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Estimation of the Steering Angle Based on Extended Kalman-Filter

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Abstract

Many vehicle state parameters such as the sideslip angle, yaw rate, and steering angle are important for the Advanced Driver Assist System and vehicle safety system. In the past, most methods used to estimate the vehicle state parameters were based on models with directly measured parameters (steering angle, yaw rate, etc.). In this paper, we propose a method to estimate the vehicle state parameters (sideslip angle, yaw rate, and steering angle) based on the Extended Kalman Filter (EKF). The EKF is designed to deal with the bicycle model, linear tire model, and steering wheel model with measurements from in-vehicle sensors such as the electronic stability control system. Therefore, the results show that the proposed algorithm for estimating the vehicle state parameters, sideslip angle, yaw rate, and steering angle can effectively estimate the vehicle state parameters when the speed of the vehicle varies. The results from this study can be evaluated and analyzed by evaluating the root mean square error. In future, the proposed algorithm can be used not only for the design of an automatic control system for the tracking vehicle but also for steering system fault diagnosis.

Keywords*: Vehicle State Estimation, Lateral dynamics of the vehicle, Steering Angle, Side slip angle, Yaw rate, Extended Kalman Filter*

1. Introduction

Intelligent vehicles, *i.e*., automobiles that recognize and judge the surrounding environment, generate paths, and drive themselves, are under development in nations with advanced automobile technology. In particular, Advanced Driver Assistance System (ADASs) such as Do Not Pass Warning, Collision Avoidance System, Lane Keeping Assist System, and Improved Cooperative Collision Warning System [1, 2] are the subject of active research. In addition, vehicle safety systems such as the electronic stability control (ESC) system, antilock braking system, and traction control system are also under research. These systems function by obtaining the vehicle state data (velocity, acceleration, yaw rate, sideslip angle, steering wheel angle, *etc.*). In particular, ADASs and vehicle safety systems require the sideslip angle, yaw rate, and steering wheel angle information to be supplied accurately and continuously in different driving environments to ensure their stable operation.

Most of the vehicles manufactured these days are equipped with ESC systems. ESC systems pre-vent the vehicle from under-steering and over-steering when it corners. A sensor inside the ESC module measures the longitudinal and lateral accelerations and the yaw rate [3]. Therefore, accurate values of the yaw rate can be obtained directly from the ESC module attached to the vehicle. The sideslip angle can be measured directly as well, but the sensor required for the measurement is very expensive. Thus, different methods

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for estimating the model-based sideslip angle using in-vehicle sensors (accelerometers, gyroscope, and steering angle sensor) or Global Positioning System (GPS) were proposed.

Most model-based sideslip angle-estimation methods are based on nonlinear tire models such as Pacejka's Magic Formula model [4] and Dugoff's tire model [5]. Nonlinear tire models provide the advantage of measuring the sideslip angle with high precision, even on low-friction road surfaces or during high-speed driving, which is a driving condition in which the sideslip angle is high. In this regard, N. Ding and S. Taheri [6] proposed a method for estimating the sideslip angle and road friction using a recursive least square algorithm. M. Doumiati, A. Victorino, A. Charara, and D. Lechner [7] proposed a method to estimate the lateral force and sideslip angle of a vehicle using the EKF. H. Du, J. Lam, K.C. Cheung, W. Li, and N. Zhang [8] designed a controller with immeasurable premise variables and suggested a method to estimate the sideslip angle and steering wheel angle using a Takagi-Sugeno fuzzy observer capable of measuring the sideslip angle. In addition, a method to estimate the sideslip angle and tire-road force using an interacting multiple model filter, which is a model in which both the linear and nonlinear tire models were applied to an Unscented Kalman Filter (UKF), was proposed to improve the estimation accuracy [9]. The nonlinear tire model provides a very high performance under various driving conditions, but its nonlinearity and complexity are high, it requires a high-end processor, and involves the calculation of various parameters. Therefore, D.M. Bevly, J. Ryu and J.C. Gerdes [10], and C. Ahn and J. Yoon [11] proposed a method to estimate the sideslip angle, roll, and tire stiffness [10], along with a method to estimate the sideslip angle and tire-road friction coefficient [11] based on a linear tire model in which the EKF is applied using in-vehicle sensors and GPS data. Furthermore, B.L. Boada, M.J.L. Boada, and V. Diaz [12] proposed a method to estimate the sideslip angle using an artificial intelligence algorithm-based adaptive neuro-fuzzy inference system and the UKF.

