Estimation of tire–road friction coefficient and its application in chassis control systems

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Knowledge of tire–road friction conditions is indispensable for many vehicle control systems. In particular, friction information can be used to enhance the performance of wheel slip control systems, for example, knowledge of the current maximum coefficient of friction would allow an anti-lock brake system (ABS) controller to start braking with the optimal brake pressure, meaning the early cycles of operation are more efficient, resulting in shorter stopping distances. Also, from a passive safety perspective, it may be useful to present the driver with friction information so they can adjust their driving style to the road conditions. Hence, it is highly desirable to estimate friction using existing onboard vehicle sensor information. Many approaches for estimating tire–road friction estimation have been proposed in the literature with different sensor requirements and relative excitation levels. This paper aims at estimating the tire–road friction coefficient by using a well-defined model of the tire behavior. The model adopted for this purpose is the physically based brush tire model. In its simplest formulation, the brush model describes the relationship between the tire force and the slip as a function of two parameters, namely, tire stiffness and the tire–road friction coefficient. Knowledge of the shape of the force–slip characteristics of the tire, possibly obtained through the estimation of both friction and tire stiffness using the brush model, provides information about the slip values at which maximum friction is obtained. This information could be used to generate a target slip set point value for controllers, such as an ABS or a traction control system. It is also important to realize that a model-based approach is inherently limited to providing road surface friction information when the tire is exposed to an excitation with high utilization levels (i.e. under high-slip conditions). To be of greatest use to active safety control systems, an estimation method needs to offer earlier knowledge of the limits. In order to achieve the aforementioned objective, an integrated approach using an intelligent tire-based friction estimator and the brush tire model-based estimator is presented. An integrated approach gives us the capability to reliably estimate friction for a wider range of excitations (both low-slip and high-slip conditions).

Keywords: Brush model; friction estimation; Levenberg–Marquardt; nonlinear least squares; intelligent tire

1. Introduction

Tire friction forces, as the primary forces affecting planar vehicle motions, are physically limited by the road surface coefficient of friction ($\mu$) and the instantaneous tire normal forces (Figure 1). Therefore, the ability to reliably estimate the tire–road friction coefficient is important for maximizing the performance of vehicle control systems, which work well only when the tire force command computed by the safety systems is within the friction limit.

Instantaneous knowledge of the friction potential will result in improved performance by several of the active chassis control systems. Examples of vehicle control systems that can benefit from the knowledge of tire–road friction include anti-lock braking systems (ABS), electronic stability control (ESC), adaptive cruise control (ACC), and collision warning or collision avoidance systems (Braghin et al., 2009; Cheli, Leo, Melzi, & Sabbioni, 2010; Cheli et al., 2011a, 2011b; Erdogan, Hong, Borrelli, & Hedrick, 2011; Sabbioni, Kakalis, & Cheli, 2010; Singh, Arat, & Taheri, 2012, 2013). The quality of traffic management and road maintenance work (e.g. salt application and snow plowing) can also be improved if the estimated friction value is communicated to the traffic and highway authorities.

The importance of friction estimation is reflected by the considerable amount of work that has been done in this field (Google Scholar) (Table 1). In normal driving conditions, the frictional force is not fully utilized, and the developed tire forces will be somewhere in the interior of the friction circle. When inputs are imposed on a tire, a relative motion between the tire structure and the road surface will arise. This relative motion is referred to as tire slip. The relation between the resulting tire forces and slip depends on many factors, namely, tire inflation pressure, vertical load, tire wear state, temperature, etc., and contains information about the available friction. When the

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tire is exposed to excitation with high utilization, beyond the point corresponding to the maximum available friction force, the tire starts sliding and the resulting tire force directly corresponds to the friction coefficient.

