

Wheel-Individual Estimation of the Friction Potential for Split Friction and Changing Friction Conditions for the Application in an Automated Emergency Braking System

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Abstract: Including information of the current road surface conditions can significantly improve the effectiveness of an AEB (automated emergency braking) system to avoid accidents or reduce the injury severity in rear-end crashes. A method to estimate the friction potential based on on-board sensor information is shown in this work. This work expands the scope of existing investigations on whether the accuracy needed for the warning and intervention strategies of AEB can be reached with the proposed method. First, the bandwidth of surface conditions investigated is extended by including low friction surfaces comparable to ice. Second, situations of changing surface conditions and wheel-individual surface conditions were evaluated. Finally, estimation based on different sensor sets was conducted with regard to series application. The investigations are based on measurements performed on a proving ground. The main emphasis was placed on estimation during longitudinal driving conditions. The used sensors include advanced vehicle dynamics measurement equipment as well as standard on-board sensors of the vehicle.

Key words: Tire road friction estimation, automated emergency braking system, recurrent neural networks, echo state networks

1. Introduction

AEB (automated emergency braking) systems will soon be required for all new type approvals of vehicles according to EU directive 347/2012, starting with commercial vehicles above 3.5 tons in November 2013 and applying for all new vehicles beginning in November 2015. The effectiveness of AEB to avoid collisions or reduce the injury severity in rear-end crashes has been proven in several studies [1, 2]. The standardization of testing procedures for AEB is currently in progress, but testing will have to be conducted only on dry roads. Also, AEB already introduced are developed to meet the requirements of

collision avoidance and mitigation on dry road conditions. But in contrast, collision avoidance systems are supposed to show more benefit on low friction surfaces [3].

AEB brake a vehicle autonomously in order to avoid or mitigate rear-end collisions. In case the system has detected a collision in the near future and the driver fails to react, the driver is warned about 1.5 seconds to 2.5 seconds before the predicted collision and has the possibility to set an intervention. In case of no driver reaction, a partial braking manoeuvre is initiated that still allows an alternative intervention of the driver, e.g., a steering input for an evasive movement, while already decreasing potential impact energy. If the driver still fails to react, a full braking manoeuvre is initiated at about 0.6 seconds to 1.0 seconds before the

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predicted collision until the vehicle stands still.

The rate of missed interventions of the system has to be kept low in order to maintain a high level of driver's trust. False interventions have to be omitted in any case as they can result in severe accidents. The before mentioned activation times for warning and braking apply for dry roads. On low friction surfaces, these activation times have to be adjusted in order to take advantage of the full potential of the AEB. As a measure for the road condition, the maximum coefficient of friction between tire and road is used. It is further on referred to as the friction potential μ .

If an estimate of the friction potential is about to be used to adapt the activation times, a high accuracy of the estimate is necessary in order to achieve the high requirements to avoid missed and false interventions. In a previous investigation [4], an acceptable accuracy for an estimate of the friction potential for the application in an AEB was given. Fig. 1 shows this necessary accuracy in dependence of the real value of the friction potential and the longitudinal velocity when overestimating the friction potential.

The aim of the presented research is to extend previous investigations of the feasibility to estimate the friction potential with the method proposed in Section 2 in order to fulfil the requirements on the accuracy of an AEB. Therefore, measurements have been conducted on a proving ground with high and low friction surfaces. Thus, the bandwidth of tested friction potentials was increased compared to Ref. [4].

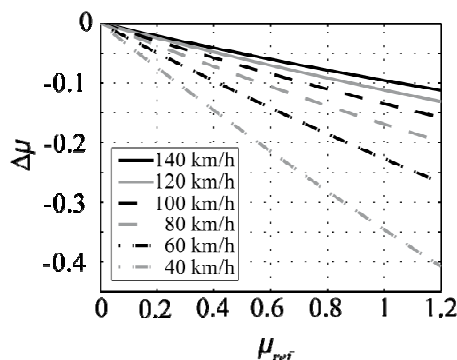


Fig. 1 Relation between acceptable accuracy $\Delta\mu$ and the real friction potential μ_{ref} for different initial longitudinal speeds [4].

Mu jump manoeuvres were performed to evaluate the detection of a change in the friction potential. In these manoeuvres, the road conditions changes suddenly, i.e., the front axle enters the new surface earlier than the rear axle. Unequal distribution of friction potentials on the four wheels also accounts for the investigated mu split manoeuvres, where the left side of the vehicle passes over another surface type then the right side.

Longitudinal manoeuvres were the main emphasis of this investigation. It is assumed that it is more difficult to detect the friction potential in longitudinal driving conditions due to the slower vehicle reaction compared to lateral excitation.