Although different sideslip angle-estimating fusion algorithms based on the tire model were pro-posed, the steering wheel angle is always required to estimate the sideslip angle of a vehicle. Several methods estimate the steering wheel angle of a vehicle directly. These methods include attaching an absolute rotary encoder that prints out the revolution count [13], or attaching sensors such as gyro-scopes [15] or potentiometers that print out analog voltage signals [14]. In addition, recent vehicles are equipped with electric power steering systems that use electric motors as a result of the electrification/digitalization of vehicles [3]. However, ADASs and vehicle safety systems stop functioning normally if a fault occurs in the steering wheel angle-estimating sensor. Therefore, new technologies that can estimate the steering wheel angle indirectly by combining in-vehicle sensor data are required. Moreover, this can be used for troubleshooting sensors that directly estimate the steering wheel angles, which is expected to contribute to increase the safety.

This study proposes a vehicle state data (side-slip angle and steering wheel angle) estimating algorithm, which is essential for the stable operation of ADASs and vehicle safety systems. The EKF algorithm was used to combine nonlinear vehicle models with different sensor data. Furthermore, the ability to estimate vehicle state data for varying speeds was evaluated through simulations.

2. Estimation of the Steering Angle

2.1. System Configuration

The proposed vehicle state data-estimating algorithm uses the lateral acceleration and yaw rate data measured by the in-vehicle sensors of the ESC as shown in Figure 1. The data obtained from the in-vehicle sensors is used to estimate the steering angle using the EKF based on the bicycle model, linear tire model, and steering wheel angle model.

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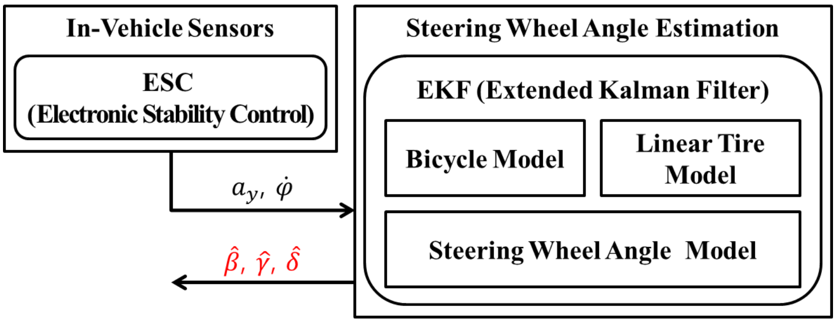

Figure 1. System Architecture

2.2. Vehicle Dynamic Model

In this paper, the three degrees of freedom (DOF) vehicle model, which expresses the lateral vehicle dynamics including roll and yaw, was used to analyze/predict the vehicle's lateral motion. Here, the sideslip angle and yaw rate can be expressed as shown in Eq. (1) and (2) through a simple model called the bicycle model, provided the roll motion is neglected [16].

$$\sum F_y = mv_x\left(\frac{d\beta}{dt} + \dot{\varphi}\right) = mv_x\left(\frac{d\beta}{dt} + \gamma\right) = F_{yf} + F_{yr} \tag{1}$$

$$\sum M_z = I_z\ddot{\varphi} = F_{yf}l_f - F_{yr}l_r \tag{2}$$

Assuming that the sideslip and steering angles have low values, the tire lateral force of the linear tire model is proportional to the tire sideslip angle as shown in Eq. (3). In addition, the tire sideslip angle can be approximated by a kinematic relation as shown in Eq. (4).

$$F_{yf} = C_{\alpha f}\alpha_f = C_{\alpha f}(\delta - \theta_{v_f}) = C_{\alpha f}\left(\delta - \beta - \frac{l_f\gamma}{v_x}\right) \tag{3}$$

$$F_{yr} = C_{\alpha r}\alpha_r = C_{\alpha r}(-\theta_{v_r}) = C_{\alpha r}\left(-\beta + \frac{l_r\gamma}{v_x}\right) \tag{4}$$

$$\alpha_f = \delta - \theta_{v_f} = \delta - \beta - \frac{l_f\gamma}{v_x} \tag{5}$$

$$\alpha_r = -\theta_{v_r} = -\beta + \frac{l_r\gamma}{v_x} \tag{6}$$

Calculating the three DOF vehicle model as a differential equation after substituting Eq. (3) and (4) into Eq. (1) and (2) provides Eq. (7) and (8) as the result. The state-space representation of this is shown in Eq. (9) [19].

