ROAD CONDITION ESTIMATION FOR AUTOMATED DRIVING CONSIDERING DRIVERS' ACCEPTANCE

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ABSTRACT

To improve road safety, the implementation of automated driving functions is considered a crucial factor. Conventional systems with an automation level below SAE 3, as they are already available in production vehicles, are designed to meet the requirements for collision avoidance and mitigation on dry roads. In contrast to that, investigations show that collision avoidance systems have the highest benefit on low friction surfaces when the activation times (time-to-collision) can be adapted to the road condition.

Up to now, there is no method on the market to estimate or detect the road condition with an accuracy required to adapt safety-critical driving functions. However, research activities in this field are numerous and conducted for many years. In the development of future automated functions, it is often assumed that the road condition is known with high accuracy and reproducibility, without discussing how it is measured. Implications on the activation strategy by imperfect values of the road condition are seldom discussed. On the other side, developers of friction estimation techniques need requirements on accuracy and robustness for their methods. Since these values change with the application case (e.g. steering or braking, etc.), requirements cannot be defined in general.

In the present article, different considerations are presented when designing an automated driving function that adapts to the road condition. Both physical effects and human factors have to be considered. Using an Autonomous Emergency Braking System as application case, the influence of imperfect road condition estimation on the activation strategy is discussed. The effect of the road condition on the time-to-collision is shown, and how over- or underestimation of the road condition may affect the time-to-collision. In a second step, a survey among drivers was conducted to better understand the driver's perception of the road conditions. Activation times do not only depend on physical considerations, but have to be designed so that occupants have a high level of trust and acceptance in these systems. Finally, a method to estimate the road condition based on the vehicle's dynamic response is presented, and strengths and weaknesses of this approach is discussed.It is shown that different considerations including different physical effects and human factors have to be taken into account when designing an automated driving function that adapt to the road condition.

1 INTRODUCTION

The implementation of automated driving functions is considered a crucial factor to improve road safety and reduce the numbers of fatalities and injuries in traffic, [1,2]. In conventional vehicles with automated driving functions below SAE level 3, [3], the driver is legally liable to adapt the driving style to the road conditions. The driver has to choose a suitable distance to other vehicles, e.g. in the case of Adaptive Cruise Control (ACC), or to set interventions in time and with respect to the road condition. Systems like the Autonomous Emergency Braking Systems (AEB) are developed to fulfil requirements of accident prevention on dry roads. These systems are able to reduce the impact speed and thus the injury risk on low friction surfaces, but cannot always avoid accidents under these conditions.

For SAE Level 3+, when the driver is allowed to not monitor the driving environment continuously, the adaption of the vehicle control to the road condition has to be done by the automated driving controller for course planning and stabilization interventions like steering or braking. When e.g. planning braking interventions on low friction surfaces in winter periods, collisions will have to be avoided in order to keep a high occupant's acceptance and trust in these autonomous functions. It is expected that automated driving functions will have to lead to less traffic accidents than human drivers in order to be accepted by society, [4].

1.1 Aspects in the design of automated functions

In order to avoid a collision, interventions of both human drivers and automated systems have to be engaged at a certain time ahead which is described by the time-to-collision

$$TTC = \frac{\Delta s}{\Delta v}. \qquad \textbf{(Equation 1)}$$

Therein, Δs is the relative distance between the ego and the target vehicle and Δv is the relative velocity, [5]. Both variables have to be measured by environmental sensors in the case of automated driving functions and are subject to measurement uncertainties. To keep the number of false interventions due to imperfect sensor signals as low as possible, interventions are set at the latest possible time, [5]. TTC of automated functions in production vehicles are designed for dry roads, leading to small values of TTC and thus late interventions. An investigation showed that if the road condition was known during an evasion maneuver, TTC could be significantly decreased on low friction surfaces [Referenz bereits hier]. [6]. In this investigation, different system configurations were considered with and without active front steering, active rear steering, individual four wheel drive and brake system. A reduction of TTC depended more on the actual coefficient of friction than on the vehicle configuration, One conclusion was that with automated driving functions, the potential to prevent accidents on low friction surfaces with a TTC reduction of up to 1 s is higher than that on dry roads with a maximum TTC reduction of 0.2 s.

