

Enhanced Vehicle Dynamics and Safety through Tire–Road Friction Estimation for Predictive ELSD Control under Various Conditions of General Racing Tracks

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Abstract: This study focuses on the tire–road friction estimation for the predictive control strategy of electronically limited slip differential (ELSD) to improve the handling and acceleration performance of front-wheel drive cars, which typically suffer from excessive understeer and inner drive wheel spin during acceleration while turning due to reduced vertical load on the wheel. To mitigate this, we propose a control logic for ELSD that enhances course followability and acceleration by pre-transferring the driving torque from the inside to the outside wheel, considering the estimated traction potential for rapid response. It is essential to improve the control accuracy of wheel spin prediction by predicting the friction coefficient of the road surface. Furthermore, this study extends to the analysis of vehicle dynamics during lane-change maneuvers on low-friction surfaces, emphasizing the role of accurate tire–road friction estimation in vehicle safety. A CarSim 2023-based simulation study was conducted to investigate the vehicle response on snowy roads with low friction coefficients ($\mu = 0.2$) and low temperatures ($-5\text{ }^{\circ}\text{C}$). The results demonstrated that even minimal steering input could result in significant side-slip angles, highlighting the nonlinear vehicle behavior and the critical need for robust traction estimation in such challenging conditions of general racing tracks. The proposed friction-estimation method was evaluated through vehicle testing and has been substantiated by patents for its originality in control and friction-estimation approaches. The outcomes of these combined methodologies underline the critical importance of tire–road friction coefficient estimation in both the effectiveness of the ELSD system and the broader context of active safety systems.

Keywords: electronically limited slip differential; friction coefficient; friction circle; predictive control; ADAS; data visualization; driving behavior; ride comfort; human factor



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1. Introduction

Lateral control systems for high-performance vehicles are developed to prevent the driver from losing control of the vehicle and to improve the cornering agility of the vehicle. Nevertheless, front-wheel drive (FWD) high-performance cars can be developed in combination with high-power engines based on existing small vehicle platforms or subcompact vehicle platforms [1]. Therefore, such FWD high-performance cars can be developed at a relatively low cost. However, the inner wheels of FWD vehicles spin when a driving torque greater than the inner-wheel grip is applied due to the weight transfer during acceleration while turning. This spinning results in understeer and a reduction in exit acceleration.

This can be overcome by controlling the inner-wheel slip via an electronically limited slip differential (ELSD) when the inner-wheel speed becomes greater than the outer-wheel

speed and spins during an accelerated exit. The ELSD can apply friction torque to restrict the rotational degrees of freedom of the left and right wheels [2]. Wheel torque is reduced when the wheel spins without traction by transferring the driving torque from the fast shaft to the slow shaft when the degrees of freedom of the left and right wheels are restricted by the friction torque. Therefore, the torque can be transferred to the wheel that has traction. However, if control is performed after the wheel slip occurs, then the initial wheel spin cannot be controlled properly because of the time delay in the system operation. Thus, a controller that can predict inner-wheel slipping in advance and perform appropriate pre-emptive control is needed.

We created a control algorithm that predicts inner-wheel spinning during acceleration while turning by calculating the friction limit at which the inner wheel can be driven in real time [3]. A concept is designed for the ELSD clutch to engage based on the difference between the real driving force from the powertrain and the allowable driving force of the inner wheel, as shown in Figure 1.

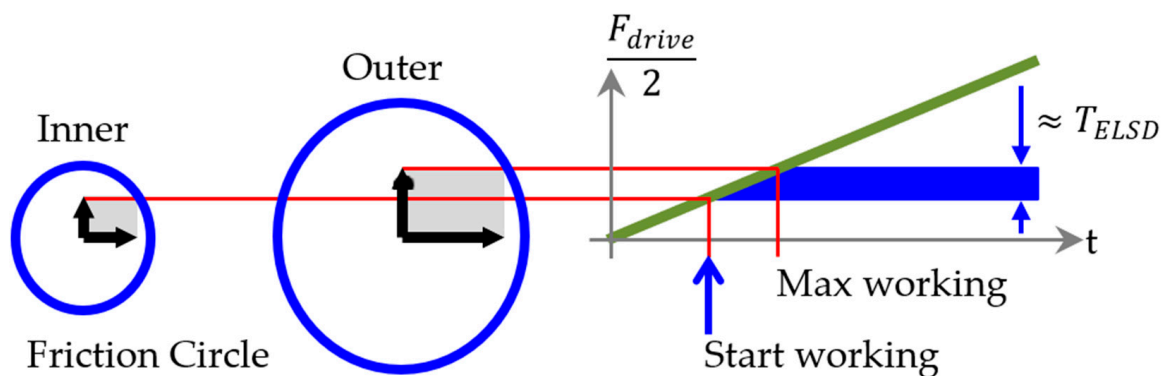


Figure 1. The concept of wheel spin predictive control.

The accuracy of the wheel spin predictive control can be improved by predicting the friction coefficient of the road surface. In addition, one of the factors that greatly affect the driving and safety performance of a vehicle is the real-time change in the tire–road friction coefficient. The vehicle motion caused by steering, traction, and braking forces of the vehicle is affected by the tire–road friction coefficient. Therefore, tire–road friction coefficient information is important for the performance of the vehicle control system. If the vehicle is driven in an unusual road environment, the driving system will fail to produce the original performance, which results in an unstable vehicle control process.

If the accurate estimation of the tire–road friction coefficient is possible, vehicle control performance can be stabilized through better system operation. The vehicle predictive control system automatically adjusts the timing and amount of system intervention by reflecting the friction characteristics of the road surface changes, thereby maximizing the functionality of the control system. Therefore, various research efforts are underway to ensure the stable performance of vehicle driving systems by estimating the tire–road friction coefficient using different methods.

1.1. Literature Review

The first research approach involves detecting substances covering the road, such as water, ice, or snow, either visually, through temperature, or by using specialized sensors [4–6]. Current methods that employ light or ultrasonic sensors to estimate friction coefficient require expensive additional sensors.

The friction characteristics of asphalt can vary significantly depending on the distributed conditions of dryness, moisture, snow, or ice and the presence of localized specificities, such as oil traces and potholes (associated with weather conditions). However, stable performance across various environmental scenarios is essential. The mentioned research approach has limited application in production vehicles owing to its real-time performance

being compromised by accuracy fluctuations based on external conditions. In particular, methods involving light or ultrasonic sensors require additional costly equipment, making it challenging to apply them to production vehicles.