Additionally, the estimation of the friction potential using different sensor sets was investigated. First, all available sensors including advanced vehicle dynamics measurement equipment were used to train the Echo State Networks. In a second step, only the information of standard on-board sensors was used.

2. Estimation of the Friction Potential Using Echo State Networks

The aim of this investigation is to prove the feasibility of the estimation of the wheel-individual friction potential during driving based on measurement data from a given set of sensors using ESNs (echo state networks) [5]. ESNs are a new approach to train RNN (recurrent neural networks) which are artificial neural networks inspired by biological neural networks like in the brain. Other than widely used FFNNs (feed forward neural networks) that rather behave like implemented mathematical functions, RNNs are dynamical systems [6]. This dynamical behaviour originates from feedback loops within the network (Fig. 2). At each time step, the previously received inputs are still present in the network. This enables RNNs to detect high-dimensional temporal patterns. Thus, models of highly non-linear systems can be learned. RNNs can be used for simulation, pattern matching, classification, and prediction of time series.

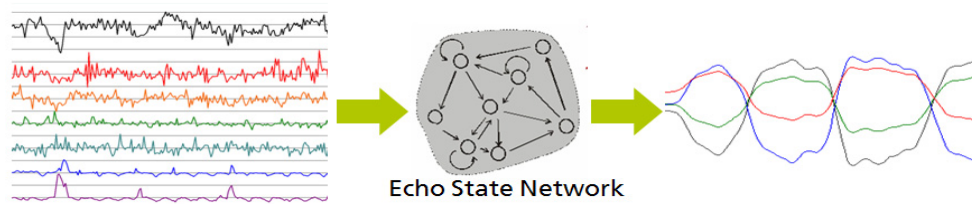


Fig. 2 An echo state network can learn the input output behaviour of a dynamical system.

The potential of RNN depends on a stable and efficient method to train the RNN. So far, the size of used nets was limited by usage of gradient-based methods like BPTT (back-propagation through time) [6].

With ESN, only the connections to the output nodes are computed during training using linear regression [7, 8]. This enables a faster and more stable training and the use of large nets with several thousand internal nodes.

2.1 Data Acquisition

Altogether, 193 measurements were evaluated that resulted from driving manoeuvres that were conducted on the proving ground Wachauring in Melk (Austria) with an Audi A4 Avant 1.8 TFSI.

Two different tires were evaluated on both dry asphalt and a watered low friction surface with a friction potential similar to that of ice, see Tables 1 and 2. In addition to pure dry and low friction conditions, changing road conditions (mu jump), e.g., the front axle enters the low friction surface before the rear axle, and different surface conditions on the right and left side of the vehicle (mu split) have been considered. Also, double lane change manoeuvres were conducted with mu split condition. The vehicle changed from a lane having dry asphalt to a lane having low friction surface

Table 1 Performed driving manoeuvres and road surface condition.

Driving manoeuvre	Road surface condition	Number of manoeuvres
	Dry asphalt (d)	20
Full and partial braking and acceleration tests, free rolling	Low friction (l)	20
	mu jump (mj)	53
	mu split (ms)	60
Steady-state circle based on Ref. [9]	d	2
	l	3
	ms	2
Double lane change based on VDA lane change ([10])	d-l-d	12
	l-d-l	15
Handling course	d	2
Sinus tests based on Ref. [11]	d	2
	l	2

Table 2 Tire types.

	Number of manoeuvres
Summer tire, Dimension 245/40 R18	116
Winter tire, Dimension 205/55 R16	77

and then again back to the dry lane. This manoeuvre was also done starting on a low friction lane, changing to a dry lane, and back again.

Advanced measurement equipment for vehicle dynamics evaluation has been used as well as standard on-board sensors. For further information on the advanced measurement equipment, see Table 3. The

Table 3 Advanced vehicle dynamics measurement equipment.

Signal	Sensor	Unit	Accuracy
Spring deflections	-	mm	$< \pm 0.5\%$ FSO ¹ (625 mm)
Braking pressure for 2 brake circuits	-	bar	$< \pm 0.5\%$ FSO (350 bar)
Chassis velocities	SHR	m/s	$< \pm 0.2\%$ FSO (250 km/h)
Chassis side-slip angle	SHR	°	$< \pm 0.1^\circ$
Chassis Accelerations ² in COG	ADMA	mG	< 1 mG
Chassis Rotational Velocities 2	ADMA	°/s	< 0.00004 °/s

¹Full Scale Output

²Longitudinal, lateral and vertical according to Ref. [12]

sample frequency for all signals was 200 Hz. Other than in previous investigations, no dynamic wheel camber angle and no wheel velocities were measured, compare to Ref. [4].

Concerning the standard on-board sensors, the following signals have been recorded: wheel speeds of all four wheels, steering wheel angle, vehicle's longitudinal velocity at the COG (centre of gravity), engine's rotational speed, engine torque, accelerator pedal position, vehicle's yaw rate and the environment temperature.