The design of automated systems often aims to compensate for human limitations in driving. Only at the highest level of automation, no driver will be required at any driving situation. Until then, drivers' behavior also has to be taken into account. Studies showed that women have significantly lower driving comfort than men on days with adverse weather conditions, and are less likely to drive on these days, [7]. Other investigations showed that accident rates increase on road conditions with reduced grip. However, different tendencies for the injury severity in dependence on the road conditions were investigated, especially when the factors age and gender were considered. Men under 45 years showed a higher risk for severe injuries on dry road, whereas women in general and men older than 45 years show a higher risk on wet, snowy and icy road, [8]. In another study it was shown that the probability of injury was lower for both male and female drivers on wet, snowy or icy roads, [9].

Another aspect in the design of automated driving is the occupant's trust and acceptance in automated driving functions. High values of trust and acceptance are a prerequisite for the use of automated driving functions or driverless vehicles. Acceptance depends on one hand on the noticeable benefits for the user like comfort, and on the other hand on the fail-safe characteristics of automated systems, [10]. Exemplarily, the acceptance of a congestion assistant was proven to better when the system mimicked human driving behavior, [11]. It is assumed that the intervention strategy of automated driving functions and driverless vehicles will also have to consider the road condition similar to human drivers in order to be accepted.

1.2 Scope of the article

The following article addresses the design of automated driving functions that adapt to the current road conditions. An Autonomous Emergency Braking System is used as an application case to discuss the influence of imperfect road condition estimation on the activation strategy in Section 2. The influence of the road condition on TTC for both braking and steering maneuvers is shown in Section 2.1. Effects of uncertainties in road condition estimates are discussed in Section 2.2 and the application of discrete categories of the road condition is shown in Section 2.3.

The design of intervention strategy of an automated system does not only depend on physical considerations. To keep trust and acceptance of the occupants high, human perception of the current road and traffic situation needs to be considered. To better understand driver's perception of the road conditions, a survey was conducted which is presented in Section 3.

In Section 4, the strengths and limitations of a vehicle-dynamics based method to estimate the road friction is discussed, considering the findings in the previous sections.

2. IMPLICATIONS ON AUTONOMOUS EMERGENCY BRAKING SYSTEMS

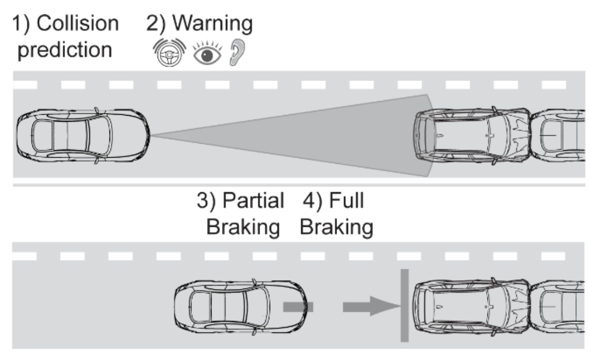
Accidents in longitudinal traffic are the largest group of types of accidents, and the second largest group within severe injuries and fatalities, [12]. Benefits of systems like the Frontal Collision Warning Functions (FCW) and Autonomous Emergency Braking functions (AEB) were investigated in several investigations, e.g. [5], and are already available in different production vehicles.

Autonomous Braking Systems are classified in three different categories according to the car safety performance assessment program Euro NCAP:

1) AEB city:
   function for typical urban speeds between 10 and 50 km/h, [13]. Often, warning and braking intervention are engaged at the same TTC
2) AEB inter-urban:
   function for driving speeds outside a city environment like urban roads or highways, and are tested by Euro NCAP between 30 and 80 km/h, [14]. Often, these functions include the four phases shown in Figure 1 including wrnings to the driver.
3) AEB Vulnerable Road User (VRU):
   systems including the detection of vulnerable road users like pedestrians or cyclists, and specifically adapting the intervention strategy to these road users, [15].

Figure 1 shows the typical phases of an AEB for inter-urban applications.

Figure 1. AEB inter-urban with four phases, based on [16]



In the first phase, a conflict situation is detected that, without any intervention, would lead to a collision. This situation detection is based on environmental sensors like radar or camera. A warning is addressed to the driver in the second phase. The aim is to alarm the driver to set an intervention to avoid a collision. If the driver fails to react, a partial braking phase (third phase) is autonomously engaged. This leads again to alarming the driver by the sudden deceleration, and also reduces the impact velocity in case of a collision. Only in the fourth phase, if the driver still fails to react, full braking is autonomously engaged. The warnings and interventions are initiated at certain TTC that are pre-defined by the system manufacturer. These activation times thus depend on Δs and Δv according to Equation 1.