Another method uses acceleration sensors in the vehicle body to estimate tire–road friction [7,8]. Using vehicle acceleration sensors to convert the acceleration of the center of mass into sprung mass acceleration to calculate tire acceleration enables the estimation of the tire–road friction coefficient by calculating the dynamic tire force and effective vertical force, considering the amount of load transfer. This approach considers the amount of slip that reaches the maximum tire force and calculates the effective dynamic tire force, which is similar to the friction estimation technique proposed in this paper. However, this method involves calculating the friction coefficient using only the acceleration of the vehicle. Therefore, the calculated value is used as is in stable situations; in sections where there is no rapid acceleration, the problem of the friction coefficient falling to a lower value than the actual friction coefficient can occur. Additionally, it has only been verified in certain driving conditions where the vehicle brakes while driving straight. It is necessary to verify whether the friction estimation is also effective in various driving environments with different road conditions and in situations where there is significant lateral acceleration due to turning. In turning situations where both longitudinal and lateral accelerations increase, leading to an increase in both longitudinal and lateral tire forces, the accuracy of tire–road friction estimation decreases if the effective normal acceleration cannot be calculated. Therefore, the aforementioned method needs additional strategies to accurately estimate the friction coefficient in stable vehicle states, which is a section where longitudinal and lateral accelerations are small.

The second approach uses the vehicle–tire model to estimate the tire–road friction coefficient based on wheel slip ratio and braking-force characteristics [9–12]. Using a linear vehicle–tire model provides high friction estimates across various environments. However, as it relies on simulation-based data, its implementation in real vehicle environments is inappropriate.

In situations where the friction coefficient changes with driving conditions, estimating the limit value of the tire–road friction coefficient based on maximum braking force results in decreased accuracy. Additionally, the virtual environment vehicle model may not align with the actual vehicle, leading to a decrease in the performance of real-time tire–road friction estimation when applying such systems.

The third approach estimates tire–road friction based on a discrete-time extended Kalman filter using a nonlinear vehicle–tire dynamics model [13,14]. Estimating the lateral velocity of the vehicle to calculate the slip angle of the wheels enables accurate estimation of tire–road friction. However, this method faces challenges in real-time application due to the computational complexity of the nonlinear model and time considerations.

The fourth approach uses open-loop fuzzy logic to estimate tire–road friction coefficients [15]. Precomputed friction coefficient tables based on fuzzy logic tailored to predefined driving scenarios are not suitable for real vehicle environments. This is because the accuracy of friction coefficient estimation decreases when the dynamic characteristics of the vehicle change or when applied to different driving situations.

1.2. Study Objective

In this study, we propose a method to overcome the problems in previous research to estimate the friction coefficient used in the ELSD system of actual mass-produced high-performance vehicles. Therefore, an algorithm with a small computational load is constructed using only the driving torque and acceleration data that can be used in mass-produced vehicles. To operate the ELSD before the tire slips, we propose a method to predict the friction coefficient as accurately as possible, not only in the tire–road friction limit area but also in a section smaller than the friction limit.

Since the various traction control and stability control methods in vehicles operate for a long time in the region of the grip limit, the friction coefficient calculated at this time is close

to the actual friction value. However, it is necessary to estimate the friction coefficient for ELSD at all times while in operation. Therefore, in order to estimate the friction coefficient as accurately as possible, even in a situation where an acceleration smaller than the grip limit acts on the vehicle, the algorithm is designed to store and use the largest friction coefficient value calculated as the sum of the largest accelerations experienced so far.

This study aims to improve the agility of high-performance vehicles, which differs from the ELSD study of sports utility vehicles. To enhance the driving performance of high-performance vehicles, the operation time delay and performance of the ELSD system play a crucial role. Therefore, precise estimation of tire–road friction coefficients is important in improving vehicle agility.

In research related to electronic differential device control, an electronic differential device controller is designed to improve the performance of high-performance electric vehicles [16,17]. Slip angle proportional–integral–derivative feedback control is performed to improve cornering stability through side-slip angle reduction and yaw-rate optimization. When controlling the electronic differential device, since the limited performance of the vehicle and the control intervention point are not considered, the driving torque feedback control to satisfy the target behavior may cause unstable vehicle behavior. Another problem is that the system may find it difficult to intervene when control is required because of the delay time up to the maximum torque when operating the drive motor actuator. The predictive control algorithm proposed in this study can solve this problem by predicting the driving wheel spin in advance through tire–road friction estimation and enable improved control.

2. Model-Based Wheel Spin Predictive Control

The inner wheels of FWD vehicles spin when a driving torque greater than the inner-wheel grip is applied because of an increase in acceleration during turning. This spinning results in understeer and a reduction in exit acceleration. Therefore, these can be overcome by controlling the inner-wheel slip via ELSD when the inner-wheel speed becomes greater than the outer-wheel speed via inner-wheel spin during an accelerated exit, as shown in Figure 2.

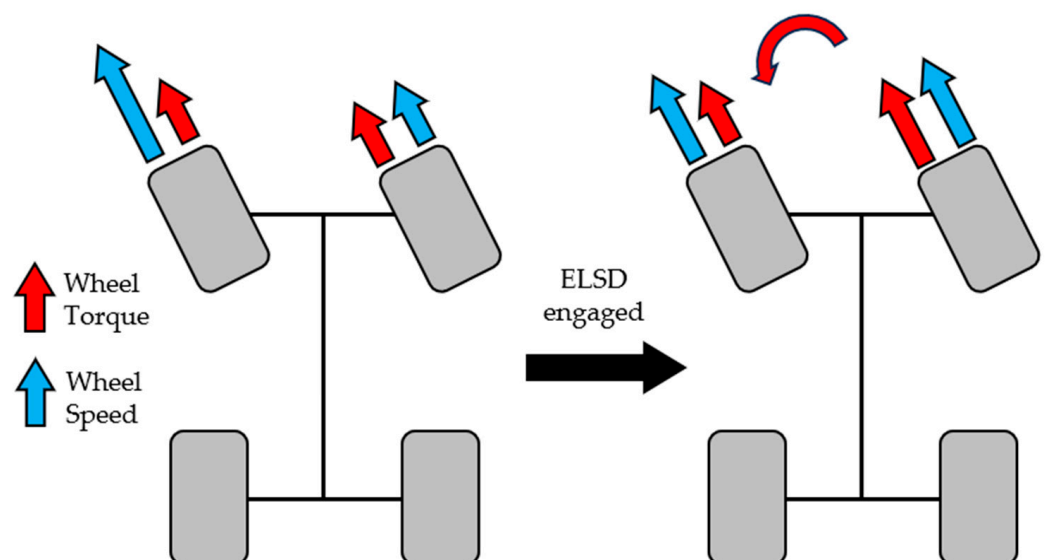


Figure 2. Wheel spin and understeer reduction when ELSD is operated.

However, if control is performed after wheel slip is observed, then the initial wheel spin cannot be controlled properly because of the time delay in the system operation, as shown in Figure 3.