$$\frac{d\beta}{dt} = -\frac{1}{mv_x}(C_{\alpha f} + C_{\alpha r})\beta - \left\{1 + \frac{1}{m{v_x}^2}(C_{\alpha f}l_f - C_{\alpha r}l_r)\right\}\gamma + \frac{C_{\alpha f}}{mv_x}\delta \tag{7}$$

$$\frac{d\gamma}{dt} = \frac{1}{I_z}(-C_{\alpha f}l_f + C_{\alpha r}l_r)\beta - \frac{1}{I_z v_x}(C_{\alpha f}{l_f}^2 + C_{\alpha r}{l_r}^2)\gamma + \frac{C_{\alpha f}l_f}{I_z}\delta \tag{8}$$

$$\begin{bmatrix}\dot{\beta}\\ \dot{\gamma}\end{bmatrix} = \begin{bmatrix} -\frac{1}{mv_x}(C_{\alpha f} + C_{\alpha r}) & -\left\{1 + \frac{1}{m{v_x}^2}(C_{\alpha f}l_f - C_{\alpha r}l_r)\right\} \\ \frac{1}{I_z}(-C_{\alpha f}l_f + C_{\alpha r}l_r) & -\frac{1}{I_z v_x}(C_{\alpha f}{l_f}^2 + C_{\alpha r}{l_r}^2)\end{bmatrix}\begin{bmatrix}\beta\\ \gamma\end{bmatrix} + \begin{bmatrix}\beta\frac{C_{\alpha f}}{mv_x}\\ \frac{C_{\alpha f}l_f}{I_z}\end{bmatrix}\delta \tag{9}$$

The steering wheel angle model can be approximated as shown in Eq. (10) assuming that the sideslip angle is low. Here, R is the radius of the curve, which is calculated using Eq. (11).

$$\delta = \frac{l_f + l_r}{R} = \frac{l_f + l_r}{v_x}\gamma \tag{10}$$

$$R = \frac{v_x}{\gamma} \tag{11}$$

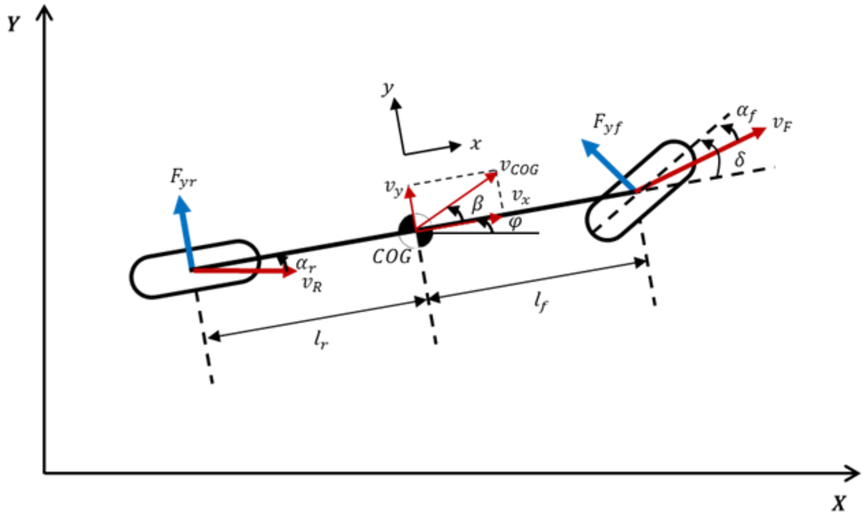

Figure 2. Bicycle Model

v_x: vehicle velocity on x-axis, β: side slip angle, $\dot{\varphi}$: yaw rate, I_z: vehicle moment of inertia on z-axis, α_f: tire front slip angle, α_r: tire rear slip angle

2.3. Extended Kalman Filter (EKF)

In this paper, the three degrees of freedom (DOF) vehicle model, which expresses the lateral vehicle dynamics including roll and yaw, was used to analyze/predict the vehicle's lateral motion. Here, the sideslip angle and yaw rate can be expressed as shown in Eq. (1) and (2) through a simple This study aims to predict the state variables of vehicles in the lateral direction (sideslip angle, yaw rate, and steering angle). The EKF is widely used as a vehicle state predicting method that combines various sensor data [17]. It has the advantage of being directly applicable to nonlinear systems without requiring any linearization processes. The EKF can be divided into time update and measurement update, as shown in Figure 3.