Hence, determination of friction coefficient is straightforward in cases where tire forces are saturated, such as under hard braking conditions. The difficulty lies in obtaining a friction estimate under more normal driving circumstances, in which the tire slip is smaller (lower utilization conditions). In these cases, a model-based approach can be advantageous (Andersson et al., 2010). By fitting tire force and moment data to a model of the tire, the model parameters, including friction coefficient ($\mu$), may be estimated. This approach may allow the estimation of friction without requiring tire force saturation. This study investigates the use of a model-based approach to estimate the tire-road friction coefficient and, more importantly, determines the level of tire force excitation necessary to allow the estimate to converge within a specified range of accuracy.

2. Estimation of vehicle states and tire forces

A model-based friction estimation method is based on the assumption that the lateral force, traction/braking force, aligning torque, vertical load and the two tire kinematic variables, slip angle and wheel slip, can be estimated indirectly using observers developed based on vehicle dynamics measurements (acceleration, yaw and roll rates, suspension deflections, etc.), or measured directly using certain sensor-based advanced tire concepts. In this study, we propose using an integrated vehicle state estimator, comprising a series of model-based and kinematics-based observers and an effectively designed merging scheme that ensures robust estimation performance even during the vehicle maneuvers which show highly nonlinear tire characteristics and in the existence of road inclination or bank angle. It is assumed that measurements from a six-axis inertial measurement unit (three axes of rotation rate measurement and three axes of acceleration measurement), wheel speed sensors and steering wheel angle sensor are available.

The block diagram in Figure 2 explicitly shows the estimation process in its entirety.

The entire process is separated into five blocks: the first block serves to identify the road bank and grade angles (using a kinematics-based observer) and vehicle chassis roll (using a Kalman filter) and pitch angles (with vehicle mass adaptation); the second block contains a bias compensation algorithm (gravity compensation in accelerometer measurements), a vehicle longitudinal speed estimation algorithm (based on the measurements of the four wheel rotational speeds and the gravity-compensated longitudinal vehicle acceleration) and a tire load estimation algorithm (using gravity-compensated acceleration information and roll/pitch states); the third block contains a tire longitudinal/lateral force estimation observer (sliding-mode observer based), while the fourth block contains a nonlinear vehicle longitudinal and lateral velocity observer (based on an unscented Kalman filter), designed for the purpose of vehicle sideslip estimation. Finally, the fifth block makes use of the estimations provided by the third and fourth blocks to estimate the tire slip ratio and slip angle (Luenberger observer based).

It is worth stressing the fact that the present work is concerned with examining the feasibility of estimating the tire-road friction coefficient ($\mu$) in real time. Hence, a complete description of the integrated vehicle state estimator as shown in Figure 2 is beyond the scope of this work. A thorough coverage of this topic with specific details about the different schemes used for tire/vehicle state and parameter estimation is included in our previous work (Arat, Singh, & Taheri, 2013, 2014; Singh, 2012; Singh et al., 2012; Singh and Taheri, 2013).
3. Tire model selection

Critical to the success of a model-based approach is the choice of model structure. Li, Fei-Yue, and Qunzhi (2006) provide a comprehensive summary of various models that have been developed to describe the complex nonlinear behavior of a tire. As this study focuses on parameter estimation, it is desirable to choose a model with a small number of parameters. The brush model (Pacejka, 2005) is well suited to these requirements, containing only stiffness and friction parameters. The basic concept of the brush model is to represent the tire as a row of elastic bristles which touch the road plane and can deflect in a direction that is parallel to the road surface (Figure 3).

As a result, a tire can be modeled as a thin disk with brushes along the circumference that represent the tire treads. Treads in the contact patch are compressed and experience vertical stresses. The distribution of vertical stress is assumed to be parabolic. The generated forces or moment can be computed by integrating the stress of all brushes in the contact patch. A thorough coverage of the brush model is included in Pacejka (2005).