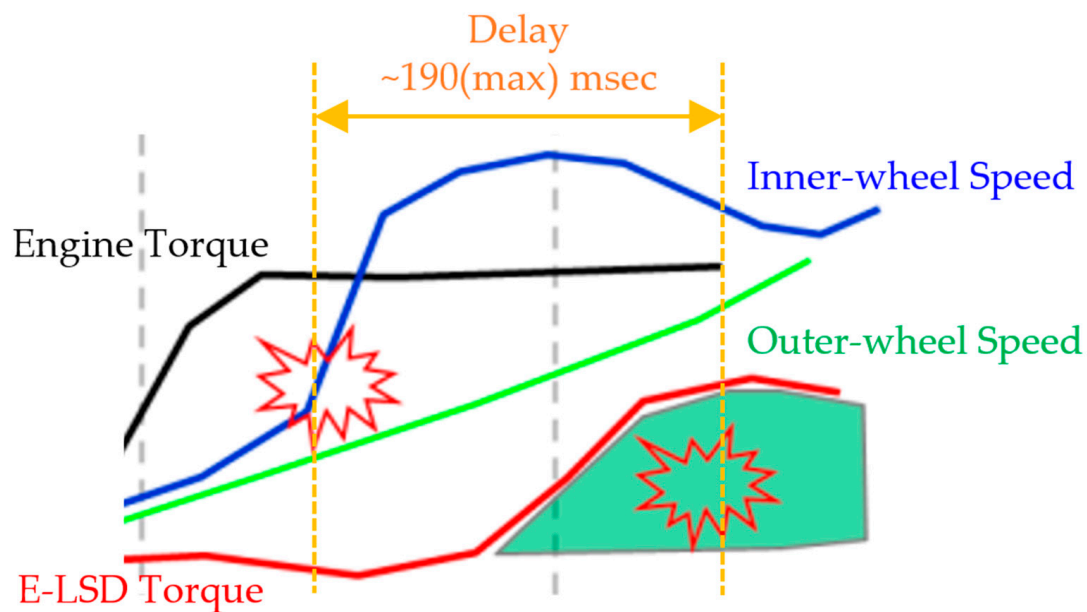


Figure 3. The concept of ELSD intervention time delay.

Figure 3 shows the engine torque, wheel speed, and ELSD engaging torque, respectively, with respect to time. The driving torque from the engine is presented in a black line. The inner-wheel speed is illustrated in a blue line. The green line represents the outer-wheel speed. The red line represents the engaging torque of ELSD. The time delay consists of two parts. One is the slew rate via the ELSD actuator, and the other is zero-order hold by the sampling time of the controller. The maximum delay by the actuator to ramp up to maximum torque is 180 msec. The sampling time of the control logic is 10 msec; therefore, the maximum total time delay is 190 msec, and the intermediate total time delay is 95 msec, as shown in Figure 4.

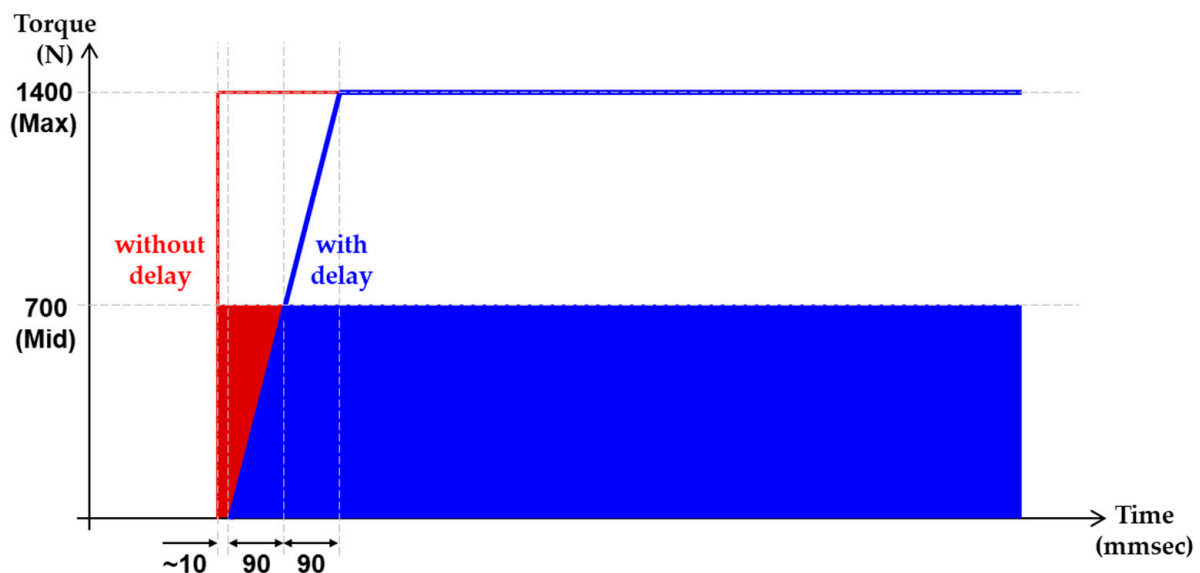


Figure 4. Delay characteristic of ELSD with proposed logic.

Figure 4 represents ELSD engaging torque with respect to time. If the ELSD intervention time is moved too far forward to prevent, this problem and the differential gear is locked when the speed of the outer wheel increases, then a reverse effect that increases understeer occurs, as shown in Figure 5. Thus, a controller that can predict inner-wheel slipping in advance and perform suitable pre-emptive control is required.

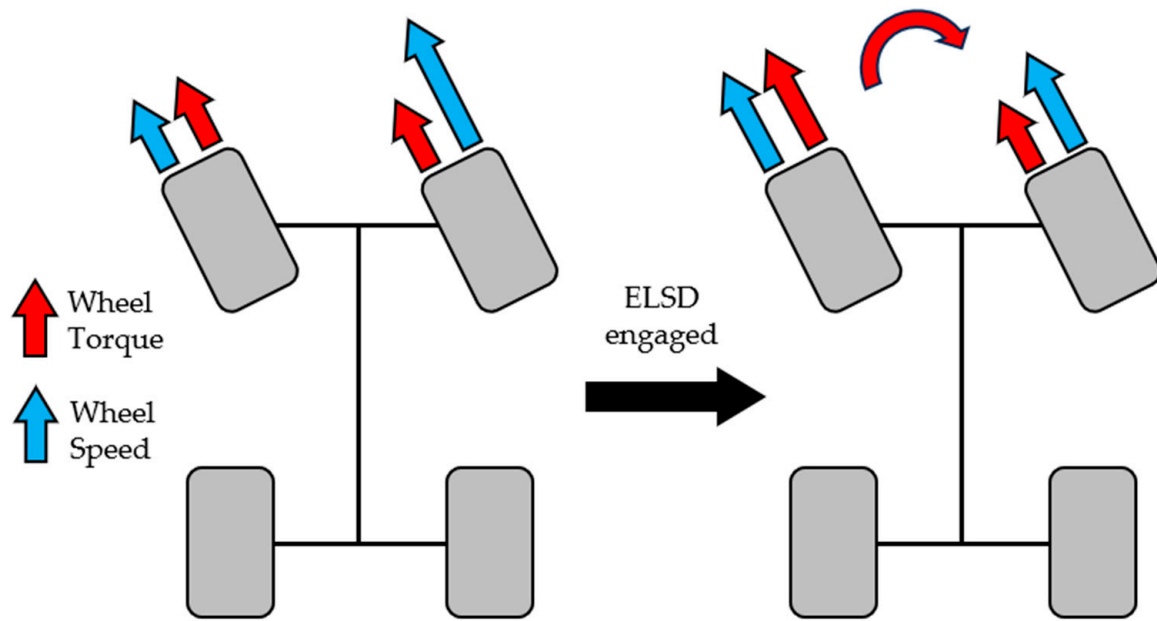


Figure 5. Increase in understeer due to early operation of ELSD.

