Adaptive Scheme for the Real-Time Estimation of Tire-Road Friction Coefficient and Vehicle Velocity

Kyoungseok Han, Eunjae Lee, Mooryong Choi, and Seibum B. Choi, *Member, IEEE*

***Abstract*—It is well known that both the tire-road friction coefficient and the absolute vehicle velocity are crucial factors for vehicle safety control systems. Therefore, numerous efforts have been made to resolve these problems, but none have presented satisfactory results in all cases. In this paper, cost-effective observers are designed based on an adaptive scheme and a recursive least squares algorithm without the addition of extra sensors on a production vehicle or modification of the vehicle control system. This paper has three major contributions. First, the front biased braking characteristics of production vehicles such that the front wheel brake torques are saturated first are exploited when estimating the tire-road friction coefficient. Second, the vehicle absolute speed is identified during the friction coefficient estimation process. Third, unlike the conventional method, this paper proposes using already available excitation signals in production vehicles. In order to verify the performance of the proposed observers, experiments based on real production vehicles are conducted, and the results reveal that the proposed algorithm can enhance the performance of any vehicle dynamics control systems.**

***Index Terms*—Adaptive law, braking characteristics, excitation signal, tire-road friction coefficient, tire stiffness, vehicle absolute speed.**

I. Introduction

MOST DRIVERS rarely experience dangerous situations such as wheels locking up or un-steerable conditions during general driving. For this reason, the importance of vehicle safety control systems has become increased only after avoiding such situations with an aid of active chassis control systems. Consequently, the mandatory installation of safety control systems for newly released vehicles is becoming more common in automotive companies and institutes.

According to a technical report on chassis control [1], rule-based control algorithms are predominantly used to manage the numerous practical concerns. Because unpredictable situations occur frequently in the real world, and these cannot be described using prevailing theory, the use of a rule-based algorithm that considers as much data as possible is inevitable to provide appropriate safety margins for production vehicles. However, these algorithms typically impose very severe computational burdens on the vehicle's electronic control units (ECU) because the control systems should be designed to consider all possible driving conditions.

For this reason, numerous attempts have been made to resolve this problem. For example, the state feedback control for the active control system [2]–[5] can simplify the algorithm complexity where tire-road friction coefficient is well known as the most important state enabling the prediction of a vehicle's behavior. However, the tire-road friction coefficient varies significantly for different road surfaces and cannot be easily obtained in real-time for numerous reasons.

Some notable conventional safety control systems include antilock brake system (ABS) [6], [7] and electronic stability control [2]. Both systems have areas of commonality, i.e., they need to adjust the individual tire force in order to achieve the desired vehicle motion. If the maximum tire-road friction coefficient is accurately estimated in real-time using the data given in a production vehicle, novel safety control laws can be designed that resolve the above problems.

Such a necessity for the accurate state estimation has increased the importance of studies on peak friction coefficient estimation and numerous published studies have proposed various approaches. Within these approaches, one widely chosen for estimating the friction coefficient is the tire stiffness-based method originally proposed in [8] with more recent developments being presented in [9]–[12]. Another approach is the dynamic-based method [13], which often requires additional sensor information such as global positioning system (GPS) information or specific motor signals associated with steering

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K. Han and S. B. Choi are with the Department of Mechanical Engineering, Korea Advanced Institute of Science and Technology, Daejoen 305701, South Korea (e-mail: hks8804@kaist.ac.kr; sbchoi@kaist.ac.kr).

E. Lee is with Hankook Tire Co., Ltd., Daejoen 305701, South Korea (e-mail: asphaltguy@hankooktire.com).

M. Choi is with Hyundai Motors Group, Uiwang-si 16082, South Korea (e-mail: mucho@hyundai.com).

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[14]–[16] and driving [17]. In these methods, lateral dynamics are usually considered in order to excite the estimators, but the longitudinal dynamics are excluded from the algorithms. In [18]–[21], both longitudinal and lateral dynamics are considered in order to deal with the combined slip condition.

Although significant developments have been made in tire-road friction coefficient estimation in recent decades, the proposed algorithms are yet to be used in production vehicles for numerous reasons. One of the challenges is that several of the proposed methods require extensive maneuvering of the vehicle such as severe accelerating, decelerating, and steering. That is, specific vehicle motions are required to excite the estimation algorithm before the goal is achieved.

In order to resolve this problem, this paper proposes an early detection algorithm of the friction coefficient using only the signal when the vehicle is decelerating mildly.

Furthermore, as in the previous studies, the tire model is used to represent the friction coefficient as a state [22]–[25]. For example, the most well-known tire model for vehicle dynamics, i.e., the Fiala brush tire model, can express the tire force using the normal force, tire slip, cornering stiffness, and tire-road friction coefficient. A challenge in this model is that additional estimations should be conducted in order to obtain the ultimate state like friction coefficient or tire force. That is, the normal force, individual tire slip, and cornering stiffness should be identified accurately in order to represent the tire force. If the aforementioned additional estimations have inferior results, they can also deteriorate the estimation performance of the final state. This issue is the reason why the previous methods assume that these states are measurable or have known values.

In order to increase the feasibility of the proposed algorithm being implemented in production vehicles, these practical concerns are considered and a solution to this problem is proposed in this paper.

In addition, the individual tire slip is the most difficult to obtain since the absolute vehicle velocity is required to represent the tire slip, but it cannot be obtained easily while braking. In fact, the vehicle velocity at a constant speed or while accelerating has almost the same value as the un-driven wheel speed, which is a readily available signal in production vehicles. Therefore, the vehicle velocity can be replaced with the un-driven wheel speed in those conditions. However, it is not the case during the braking. For this reason, an accurate vehicle velocity estimation method while braking is also proposed in this paper, based on the tire-road friction coefficient estimation results.

This paper uses some assumptions from previous works, particularly in [8], [9]. In those works, the peak tire-road friction coefficient is assumed to be represented by the tire stiffness, and they concentrated on estimating the tire stiffness in real-time.

In this paper, the proposed algorithm also identifies the tire stiffness using an adaptive scheme, but the braking characteristics of the production vehicle are used to improve the estimation performance.

The main differences that clearly distinguish this paper from the previous methods are summarized as follows. First, the estimation steps are reduced using the vehicle's braking characteristics. Unlike the previous works, this paper eliminates the tire slip identification step from the overall structure, thereby reducing the likelihood of performance degradation associated with the tire slip estimation.

In order to prevent oversteering, most production brake systems are designed to be front biased such that the front wheel brake torques are saturated first. Therefore, front wheel slips tend to be larger than the rear ones during the braking. Using these characteristics, it is possible to take an advanced approach to removing the tire slip estimation step.