If an intervention will be set by the system also depends on the expected accuracy of the collision prediction, [5]. If the algorithm identifies a situation as critical, an intervention is initiated. This intervention is correct, when the driving situation really is critical (true positive). If the situation is safe and prediction also identifies it that way, no intervention is engaged which is also correct (true negative). These two cases are expected by a human driver when interacting with these systems. Due to uncertainties and limitations of the system's situation detection, two other cases are possible:

1) Missed intervention (false negative):
   The driving situation is critical, but the prediction rates it as *safe*. In this case there is no interventions and a collision is not avoided by the system. The legal responsibility still remains with the driver.
2) False intervention (false positive):
   The driving situation is safe, but the prediction rates it as *critical*, leading to an intervention without an apparent cause for the driver or occupants.

These two cases of incorrect interventions also occur in intervention strategies. An investigation of FCW and AEB showed that in general, these systems have a higher rate of detecting safe situations than critical ones, [17]. This implies that algorithms are calibrated in a way that false alarms are reduced, leading to a higher rate of missed interventions.

2.1 Adaptation of TTC to the road condition

Current values of TTC are chosen to avoid accidents on dry roads. For slippery roads, TTC values for warning and intervention activation have to be higher for the same values of Δs and Δv to avoid an accident or accomplish the same injury probability compared to dry roads.

To consider the road condition, the activation times $TTC_b(\mu)$ for braking can be described as a function of the maximum coefficient of friction μ between tire and road. Based on physical considerations, the required activation times for a certain μ are given by

$$TTC_b(\mu) = \frac{TTC_d}{\mu}, \qquad \textbf{(Equation 2)}$$

with TTC_d being the activation value for dry roads, compare [12].

At large relative velocities Δv, evasive maneuvers are more effective than braking maneuvers, as long as this intervention does not lead to another accident, [12]. Future collision avoidance systems will be able to choose the most suitable intervention strategy. In this decision, the road condition also has to be considered since the activation times $TTC_S(\mu)$ for a steering maneuver are given by

$$TTC_S(\mu) = \frac{TTC_d}{\sqrt{\mu}}, \qquad \textbf{(Equation 3)}$$

according to [12], adding further complexity to the intervention decision.

2.2 Effects of uncertainties in road condition estimation or detection

Similar to the prediction of the driving situation, the detection or estimation of the current road condition is subject to uncertainties.

It is further assumed that μ_t describes the true value of the current road condition. An autonomous system adapts the activation times to an imperfect estimate $\hat{\mu}$. The following two cases can occur:

1) $\hat{\mu} > \mu_t$ (over-estimation):
   The true value is smaller than the estimate, leading to smaller activation times than required to avoid a collision.
2) $\hat{\mu} < \mu_t$ (under-estimation):
   The true value is larger than the estimate, leading to earlier activation times then required to avoid an accident.

Current AEB as available in production vehicles (SAE level 1) assume dry road. This automatically leads to overestimation on surfaces with lower friction. It can be assumed that an activation strategy would be calibrated to over-estimate the road condition in order to minimize false interventions. A collision will not be avoided on surfaces with lower friction, but false interventions are minimized. This is suitable since the AEB is supposed to react at the latest possible time if the driver fails to react. Legally, the driver is still responsible to adapt to the road condition and false interventions can be minimized.

For braking interventions at SAE level of 3 and higher, this strategy is not suitable, since every emergency braking intervention on lower friction surface would lead to a collision. If a strategy is chosen where the road condition is in general under-estimated, a collision is avoided at all times. However, valuable time is lost to improve the prediction accuracy of the driving situation to avoid false interventions. Another aspect is that if these interventions are too early, drivers and occupants may also perceive them as inappropriate, leading to lower trust and acceptance. In addition, following traffic may be forced into an emergency situation.

The requirements on accuracy of a road condition estimation depend on physical considerations and on occupant's perception of the road and traffic conditions. Summarizing, the following considerations apply for automated functions that adapt to the road condition:

- The accuracy demands due to physical considerations depend on the planned maneuver (e.g. braking, steering or decision between the both), the current road condition itself, and the relative velocity and distance to an obstacle or target.
- An intervention that is *too late* (as in the case of over-estimation of μ_t) always leads to a collision.
- An intervention that is *too early* (underestimation) avoids an imminent collision, but leads to an inacceptable number of false interventions and thus in a decrease of occupant's acceptance and trust
- driver's acceptance and trust in general increases with systems mimicking human behaviour (see Introduction section)

The latest possible TTC only depends on physical considerations, enabling a mathematical description for an accuracy demand for a road condition estimate, e.g. see [16] or [18]. A TTC for early interventions depend on the accuracy of the collision prediction (compare Section 2) and human factors like trust and acceptance of the system.