In a purely longitudinal slip case, the tire longitudinal force can be represented as follows:

\[
F_x = \begin{cases} 
C_x \left( \frac{\lambda}{\lambda_{sl} + 1} \right) & \text{for } |\lambda| \leq |\lambda_{sl}|, \\
\frac{1}{27} C_3 \left( \frac{\lambda}{\lambda_{sl} + 1} \right)^{2} + \mu F_z \frac{\text{sign}(\lambda)}{\mu F_z} & \text{for } |\lambda| > |\lambda_{sl}|,
\end{cases}
\]

where \(F_x, F_z, C_x, \mu, \lambda, \text{ and } \lambda_{sl}\) stand for tire longitudinal force, tire normal force, tire longitudinal stiffness, tire–road friction coefficient, slip ratio and slip ration where transition from partial to full sliding occurs, respectively.

![Figure 2. Functional diagram of the estimation process.](image)

![Figure 3. Tire and brush model (Ahn, 2011).](image)
In a purely lateral slip case, the tire lateral force and tire aligning moment can be represented as follows:

\[
\begin{align*}
F_y &= -C_y \tan(\alpha) + \frac{C^l_y \tan(\alpha) \tan(\alpha)}{\mu_F} \quad \text{for } |\alpha| \leq |\alpha_d|, \\
F_y &= -\mu F_z \text{sgn}(\alpha) \quad \text{for } |\alpha| > |\alpha_d|, \\
\tau_a &= \frac{C_y \tan(\alpha) \tan(\alpha)}{3} (1 - \frac{C_y \tan(\alpha)}{3\mu F_z})^3 \quad \text{for } |\alpha| \leq |\alpha_d|, \\
\tau_a &= 0 \quad \text{for } |\alpha| > |\alpha_d|, 
\end{align*}
\]

where in addition to the above terms \(F_y, \tau_a, C_y, \alpha, \alpha_d\) and \(a_{cpl}\) stand for tire lateral force, tire aligning moment, tire cornering stiffness, slip angle, slip angle where transition from partial to full sliding occur and half of tire contact patch length, respectively.

The force and moment equations in combined slip cases are similar to the equations for pure slip cases. If both lateral slip and longitudinal slip exist, the treads are deformed in the direction determined by the magnitudes of both slips. The brush model for the combined slip case can be represented by the following equation:

\[
\begin{align*}
F_x &= F \sigma_x \alpha, \\
F_y &= F \sigma_y \lambda, \\
M_z &= -t(\sigma) \times F_y, 
\end{align*}
\]

where

\[
\begin{align*}
F(\lambda, \alpha, \mu) &= \begin{cases} 
\mu F_z (1 - \rho^3) & \text{for } |\sigma| \leq |\sigma_d|, \\
\mu F_z \text{sgn}(\alpha) & \text{for } |\sigma| > |\sigma_d|, 
\end{cases} \\
\sigma_x &= \frac{\lambda}{\lambda + 1}, \\
\sigma_y &= \frac{\tan(\alpha)}{\lambda + 1}, \\
\sigma &= \sqrt{\sigma_x^2 + \sigma_y^2}, \\
a_{cpl} &= a_{cpl} \sqrt{\frac{F_z}{F_{\mu}}}, \\
C &= 2c_l \sigma_{cpl}^2 \\
\theta &= \frac{C}{3\mu F_z}, \\
\alpha_d &= \frac{1}{\theta}, \\
\rho &= 1 - \theta \sigma, \\
t(\sigma) &= \frac{\lambda(1 - |\theta \sigma|)^3}{(3 - 3|\theta \sigma| + |\theta \sigma|^2)},
\end{align*}
\]

5. Real-time implementation

The real-time parameter estimation algorithm used in this study is similar to the one presented in Hsu (2009). The complete real-time estimation algorithm is outlined below:

- Iteratively perform nonlinear least squares (NLLS) to the brush model on the batch of force–slip/moment–slip data, starting with initial estimates of braking/cornering stiffness and friction coefficient.
- To ensure that there is enough data for the NLLS fit to be meaningful, first initialize the process by placing a tire slip level threshold. The tire slip must exceed the threshold value before parameter estimation begins.
- The next step is to determine whether the tire force/moment has saturated sufficiently enough to estimate \(\mu\). In parallel to the NLLS fit, apply the method of least squares to the data points to find the slope of the line through the origin. Calculate the incremental mean-squared error of both fits from the most recent vector of data points of length \(N\). If
Figure 4. (a)–(f) Adaptation of the brush–tire model to tire measurement data (ref. Table 2 for a description of the test conditions). (a) Case 1, (b) case 2, (c) case 3, (d) case 4, (e) case 5 and (f) case 6.
Table 2. Tire test conditions.

| Test description         | Surface condition | Measured/estimated signals | Estimated parameters |
|--------------------------|-------------------|----------------------------|----------------------|
| Case 1 Longitudinal force test | High μ | $F_x$, $F_z$, $\lambda$ | $C_x$, $\mu$ |
| Case 2 Longitudinal force test | Low μ | $F_x$, $F_z$, $\lambda$ | $C_x$, $\mu$ |
| Case 3 Lateral force test  | High μ | $F_y$, $F_z$, $\alpha$ | $C_y$, $\mu$ |
| Case 4 Lateral force test  | Low μ | $F_y$, $F_z$, $\alpha$ | $C_y$, $\mu$ |
| Case 5 Self-aligning moment test | High μ | $\tau_a$, $F_z$, $\alpha$ | $C_y$, $\mu$ |
| Case 6 Self-aligning moment test | Low μ | $\tau_a$, $F_z$, $\alpha$ | $C_y$, $\mu$ |

Figure 5. Tire parameter estimation algorithm – Lateral Force–Slip Regression Method.

...and slip ratio data are post-processed to yield longitudinal stiffness and friction coefficient estimates (Figure 6).

6.2. Estimation based on the Lateral Force–Slip Regression Method

With $\alpha_{\text{thres}} = 2^\circ$, $\mu_{\text{initial}} = 0.8$ and $C_{y_{\text{initial}}} = 110000$, force and slip angle data is post-processed to yield cornering stiffness and friction coefficient estimates (Figure 7).

6.3. Estimation based on the Moment–Slip Regression Method

With $\alpha_{\text{thres}} = 0.5^\circ$, $\mu_{\text{initial}} = 0.8$ and $C_{y_{\text{initial}}} = 110000$, moment and slip angle data are post-processed to yield cornering stiffness and friction coefficient estimates (Figure 8).

Based on the results shown in Figures 6–8, the required utilization of friction necessary to provide a friction estimate within the specified accuracy of ±10% is presented in Table 3. In the case of the “Force–Slip Regression Method,” more than 75–80% of the available friction force must be generated before an accurate estimate can be derived. However, it is possible to estimate the tire road friction coefficient for lower levels of utilization (~30–40%) if SAT (“Moment–Slip Regression Method”) is used as a basis for the estimator instead of the lateral force (“Lateral Force–Slip Regression Method”).

The “Moment–Slip Regression Method” presents a better opportunity of estimating the friction coefficient for lower levels of utilization, since the SAT saturates before the lateral force is saturated (Figure 9).

It is also important to realize that the force-based approach is inherently limited to operate during either longitudinal or lateral excitation, that is, either during acceleration/braking or cornering. Since they are active during different instants, it is advisable to combine two or more methods (Figure 10) as also suggested in previous work (Ahn, 2011) and hence provide a continuous estimate of friction.

To be of greatest use to active safety control systems, an estimation method needs to offer earlier knowledge of the limits. The next section presents an implementation strategy for estimating the tire–road friction coefficient under low-slip conditions.
7. Integrated tire–road friction estimation scheme

Availability of certain new technologies, popularly known as “intelligent tires” or “smart tires” (Morinaga; Yasushi Hanatsuka and Morinaga, 2013), hold the potential of providing real-time road surface condition information under low-slip rolling conditions. The implementation strategy for one such algorithm that utilizes sensor signals from an instrumented tire is presented in this section. The instrumented tire system was developed by placing accelerometers on the inner liner of a tire (Figure 11(a)). Figure 11(b) shows the final assembly of the instrumented tire with a high-speed slip ring attached to the wheel. Extensive
The dynamic tests of the tire were conducted using the in-house mobile tire test rig shown in Figure 11(c) and 11(d). An example of the acceleration signal is shown in Figure 12.