The EKF is a state space model-based algorithm. The system model f_{k-1} and measurement model h_k can be calculated directly from the discrete state-space model of a nonlinear system. ω_k and v_k represent the system noise and measurement noise, respectively. Assuming that they feature a Zero Mean White Gaussian distribution, this can be expressed as shown in Eq. (12) and Eq. (13) [18].

$$x_k = f_{k-1}(x_{k-1}, u_{k-1}, \omega_{k-1}), \quad \omega_k \sim (0, Q_k) \tag{12}$$

$$z_k = h_k(x_k, v_k), v_k \sim (0, R_k) \tag{13}$$

The discrete time state-space equation of the actual system can be expressed in terms of the sampling time as shown below. It can be separated through the approximation process of Euler's method as follows.

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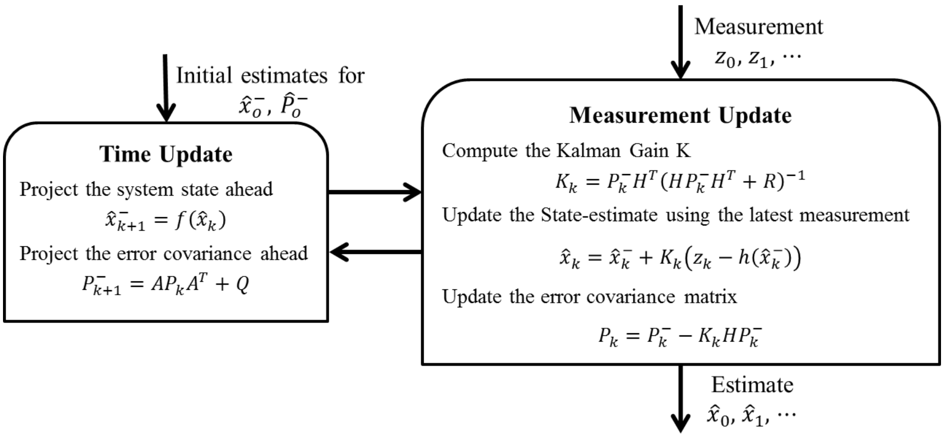

Figure 3. Extended Kalman Filter

$$\dot{x} = \frac{x_k - x_{k-1}}{T} \tag{14}$$

$$x_k \cong x_{k-1} + \dot{x} \cdot T \tag{15}$$

The predictive values of the system state vector and the error covariance are calculated in the time update part. The system state vector was defined as shown in Eq. (16). In addition, the system model can be defined using the vehicle dynamic model from Eq. (9) and (15) as shown in Eq. (16).

$$x_k = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}_k = \begin{bmatrix} \beta \\ \gamma \\ \delta \end{bmatrix}_k \tag{16}$$

$$u = v_x \tag{17}$$

$$x_k = f_{k-1}(x_{k-1}, u_{k-1}, \omega_{k-1}) = \begin{bmatrix} \hat{\beta} \\ \hat{\gamma} \\ \hat{\delta} \end{bmatrix}_k =$$

$$\begin{bmatrix} \hat{\beta}_{k-1} + \left[-\frac{1}{m v_x}(C_{af} + C_{ar})\hat{\beta}_{k-1} - \left\{ 1 + \frac{1}{m {v_x}^2}(C_{af} l_f - C_{ar} l_r) \right\} \hat{\gamma}_{k-1} + \frac{C_{af}}{m v_x}\hat{\delta}_{k-1} \right] \cdot T \\ \hat{\gamma}_{k-1} + \left[\frac{1}{I_z}(-C_{af} l_f + C_{ar} l_r)\hat{\beta}_{k-1} - \frac{1}{I_z v_x}(C_{af} {l_f}^2 + C_{ar} {l_r}^2)\hat{\gamma}_{k-1} + \frac{C_{af} l_f}{I_z}\hat{\delta}_{k-1} \right] \cdot T \\ \frac{L}{v_x}\hat{\gamma}_{k-1} \end{bmatrix} + \omega_{k-1} \tag{18}$$