2.3 Considering discrete road condition categories

In combination with the required accuracy of an estimation method, the question arises whether pre-defined categories might be sufficient. On asphalt, concrete or cobblestone, μ_t typically varies between $\pm$ 0.1 for dry road conditions, see e.g. [19], [20], [21] and [22]. For both snowy and icy conditions, the situation is comparable, see e.g. [19], [20] and [22]. In contrast to that, the variation on dry roads can be very high. In both [21] and [22], a variation for wet roads between about 0.3 and 0.9 is given depending on the type of road surface (asphalt, concrete or cobblestone), the micro texture of the road and the depth of the water film. The micro texture influences the drainage capability of water. The condition of the micro texture cannot be seen from the driver's seat and not directly be estimated by drivers only using visual cues. Therefore, two categories for wet road condition are chosen due to the high range of possible μ_t at wet conditions.

The following five discrete categories are considered:

- Category 1 (dry) $0.8 \leq \hat{\mu} \leq 1.0$
- Cat. 2 (moderately wet) $0.6 \leq \hat{\mu} < 0.8$
- Cat. 3 (very wet) $0.4 \leq \hat{\mu} < 0.6$
- Cat. 4 (snowy) $0.2 \leq \hat{\mu} < 0.4$
- Cat. 5 (icy) $0.05 \leq \hat{\mu} < 0.2$

The names of these five categories do not include all possible road conditions, e.g. leaves on the road influence the road condition. Dry leaves result in $\mu_t \geq 0.6$, whereas wet leaves are about 0.3, [21]. An automated system would have to assume Cat. 2 for dry leaves and Cat. 3 for wet leaves. Conditions like gravel are more tricky since μ_t may vary rapidly and in a high range on unpaved roads, [23].

Assuming that a detected or estimated value $\hat{\mu}$ is accurate enough to be within the correct category of μ_t, the influence of under- or over-estimation can be quantified using the influence on the braking distance. An emergency braking is assumed, where the maximum coefficient of friction μ_t is used.

The brake distance is given by

$$s = \frac{v_0}{2 * g * \mu}, \qquad \textbf{(Equation 4)}$$

with v_0 being the initial speed and g the gravitational acceleration, [12]. It is assumed that the brake is conditioned (no brake pressure build-up time) and that there is no reaction time of the driver. The expected value for the brake distance $\hat{s}$ when over-estimating the road condition is lower than the actual brake distance s_t, thus the difference

$$\Delta s = s_t - \hat{s} \qquad \textbf{(Equation 5)}$$

is positive. In the case of under-estimation, the values in Table 1 of μ_t and $\hat{\mu}$ are switched, leading to negative values of Δs. The worst case for the values of μ_t and $\hat{\mu}$ when over-estimating the road condition is shown in Table 1.

Table 1.

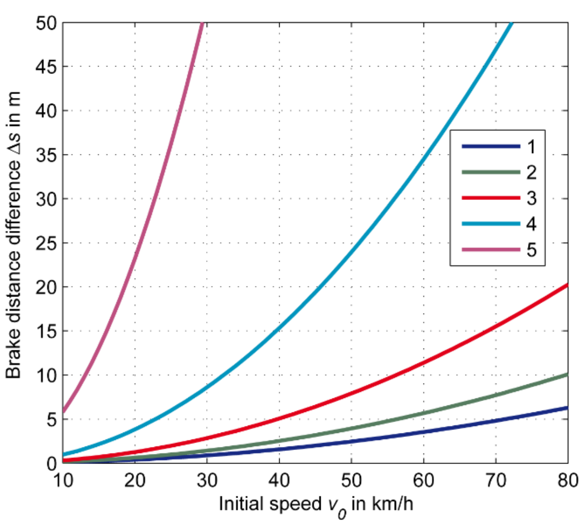
Worst case values for μ_t and $\hat{\mu}$ when using five categories of the road condition in the case of over-estimation

	Cat. 1	Cat. 2	Cat. 3	Cat. 4	Cat. 5
μ_t	0.8	0.6	0.4	0.2	0.05
$\hat{\mu}$	1	0.79	0.59	0.39	0.29

Figure 2 shows the braking distance difference when over-estimating μ_t using five categories. It is assumed that using discrete categories is possible when the value of the brake distance difference Δs is acceptable. With higher Δs, the accuracy of $\hat{\mu}$ also increases and a smaller category has to be chosen.