3. Allowable Driving-Force Prediction Modeling

A control algorithm was created to predict inner-wheel spinning during acceleration while turning and calculate the friction limit at which the inner wheel can be driven in real time. The results were used to transfer the driving force acting on the inner wheel to the outer wheel by the amount that exceeds the calculated limit. In the model that calculates the inner-wheel friction limit in real time, the lateral acceleration sensor signal value was used as the input to calculate the load transfer through which the vertical load of the inner wheel could be estimated during turning, as shown in Figure 6. The inner-wheel friction limit was then calculated as the product of the friction coefficient of the road surface and the inner-wheel vertical load [18].

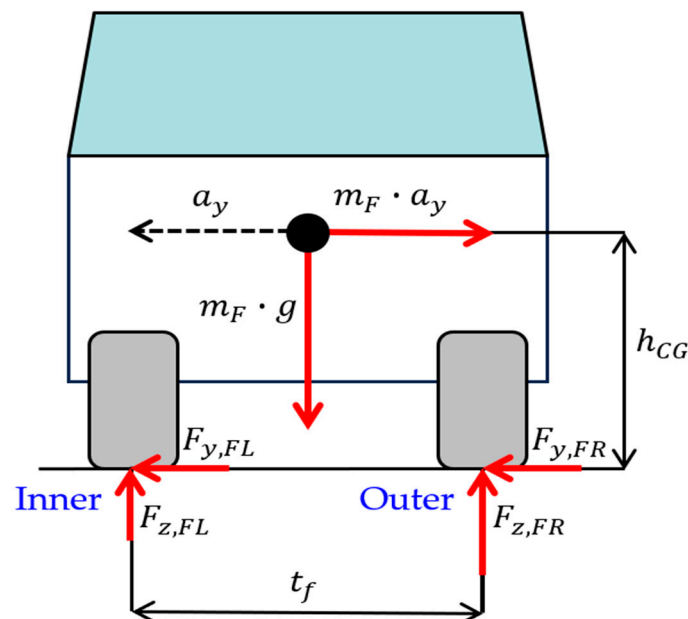


Figure 6. Load transfer model that uses lateral acceleration.

However, according to the tire-friction circle concept, the driving force limit can be reduced by the extent of the lateral force, even with the same resulting friction limit.

Therefore, an allowable driving-force prediction model was created according to the lateral force, as shown in Figure 7, using the following equations.

$$F_{x_max}^2 + F_y^2 = (\mu \cdot F_z)^2 \quad (1)$$

$$F_{x_max} = \sqrt{\mu^2 - \left(\frac{a_y}{g}\right)^2} \cdot F_z \quad (2)$$

where F_{x_max} is the allowable tire driving force, F_y is the tire lateral force, μ is the friction coefficient, F_z is the tire vertical force, a_y is the lateral acceleration, and g is the gravity acceleration. Hence, the logic is designed for the ELSD clutch to be engaged in proportion to the amount that the real driving force from the powertrain exceeds the allowable driving force of the inner wheel. Therefore, ELSD is activated when the engaging value is greater than F_{On} , which means that inner-wheel spin occurs because the driving force of the engine is greater than the allowable driving force, as shown in Figure 1 and determined by the following equations.

$$\frac{F_{Drive}}{2} = \frac{T_{drive} - I_{drive} \cdot \ddot{\theta}_{drive}}{2 \cdot R_{tire}} \quad (3)$$

$$T_{ELSD_WSP} = 2 \cdot \left(\frac{F_{drive}}{2} - F_{x_max_in} \right) \cdot R_{tire} \quad (4)$$

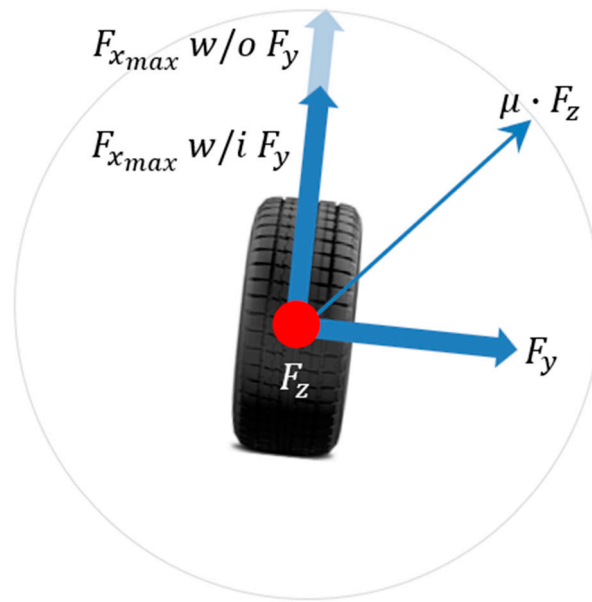


Figure 7. The driving force limit according to the acting lateral force.

Activate when

$$\left(\frac{F_{drive}}{2} - F_{x_max_in} \right) \geq F_{On} \quad (5)$$

Deactivate when

$$\left(\frac{F_{drive}}{2} - F_{x_max_in} \right) < F_{Off} \quad (6)$$

where T_{ELSD_WSP} is the ELSD control torque determined by the wheel spin predictive control, $\frac{F_{drive}}{2}$ is the driving force from the powertrain to each wheel, I_{drive} is the rotational inertia of the driveline, $\ddot{\theta}_{drive}$ is the rotational acceleration of the driveline, R_{tire} is the tire radius, $F_{x_max_in}$ is the inner-wheel traction limit, $F_{x_max_out}$ is the outer-wheel traction

limit, F_{On} is the driving force offset to activate the predictive control, and F_{Off} denotes the driving force offset to deactivate the predictive control.

4. Tire-Friction Coefficient Estimation and Vehicle Safety

The fidelity of tire–road interaction modeling is a critical factor in predicting vehicle behavior under various driving conditions. We present a simulation study using CarSim software to explore the vehicle dynamics during lane-change maneuvers on a low-friction surface, focusing on the impact of the tire-friction coefficient on vehicle safety.

