discrete probability distributions over the Na bins are used to represent the acceleration.
- Current Velocity (v_k): the velocity is discretized with a bin width of 5 km/h. In total N_v bins can be defined. The velocity at time instant k is element of bin b_{jj}^v will be notated as $v_k \in b_{jj}^v$ with $jj \in [1, N_v]$. Again, probability distributions will be used to represent the velocity.
- Current Acceleration direction (J_k) : this variable can be either negative (-1), close to zero (0), or positive (1). The bins will be notated as $J_k \in b_{jjj}^J$. The number of bins for the acceleration direction equals N_J = 3. The state transition matrix that expresses the expected acceleration direction at time k+1 given the current acceleration direction, velocity and acceleration is defined as follows:

$$P(J_{k+1} \in b_{iii}^J | J_k \in b_{jjj}^J, a_k \in b_j^a, v_k \in b_{jj}^v) =$$

$$\begin{bmatrix} P(J_{k+1} = 1|J_k = -1) & P(J_{k+1} = 0|J_k = -1) & P(J_{k+1} = -1|J_k = -1) \\ P(J_{k+1} = 1|J_k = 0) & P(J_{k+1} = 0|J_k = 0) & P(J_{k+1} = -1|J_k = 0) \\ P(J_{k+1} = 1|J_k = 1) & P(J_{k+1} = 0|J_k = 1) & P(J_{k+1} = -1|J_k = 1) \end{bmatrix} \text{ for } a_k \in b_j^a, v_k \in b_{jj}^v$$

  This matrix $P \in \mathbb{R}^{N_J \times N_J \times N_a \times N_v}$ is calculated based on measurement data.

Discretization of these variables reduces the influence of measurement noise on the transition matrices and also enables fast calculation times.

Assume the future state for the acceleration follows the Markovian property: the future state a_{k+1} depends only on the present state a_k. Let $P \in \mathbb{R}^{N_a \times N_a}$ denote the matrix of one-step transition probabilities P_{ij}, and define the probability of the acceleration at the next time step a_{k+1} to be in bin b_i^a, given the current acceleration a_k to be in bin b_j^a as:

$$P(a_{k+1} \in b_i^a \,|a_k \in b_j^a\,) = P_{ij}$$

The set of b_j^a is mutually exclusive and represents exhaustive events, so the total probability for any acceleration in b_i^a can be represented by:

$$P(a_{k+1} \in b_i^a) = \sum_{j=1}^{N_a} P(a_{k+1} \in b_i^a|a_k \in b_j^a\,)P\big(a_k \in b_j^a\big)$$

Further, a normal distribution is assumed for the (current) measured acceleration a_k: $a_k \sim N(a_k, \sigma_a)$ with a standard deviation equal to the standard deviation of the measurement noise σ_a. Here, σ_a is assumed to equal 0.05 m/s^2.

However, this probability function does not distinguish between the direction of the current acceleration (positive, constant or negative jerk), and neither does it include the velocity. Therefore an extension is proposed:

$$P(a_{k+1} \in b_i^a \left| a_k \in b_j^a, v_k \in b_{jj}^v, J_k \in b_{jjj}^J \right.) = P_{ij}(v_k, J_k)$$

Now, the transition matrix includes more dimensions: $P \in \mathbb{R}^{N_a \times N_a \times N_J \times N_v}$. This matrix is created using the measurement data. Now the total probability can be expanded with the direction of the acceleration (J):

$$P(a_{k+1} \in b_i^a, J_{k+1} \in b_{iii}^J) =$$

$$\sum_{j=1}^{N_a} \sum_{jjj=1}^{N_J} P(a_{k+1} \in b_i^a \left| a_k \in b_j^a, v_k \in b_{jj}^v, J_k \in b_{jjj}^J \right.) P(a_k \in b_j^a) P(J_{k+1} \in b_{iii}^J | J_k \in b_{jjj}^J, a_k \in b_{jj}^a, v_k \in b_{jj}^v)$$

Here, it is assumed that the probability $P(J_k \in b_{jjj}^J) = 1$.

Now that the model is given, the predictions at time $k+n$ can be made. The n-step predictions can be obtained by applying an iterative process. A few examples of the prediction and the validation are shown in the next section.

VII Results and validation

Assume an initial velocity of 80 kph, an initial negative jerk and an initial acceleration of 0 m/s^2. When we predict the acceleration behaviour for a time period of 3 seconds, based on the model described in the previous section, the acceleration is expected to behave as shown in Figure 7. The 2.5 percentile and 97.5 percentile boundaries are marked with the red dotted line. The boundaries are wider for predictions longer than 1.5s. So, a prediction of the acceleration at t = 1.3s is expected to be in the same order of magnitude as the initial acceleration.