It can be seen that the influence of the accuracy is low on dry roads (category 1), and increases with increasing initial speed. With decreasing μ_t, the distance difference increases, being at already 50 m at 30 km/h in category 5.

Figure 2. Initial speed v_0 vs. brake distance difference Δs for the five categories of the road condition



In contrast to that, the distance at which a steering intervention has to be initiated is

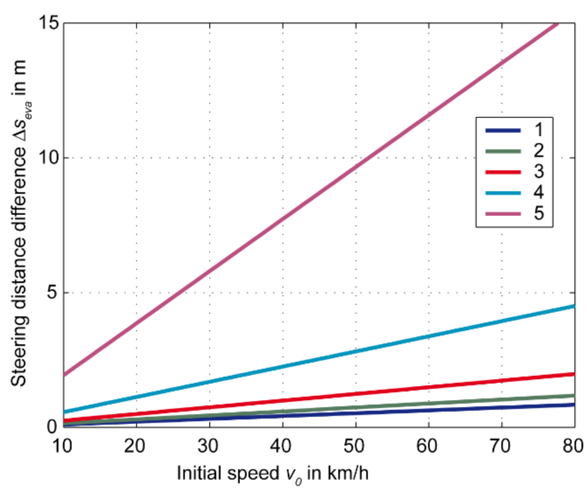
$$s_{eva} = v_0 * \sqrt{\frac{2 * y_e}{g * \mu}}, \qquad \textbf{(Equation 6)}$$

with y_e being the lateral displacement in meters during the evasion maneuver, [12]. Similar to Equation 5, the difference Δs_{eva} for μ_t and $\hat{\mu}$ in the case of steering can be calculated.

Figure 3 shows the distance in which a steering maneuver has to be initiated in order to avoid a collision. A lateral displacement y_e of 0.5 m was assumed. In the case of steering, the distance is linearly dependent on the initial speed. Similar to braking, the distance difference is increasing with decreasing μ_t.

On dry roads, both the brake distance difference and the steering distance difference are not very sensitive to the road category. With decreasing μ_t, this sensitivity increases. The results indicate that for both braking and steering, the categories for surfaces with a low μ_t need to be smaller. This implies a higher required accuracy for estimation values of low friction surfaces than for dry roads.

Figure 3. Initial speed v_0 vs. steering distance difference Δs_{eva} for the five categories of the road condition



3. DRIVERS' PERCEPTION OF ROAD CONDITIONS

For identifying the categories of tire-road grip distinguished by the drivers and the criteria they use for estimating the road condition a survey with a representative sample of 96 drivers (48 women) from five age groups was conducted. There were 10 female and 10 male drivers in each of the age groups 20-29, 30-39, 40-49, 50-59 years and 8 female and 8 male drivers in the age group 60 plus. An equal distribution of the driving activity in driven kilometers per year for the age groups was targeted.

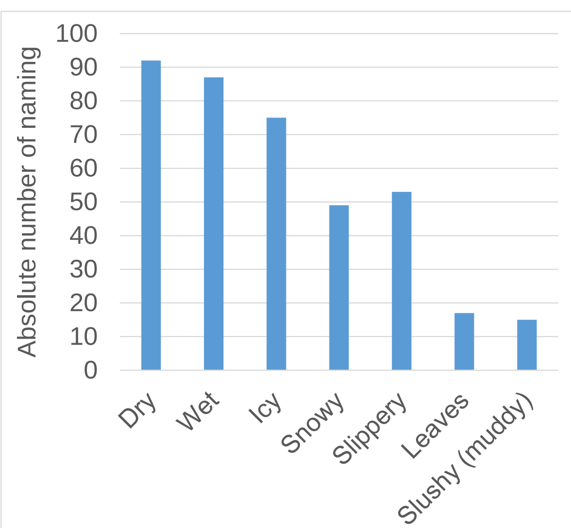
The following two questions were asked:

1) Which categories of road condition or friction coefficient do you differentiate?
2) Which criteria/cues do you use to estimate the road condition / friction coefficient?