The simulation replicates a lane change at 60 km per hour on a snowy road with a friction coefficient (μ) of 0.2. The steering wheel angle input is modeled as a sine wave, representing the response to the driver-initiated maneuver. This input is particularly used to study the effect of minimal steering on the side-slip angle of the vehicle in low-friction environments. The results in Figures 8 and 9 highlight a pronounced sensitivity of the vehicle side-slip angle to small steering inputs under low friction conditions. The simulated lateral dynamics in Figure 8 show that even with minimal steering angle inputs, the side-slip angle can significantly increase, leading to potential instability, as shown in Figure 9. These findings are critical as they demonstrate the nonlinear vehicle response to steering inputs under lowfriction surfaces.

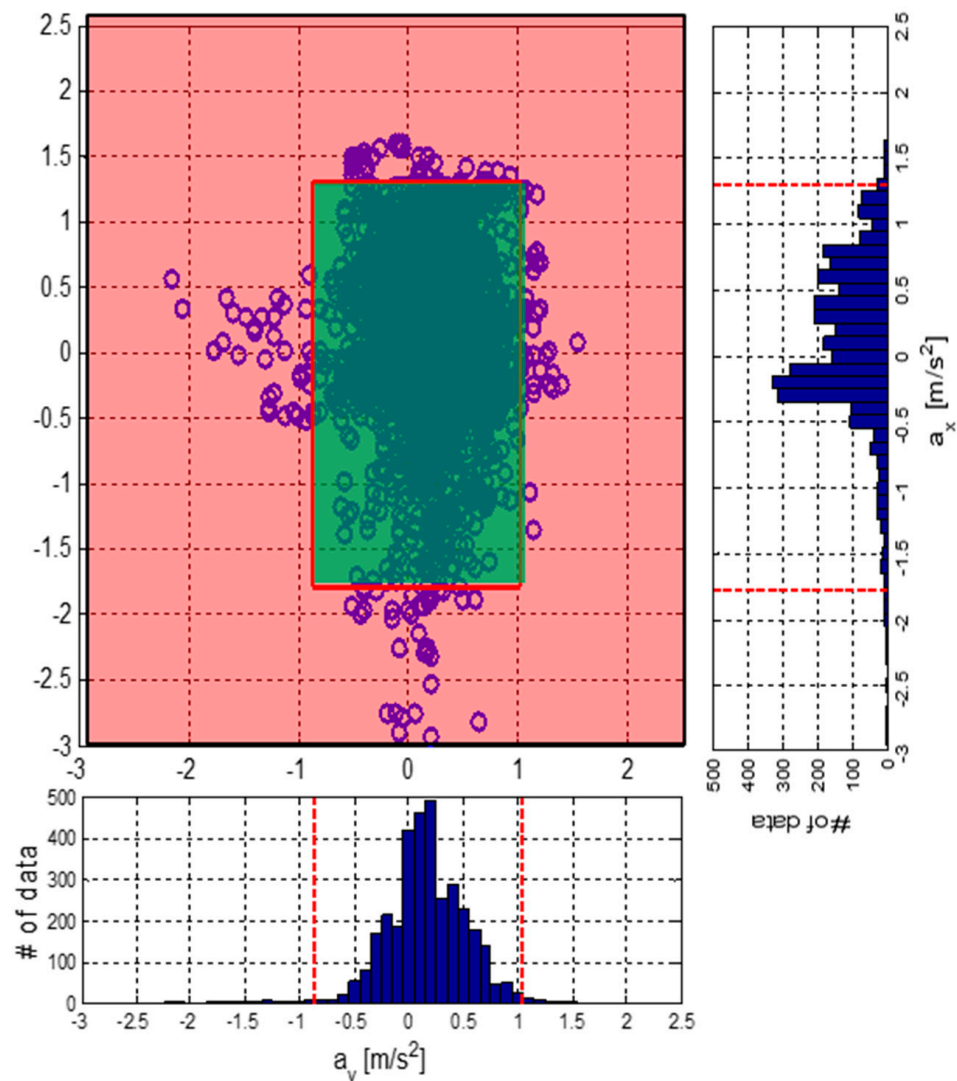


Figure 8. Simulation studies: lateral dynamics.

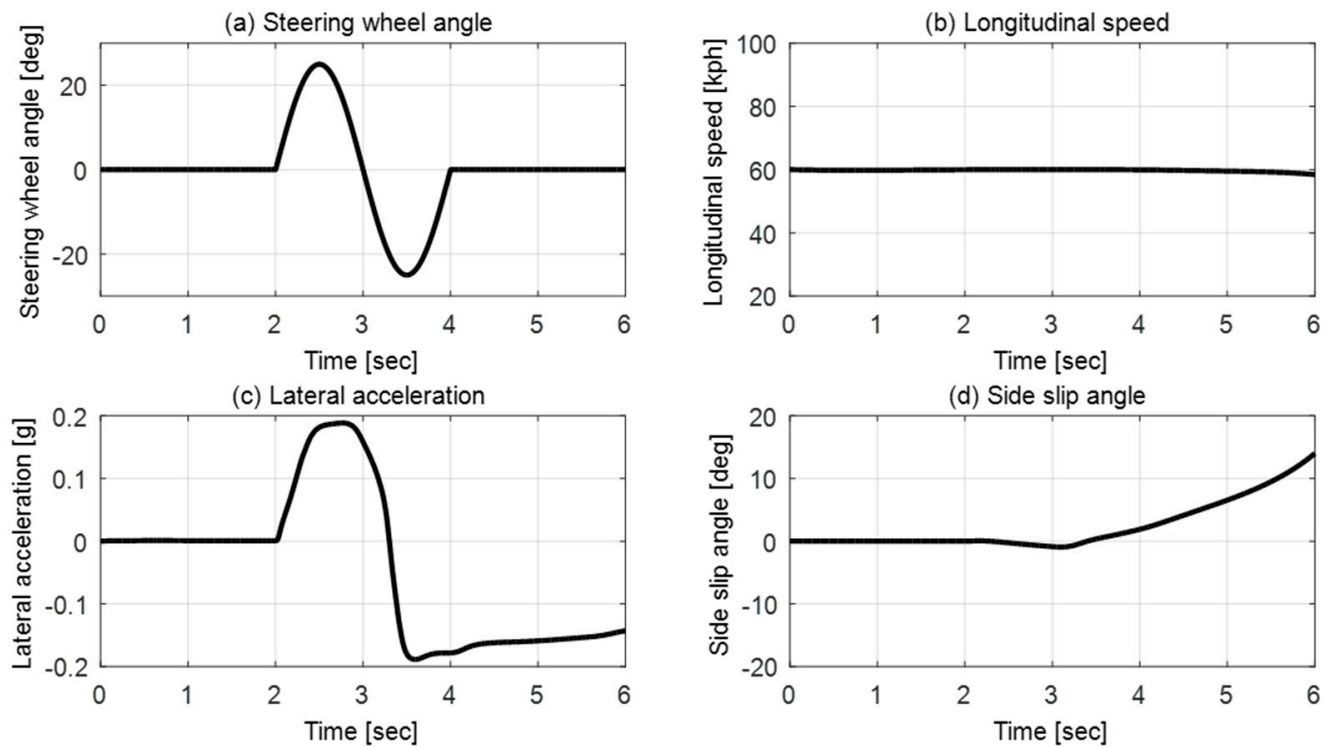


Figure 9. Simulation studies. (a) Steering wheel angle; (b) longitudinal speed; and (c) lateral acceleration; (d) side slip angle.

