VEHICLE ACCELERATION PREDICTION USING SPECIFIC ROAD CURVATURE POINTS

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Abstract: In the work vehicle acceleration prediction issue is discussed. Three types of parameters are used for prediction system input: CAN-bus parameters – speed and curvature, derived speed parameters and newly offered specific curve point parameters, denoting changes in a curve. The real road data was used for predictions. Road curvature segments were divided into single and S-type curves. Acceleration was predicted using artificial neural networks and look-up table. The look-up table method showed the best results with newly offered specific curve parameters.

1 INTRODUCTION

Driving assistance systems are becoming a usual component of modern cars. Here we are developing an algorithm that could aid to driver's assistance on a curved country road. One way to develop such algorithms is through modelling driver's behaviour. Once we have a model that predicts driver's behaviour, we can compare actual behaviour with the prediction, and warn the driver if there is inconsistency.

In the field of driving action description several clear-cut situations have been studied exhaustively: lane following (Fenton, 1988; Mammar et al., 2006), car following at a safe distance (Gipps, 1981; Olstam et al., 2004), lane change (Gipps, 1986; Salvucci et al., 2007). For lane following on a curved road an extensive theory has been developed, mainly based on control engineering approaches (Hsu et al., 1998; Yuhara et al., 2001; Chen et al., 2006; Mammar et al, 2006). Yet speed control (so called longitudinal control), including speed on curves, has only been studied extensively from a car stability perspective (Jin et al., 2007; Hel et al., 2007; Song, 2008). Alternatively, we focus on predicting speed (or acceleration) profiles of individual drivers, where they are performing not at the limits of car possibilities, but rather in their comfort-driving modes. Speed prediction of an individual driver is a much more complicated problem as compared to steering prediction, because of much stronger influence of contextual information, and less constraint for a driver in choosing the actual speed profile. There are only singular investigations concerning speed prediction based on speed profiles of individual driver, e.g. (Partouche et al., 2007), and success of such work until now is quite limited.

In this study we apply learning techniques to predict individual driver's acceleration on a curve. Neural networks and look-up tables are employed for prediction. Real road driving data is used, and input parameters for driver's action prediction are analyzed.

Relatively long real road data sequences are required for predicting acceleration on a curve. This is because speed control process has a wider time scale than steering, i.e. for generating velocity control the driver reacts rather to future events, like upcoming curves, than immediate situations. E.g. it was observed in this study that deceleration in front of a curve starts 3-6 s or on some occasions even up to 10 s in advance. Consequently, multiple curve taking situations in the recordings are required to derive the algorithm that predicts an expected acceleration profile for a particular driver on a particular curve. This makes the problem of speed (or acceleration) prediction on a curve difficult to address, especially when using real-road data.

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2 DATA FOR ACCELERATION PREDICTION

Two data sets were used for the study. The first data set was collected during November-December, 2006. The second data set was collected in December, 2007. Both data sets were obtained on country roads nearby Lippstadt, Germany; at day light, on a test car (Volkswagen Passat). In the data set from 2006, ten recordings, approximately six minutes length each were provided. Five of those recordings were obtained on the same road, using forward direction, and the other five were obtained using backward direction. The recordings were coming from two drivers: eight recordings of the first driver, and two recordings of the second driver. The second set of data (year 2007) consisted of six recordings. Those recordings were obtained on a different road as compared to the recordings from the year 2006. The recordings were again obtained in forward and backward directions, duration of ten minutes each. This set of recordings was repeated three times for three different drivers.

The test car control data were recorded using CAN-bus with a sampling interval of 0.06 s. The following signals were extracted from the CAN-bus and used in the study:

- velocity $v(t)$,
- acceleration $a(t)$,
- curvature of the road $c(t)$; curvature was measured using a gyroscope installed in the car.

3 METHODS

Curvature-based parameters combined with car velocity were employed to predict driver's acceleration. In this work gyroscopically measured curvature was used, as a shortcut proceeding towards further systems, where image processing or digital map information will be used to obtain the curvature in front of a car.