3.1 Categories of road conditions named by drivers

The answers of the participants were analyzed qualitatively. Figure 4 shows the top seven categories named by drivers, and the absolute number of drivers naming the particular category. The categories of the road condition/ friction coefficient distinguished by the drivers were: *dry*, *wet*, *icy*, *snowy*, *slippery*, *leaves*, *slushy* (*muddy*).

Figure 4. Top seven categories of road condition/friction coefficient identified by the drivers, and the absolute number of naming by the drivers



The difference in responses for age groups and gender is clearer when comparing relative distributions of the answers. Thus in a first step, Figure 5 shows the same results as in Figure 4 as the relative distribution of all responses for the categories. It can be seen that 24% of all driver naming were *dry*, and 22% were *wet*, being followed by 19% for *icy* and 13% for *snowy*. As Figure 6 shows, there was a similar distribution of these categories in different age and gender groups.

Figure 5. Distribution of the categories of road condition/friction coefficient identified by the drivers

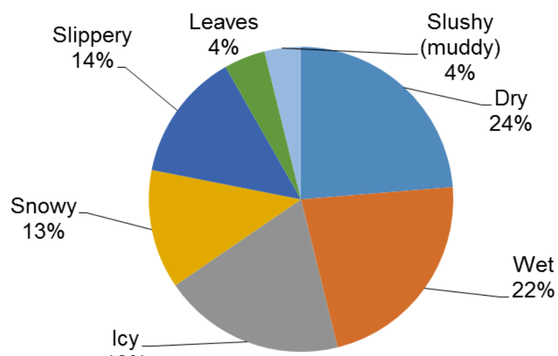
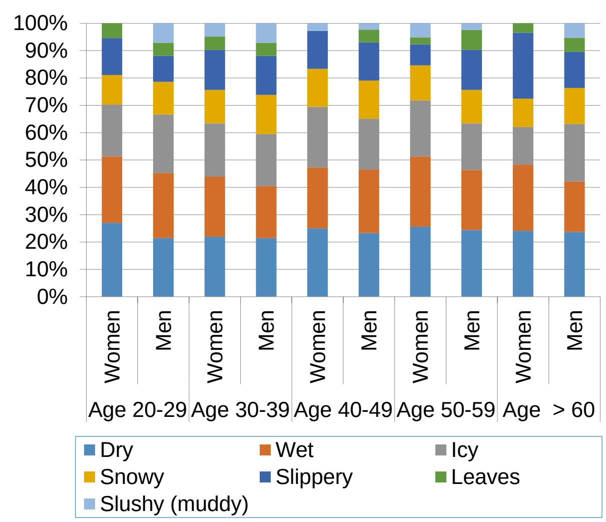


Figure 6. Age and gender distribution of the categories of road condition/friction coefficient identified by drivers



The category *slippery* is not useful, because it includes a wide range of μ_t values and overlaps with other categories. A subdivision of the category *slippery* would be more appropriate. The categories *dry*, *wet*, *icy* and *snowy* can be better attributed to specific ranges of μ_t. However, snow and ice may not be encountered in all geographical regions. The categories *leaves* and *slushy (muddy)* may not be encountered often enough to justify the use of a particular mode of operation for driver assistance systems. The results indicate that subjective categories named by the drivers can be transferred to objective categories as shown in Section 2.3. However, more detailed investigation is required to prove this.

3.2 Cues used by drivers to estimate the road condition

The answers of the participants were analyzed qualitatively. The cues used by drivers for estimating the tire-road grip have been classified in six categories: *visual cues*, *sound*, *vehicle response*, *weather*, *temperature* and *season of the year,* as shown in Figure 7. *Vehicle response* is the largest category, including responses in both longitudinal (e.g. during braking) and lateral direction (e.g. steering). The results of the chi-square test shows that the distribution of the cue categories varies significantly from one another (χ^2 =225.55, df=5, p <.0001).

As illustrated in Figure 8, the distribution of the cue categories does not vary significantly with the age and gender of the driver. Female drivers reported 139 cues and male drivers named 141 cues. Within different age groups, the number of reported cues was also comparable: Age group 20-29 named 53 cues, age group 30-39 named 56, age group 40-49 named 59, age group 50-59 named 66 and age group 60 plus named 46.

Visual cues, weather and *temperature* can be used to anticipate or predict a reduced value of μ_t and use an adequate driving mode (manual or automated). *Sound* and the *vehicle response* are feedback-cues which can be noticed in response to a control action. The latter may be less useful, if an inappropriate braking or steering intervention can already cause an incident or accident. However, previous interventions can be used to estimate the tire's condition and for validation within sensor fusion approaches. The *season of the year* is a category with different meanings in different geographic regions.