These findings underscore the critical role of accurately estimating the tire–road friction coefficient for the development and refinement of advanced driver-assistance systems (ADAS) and active safety systems. Given the challenges in obtaining extensive experimental data under varied conditions, our study utilizes the highly realistic CarSim simulator to model vehicle responses. This simulation-based methodology supports our analysis of vehicle stability limits and the activation of countermeasures, offering a viable alternative to direct experimental comparison yet delivering credible insights into enhancing vehicle safety.

5. Tire–Road Friction Estimation to Improve Predictive Control

To reduce wheel speed feedback control intervention, the accuracy of the wheel spin predictive control can be improved by predicting the friction coefficient of the road surface. The prediction model for the allowable driving force is based on the road-friction coefficient; thus, an accurate estimation of the tire–road friction is required. If a tire–road friction estimation error occurs and the estimated value is smaller than the actual, as shown in Figure 10, the ELSD control intervenes before the optimal time, which means that the clutch is engaged before the inner wheel spins. It can cause the opposite effect, which increases the understeer as a result of limited side differential effect in no wheel spin condition. Conversely, if the estimated tire–road friction is larger than the actual tire–road friction, the amount of understeer control may be insufficient during inner-wheel slip because of the delay in the ELSD operation.

5.1. Tire–Road Friction Estimation System

The friction-estimation circles are presented using three lines. The exact estimation, under-estimation, and over-estimation cases are presented in green, red, and blue, respectively. There are several methods for estimating tire–road friction. For the ELSD system to provide optimal control at the time of wheel slip, the friction value is estimated by real-time monitoring of the driving torque when wheel slip occurs, as shown in Figures 11 and 12, and the following equations.

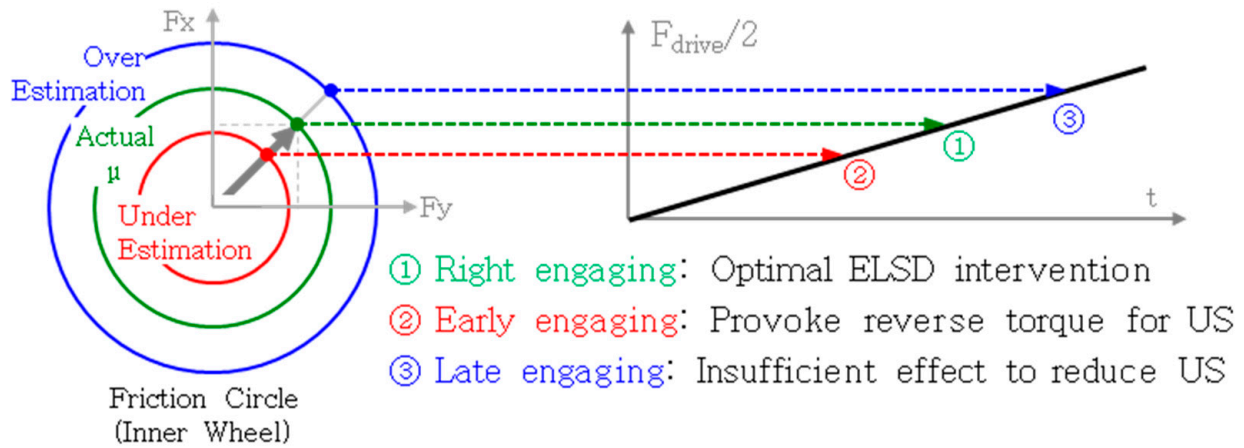


Figure 10. The concept of ELSD intervention time via friction estimation.

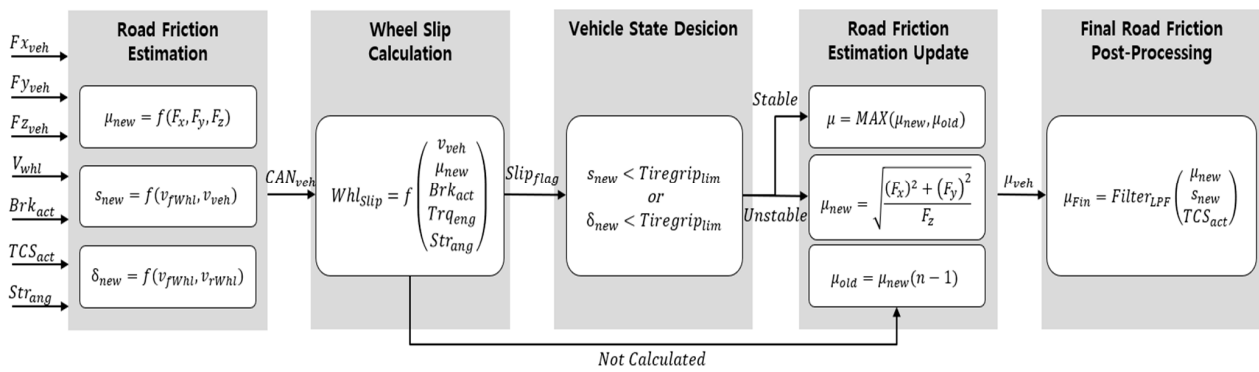


Figure 11. Tire-road friction estimation system architecture.

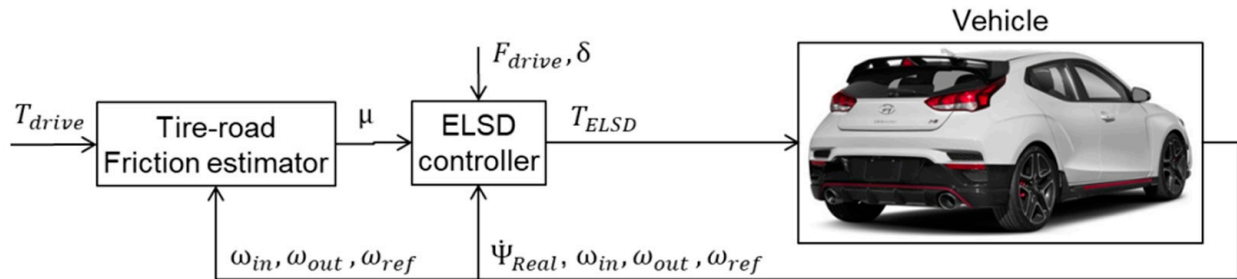


Figure 12. Control logic diagram for tire-road friction estimation.

The road-friction coefficient estimation system uses information from the controller area network communication of the vehicle to calculate longitudinal, lateral, and vertical forces, thereby estimating the primary friction coefficient. To update the initially estimated friction coefficient, the system checks the feasibility of calculating wheel slips based on the current road conditions. It assesses the driving state of the vehicle by examining the speed difference between the vehicle and the driven wheels, as well as the speed difference between the front and rear wheels.