In addition, a novel vehicle velocity observer is constructed using only the wheel speeds and longitudinal acceleration. The inverse tire model is used in this process to estimate the tire slip, which contains the vehicle velocity, and the recursive least square (RLS) method is adopted to obtain the tire slip. This scheme differs from the existing methods, where the longitudinal dynamics model including many uncertainties, such as mass, road slope, and other related forces, is used to obtain the vehicle speed [26]. The most widely adopted method to obtain the vehicle velocity is the use of an additional sensor such as GPS or an estimation scheme [11]. However, accurate estimation of the vehicle velocity is difficult for many reasons.

Last, the proposed algorithm is verified in a real production vehicle in order to manage practical concerns. The experimental results reveal that early identification of the tire-road friction limit is possible with fewer estimation steps than the conventional works.

The remainder of this paper is organized as follows. In Section II, the existing approaches are reviewed briefly in order to differentiate this study from previous works. The detailed description of the proposed algorithm is presented in Section III. Experiments with a production vehicle on various road surface conditions demonstrate the performance of the proposed observers in Section IV. Finally, conclusions are presented in Section V.

II. Literature Review

Several authors have assumed that tire stiffness, which is proportional to its slip ratio in the low slip region, has differentiable values according to the road surface conditions. Therefore, they have insisted that a well-estimated tire stiffness can be used to calculate the tire-road friction coefficient.

These approaches have been adopted in [8]–[12] and this paper is also motivated from the tire stiffness-based approaches. Differing to the works in [8]–[12], this paper establishes a new observation strategy using the vehicle's braking characteristics.

In this section, an important aspect of the published results [8]–[12] is briefly reviewed and the limitations of its performance are discussed. The tire stiffness-based approaches use the following common framework as depicted in Fig. 1, where the ultimate goal is to obtain the tire stiffness in real-time. The critical issue of the previous architecture is that additional tire force and tire slip estimations should be performed in order to achieve the goal.

If satisfactory additional estimation results are not guaranteed, the tire stiffness estimation result is also significantly

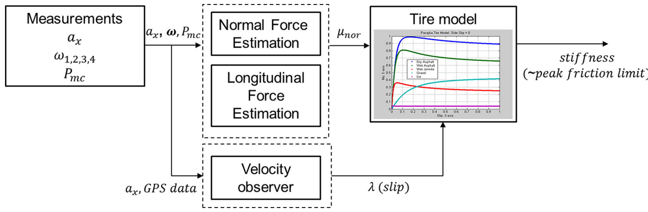

Fig. 1. Tire stiffness-based tire-road friction coefficient estimation framework.

affected by the estimation results. It is generally believed that the tire force can be predicted relatively easily when the vehicle is traveling in a straight line. However, none of the tire slip estimations are accurate during braking, although there have been many efforts to estimate it. For this reason, the algorithm to estimate the tire forces proposed in this paper is very similar to the previous algorithms, but a novel tire slip estimation algorithm is introduced with the objective of being implemented on a production vehicle without the addition of extra sensors.

The relationship between the normalized tire force and the tire slip is formulated using (1)

$$\mu_{\text{nor}} = \frac{\hat{F}_x}{\hat{F}_z} = C_x \cdot \lambda \tag{1}$$

where μ_{nor} is the normalized tire force, $\hat{F}_x$ and $\hat{F}_z$ are the estimated longitudinal tire force and normal force, respectively, C_x is the tire stiffness, and λ is the tire slip.

The ultimate goal of the tire stiffness-based approach is to estimate C_x (estimated parameter) in real-time based on λ (input regression, an estimated or measured value) and μ_{nor} (measured output, an estimated value).

The RLS method [27] has been widely adopted to identify tire stiffness in real-time. Details of the background principles are described comprehensively in [9] and [11].

The tire slip during braking can be written as follows:

$$\lambda_f = \frac{V - rw_f}{V} \tag{2}$$

$$\lambda_r = \frac{V - rw_r}{V} \tag{3}$$

where λ_f and λ_r are the front and rear tire slip, respectively, V is the absolute vehicle speed, r the effective radius of wheel, and w_f and w_r are the front and rear wheel speed, respectively.

The only unknown value in (2) and (3) is the absolute vehicle speed because production vehicles equipped with ABS provide accurate wheel speed information in real-time, if the vehicle travels faster than 10 km/h. Also, the effective radius of the wheel is assumed to be known. The absolute vehicle speed can be calculated out of GPS signal [28], [29]. However, influenced by the noise of wheel speed and GPS measurements, the calculated slip ratio oscillates significantly as described in the next section. In addition, the effective radius of wheel, which is assumed to be constant, can fluctuate significantly by many factors such as tire pressure and type of road surface. Consequently, inaccuracy in the effective radius of wheel also affects the estimation performance.

Furthermore, GPS-based measurements are not quite dependable in some environments such as urban and forested regions. As a resolution for this issue, an estimation scheme for vehicle speed has been proposed in [11], [26], [30], and [31] using longitudinal dynamics as follows:

$$m\dot{\hat{V}}_x = \underbrace{-F_{\text{aero}}}_{\text{aerodynamic force}} + \underbrace{F_{xf} + F_{xr}}_{\text{longitudinal tire force}} - \underbrace{(R_{xf} + R_{xr})}_{\text{rolling resistance}} - \underbrace{mg\,\sin\theta}_{\text{road inclination}}. \tag{4}$$

Note that many uncertainties that are included in (4) influence the longitudinal dynamics. For example, vehicle mass, which changes according to the number of passengers or amount of luggage, should be estimated as in [32]. Moreover, the road inclination information is not available without an additional estimation scheme as in [33]. The details of the vehicle speed observer well described in [11].

In summary, longitudinal dynamic-based vehicle speed estimation approaches require additional estimation steps, which can affect the final estimation result. In consideration of the practical issues, a more simplified estimation approach for vehicle speed is required.

III. Algorithm Descriptions

A. Braking Characteristics

The wheel dynamics can be described by the following equation:

$$J_\omega \dot{\omega}_\omega = R_e F_x + T_d - T_b - R_e F_{rr} \tag{5}$$

where J_ω is wheel rotational inertia, ω_ω is the wheel angular velocity, R_e is the wheel effective radius, F_x is the tire longitudinal force, F_{rr} is the rolling resistance, and T_d and T_b are drive torque and brake torque, respectively.