Figure 7. Cues used by the drivers for estimating the road condition

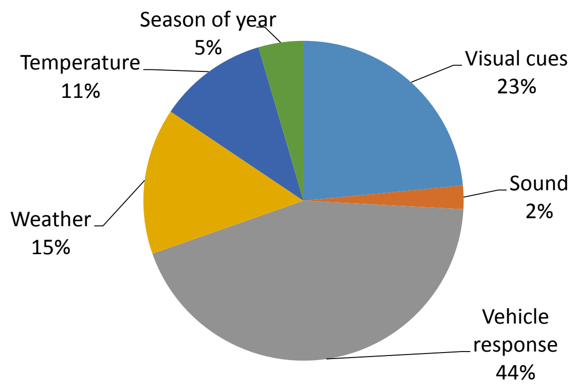
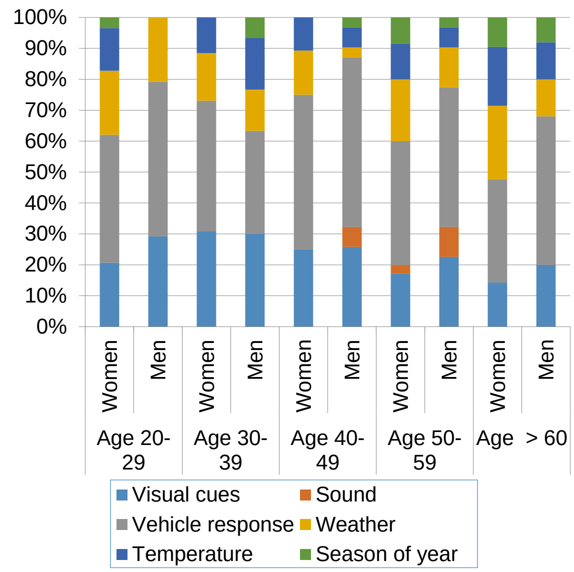


Figure 8. Distribution of cues used by the drivers for estimating the road condition



4. VEHICLE DYNAMICS-BASED FRICTION ESTIMATION

Vehicle dynamics-based estimation methods try to estimate the current tire and road condition by evaluating the vehicle's response. For example, the expected vehicle behavior for the driver's inputs are compared to the measured vehicle's response to determine the most likely value of the maximum coefficient of friction that describes this behavior. Driver's input and important measures to describe the vehicle behavior are already measured in production vehicles equipped with electronic stability control. In this case, no additional sensors are required.

A model based approach to determine the maximum coefficient of friction between tire and road especially during longitudinal driving is presented in [16]. Therein, a particle filter was used which is an extension of a recursive Bayesian state estimator, like the Kalman filter. This type of state estimator enables to consider inevitable model and measurement uncertainties, as long as statistical properties are known.

These estimators require a model of in the form of

$$\begin{aligned} \mathbf{x}_k &= \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{w}_k) \\ \mathbf{z}_k &= \mathbf{h}(\mathbf{x}_k, \mathbf{v}_k), \end{aligned} \qquad \textbf{(Equation 7)}$$

with internal state $\mathbf{x}_k$ to be estimated and $\mathbf{z}_k$ being the measurement vector. The functions can both be non-linear. The variables $\mathbf{w}_k$ and $\mathbf{v}_k$ describe the probability density functions of model and measurement noise.

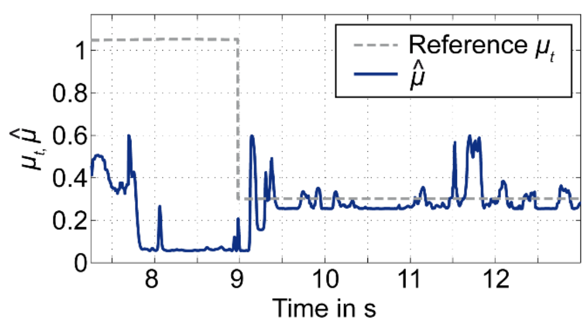
The internal state $\mathbf{x}_k$ to be estimated is given by the four wheel-individual coefficients of friction $\begin{bmatrix}\hat{\mu}_1 & \hat{\mu}_2 & \hat{\mu}_3 & \hat{\mu}_4\end{bmatrix}^{\mathrm{T}}$, with the inputs $\mathbf{z}_k = \begin{bmatrix}F_1^x & F_2^x & F_3^x & F_4^x\end{bmatrix}^{\mathrm{T}}$, comprising the longitudinal force F_i^x for the i-th wheel. Since the forces are not directly measured, a vehicle model is required to calculate forces from measured accelerations or engine and brake torques.