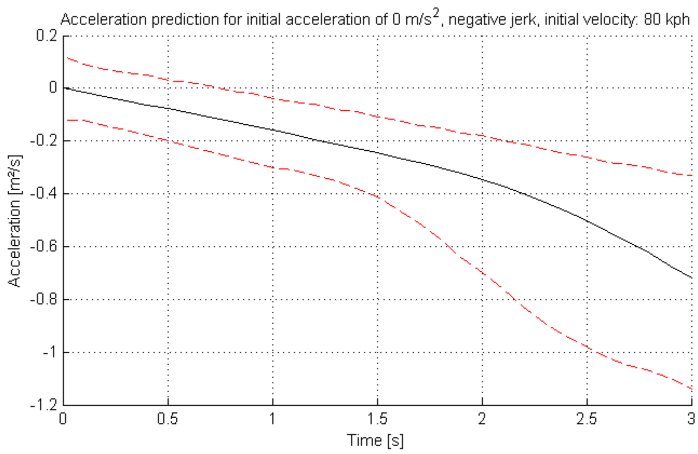

Figure 7: Acceleration prediction for an initial velocity of 80 kph, an initial negative jerk and an initial acceleration of 0 m/s². The 2.5 percentile and 97.5 percentile are marked with the red dotted lines.

Another prediction is shown for an initial acceleration of 1 m/s^2 in Figure 8. Here, the lower accuracy bound shows an increase to the expected value. To check the absolute error of the predictions, a validation is required.

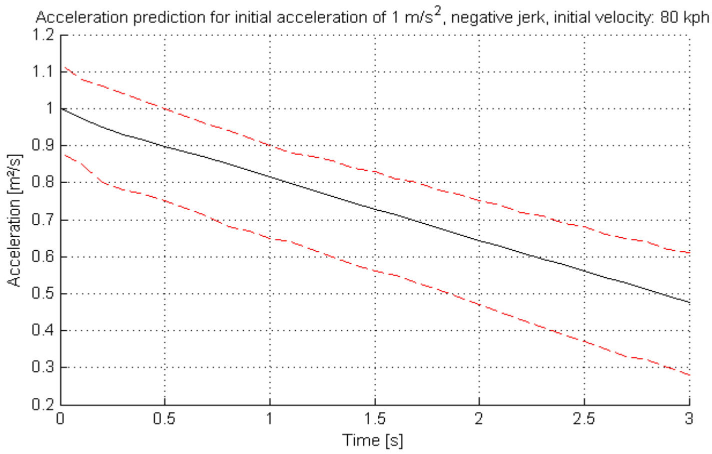

Figure 8: Prediction of acceleration, for an initial acceleration of 1 m/s².

The validation is based on the leave-one-out method where the transition matrix is build based upon 19 volunteers. One volunteer is left out and its data is used for validation. This procedure is done for all 20 volunteers.

Figure 9 to Figure 11 show the absolute error as a function of prediction horizon for constant driving, braking events and acceleration events. Furthermore it shows the simple linear extrapolation model as a reference.

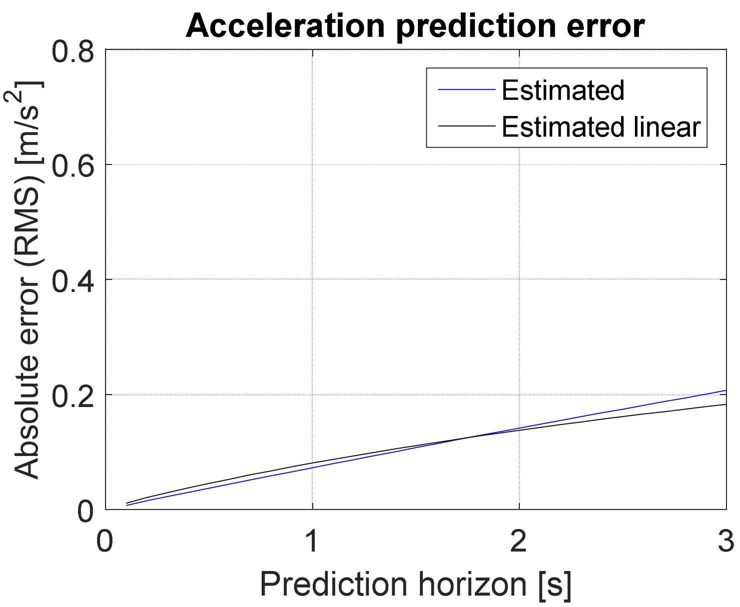

Figure 9: Absolute error as a function of prediction horizon for constant driving (-0.5 m/s² acceleration < 0.5m/s², n= 12301). Current model in blue and simple linear extrapolation model in black.