The brake torque can be written with the following design parameters for the front and rear wheels:

$$T_{b,f} = k_f P_{\text{mc}} = \mu_{\text{pad}} A_f r_f P_{\text{mc}} \tag{6}$$

$$T_{b,r} = k_r P_{\text{mc}} = \mu_{\text{pad}} A_r r_r P_{\text{mc}} \tag{7}$$

where $T_{b,f}$ and $T_{b,r}$ are brake torques of front and rear wheel, respectively, k_f and k_r are the brake gains, P_{mc} is the master cylinder pressure, μ_{pad} is the pad friction coefficient, A_f and A_r are brake piston effective areas, and r_f and r_r are the brake disc effective radii.

In general, the brake gain at the front wheel is configured to be much larger than the rear one for safety reasons. The tire force has highly nonlinear characteristics including the friction ellipse effect and tire force saturation [22], [34]. If the longitudinal slip goes beyond the stable area, the vehicle cannot be steered due to the coupled effect between the longitudinal force and lateral force. Especially, the tire force saturation at the rear wheel usually causes oversteering, which is the most critical condition to be prevented, due to the loss of lateral force.

Considering these concerns, it should be remembered that the rear wheels are managed to stay in the stable region as much

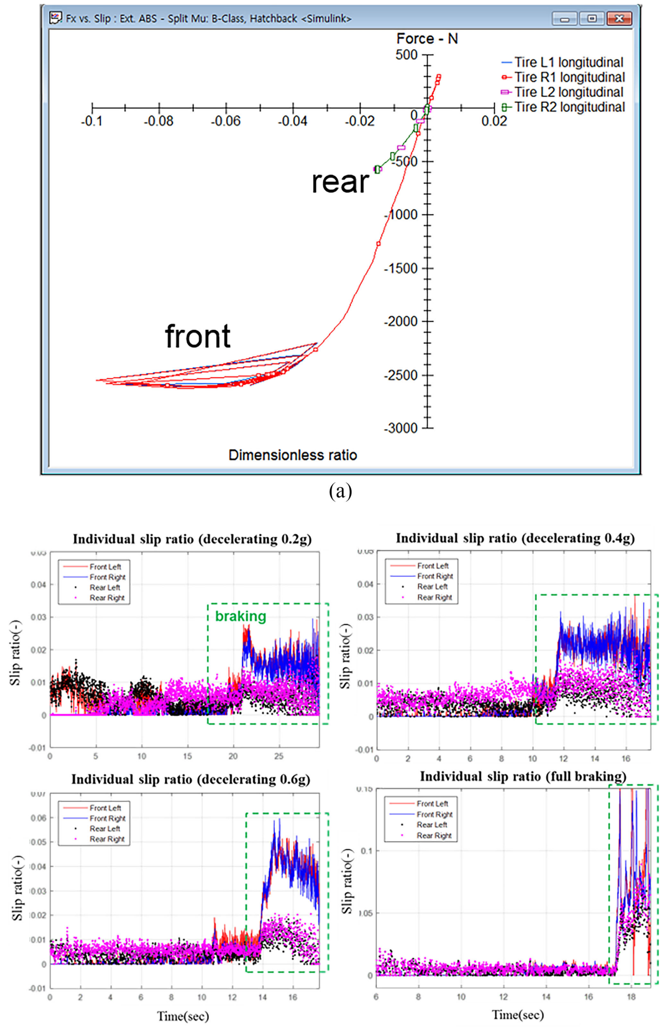

Fig. 2. Braking characteristics. (a) Individual longitudinal tire force versus slip ratio in CarSim. (b) Individual slip ratios with different decelerations in real vehicle.

as possible even when the front wheels move into an unstable region.

In order to verify the aforementioned braking characteristics, the simulation using CarSim, which is a widely adopted vehicle dynamics solver, was conducted as depicted in Fig. 2(a). The target vehicle decelerated on a high mu road surface and the individual longitudinal tire force versus slip ratio plot could be obtained. The plot illustrated the slip difference that existed between the rear wheels and front wheels. The rear tire slip remained in the stable region when the front tire slip reached an unstable region, where ABS was activated.

In order to extend these aspects to a real vehicle, experiments were also conducted. Fig 2(b) depicts the slip ratio for a medium sized car tested on a dry asphalt surface with different levels of deceleration. The slip difference between rear wheels and front wheels was quite distinguished when a greater level of brake force was commanded by the driver.

It should be noted that the goal of this study is detecting the peak friction coefficient of a road surface before the friction

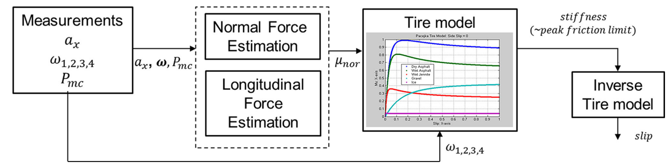

Fig. 3. Overall architecture of the proposed algorithm.

force is saturated and ABS is activated. Thus, consistency of the objective can be maintained. That is, the vehicle speed and tire-road friction coefficient observations for the unstable region are excluded from the scope of this study that is depicted in right bottom plot in Fig. 2(b).

B. Proposed Algorithm Architecture

In this section, overall architecture of the proposed algorithm is introduced, and the improvement of its functionality is briefly discussed.

Most tire-road friction coefficient estimation algorithms are designed based on the tire stiffness estimation, which is depicted on Fig. 1. The most recent study on tire stiffness-based tire-road friction coefficient estimation [11] exhibited satisfactory performance. However, the method requires an additional GPS sensor or vehicle velocity observer in order to estimate the tire stiffness, and its limitation was discussed in Section II.

Fig. 3 describes the overall architecture of the proposed algorithm. The primary difference compared with Fig. 1 is that the tire stiffness can be estimated using only the estimated tire forces and measured wheel speeds.

Moreover, the tire slip is obtained using the inverse tire model. The tire force estimation scheme itself is not significantly different from previous works.

In this way, the estimation scheme can be made to be free from the effect of the error associated with the vehicle speed estimation.

C. Tire Force Estimation

Several estimation schemes for the individual tire forces have been introduced in previous studies [35], [36]. In this paper, a tire force observer that does not require a significant computational burden is developed using both vehicle longitudinal dynamics and wheel dynamics.

It is generally assumed that an individual wheel speed can be measured at all times. Therefore, the longitudinal force can be estimated based on the wheel dynamics in (5) for individual wheels,

$$F_x = \frac{J_\omega \dot{\omega}_\omega - T_d + T_b}{R_e}. \tag{8}$$

The rolling resistance, which is relatively small compared with the other terms, is neglected. Furthermore, the drive torque is assumed to be zero because only the braking condition is considered in this paper.