Here, the matrix A_k, which is required to predict the error covariance, is separated and calculated as shown in Eq. (19) after partially differentiating the system model into state vectors. The matrices obtained through this method are called Jacobians. The matrix Q_k represents the system noise. The noise was established by dispersing , γ, and δ, which are sub elements of the system state vectors, as shown in the diagonal matrix of Eq. (20).

$$A_k \equiv \left.\frac{\partial f}{\partial x}\right|_{x = x_k} = \begin{bmatrix} \left\{ 1 - \frac{1}{m v_x}(C_{af} + C_{ar}) \right\} \cdot T & \left\{ -1 - \frac{1}{m {v_x}^2}(C_{af} l_f - C_{ar} l_r) \right\} \cdot T & \frac{C_{af}}{m v_x} \cdot T \\ \frac{1}{I_z}(-C_{af} l_f + C_{ar} l_r) \cdot T & \left\{ 1 - \frac{1}{I_z v_x}(C_{af} {l_f}^2 + C_{ar} {l_r}^2) \right\} \cdot T & \frac{C_{af} l_f}{I_z} \cdot T \\ 0 & \frac{l_f + l_r}{v_x} & 0 \end{bmatrix} \tag{19}$$

$$Q_k = diag\left[\sigma_\beta^2 \quad \sigma_\gamma^2 \quad \sigma_\delta^2 \right] = \begin{bmatrix} \sigma_\beta^2 & 0 & 0 \\ 0 & \sigma_\gamma^2 & 0 \\ 0 & 0 & \sigma_\delta^2 \end{bmatrix} \tag{20}$$

The Kalman gain, error covariance, and state-estimating value are calculated in the measurement update part. The estimation vector of this system is defined as shown in Eq.

(21). In addition, the measurement model of the system can be defined using the vehicle dynamics model as shown in Eq. (22).

$$z_k = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}_k = \begin{bmatrix} a_y \\ \gamma \end{bmatrix}_k \tag{21}$$

$$z_k = h_k(x_k, v_k) = \begin{bmatrix} a_y \\ \gamma \end{bmatrix}_k = \begin{bmatrix} -\frac{1}{m}(C_{af} + C_{ar})\hat{\beta}_{k-1} + \frac{1}{mv_x}(-C_{af}l_f + C_{ar}l_r)\hat{\gamma}_{k-1} + C_{af}\hat{\delta}_{k-1} \\ \hat{\gamma}_{k-1} \end{bmatrix} + v_k \tag{22}$$

Here, the Jacobian of matrix H_k, which is required to calculate the Kalman gain and error covariance, is calculated by partially differentiating the system's measurement model into a state vector as shown in Eq. (23). The matrix R_k represents the sensor noise. Each noise was established by dispersing the vehicle's lateral acceleration (a_y) and yaw rate ($\dot{\psi}$), as shown in the diagonal matrix of Eq. (24).

$$\mathrm{H}_k \equiv \frac{\partial h}{\partial x}\bigg|_{x=x_k} = \begin{bmatrix} -\frac{1}{m}(C_{af} + C_{ar}) & \frac{1}{mv_x}(-C_{af}l_f + C_{ar}l_r) & C_{af} \\ 0 & 1 & 0 \end{bmatrix} \tag{23}$$

$$R_k = diag\begin{bmatrix} \sigma_{a_y}^2 & \sigma_\gamma^2 \end{bmatrix} = \begin{bmatrix} \sigma_{a_y}^2 & 0 \\ 0 & \sigma_\gamma^2 \end{bmatrix} \tag{24}$$

3. Simulation and Results

The Automotive Simulation Models (ASM), Vehicle Dynamic Models (dSPACE) and Matlab/Simulink were interworked to perform an off-line simulation to analyze the performance of the proposed steering angle estimator. In addition, the vehicle parameters were established as shown in Table 1 using the ASM's demo vehicle data. The noise covariation for in-vehicle sensor setting was established as shown in Table 2 in order to incorporate noise into the ideal vehicle state data.