Neural networks and look-up tables were used as function approximation means for prediction. For neural network analysis a simple neural network with one hidden layer was used. There were from two to four neurons in the hidden layer, according to the number of input parameters. Separate learning data sets and test sets were employed. The average of prediction error from ten initializations was calculated to make results more reliable.

In the look-up table approach input parameter values obtained at discrete time moments were stored together with corresponding acceleration signal value. The predictions were made as follows: for the input parameter vector obtained at a specific time moment mean squared error (MSE) was calculated between that vector and every instance of the look-up table. The predicted acceleration was calculated as the mean of ten acceleration values, with the smallest MSE to input parameters. In addition, the acceleration signal was smoothed using 20 point moving average filter (corresponds to 1.2 s) from the previous predictions.

As part of the input vector raw CAN-bus signals: curvature and speed were used, but also a large set of derived parameters was introduced.

Among the derived parameters we used centrifugal acceleration (Hong et al, 2006):

$$a_c = \frac{v^2}{R} \tag{1}$$

where R denotes the curve radius, and v is the speed. The centrifugal acceleration is considered to be a parameter influencing driving comfort and possibly driver’s actions (Hong et al, 2006).

We used speed differences $S_d=v(t)-v(t-\Delta t)$ over several second intervals (Δt=0.5, 1.0, 1.5, 2.0, 2.5, 3.0 s) to account for previous acceleration or deceleration actions. If a car decelerated, the speed difference was negative, and if the car was accelerating, the speed difference was positive.

For acceleration on a curve, features like the distance to a start of a curve or the distance to the end of a curve are important. We introduced a set of curve shape based points (see Fig. 1), that later were employed to derive features for acceleration analysis. All the parameters’ notations are listed in Table 1.

Table 1: Curve- and speed-derived parameters.

Parameter class	Parameter	Notation
CAN-bus derived parameters	Centrifugal acceleration	CA
	Speed difference (now-Xs back)	SD-X
Single curve parameters	Start	S
	Start peak	SP
	End peak	EP
	End	E
S-curve parameters	S-curve start peak	SSP
	S-curve zero crossing	S0
	S-curve end peak	SEP

Two different curve shapes were analyzed in this work:

- Single curve that has 4 specific points (start, start peak, end peak and end; see Fig. 1a),
- S-shaped curve that has 7 specific points (start, start peak, S start peak, S zero crossing, S end peak, end peak and end; see Fig. 1b).

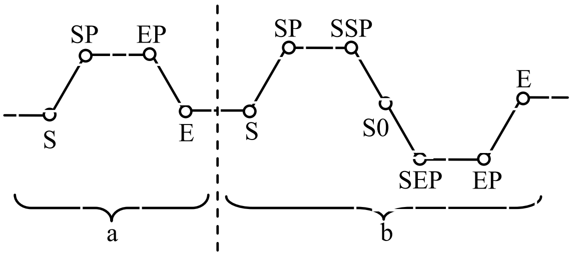

Figure 1: Specific curve-based points' scheme: a) single curve with 4 specific points: start (S), start peak (SP), end peak (EP) and end (E); b) S-shaped curve with 7 specific points: start (S), start peak (SP), S start peak (SSP), S zero crossing (S0), S end peak (SEP), end peak (EP) and end (E).

The features were described as distances from specific points. Examples of feature time series are provided in Fig. 2.

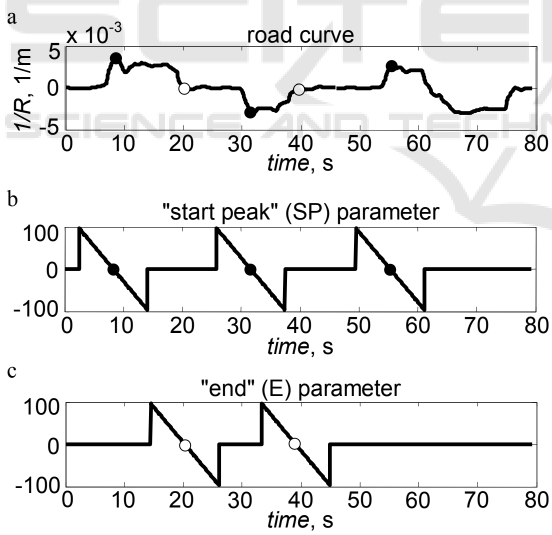

Figure 2: Curvature (a) and features describing distances to specific points on a curve (b and c). Features for the points 'Start peak' and 'End' are shown. The points 'Start peak' are marked by black points and the points 'End' in circles.