In parallel, the longitudinal tire forces expected for different road conditions are calculated using a tire model and the inputs longitudinal slip and vertical tire load at each time step. These inputs are also calculated using a vehicle model.

In the particle filter, the longitudinal forces derived from measurements are now compared to the ones from the tire model. Assumed road conditions within the tire model may be chosen to be fixed at all time steps, to be randomly varied or to converge to an expected real value based on results from previous time steps. If the estimate converges with time, the estimate will be more accurate in areas with constant μ_t, but changes in road condition will not be detected. Thus, a compromise has to be met when calibrating the estimation strategy. Alternatively, two different algorithms can be used in parallel. Thus it is possible to get an accurate estimate on constant road conditions, while detecting fast changes in the road condition with the other algorithm. A more detailed investigation is given in [16].

An exemplary result is shown in Figure 9, where the estimation result is shown during a braking maneuver with a maximum deceleration of – 2 m/s². During the braking maneuver, the road condition changes from μ_t of slightly above 1 to 0.3 at 9 seconds. On the high friction surface with μ_t more than 1, the estimate shows high deviation to the reference value. In this area, the dynamic excitation is not sufficient to determine a reliable estimate.

Figure 9. Estimation results during braking maneuver with a maximum deceleration of - 2 m/s² with μ_t changing from 1 to 0.3 at 9 seconds, [16]



After 9 seconds in Figure 9, with the vehicle being on a low friction surface, the estimation accuracy increases significantly. At almost all vehicle dynamics-based methods, the estimation accuracy depends on the ratio between dynamical excitation, in this case the horizontal vehicle accelerations, and the physical limits given by μ_t. On low friction surfaces, this ratio is higher for a given value of longitudinal acceleration, leading to a better estimate.

One advantage is that this method does not only consider the road condition, but also the tire's condition. No additional sensors are required in a vehicle equipped with electronic stability control. For a given longitudinal acceleration, low friction surfaces can be estimated more accurately than dry roads. This behavior is desired, compare Section 2.

A disadvantage of the method is that some vehicle parameters like the payload, and tire parameters like the tire-force characteristics need to be known. Another disadvantage is that dynamic response of the vehicle is required, meaning an acceleration or deceleration maneuver. During free rolling or very low accelerations, no estimate of μ_t can be delivered. However, within a sensor fusion approach, a vehicle-dynamics based method can be very useful to validate current estimates and include the tire condition. Other detection and estimation techniques like optical sensors have their strengths and shortcomings in other areas. Sensor fusion of different approaches seems promising for future application in safety-related functions.

5. SUMMARY

For the design of automated driving functions that are already available in production vehicles, dry roads are assumed for the activation strategy. For automated functions below SAE level 3, this is favored to reduce the number of false interventions of the system and due to legal reasons. For functions of SAE level 3 and higher, the responsibility to adapt to the environment including the road condition transfers from the driver to the system. During the design of automated driving functions that adapt to the road condition both physical considerations and human factors have to be considered.

Using the example of an Autonomous Emergency Braking System, the influence of imperfect road condition estimation on the activation strategy is discussed. This includes the influence of the road condition on the time-to-collision for both braking and steering maneuvers and how over- and under-estimation of the road condition may affect a strategy. Considerations are shown when using discrete categories of the road condition within the activation strategy of an automated function. The results show that for low friction surfaces, a higher accuracy for the estimation value is required compared to dry roads.

To keep trust and acceptance of the occupants high, human perception of the current road and traffic situation needs to be considered. To better understand driver's perception of the road conditions, a survey was conducted. 96 male and female drivers from five age groups were asked which categories of road condition they differentiate, and which criteria and cues they use during driving to get to know about the current road condition. The categories and the used cues named by the drivers fit well with physical considerations. The results indicate that subjective categories named by the drivers can be transferred to objective categories, e.g. values of maximum coefficient of friction, for automated systems. Finally, a method to estimate the road condition based on the vehicle's dynamic response is presented, and strengths and weaknesses of the approach are shown.

Adapting to the road condition will be crucial for future automated systems. The present article addresses both physical considerations and human factors that are relevant for the design of these functions.

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