The effect of tire load, translational speed, varying pressure conditions and road surface roughness on the tire vibration spectra were studied by varying each of these parameters by carrying out extensive outdoor testing of the instrumented tire under free-rolling, traction/braking and steering conditions.

The power spectrum road of each accelerometer signal from these tests was computed using Welch’s averaged modified periodogram method for spectral estimation (Figure 13). Analyzing the dynamic test results, it was
concluded that, a marked difference was noticed in the concentration of the higher frequencies on the spectrum of the circumferential acceleration signal of the tire tested on different surface conditions (Figure 13(d)). This variation in the circumferential acceleration signal power spectral density (PSD) on different road surface conditions presented an opportunity to characterize the road condition using the tire vibration pattern information.

The proposed intelligent tire-based surface condition estimating algorithm consists of detecting the circumferential vibration of a tire of a running vehicle; dividing the detected tire vibration into vibration in a pre-trailing domain, the domain existing before a trailing edge position; and vibration in a post-trailing domain, the domain existing after a trailing edge position. Thereafter extracting signals of tire vibration only from the pre-trailing domain;
obtaining a time-series waveform of tire vibration including only the frequencies in a predetermined frequency band by passing the extracted signals through a band-pass filter of the predetermined frequency band; calculating a vibration level in the predetermined frequency band and estimating a road surface condition based on the calculated vibration level.

The predefined frequency bands being a low-frequency band (e.g. 10–500 Hz band) and a high-frequency band (e.g. 600–2500 Hz). The motivation for only using the pre-trailing domain signal is the larger difference in the PSD of the pre-trailing domain signal, when compared with the PSDs obtained using the entire signal or using the signal from the post-trailing domain. To determine these differences, the instrumented tire was first driven on a dry surface and then on a wet road surface at different speeds and the change in the vibration level ratio (R) was measured, where R is the ratio of the aforementioned

| Estimation methodology                  | Friction coefficient (μ) | Required utilization of friction (%) |
|-----------------------------------------|--------------------------|-------------------------------------|
| Longitudinal Force–Slip Regression Method | High μ                   | 70                                  |
| Lateral Force–Slip Regression Method     | Low μ                    | 85                                  |
| Moment–Slip Regression Method            | Low μ                    | 90                                  |
|                                         | High μ                   | 35                                  |

Table 3. Required utilization of friction (in percent) to achieve a friction estimate within an accuracy of ± 10%.

Figure 10. Integrated friction estimation algorithm – flow diagram.
Figure 11. Intelligent tire application: (a) sensor mounting location, (b) instrumented tire assembly, (c) mobile tire test rig and (d) test rig attached to the towing vehicle.

Figure 12. Measured acceleration signal for one rotation.

high-frequency band and the low-frequency band vibration level. It is evident from Figure 14 that the vibration level ratio $R$ increased as the tire was tested on the wet road surface. This change in the vibration level ratio can be attributed to the increased slippage of the tire, and thus, it has been confirmed that the slipperiness of a road surface can be decided by setting a proper threshold value.

For this purpose, a fuzzy logic classification approach was developed for the real-time implementation of the proposed algorithm. The application of fuzzy logic to solve the classification problem is motivated by its noise tolerance to the vibration data retrieved from sensors, and its ability for real-time implementation while ensuring robustness with respect to imprecise or uncertain signal interpretation. Figure 15 shows the fuzzy controller architecture.