As seen from Fig. 3, the tire normal forces are also needed to formulate the normalized force in (1), where the deceleration can cause the weight shifting from the rear to the front while

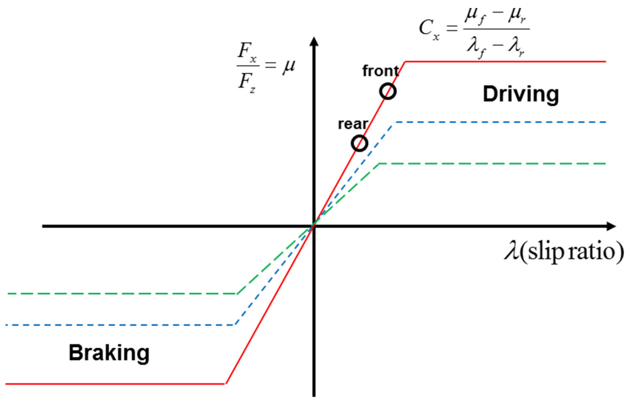

Fig. 4. Mu-slip curve of the linear tire model.

braking. Considering dynamic weight sifting due to the vehicle deceleration, front and rear wheel normal loads are calculated as follows:

$$F_{zf} = \frac{mgl_r - m\ddot{x}h}{l_f + l_r} \tag{9}$$

$$F_{zr} = \frac{mgl_f + m\ddot{x}h}{l_f + l_r} \tag{10}$$

where $\ddot{x}$ is the longitudinal acceleration, g is the gravitational constant, l_f and l_r are the distances from the center of gravity to the front and rear axles, h is the height of the center of gravity, and m is the vehicle weight.

D. Tire-Road Friction Coefficient Estimation

Note that the tire-road friction coefficient should be estimated early enough within the stable area of the mu-slip curve since the goal of the estimation is to obtain the surface condition before ABS is engaged. In this way, ABS can be tuned fully utilizing the estimated value, and significant reduction of the stopping distance is expected. For this reason, the wheel slip at the saturated region of the mu-slip curve is not considered.

It is generally accepted that the relationship between the normalized tire force and tire slip in a stable area exhibits a linear shape regardless of the type of road surface as depicted in Fig. 4. Therefore, a simple linear tire model is used in stable regions in this paper.

One distinction in this paper is that the slip difference between the front and rear wheel in Fig. 4 is used to identify the tire stiffness and such differential braking pattern was confirmed by simulations and experiments in Section III-A.

Using (2) and (3), the vehicle speed can be expressed as follows:

$$V = \frac{rw_f}{1-\lambda_f} = \frac{rw_r}{1-\lambda_r}. \tag{11}$$

Next, (11) is divided into measurable and unknown parts as follows:

$$\eta = \frac{1-\lambda_r}{1-\lambda_f} = \frac{w_r}{w_f} \geq 1 \text{ (during braking)}. \tag{12}$$

It must be noted that this paper uses η as an excitation signal for estimating the tire stiffness while others use λ_f and λ_r in [8]–[12]. The reason for changing the excitation signal is that the tire slip is influenced by the wheel speed measurement noise greatly as well as the vehicle speed estimation which is not accurate enough during braking. However, the new excitation signal η is calculated using only the directly measured individual wheel speeds.

Manipulating (12) leads to the following:

$$\lambda_f - \lambda_r = (\eta - 1)(1 - \lambda_f). \tag{13}$$

Using the definition of a slope in a coordinate system, the tire stiffness, C_x can be expressed as follows:

$$C_x = \frac{\mu_f}{\lambda_f} = \frac{\mu_r}{\lambda_r} = \frac{\mu_f - \mu_r}{\lambda_f - \lambda_r}. \tag{14}$$

Substituting (13) into (14)

$$C_x = \frac{1}{\eta - 1}\frac{\mu_f - \mu_r}{1-\lambda_f}. \tag{15}$$

Manipulating (15) using $\lambda_f = \mu_f / C_x$, then tire stiffness can be express as follows:

$$C_x = \frac{\eta\mu_f - \mu_r}{\eta - 1}. \tag{16}$$

Since the measurements of η is not noise free, the adaptive scheme [37] is used to estimate C_x. To formulate standard adaptation form (16) is divided into two parts:

$$y = \eta\mu_f - \mu_r = (\eta - 1)\cdot C_x \tag{17}$$

where η is the excitation signal, μ_f and μ_r were obtained from the tire force estimations, and y is the output that can be measured or estimated.

Considering the following:

$$y = \theta^* u(t) \tag{18}$$

where $\theta^* = C_x$ and $u(t) = \eta - 1$.

Based on this, the adaptation law can be established using the gradient method, as follows:

$$\dot{\hat{\theta}}^* = \gamma\varepsilon u(t) \tag{19}$$

where γ is a positive adaptation gain and $\varepsilon = y - \hat{y}$.

For stability analysis, the Lyapunov function is chosen as follows:

$$V(\tilde{\theta}) = \frac{\varepsilon^2}{2\gamma}. \tag{20}$$

Differentiating above (20) with respect to time leads to

$$\dot{V}(\tilde{\theta}) = \frac{\varepsilon\dot{\varepsilon}}{\gamma} = \frac{\varepsilon(-\dot{\hat{y}})}{\gamma} = -\frac{\varepsilon(\dot{\hat{\theta}}^* u(t))}{\gamma}. \tag{21}$$

If adaptive law such as (19) is selected, then the time derivative of the Lyapunov function is always negative semidefinite as follows:

$$\dot{V}(\tilde{\theta}) = -\frac{\varepsilon\left[\{\gamma\varepsilon u(t)\}u(t)\right]}{\gamma} = -\varepsilon^2 u^2(t) \leq 0. \tag{22}$$

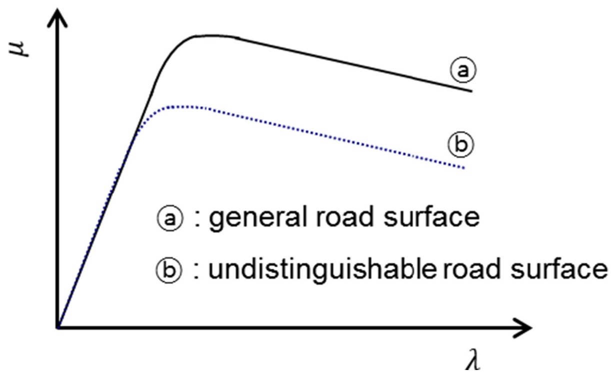

Fig. 5. Comparison of a general road surface and an undistinguishable road surface.