In unstable conditions, such as significant wheel slip where tire grip exceeds the road-friction limit, the system employs values close to the road-friction coefficient. In stable conditions with minimal wheel slip, it selects the larger value between the calculated and the existing friction coefficient values, facilitating a rapid convergence to the actual friction coefficient. While adjusting the cutoff frequency of the low-pass filter according

to the driving state of the vehicle, the system ultimately filters the estimated road-friction coefficient for use in ELSD predictive control.

$$\mu = \frac{\sqrt{F_x^2 + F_y^2}}{F_z} \quad (7)$$

$$F_x = \frac{T_{drive} - I_{drive} \cdot \ddot{\theta}_{drive}}{R_{tire}} \quad (8)$$

$$F_y = m \cdot g \quad (9)$$

$$F_z = m \cdot g \quad (10)$$

The road-friction coefficient estimation considers not only longitudinal forces based on driving torque (T_{drive}), driveline rotational inertia (I_{drive}), and rotational acceleration ($\ddot{\theta}_{drive}$) but also lateral forces generated by steering maneuvers.

Because the electronic stability control (ESC) system operates in the region of the grip limit, the friction coefficient calculated at this time is close to the actual friction value. However, it is necessary to estimate the friction coefficient for ELSD at all times while in operation. Therefore, in the region of the grip limit (unstable wheel slip region that is above the wheel slip criterion value), the instantaneous calculated value is estimated to be the real-time friction coefficient, as in ESC shown in Table 1.

Table 1. Tire–road friction values according to the wheel slip rate category.

Situation	Mu Estimation	Low-Pass Filter
Unstable (Big Slip Ratio)	$\mu(n)$	Cutoff Frequency Low
Stable (Small Slip Ratio)	$\max[\mu(n-1), \mu(n)]$	Cutoff Frequency High

$\mu(n)$: Friction coefficient calculated in real time.

$M(n-1)$: Friction coefficient calculated just before in other regions, minor speed differences occur between the driving and non-driving wheels during moderate acceleration, and the corresponding engine torque is low. Therefore, the calculated friction values are continuously low. Hence, this was defined as the stable region (stable wheel slip region, below the wheel slip criterion value). In this region, the friction coefficient is estimated to be the larger of the current friction coefficient and the previous friction coefficient.

5.2. Tire–Road Friction Estimation Results

The above method was used to increase the tire–road friction estimation accuracy while also resolving the problem of underestimating the tire–road friction value during normal grip driving conditions, as shown in Figure 13 and Table 2.

Figure 13 presents the unstable status flag and friction values with respect to time. The unstable status flag is represented by the green line. The friction coefficient calculated in real time is illustrated by a blue line. A black line represents the friction coefficient estimated at the end.

To confirm the superiority of the tire–road friction coefficient estimation logic proposed in this paper, we compared the friction coefficient estimation results with previously studied estimation methods. In Figure 14, Type 1 is a method used to calculate the friction coefficient using only longitudinal acceleration. Unlike the proposed method (Type 3), the calculated value is used as is in stable situations; thus, in sections where there is no rapid acceleration, the problem of the friction coefficient falling to a lower value than the actual friction coefficient can occur. Since lateral acceleration was not used, there is a situation where the

friction coefficient is calculated using a small amount of acceleration, underestimating the friction coefficient. Type 2 predicts the tire–road friction coefficient using a tire model based on longitudinal force and wheel slip ratio. Figure 15 presents the measuring data about the relationship between wheel slip ratio, longitudinal force, and tire–road friction coefficient and the fitting curve from the model, which is built using the measuring data. Since this method estimates the friction coefficient using the slope information of the longitudinal force relative to the slip ratio, it can be seen that it overestimates even when the slope measurement is slightly large and underestimates it even when the slope measurement is slightly small. In other words, the sensitivity to measurement errors is high. Moreover, when operating under conditions different from the measurement data used to build the friction estimation model, the reliability of the estimated value inevitably decreases. For example, if the operating temperature of the tire, the wear state of the tire, or the type of tire changes, it is difficult to trust a model created using existing measurement data. Type 3, proposed in this paper, calculates the friction coefficient by adding the longitudinal and lateral acceleration characteristics. Therefore, even in the turning section where the driving force is not applied as much as the friction limit, the calculated friction coefficient is close to the actual friction coefficient according to the lateral acceleration characteristics. In stable conditions, which is a section where longitudinal and lateral accelerations are small, the problem of lowering the estimated friction coefficient can be seen to be solved by maintaining the previously calculated high friction coefficient.

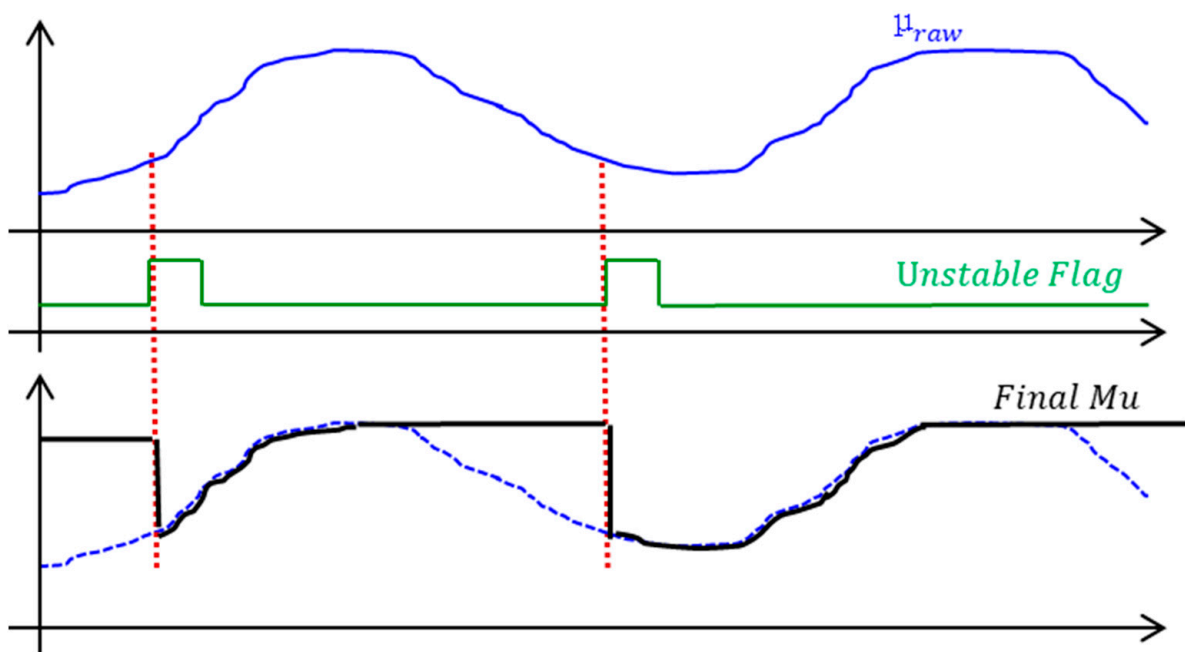


Figure 13. Tire–road friction estimation results.