2.2 Determination of Reference Value

For all combinations of mounted tires and road surfaces, a reference value of the friction potentials $\mu_{R,i}$ was determined using measurements at the maximum achievable accelerations and tire characteristics measured on a tire test bench. In different measurements, no strong variation of the reference value was observed. However, during hard braking manoeuvres on the low friction surface, for a short time higher friction values were achieved than expected. This can be explained by dispersion of the thin water layer between the surface and the tire in this driving condition.

With a validated two-track vehicle model, the dynamical vertical force $F_{z,i}$ acting on each tire was calculated. The wheel-individual friction potentials $\mu_{R,i}$ for each tire i were then calculated as a function of the reference value μ_{ref} , $F_{z,i}$ and the tire characteristics. In our previous investigation, the combination of tires and road condition did not change during one measurement; see Ref. [4]. In this investigation, the reference value μ_{ref} is not always equal to the global friction potential μ_G as road conditions were object to variation during measurements. To consider these mu jump and mu split conditions, the relation in Eq. (1) was used to calculate the global friction potential μ_G , compare to Ref. [13].

$$\mu_G = \frac{1}{F_{z,ges}} \cdot \sum_{i=1}^4 \mu_{R,i} \cdot F_{z,i} \quad (1)$$

3. Data Analysis and Results

In a first step, only measurements with summer tires were evaluated using LOOCV (leave-one-out-cross-validation). The mean absolute errors for estimating the global and the wheel-individual friction potentials with the trained ESNs can be seen in Table 4.

Figs. 3 and 4 show examples for good and bad performance during a mu jump manoeuvre with hard braking. Even in the bad example, the trend is correctly predicted and the jump is detected, but the absolute values differ. Fig. 3 also shows an effect that cannot be fully explained yet. Predicting a future state with ESNs

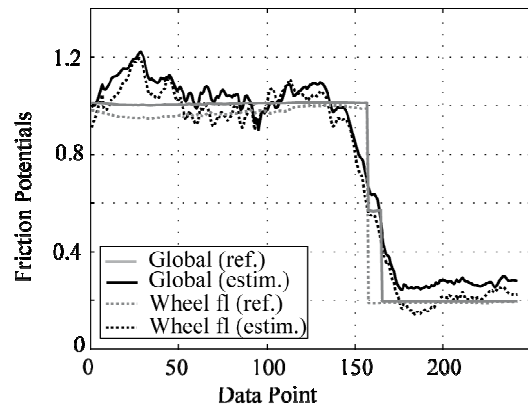


Fig. 3 Example of good estimation of μ_G (black line, above) that also leads to good estimation of the friction potential $\mu_{R,i}$ (black dotted line) of the front left wheel (wheel fl). The true values for μ_G and $\mu_{R,i}$ are plotted grey lines, respectively.

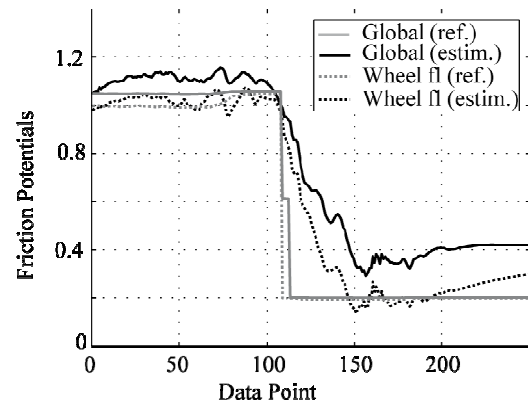


Fig. 4 Example of bad estimation of μ_G (black line, above). Accordingly, the estimation of $\mu_{R,1}$ (black dotted line) worsens. The true values for μ_G and $\mu_{R,1}$ are plotted grey lines, respectively.

is not possible, but for some measurements the jump of the friction potentials is estimated earlier than it occurred. A malfunction of the trigger to detect the jumps during the measurements cannot be completely ruled out, but is rather unlikely.

The level of dynamical excitation seems to have an impact on the accuracy. As expected, hard braking manoeuvres usually deliver better estimates than moderate braking manoeuvres. The data also suggests that better estimates can be achieved during braking than during acceleration manoeuvres. In Figs. 5 and 6, a moderate braking manoeuvre on mu split surfaces is compared to a moderate acceleration manoeuvre on mu split. It can be seen that while estimation is rather good during moderate braking, it completely fails at data point 90 at the acceleration manoeuvre.

Nevertheless, it is difficult to make general statements because the data sets always showed exceptions at similar driving manoeuvres. Until now, it is not finally understood where these discrepancies come from. As in previous measurements, the signals of the optical speed sensor partially failed on wet surfaces. However, this can only partly explain some poor performance.