Therefore, by applying Barbalat's lemma [38], it can be proved that the error, ϵ converges to zero.

E. Tire Slip Observer

Once the tire stiffness information is obtained, the tire slip can be recursively estimated as described in Fig. 3. Based on the inverse linear tire model in (23) motivated by (1), the RLS algorithm can be formulated as described in (24) and (25),

$$\hat{\mu}_{\mathrm{nor}} = \lambda \hat{C}_x. \tag{23}$$

Here $\hat{\mu}_{\mathrm{nor}}$ is obtained using the tire force estimation and $\hat{C}_x$ is estimated using the adaptive scheme defined in (21). Therefore, the only unknown parameter is the tire slip in (23).

Now, a standard RLS algorithm can be applied to the system described as (23) as follows:

$$\hat{\lambda}(t) = \hat{\lambda}(t-1) + K(t)\left\{\left(\frac{\hat{F}_x(t)}{\hat{F}_z(t)}\right) - \hat{\lambda}(t-1)C_x(t)\right\} \tag{24}$$

where

$$K(t) = \frac{P(t-1)C_x(t)}{k_f + P(t-1)C_x^2(t)}.$$

$$P(t) = \frac{1}{k_f}\left[P(t-1) - \frac{P^2(t-1)C_x^2(t)}{k_f + P(t-1)C_x^2(t)}\right]. \tag{25}$$

Here *K(t)* is an updated gain vector and *P(t)* indicates an error covariance matrix, which should be minimized. k_f is a forgetting factor that is used to reduce the influence of old data.

It may be argued that the basic principle of tire stiffness-based approaches becomes invalid for undistinguishable road surfaces as depicted in Fig. 5. The road surfaces ⓐ and ⓑ exhibit a same linear shape before they reach the tire force saturation. However, they have significantly different peak friction coefficients. Therefore, this type of unresolved problem still remains as a challenge while dealing with various types of road surface. Nevertheless, many published works [8]–[12] adopted tire stiffness-based approaches due to its intuitiveness.

This paper also cannot present a clear solution to this problem. However, the tire slip estimation result is still valid with respect to any type of road surface because undistinguishable road surfaces also maintain a linear shape in a stable region, as depicted in Fig. 5.

Therefore, it can be concluded that cost-effective estimations of the tire slip and tire-road friction coefficients can be realized. The advantage of the proposed algorithm is its ability to identify the tire-road friction coefficient estimation with better performance than the conventional tire stiffness-based approaches. Furthermore, the tire slip can be estimated even if the vehicle is traveling on an undistinguishable surface such as ⓑ in Fig. 5.

IV. Experimental Study

A. Experimental Setup

Using a real production vehicle without any modification of the control system, experiments were conducted in order to verify the performance of the developed algorithms. The data was collected at 200-Hz sampling frequency via CanBus. For verification, RT-3100 model, which is a high-accuracy vehicle dynamic testing tool, was used to measure the actual vehicle state. The only signals used for the proposed observers were longitudinal acceleration, which is the affordable signal in production vehicles, and wheel speeds.

Test scenarios were conducted on various road surface conditions but road inclination was not considered. Note again that the objective of the proposed algorithm is to improve the performance of the tire stiffness-based approach while reducing the number of necessary sensor signals at the same time.

B. Experimental Results

The focus of this study is on the estimation of the tire stiffness and tire slip in the low slip region. Hence, if the proposed observers can provide satisfactory results with a small excitation signal, it is most desirable. Experiments with various decelerations were conducted in order to verify the robustness of the developed algorithms.

The first test was performed on dry asphalt with mild deceleration to verify the responsiveness of the adaptive algorithms even for the very minimum excitation signal input. Fig. 6(a) and (b) describes vehicle speed trajectory and its deceleration. Fig. 6(c) illustrates the normalized tire forces for the front and rear wheel calculated from the estimated longitudinal force and normal force. As expected, the normalized force at the front wheel is significantly larger than the rear one and it can also be seen in Fig. 6(f), where the front slip ratio measured using RT-3100 and wheel speed sensor was approximately 0.02 but the rear slip ratio was less than 0.01. Fig. 6(d) presents the excitation signal used for the adaptations.

In order to emphasize the virtue of using an adaptive scheme without a GPS signal or additional vehicle speed estimation, the proposed algorithm is compared with the results of a conventional tire stiffness-based observer.

The same levels of low-pass filtering and rate limiting to smooth the estimated results were applied to maintain the fairness. The conventional method uses the individual tire slip ratio as an excitation signal, but it is largely influenced by the noise effect as depicted in Fig. 6(f).