Based on the interdependence of all the inputs for a given road surface condition and the way they effect the vibration spectra of a tire, a set of linguistic rules were developed to identify the road surface condition. The classifier performance was validated on smooth asphalt, regular asphalt, rough asphalt and wet asphalt (Figure 16).

Two different tests were performed to study the classifier performance. The first test involved testing the tire under free-rolling and low-slip conditions (low force utilization). The second test involved testing the tire under high-slip conditions (high force utilization). For the first test (free-rolling and low-slip conditions), the classifier was successfully able to distinguish between the different road surface conditions as shown in Figure 17. However, for the second test (high-slip conditions), classifier performance was unsatisfactory (Figure 18). Higher misclassification rates under high-slip conditions were attributed to the increased vibration levels in the circumferential
acceleration signal due to the stick/slip phenomenon linked to the tread block vibration modes (Figure 19).

The requirement of a more complex event detection algorithm for distinguishing the high-frequency content of a signal due to the tread block mobility effects, under high-slip conditions, makes the proposed fuzzy logic classifier unsuitable for friction estimation under high-slip conditions.

Hence, it was proposed to use a model-based approach as presented in the previous section to estimate road surface friction under high-slip conditions. Finally, it was proposed to use an integrated approach (Figure 20) using the intelligent tire-based friction estimator and the model-based estimator which would reliably estimate friction for a wider range of excitations (both low-slip and high-slip conditions). Using an integrated approach, the road surface friction classifier was successfully able to distinguish between the different road surface conditions as shown in Figures 21 and 22.

8. Application of road friction information in vehicle control systems – development of new control strategies

A change in the peak grip potential of the tire (Figure 23(a)) not only affects the “limit” handling behavior of the vehicle, but is also known to affect the vehicle...
“linear range” handling behavior. This change in the vehicle “linear range” behavior is due to the influence of road friction on the tire stiffness in the low-slip region (Figure 23(b)). Moreover, the peak slip ratio position of the maximum coefficient of friction varies for different road conditions (Figure 24). Hence, in the context of an anti-lock brake system (ABS) based on a fixed thresholding rule-based algorithm, it cannot be expected that an ABS controller that is optimized for dry asphalt performs as reliably and efficiently on wet or icy surfaces.

To quantify the performance benefits for an ABS controller using road friction condition information, a modified ABS algorithm has been developed, as shown in Figure 25. The modified controller leverages friction information...
Figure 19. Circumferential acceleration signal under low-slip conditions (top), and increased vibration levels in the circumferential acceleration signal under high-slip conditions (bottom).

Figure 20. Architecture of the proposed integrated approach using an intelligent tire-based friction estimator and the model-based estimator.
Figure 21. Classification performance on dry and wet asphalt.

Figure 22. Classification performance on dry asphalt, gravel and wet asphalt.
Figure 23. (a) Longitudinal tire force under different road surface conditions, and (b) longitudinal tire force in the small-slip region under different road conditions.

Figure 24. Position of slip values at which maximum friction (braking force) is obtained.

to change the optimal slip point thresholds, thus maximizing the braking force. Moreover, the controller uses a brake preconditioning algorithm with a friction adaptation strategy to start braking with the optimal brake pressure, and thus ensuring that the early cycles of braking are more efficient. Simulations were carried out on a series of braking maneuvers to examine the possible improvements in the ABS system performance. The results reveal that the presence of road condition information allows for a considerable decrease in the stopping distance (Singh et al., 2013). Most impressive improvements are obtained for the jump-$\mu$ tests (Figure 26). In light of these results, we conclude that the knowledge of road surface condition can be quite favorable for enhancing the current ABS algorithms.