Table 1. Vehicle Parameters

Vehicle Parameter	Value	Unit
Vehicle Mass, m	1,418	kg
Distance front CoG (Center of Gravity) to Front Wheel, l_f	1.064	m
Distance front CoG to Rear Wheel, l_r	1.596	m
Yaw Moment of Inertia, I_z	1,850	$kg \cdot m^2$
Lateral(Cornering) Stiffness of Front Tire, C_{af}	320,000	N/rad
Lateral(Cornering) Stiffness of Rear Tire, C_{ar}	290,000	N/rad

Table 2. Sensor Parameters

Sensor Parameter	Noise	Unit
Acceleration Sensor	1	m/s^2
Gyro Sensor	0.1	rad/s

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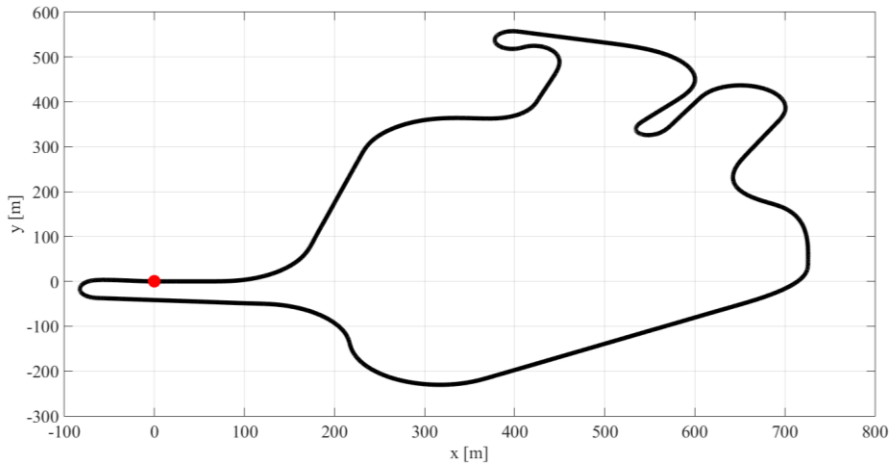


Figure 4. Simulation Scenario Track

The simulation scenario is approximately 3000[m] long and comprises curves of different radii as shown in Figure 4. The initial location, initial speed, initial yaw, and initial yaw rate were set as 0. The simulation was divided into two scenarios to analyze the performance of the proposed algorithm under driving conditions with different vehicle speeds. In the first scenario, the operator of the demo vehicle does not exceed 40[km/h] while driving along the track. In the second scenario, the operator of the demo vehicle does not exceed 80[km/h].

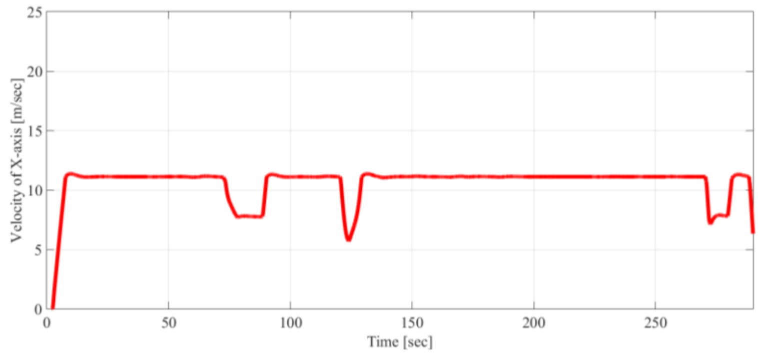
As a result, it was confirmed that in both scenarios, *i.e.*, low vehicle speed below 40[km/h] and general high speed of 80[km/h], the measured sideslip angle, yaw rate, and steering angle values are similar to the ideal vehicle state values.

The root mean squared error (RMSE) was calculated to analyze the estimated system state variables as shown in Eq. (25). The results are shown in Table 3. In Eq. (25), T is the total number of samples. Table 3 shows that there is no major difference between the estimated values and reference values. However, the estimation accuracy is higher in the first scenario at low speed (under 40[km/h]). In addition, the steering angle estimation accuracy seems to be higher in the second scenario at high speed (under 80[km/h]). However, it can be verified that the steering angle-estimation algorithm performance is satisfactory and not greatly affected in both scenarios.