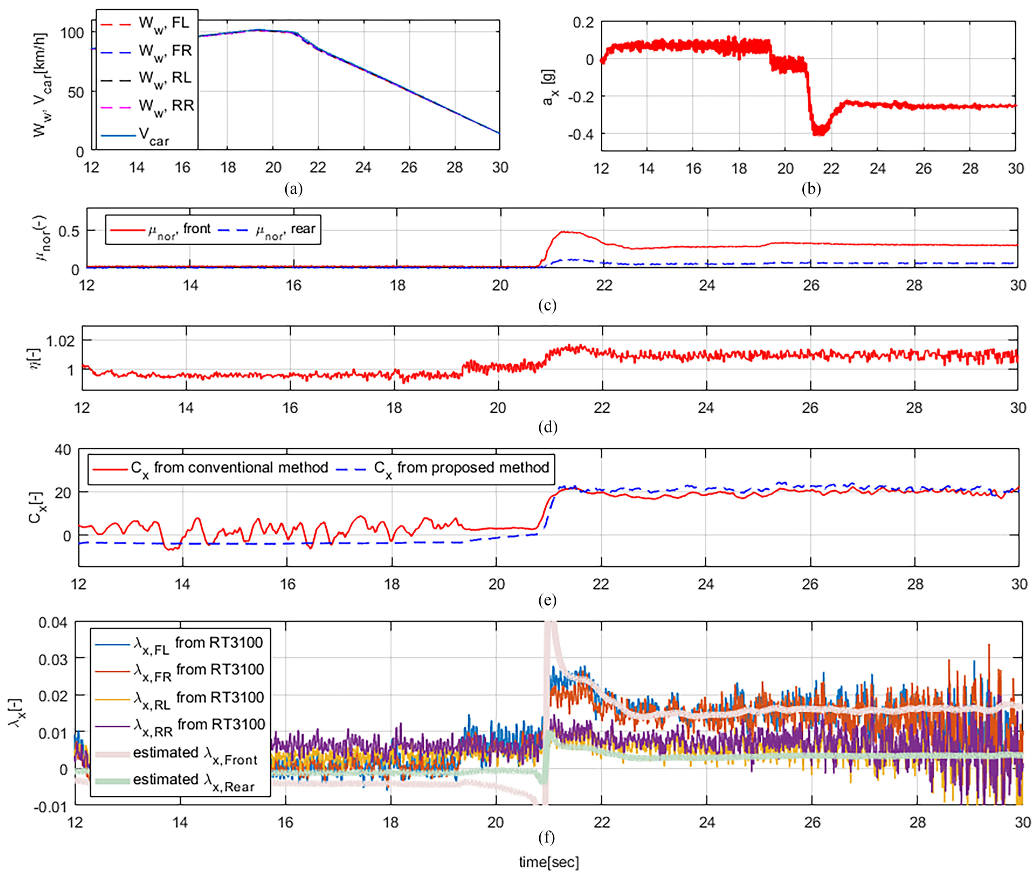

Fig. 6. Experiment results on a dry asphalt obtained by using proposed adaptive scheme with mild intensity of the brake force.

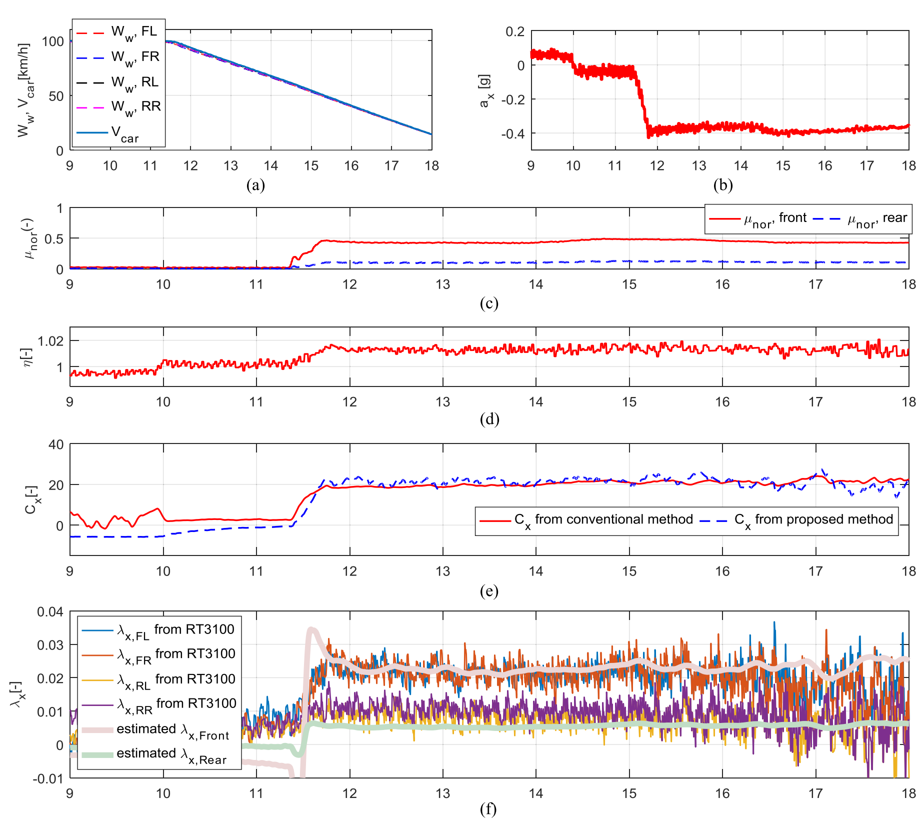

Fig. 7. Experiment results on a dry asphalt obtained by using proposed adaptive scheme with medium intensity of the brake force.

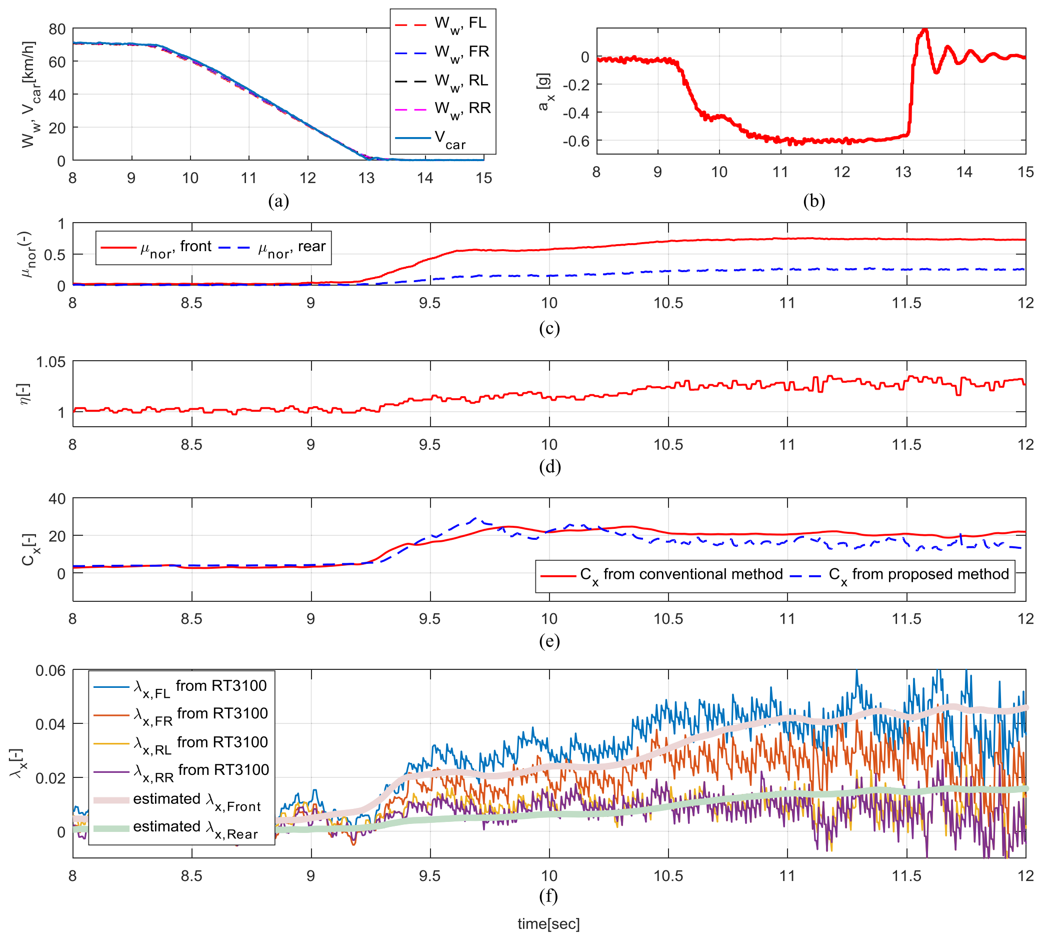

Fig. 8. Experiment results on a dry asphalt obtained by using proposed adaptive scheme with high intensity of the brake force.