In the context of a classical ESC system based on a model reference approach, the desired values of yaw rate and body sideslip angle are generated from a reference model, which takes into account the vehicle velocity, the driver input, tire/axle load and cornering stiffness (understeer/oversteer behavior). The weighting factor, which determines the balance between the yaw rate tracking and sideslip regulation, depends primarily on a term combining the estimated rear axle sideslip angle and its derivative. Therefore, an accurate online estimate of the vehicle sideslip angle is critical for the effective operation of an ESC system. In production cars, the vehicle sideslip angle is not measured because this measurement requires expensive equipment such as optical correlation sensors. Most production vehicles rely on observers based on vehicle dynamics models for indirectly estimating the vehicle sideslip angle. These observers perform reasonably well in normal driving situations, when the steering characteristics specify a tight connection between the steering wheel angle, yaw rate, lateral acceleration and vehicle sideslip angle. When a vehicle is near or at the limit of adhesion, tire forces and consequently the yaw dynamics strongly depend on the surface coefficient of friction. For example, limit tire forces on ice can be about 10 times smaller than on dry surface. The vehicle model used within the observer should therefore be adapted to the changing surface friction. The coefficient of friction, however, is unknown and has to be estimated. Thus, the estimation of sideslip angle depends on another estimate, which increases the potential for errors. Uncertainties in sideslip angle estimation lead the ESC system to be conservatively calibrated in order to balance robustness concerns with performance. This inherently sacrifices some level of performance.
From the foregoing discussion, it is apparent that the knowledge of road surface condition would be beneficial in improving the accuracy of sideslip angle observers, which eventually would enhance the performance of ESC systems. To quantify the performance benefits, an enhanced ESC controller based on active front steering (AFS) and direct yaw moment control (DYC) has been developed (Figure 27). The proposed controller consists of a full vehicle state estimator with friction adaptation (Singh, 2012). The vehicle sideslip is estimated using an extended Kalman filter (EKF)-based observer. More details pertaining to the modified ESC algorithm are given in Table 4.

Simulation results show that the new control strategy aiming to use all of the information available from the vehicle state estimator can significantly enhance vehicle stability during emergency evasive maneuvers on various road conditions ranging from dry asphalt to very slippery packed snow road surfaces (Figure 28).

Another vehicle safety system that is becoming more prevalent in the vehicle industry is the advanced driver assistance system (ADAS). Typically, ADAS features three technologies: collision mitigation braking system (CMBS), lane keeping assist system and ACC. CMBS is an active safety system that helps the driver to avoid or mitigate rear-end collisions. It uses forward-looking sensors to detect obstacles ahead of the vehicle. The systems use relative distance, relative velocity and vehicle velocity information to warn the driver or control the vehicle. Specifically, a warning critical distance is defined as a function of vehicle velocity and relative velocity.

From Figure 29, we can see that if friction information would be available, the critical warning and critical braking distances could be calculated more precisely (since the deceleration rate for the vehicles \( \alpha_1, \alpha_2 \) depends on the maximum tire–road friction available). Using a high default value for the friction coefficient causes the systems to lose some of their safety potential on low-friction surfaces. Using a low or medium default value would on the other hand cause the safety systems to activate too early in high-friction conditions, taking the driver “out of the loop” possibly unnecessarily.

The modified algorithm used in this study assumes to have full knowledge of the road conditions (Figure 30). Consequently, the collision mitigation algorithm adapts its critical distance (warning/braking distance) definitions when the road conditions change (Figure 31).

A parametric analysis aimed at evaluating the benefits induced by the introduction of friction information has been carried out. These simulations will be used to show the benefit of using friction estimation in conjunction with a collision mitigation brake system algorithm. In the test case, the host and the lead car are both traveling at 27.8 m/s with a separation of 50 m. The lead car suddenly applies the brakes and decelerates. The host vehicle maintains its velocity, which simulates a driver...
Figure 26. ABS performance – (a) without knowledge of road friction conditions and (b) with knowledge of road friction conditions.

who is unaware of the critical nature of the situation. Figure 32 shows the vehicle response when the collision mitigation brake system algorithm without the friction adaptation strategy is used (i.e. friction information is unavailable). The relative velocity at impact in this case is 14.5 m/s.
Table 4. Enhanced ESC system model details.