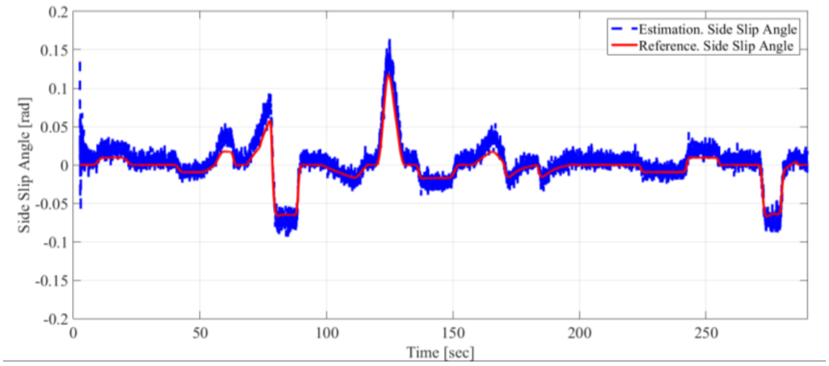
$$\mathrm{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_t - \hat{x}_t)^2} \tag{25}$$

Table 3. Results of the Estimation Parameters

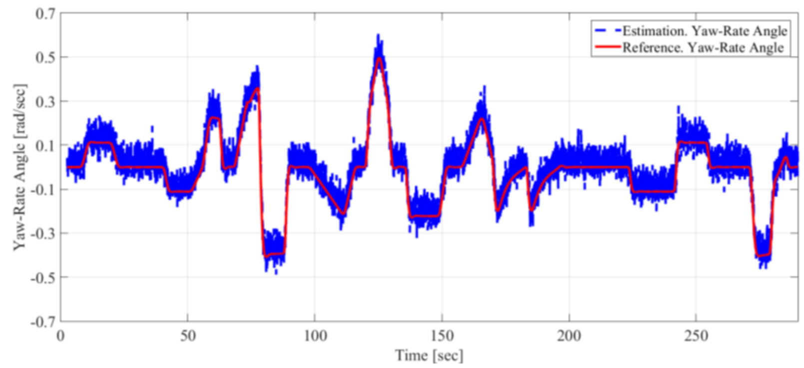
Estimation Parameter	RMSE		Unit
	under 40[km/h]	under 80[km/h]	
Side slip angle	0.054	0.063	rad
Yaw rate	0.046	0.046	rad/s
Steering angle	0.017	0.016	rad



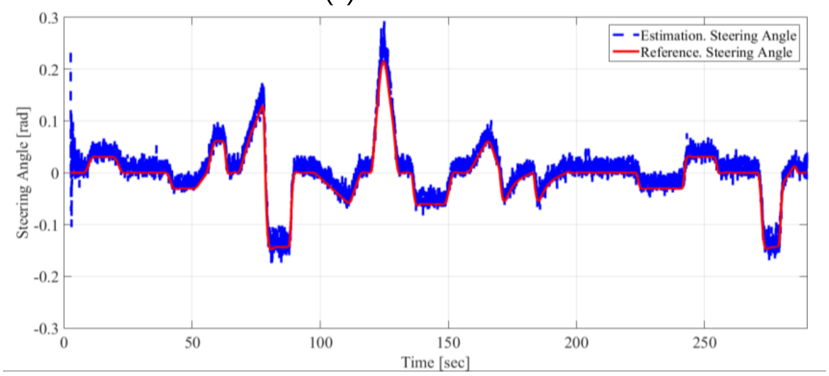
(a) Vehicle Speed



(b) Side Slip Angle



(c) Yaw Rate



(d) Steering Angle

Figure 5. Simulation Results (for Vehicle Speed Below 40[Km/H])