Before a specific point it is considered how much time is left to that point, and after the point it is pointed out how much time has passed since the specific point had been passed. A feature is started to be considered six seconds in advance before a specific point is reached and the point is "forgotten" six seconds after it has been passed. Before the point a feature is positive, at the point it is zero, and after the point it is negative.

An algorithm to derive feature values is as follows: first, the specific curve point t_p is determined and the feature value for that discrete time moment is set to zero. The feature values are calculated by adding 1 or -1 to the previous value when going through every discrete time step back and forward respectively. The calculations end when $t_{back}=t_p-100$ and $t_{forward}=t_p+100$ (100 discrete points corresponds to 6 s according to the signal discretization).

4 ACCELERATION PREDICTION RESULTS

4.1 Acceleration Predictions using Raw CAN-bus Signals

We used curvature $c(t+\Delta)$ where Δ = 4s (that is, four seconds ahead), and speed $v(t)$ to predict acceleration one step forward. The training set was composed of seven curve segments containing clear acceleration-deceleration patterns, and we predicted the segment that was not included into the learning data set. Examples of predicted signals are presented in Fig. 3.

As can be seen in the Fig. 3a, some acceleration events in the learning set are predicted accurately, but there are some other segments in the acceleration profile that the neural network fails to predict.

In the test sets (Fig. 3 b,c), if measured formally, the error between real and predicted signals would be high. Yet one can observe qualitative correspondence between real and predicted signals, and the presence of acceleration/deceleration events is predicted correctly with 1-2s precision. With slower acceleration dynamics it is a reasonable result. This could be enough for approximate detection of the moments when deceleration is required. Specifically, prediction of deceleration moment is important for driver assistance on a curved country road. However, we have observed that the results were varying a lot with different initializations of the artificial neural network. Consequently, we were looking for a method that could allow more stable acceleration predictions.

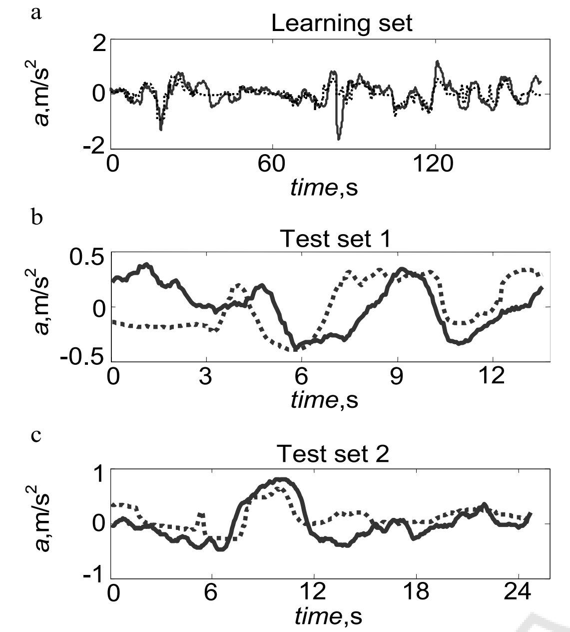

Figure 3: Two examples of acceleration prediction by ANN on a training set (a), and the test set (b and c). Input parameters: curvature $c(t+\Delta)$, where Δ=4s, and speed $v(t)$. Original signal is marked as solid curve; predicted signal is marked as dotted curve.

4.2 Acceleration Predictions using Specific Curve Features

We used specific curve point-based features to improve on acceleration prediction. A look-up table was used to map between features and actions.

For the current experiment for the learning set six minutes of driving of the same driver were used (recording from year 2007), and approximately 1.5 minute for each driver were used for testing. Data for testing were not included into the learning data set.

The resulting predictions (test sets) for two drivers are provided in Fig. 4 and 5.