In contrast, the proposed excitation signal described in Fig. 6(d) is more robust against the noise effect since it can exclude vehicle speed term in its calculation process. Accordingly, the estimated tire stiffness converged to the true value, which is approximately 20, with much less oscillation as depicted in Fig. 6(e). However, the conventional method based on the measured GPS signal oscillated due to its measurement noise.

Especially, the conventional method responded excessively to the measurement noise when the wheel slip is existing only marginally. In contrast, the adaptive scheme-based observer did not react to such level of slip. Next, Fig. 6(f) describes the estimated tire slip ratio at front and rear wheels. Because the tire slip includes an unknown vehicle speed term in (2) and (3), the results also mean the vehicle absolute speed estimation when braking is applied.

During braking, estimation of absolute vehicle speed is very difficult since brake pressure is always applied to all wheels. However, Fig. 6(e) and (f) indicates that the developed adaptive scheme and RLS algorithm can estimate tire stiffness and wheel slip accurately. Accordingly, the absolute vehicle speed can be well constructed out of those signals.

The estimation results presented in Fig. 7 exhibit a similar pattern to that in Fig. 6. In this case, medium intensity brake force was applied and the proposed method simultaneously estimated the tire stiffness and the tire slip. Since the tests were conducted on the same road surface using same tires, the estimated tire stiffness in Fig. 7(e) had the same value as that in Fig. 6(e). The estimated value, i.e., approximately 20, represents the high μ road surface, which corresponds well to the proving ground road condition. The tire slip difference between front and rear wheel in Fig. 7(f) is larger than that in Fig. 6(f) due to the increased brake force from mild to medium intensity. However, the estimated value maintained its true value well enough as shown in Fig. 7(e).

Next, the experiment for the high intensity brake force was performed as depicted in Fig. 8. It can be seen that the tire slip ratios at the front left wheel and front right wheel had a slightly different values as presented in Fig. 8(f). The reason for this phenomenon was not clearly identified, but it was suspected that surface was not quite homogeneous and also the wheel slips have reached nonlinear regions in this case. However, it should be noted that the estimated tire slip for the front wheel is the average value of the individual front wheel slip as plotted in Fig. 8(f). In addition, it is apparent that the estimated tire stiffness in Fig. 8(e) was identical to that in Figs. 6 (e) and 7(e) as expected since this test was also conducted on the same conditions.

In Fig. 9, the test vehicle was driven on a road surface covered with wet basalt that provided a friction with $\mu \approx 0.4$. The vehicle decelerated mildly as described in Fig. 9(b), and its deceleration was nearly the same as Fig. 6(b). It implied that the

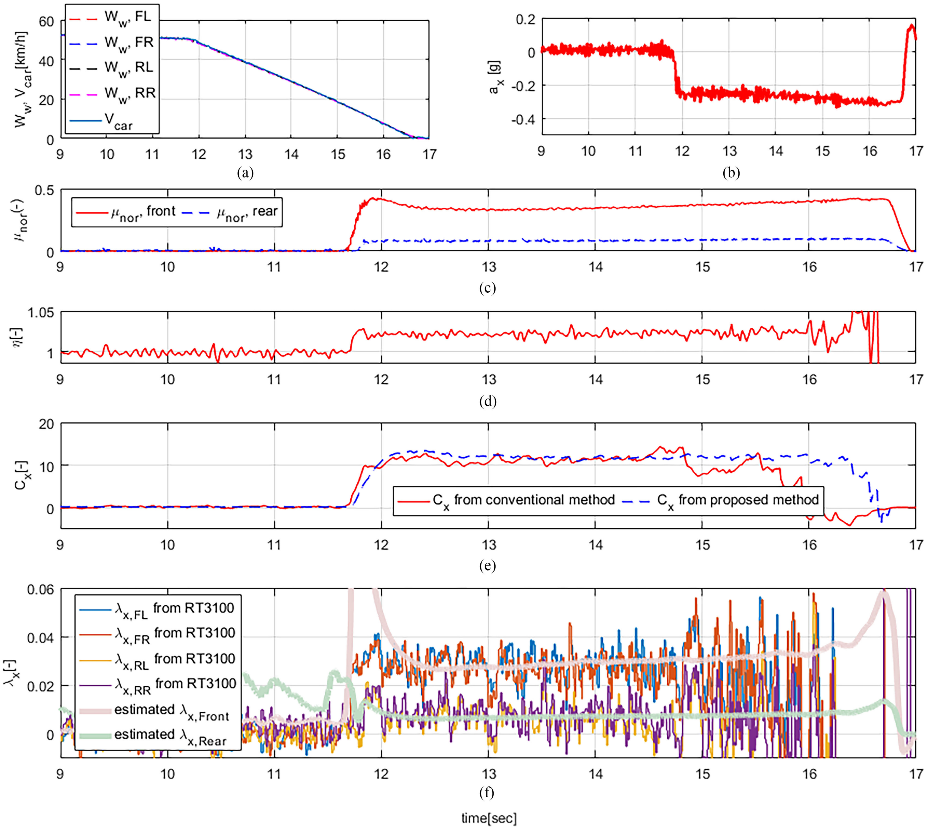

Fig. 9. Experiment results on a basalt road surface obtained by using proposed adaptive scheme with mild intensity of the brake force.