| Reference generator | Sliding mode control (SMC) strategy | The model responses of vehicle sideslip angle and yaw rate are described. Total lateral force and the total yaw moment required for the controlled vehicle to follow the model responses are estimated using an SMC strategy |
|---------------------|-------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| AFS controller      | SMC strategy                        | Difference between vehicle measured yaw rate and desired yaw rate is considered as the sliding surface. Control law is based on tire force feedback and is obtained from a nonlinear eight-degree-of-freedom vehicle model |
| DYC controller      | Rule based                          | Implemented through braking one of the four wheels based on detection of understeer or oversteer driving situations |
| Tire model          | Combined slip model                 | Tire forces are modeled using magic formula tire model with friction adaptation |
| Vehicle state estimator (Singh, 2012) | Full state estimation using a nonlinear vehicle model | Vehicle sideslip is estimated using an EKF-based observer with friction adaptation |

Figure 33 shows the vehicle response when the collision mitigation brake system algorithm with the friction adaptation strategy is used (i.e. friction information is available). In this simulation, the driver is completely out of the loop, so the collision mitigation brake system brings the vehicle to a rest. Notice that the plot shows that the vehicles collide at \( \sim 7.7 \) s. The relative velocity at impact is 9.5 m/s. Clearly, the modified algorithm with friction information (Figure 21) applies the brakes sooner during degraded road conditions, which gives the vehicle more time to slow down. As a result, the impact speed and the impact energy are reduced. These results can be improved even further by increasing the friction adaption scaling factors.

From the foregoing discussion, we can thus conclude that road friction condition information would enable slip control systems (ABS, traction control system, ESC, etc.) to be started with the optimal initial parameters for the friction situation at hand. Moreover, accurate friction information would also enable the CMBS to start intervention from a more optimal distance in every road condition.
9. Conclusion

Road friction is an important parameter for vehicle safety applications, but difficult to estimate accurately in all driving situations and weather conditions. Friction estimation methods based on the applied slip angle and slip ratio have been proposed earlier, but in the case of a freely rolling tire, the friction estimation is still an unsolved topic. This study uses a three-axis accelerometer on the inner liner of a tire to detect the tire road friction potential. More specifically, a two pronged approach was adopted to estimate tire–road friction coefficient. Firstly, a “force–slip” and “moment–slip” model-based approach is proposed. The primary shortcoming of the “Force–Slip Regression Method” identified is the requirement that the vehicle must enter the nonlinear region of handling before friction can be estimated. Thus, in the case of the “Force–Slip Regression Method,” an estimation algorithm based on the brush model will work, but high friction utilization (\(\sim 75–80\%\)) is required for an accurate friction estimate. The “Moment–Slip Regression Method” based on total aligning moment has the benefit of knowing the coefficient of friction earlier, that is, under lower levels of utilization (\(\sim 30–40\%\)).
To be of greatest use to active safety control systems, an estimation method needs to offer even earlier knowledge of the limits, that is, ideally offer knowledge on peak friction level under free-rolling conditions. To achieve this, an integrated approach using the intelligent tire-based friction estimator and the model-based estimator is proposed. This would give us the capability to reliably estimate friction for a wider range of excitations. The proposed intelligent tire-based method characterizes the road surface friction level using the measured frequency response of the tire vibrations and provides the capability to estimate the tire road friction coefficient under extremely lower levels of force utilization, that is, under free-rolling to low-slip excitation conditions. The ability to reliably estimate tire–road friction coefficient is important for maximizing the performance of vehicle control systems, which work well only when the tire force command computed by the safety systems is within the friction limit. The development of a sensorized smart/intelligent tire system is expected to eliminate some of the vehicle sensors and provide accurate, reliable and real-time information about magnitudes, directions and limits of force for each tire. Benefits of application of knowledge of friction potential have been demonstrated for an ABS, ESC system and CMBS.
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Figure 32. Friction condition unknown (assumed $\mu = 0.8$; actual $\mu = 0.25$).

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