In a second step, all measurement data obtained with winter tires was investigated and finally the ESNs were trained using all measurement data, see Table 4.

In comparison to previous work by Ref. [4], the achieved accuracy within the different data sets for summer tire, winter tire and all tires is lower. Partially, this can be explained by the slow response of vehicles to inputs in longitudinal direction. The main focus of this investigation was put on longitudinal manoeuvres, whereas previous analysis included more lateral manoeuvres. Also, the difficulty of the road conditions to be learned was greater here.

However, the tolerable accuracy (Fig. 1) has not been reached for surface conditions of $\mu_{ref} < 0.5$, even for low velocities. When only considering braking manoeuvres, the achieved mean absolute error is lower and fulfils the requirements. Since the proposed AEB

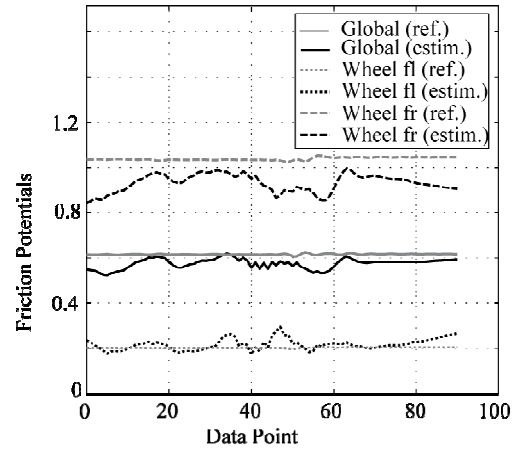


Fig. 5 Example of estimation of μ_G (black line, above) and $\mu_{R, i}$ of the front wheels (left: dotted black line, right: dashed black line) during a moderate braking maneuver on musplit. The true values for μ_G and $\mu_{R, i}$ are plotted grey lines, respectively.

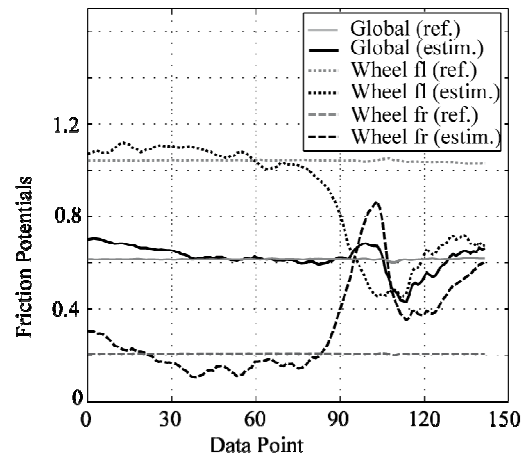


Fig. 6 Example of estimation of μ_G (black line, above) and $\mu_{R, i}$ of the front wheels (left: dotted black line, right: dashed black line) during a moderate accelerating maneuver on musplit. The true values for μ_G and $\mu_{R, i}$ are plotted grey lines, respectively. At data point 90, the estimates get worse.

Table 4 The mean absolute error for ESNs trained on different data sets.

	LOOCV on summer tires	LOOCV on winter tires	LOOCV on all tires
$\Delta\mu_{R, 1}$	0.1692	0.1109	0.1540
$\Delta\mu_{R, 2}$	0.2199	0.1456	0.2030
$\Delta\mu_{R, 3}$	0.1706	0.1137	0.1559
$\Delta\mu_{R, 4}$	0.2233	0.1492	0.2078
$\Delta\mu_G$	0.1343	0.1084	0.1342

also includes a partial braking manoeuvre before full braking, this partial braking phase may be used to achieve a higher accuracy on the estimate.

In an additional analysis, the estimation of the friction potentials based on a reduced set of sensor information was evaluated. First results using only the standard on-board sensors showed a very high mean absolute error compared to the full sensor set. This is a first indication that standard on-board sensors may not be sufficient for the proposed application.

Nevertheless, for a statistically tough statement with regard to series application, more data and data covering all driving states will be needed.

4. Conclusions

The effectiveness of current available AEB systems can be improved by adapting the activation and warning times to the current road conditions.

In this work, it has been investigated whether the estimation of the global friction potential μ_G and the wheel-individual friction potentials $\mu_{R,i}$ is possible so that the accuracy necessary for an AEB can be reached. In addition to existing work, low friction conditions comparable to icy roads as well as mu jump and mu change manoeuvres were investigated.

There are promising results, especially during braking manoeuvres. The accuracy of the estimates increases with higher dynamical excitation. However, there were many outliers in the data sets which cannot be explained yet and require further analysis.

However, it has to be mentioned that further investigations are necessary before the proposed estimation methodology is qualified to be applied in a safety-critical system like an AEB.

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