In the top panel (Fig. 4 and 5) gyroscopically measured curvature is presented. Bigger details correspond to real road curvature, while smaller details at the top of the curve may be attributed to over-steering events. Acceleration (lower panel) shows much more details, as compared to curvature, but one can observe episodes of deceleration, performed as a sequence of several (usually 2-3) deceleration events in front of a curve. Speed usually starts increasing at the second half of the curve. Those rules can be derived for single curves (seconds approx. 50 to 90 in both plots), but for more complex curves the situation is difficult to specify.

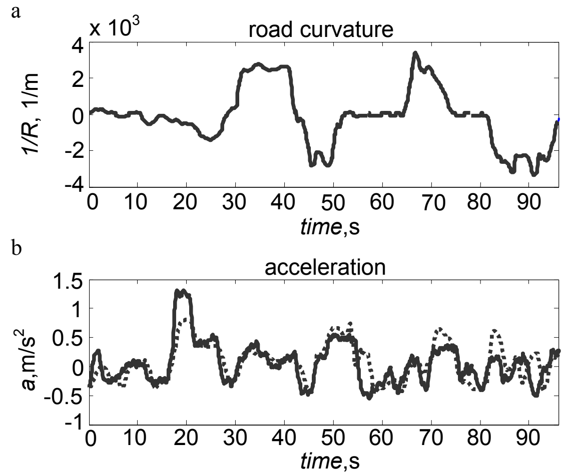

Figure 4: Gyroscopically measured curvature of the drive (a); original (solid curve) and predicted (dotted curve) acceleration signal (b); first driver. Input parameters: SP, E, CA, SD-2s.

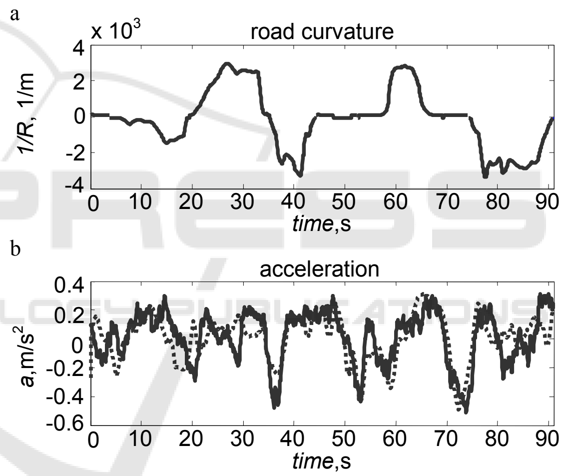

Figure 5: Gyroscopically measured curvature of the drive (a); original (solid curve) and predicted (dotted curve) acceleration signal (b); second driver. Input parameters: SP, E, CA, SD-2s.

In the first driver case (see Fig. 4b) the predicted signal corresponds to the original acceleration signal quite well. At the second 20 the predicted signal does not reach the real acceleration amplitude, but it starts to increase at the same moment as the true signal. At the intervals from 70 to 75 s and from 82 to 85 s the prediction gives bigger acceleration and decreases to the same level as original signal. The interval from 85 s to the end of test signal does not correspond to the real acceleration signal. That could be associated with over-steering that can be observed in Fig. 4a, (85 to 90 s).

With the second driver (Fig. 5) one can observe that the acceleration profile is reproduced less well between seconds 10 and 30, where there is a complex curve, but the profile is reproduced much better for single curves.

The interval from 77 s to the end of test signal does not correspond to the real acceleration signal as well. That could be also attributed to over-steering that is seen from Fig. 5a.

Summarizing the results it can be concluded that the algorithm grasps the moments of acceleration and deceleration on the curve well.

Selected parameter subsets have been analyzed to find out which parameter subset could serve best for acceleration prediction. Prediction error numerical values for various parameter combinations are listed in Tables 2 – 4.

Parameter combinations were investigated in the case when all curves were considered as single first. E.g. an S-shape curve was considered as a sequence of two single curves with appropriate single curve points. It was found that two points are most important for acceleration prediction: SP and E. When complementing curve shape features with centrifugal acceleration, and speed change from 1.5-2 seconds ago to a current moment, prediction improved for both drivers, but for driver B the result was still a small fraction better when adding point S (see Table 2).