Table 2. Tire–road friction estimation results compared to actual tire–road friction.

PG	Boxberg PG				Nürburgring
Road Surface	Wet Asphalt	Wet Concrete	Wet Basalt	Wet Urethane	Dry Asphalt
Defined Value	0.60	0.50	0.30	0.20	-
Measured	0.56	0.43	0.24	0.18	0.92
Estimated	0.58	0.44	0.26	0.19	0.94

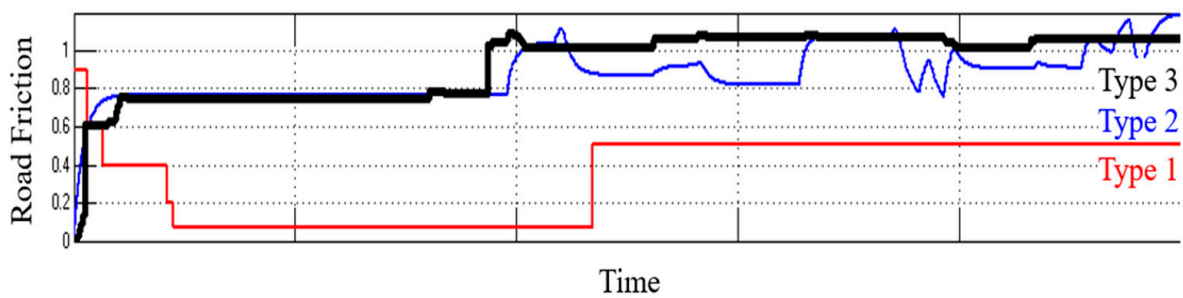


Figure 14. Validation results of tire–road friction coefficient.

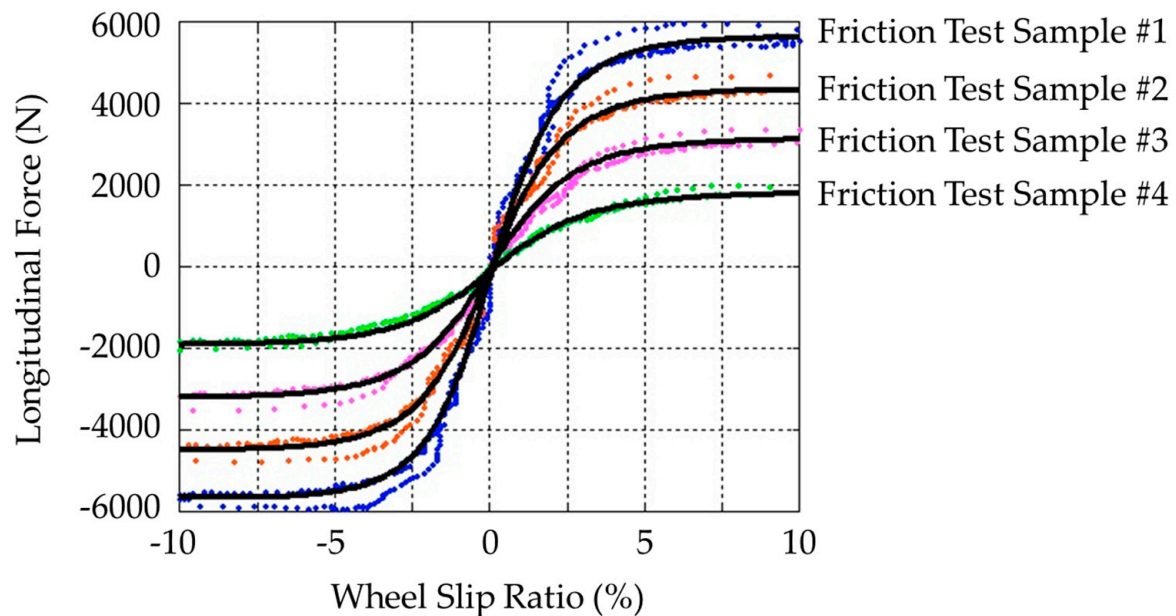


Figure 15. Correlation between wheel slip ratio and longitudinal force.

The coefficient of friction estimate obtained using the proposed method converges more quickly to the actual coefficient of friction of the road surface the closer the driver drives to the limits of road grip. Therefore, friction estimates obtained using this method are suitable for ELSD, primarily due to the racetrack driving characteristics at which ELSD is effective, as shown below.

- Use longitudinal or lateral acceleration largely.
- Repeat the designated course.

6. Conclusions

A tire–road friction estimation method for a predictive control strategy to improve the handling and acceleration performance of FWD high-performance vehicles with ELSD has been described. The disadvantages of FWD high-performance vehicles can be overcome through predictive control strategies alongside our advanced friction-estimation methods. The proposed algorithm estimates the friction coefficient of the tire–road surface with high accuracy to improve the accuracy of wheel spin predictive control. When wheel slip occurs, the driving torque is monitored in real time to estimate the coefficient of friction, and since it operates in the tire-grip limit area, it is possible to estimate the value close to the actual coefficient of friction. In stable driving conditions where wheel spin does not occur, the friction coefficient is calculated with an acceleration force smaller than the actual friction limit. Therefore, it is possible to estimate a friction coefficient close to the actual using the friction coefficient calculated as the largest value among the acceleration forces experienced so far. To experience acceleration forces that approach the actual friction limit as quickly as

possible, the friction coefficient was calculated using the total acceleration force, that is, the sum of longitudinal and lateral acceleration forces.

The results of the vehicle driving test confirmed that the friction coefficient estimated by the proposed algorithm was almost the same as the actual friction coefficient. It was possible to improve the accuracy of ELSD prediction control by estimating the friction coefficient close to the actual one. The proposed algorithm was verified through patents on the control method and friction-estimation method for the research novelty [19,20]. The ELSD with the proposed algorithm was then applied to mass production. This approach received positive feedback from international media due to the significant improvements in vehicle performance via ELSD.

The system with the proposed algorithm also won the IR52 Jang Young-shil Award for its technological importance, originality, economic value, and technical spill-over effect (Hyundai Motor Company 2020, Seoul, Republic of Korea) [21].

Author Contributions: Conceptualization: S.W. and D.S.; Methodology: S.W.; Software: S.W.; Validation: E.J. and S.W.; Formal analysis: D.S. and E.J.; Investigation: E.J. and D.S.; Resources: S.W.; Data curation: E.J.; Writing—original draft preparation: S.J.; Writing—review and editing: S.W. and S.J.; Visualization: S.J.; Supervision: S.W.; Project administration: S.W.; Funding acquisition: S.W. All authors have read and agreed to the published version of the manuscript.

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