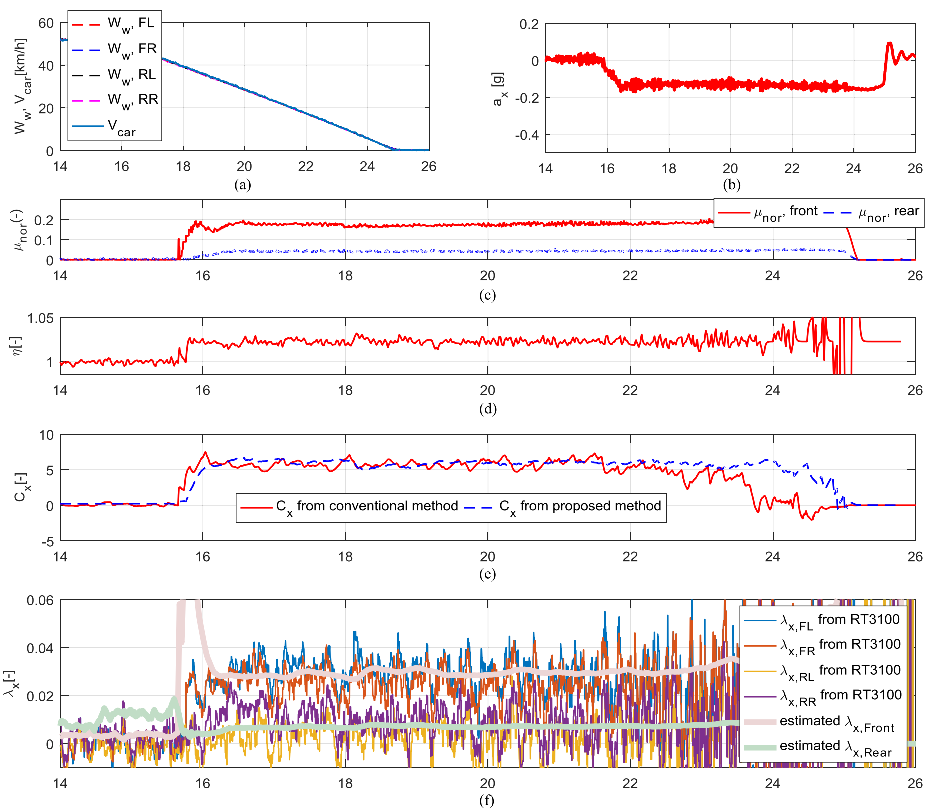

Fig. 10. Experiment results on a wet tile road surface obtained by using proposed adaptive scheme with mild intensity of the brake force.

sum of tire forces in this test was similar to that of the first test scenario in Fig. 6. However, it was observed in Fig. 9(f) that the tire slip ratios were much larger than those of Fig. 6(f), because a larger slip ratio was required to provide sufficient amount of friction brake force in low μ surface. As expected, the estimated tire stiffness in Fig. 9(e), i.e., approximately 11, was lower than that of dry asphalt. Moreover, the result is robust against noise effect when compared with the value from conventional method. This was the basis of the proposed method and well supported by this test. Using an estimated tire stiffness, fluctuation of the estimated tire slips was much less than that of measured tire slips from RT-3100. As seen from Fig. 9(e), the calculated tire slip ratios from (2) and (3) were significantly affected by the measurements noise effect. Because wheel speed was measured based on a toothed metal ring with a predetermined number of teeth, accurate measure of wheel speed was quite difficult in low speed. Therefore, the proposed estimator is promising tool in this case.

As described in Fig. 10, the vehicle was maneuvered into a wet surface which provided a very low friction with $\mu \approx 0.3$. Fig. 10(e) depicts that the estimated tire stiffness of wet tile surface was approximately 6. Based on this, the tire-road friction coefficient of this surface could be inferred. Similar to previous test, relatively large tire slip ratios were observed in Fig. 10(f) to provide sufficient amount of friction brake force. The measured tire slip ratios fluctuated significantly due to the noise effect. However, the estimated tire slip ratios did not fluctuate that much since the proposed method was much free from the noise effect.

V. Conclusion

This paper proposed a novel estimation algorithm for both tire road friction coefficient and vehicle velocity based on an adaptive scheme, which aimed to provide meaningful information to a brake controller. The proposed algorithm distinguishes itself from the previous tire stiffness-based approaches by using the differential characteristics of production brake systems. Main contributions of this works are summarized as follows. The proposed algorithm can estimate the tire stiffness, which is related to the friction coefficient, without modification of the control system or the addition of sensors. It proposes using a new excitation signal which is robust against measurement noise effects. It estimates vehicle absolute velocity from the estimated tire stiffness without extra sensors. Through various experiments using a production vehicle, the performance of the designed observers was tested and it revealed that cost-effective tire-road friction coefficient and vehicle velocity observations are possible. The estimation performance was compared with that of conventional tire stiffness-based approaches, and it can be concluded that the proposed work can be a promising tool with fewer required signals. With the application of the proposed work in any vehicle dynamics control system, improved vehicle control performance is anticipated.

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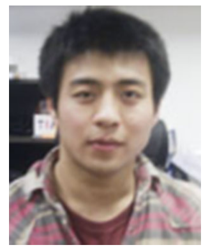
Kyoungseok Han received the B.S. degree in civil engineering (minor in mechanical engineering) from Hanyang University, Seoul, South Korea, in 2013, and the M.S. degree in mechanical engineering from the Korea Advanced Institute of Science and Technology, Daejeon, South Korea, in 2015, where he is currently working toward the Ph.D. degree in mechanical engineering.

His current research interests include vehicle dynamics and control, vehicle state estimation, and control theory.

Eunjae Lee received the B.S. degree in mechanical engineering from Inha University, Incheon, South Korea, in 2005, and the M.S. degree in division of future vehicle from the Korea Advanced Institute of Science and Technology, Daejeon, South Korea, in 2017.

He is currently a Senior Manager in vehicle dynamics with Hankook Tire Co., Ltd., Daejoen. His research interests include vehicle dynamics and subjective evaluation of chassis.



Mooryong Choi received the B.S. degree in mechanical engineering from Yonsei University, Seoul, South Korea, in 2008; the M.S. degree in mechanical engineering from the University of California, Los Angeles, CA, USA, in 2010; and the Ph.D. degree in mechanical engineering from the Korea Advanced Institute of Science and Technology, Daejeon, South Korea, in 2014.

He is currently with Hyundai-Kia Research and Development Center, Uiwang-si, South Korea. His research interests include vehicle dynamics, control, and computer vision.

Seibum B. Choi (M'09) received the B.S. degree in mechanical engineering from Seoul National University, Seoul, South Korea, in 1985; the M.S. degree in mechanical engineering from the Korea Advanced Institute of Science and Technology (KAIST), Daejeon, South Korea, in 1987; and the Ph.D. degree in control from the University of California, Berkeley, CA, USA, in 1993.

From 1993 to 1997, he was involved in the development of automated vehicle control systems at the Institute of Transportation Studies, University of California. During 2006, he was at TRW, Warren, MI, USA, where he was involved in the development of advanced vehicle control systems. Since 2006, he has been a Member of Faculty with the Department of Mechanical Engineering, KAIST. His current research interests include fuel-saving technology, vehicle dynamics and control, and active safety systems.