Table 2: Prediction with look-up table considering complex curves as composed of single curves: mean squared error for various parameter combinations.

Parameter sets	Driver A	Driver B
SP, E	0.27	0.21
SP, E, CA	0.26	0.21
SP, E, CA, S, SD-2s	0.26	0.16
SP, E, CA, EP	0.29	0.20
SP, E, CA, SD-2s	0.20	0.17

The situation was improved by separately analyzing S-type curves (see Table 3). The best result for the data set was obtained when specific S curve parameters SSP, S0, SEP were not included into the input parameter vector (that is, even from S-type curves we were analyzing only the points SP and E, that are present both on a single and an S-type curve). This could possibly change when larger data sets are analyzed.

When analyzing which time window would tell the history of driver’s acceleration best (Table 4), and consequently allow to predict drivers next action with the smallest error, it was found that time windows of 1 s, 1.5 s and 2 s performed almost equally well, and longer as well as shorter time intervals performed worse for both drivers.

Table 3: Prediction with look-up table including S-curve parameters: mean squared errors for various parameter combinations.

Parameter sets	Driver A	Driver B
SP, E, CA, SD-2s	0.16	0.13
SP, E, CA, SD-2s, SEP	0.18	0.14
SP, E, CA, SD-2s, SEP, SSP	0.18	0.15
SP, E, CA, SD-2s, SSP	0.20	0.15
SP, E, CA, SD-2s, SEP, S0, SSP	0.22	0.16
SP, E, CA, SD-2s, S0, SSP	0.23	0.15

Table 4: Prediction with look-up table: mean squared error for various speed difference parameters.

Parameter sets	Driver A	Driver B
SP, E, CA, SD-3s	0.19	0.14
SP, E, CA, SD-2.5s	0.17	0.14
SP, E, CA, SD-2s	0.16	0.13
SP, E, CA, SD-1.5s	0.16	0.13
SP, E, CA, SD-1s	0.16	0.13
SP, E, CA, SD-0.5s	0.17	0.15

5 DISCUSSION

Two methods were introduced to predict individual driver's acceleration on a curve. The method employing only simple parameters: speed of the car and curvature at a single point in front of a car, failed to stably predict driver's acceleration. The other method introducing more complicated analysis of a curve shape, supplemented by centrifugal acceleration and history of driver's actions, provided promising results.

Driver's acceleration prediction on a curve is an important task on the way towards intelligent driver's assistance systems, as a big proportion of serious traffic accidents happen due to failure to properly reduce speed on curves (Comte et al, 2000). After developing adequate prediction methods one will have to define thresholds when acceleration profile is to be considered 'unusual' for a driver. However, examples of 'dangerous' speed profiles are difficult to obtain, especially in real road driving situations. Alternatively, one can perform experiments in driving simulators. Here one necessarily needs simulators imitating forces arising while driving a car, because with real road driving we observe much different speed (and acceleration) profiles on curves as compared to those obtained on a simulator with only visual feedback (Partouche et al, 2007) .

On the other hand, some practical tasks can be solved without analysing dangerous acceleration profiles. If one manages to predict with reasonable precision the moment of deceleration in front of a curve, then one can warn on the events where a driver failed to observed the curve, e.g. due to reduced visibility (warning in this case would be based on absence of deceleration event where it should appear).

One could argue that the curve shape features we are introducing are not practical, as stable visual analysis of a scene 6s in front of a car driving at motorway speeds (100 km/h or more) is not realistic to achieve. Our experience with visual analysis prompts the same. Yet with new developments, where interactive roads are foreseen (Jakubiak et al, 2008), or systems where map integrated into the car provides upcoming curvatures (Mammar et al, 2006) would solve the problem.

Turning to details of this study, good acceleration prediction results were obtained when curve shape parameters SP, E, CA, SD-1.5 or SD-2 were provided as input parameters and S-shape curve was analyzed separately. For the first driver the mean squared error of acceleration prediction was 16% and for the second driver the mean squared error was 13%. For the second driver adding parameter S allowed to reduce the error further. Although, those conclusions should only be taken as preliminary, and experiments with more data are required to refine parameter choice.

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