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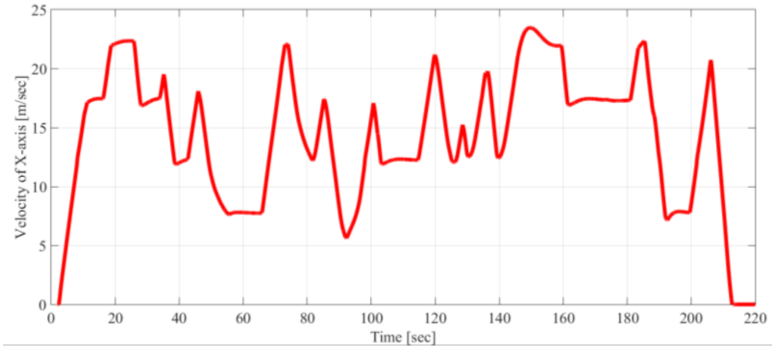
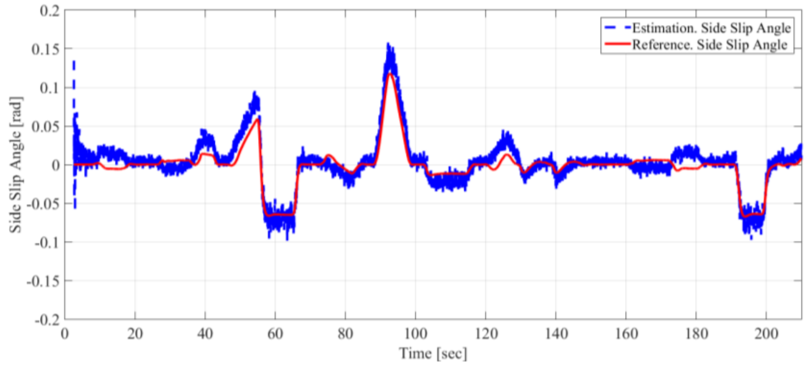
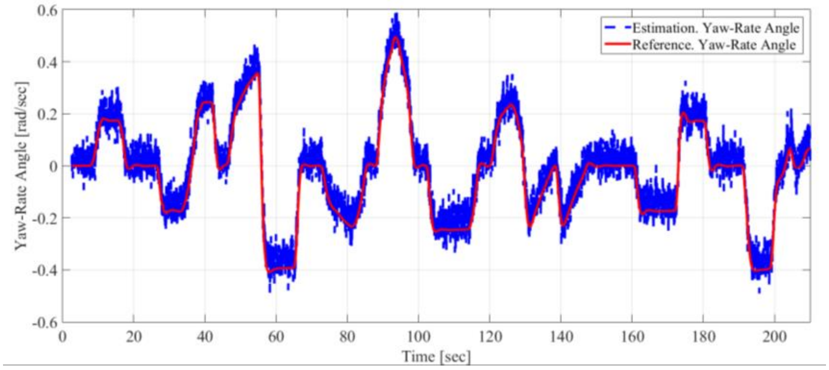


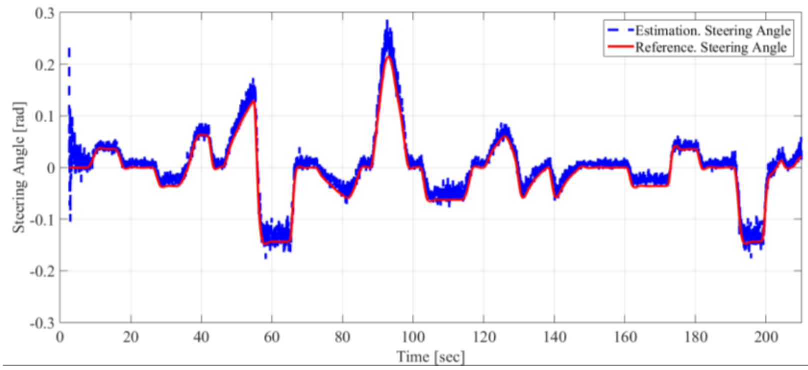
(a) Vehicle Speed



(b) Side Slip Angle



(c) Yaw Rate



(d) Steering Angle

Figure 6. Simulation Results (for Vehicle Speed Below 80[Km/H])

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4. Conclusion

This paper proposed an algorithm to estimate the vehicle state data (sideslip angle, yaw rate, and steering angle), which is essential in ADASs and vehicle safety systems. The proposed algorithm can combine different sensor data and uses the EKF, which is based on a highly nonlinear vehicle dynamic model, tire model, and steering angle model.

The vehicle state estimation performance of the proposed algorithm was analyzed at different speeds (low speed of 40[km/h] and high speed 80[km/h]). The simulation results revealed that in both scenarios, the state variables (sideslip angle, yaw rate, and steering angle) were calculated accurately. The steering angle-estimation performance indicator was verified from the RMSE values.

These results suggest that the proposed algorithm assures effective performance under different driving conditions with various speeds despite using the bicycle and linear tire models that are simpler than the Four Wheel Vehicle Model, which is complex in the vehicle state variables estimation field. Therefore, the proposed algorithm, which combines the in-vehicle sensor data to estimate the steering wheel angle indirectly, is expected to troubleshoot sensors that estimate the steering angle directly and contribute to the improvement of safety.

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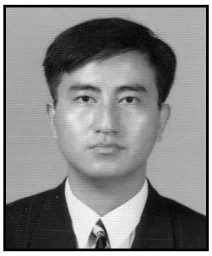

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