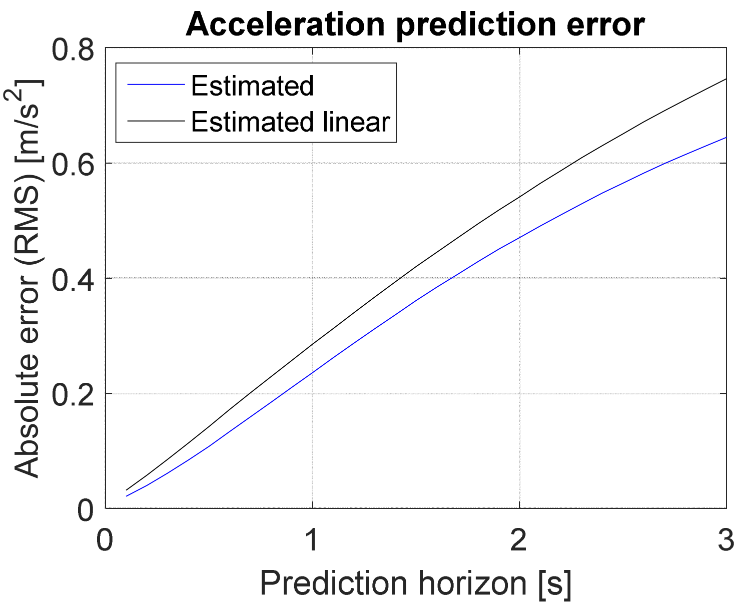

Figure 10: Absolute error as a function of prediction horizon for acceleration events (acceleration > 1.0m/s², n = 1315). Current model in blue and simple linear extrapolation model in black.

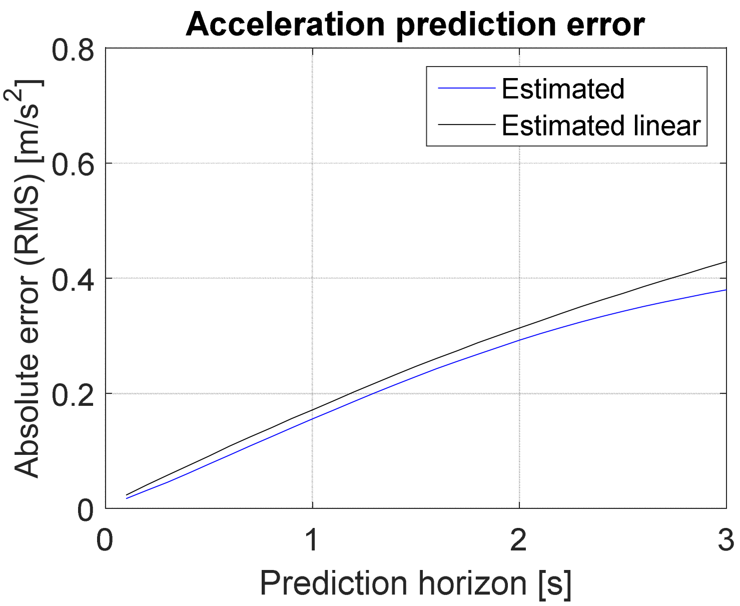

Figure 11: Absolute error as a function of prediction horizon for braking events (acceleration < -1.0m/s², n = 925). Current model in blue and simple linear extrapolation model in black.

As can be seen from Figure 9, the absolute error of the prediction model as presented in this paper is slightly less than the absolute error of the linear prediction model for a prediction horizon up to 1.5 s. When a distinction is made between only accelerating (acceleration > 1 m/s^2 or only braking (acceleration < -1 m/s^2) the prediction model presented in this paper shows lower absolute errors than the linear prediction model.

VIII Conclusions and discussion

CACC should be functional, safe, and comfortable. One of the safety aspects (a use case for operational safety) is discussed in this paper. V2V communication and knowledge on the active systems of the lead truck can help in prediction of individual traffic participants behaviour. An early prediction can help in increasing comfort and safety in case V2V communication fails and an estimated intended acceleration is needed. For comfort a time prediction of the order of 1.3 seconds is needed.

The measurement data of 20 volunteers is used to derive a prediction model, based on a Markov chain. Also, a simple linear prediction (based on extrapolation of 2 datapoints) is used as a reference prediction, to enable a comparison for the absolute errors in acceleration. Applying the leave-one-out method for validation shows that braking actions with an acceleration < -1 m/s^2 and accelerations > 1 m/s^2 can be predicted much more accurate with the model proposed in this paper when compared to the reference prediction. The total error in the prediction of the total data set, which contains many datapoints of constant driving is slightly better than the reference prediction for a prediction horizon up to 1.5 s. The method shows potential, but future work is needed to improve the accuracies of the predictions further. The prediction model is currently based on the input variables jerk, acceleration and velocity. Probably more variables can be added in future, such as traffic density or traffic light information. Also more data may improve the accuracy of the predictions.

The next step is to use these predictions in the controller of the following truck, aiming for comfort and avoiding hazardous situations, caused by other traffic participants (and possibly in combination with a V2V failure).

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