Vehicle Sideslip Angle Estimation Using Deep Ensemble-based Adaptive Kalman Filter

Dongchan Kim, Kyushik Min, Hayoung Kim and Kunsoo Huh

Department of Automotive Engineering at Hanyang University, Korea

jookker@hanyang.ac.kr

Motivation and Objective

The objective is to estimate vehicle sideslip angle **accurately and robustly** with a novel scheme **combining** deep neural network and nonlinear Kalman filters

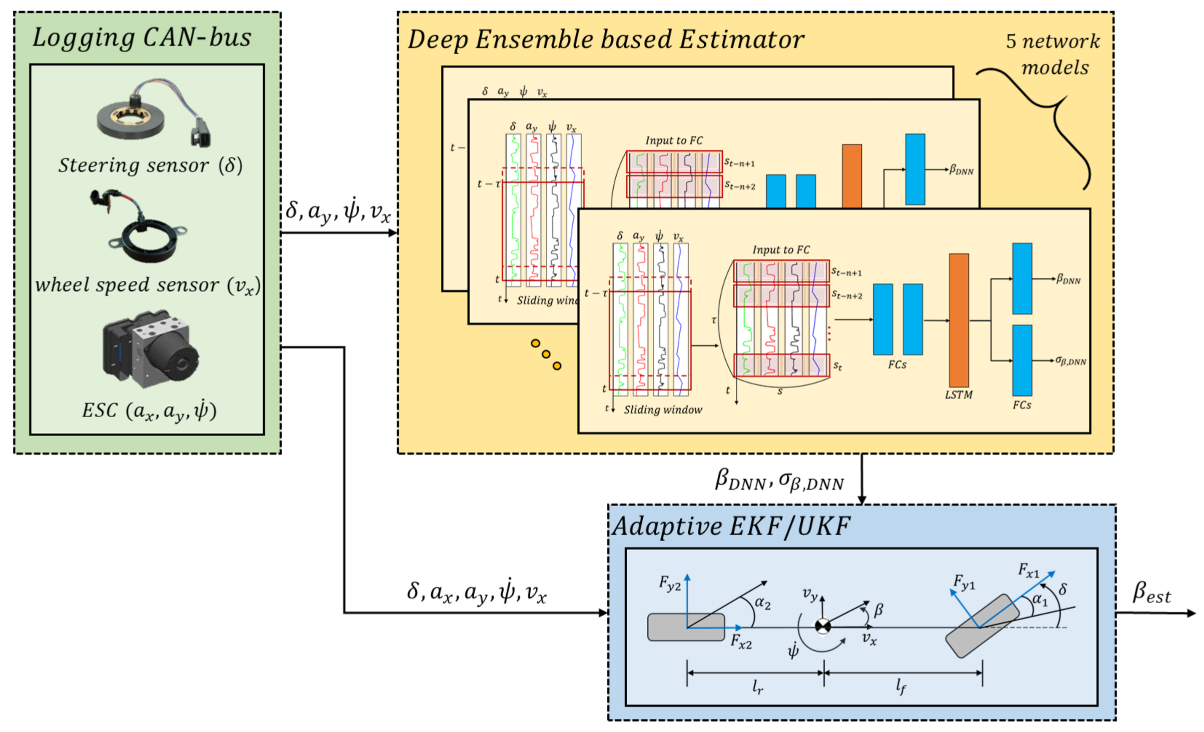


Fig. 2. Overall architecture of the proposed method

Highlights

A novel sideslip angle estimation scheme is proposed combining DNN and EKF/UKF

The initial estimate and its uncertainty are obtained from deep ensemble

The outputs of deep ensemble are utilized in EKF/UKF for the final estimate

Combining the DNN with EKF/UKF improves the estimation performance significantly

The proposed method is validated under various road surface conditions

Approach

1. Deep Ensemble-based Virtual Sensor

Deep ensemble is used to obtain not only the **robust estimate** but also **the uncertainty of the estimate**.

$$\beta_{DNN} = \frac{\sum_i \beta_{DNN,i}}{5} \qquad \sigma_{\beta,DNN} = \sqrt{\frac{\sum_i (\sigma_{\beta,DNN,i}{}^2 + \beta_{DNN,i}{}^2)}{5} - \beta_{DNN}{}^2}$$

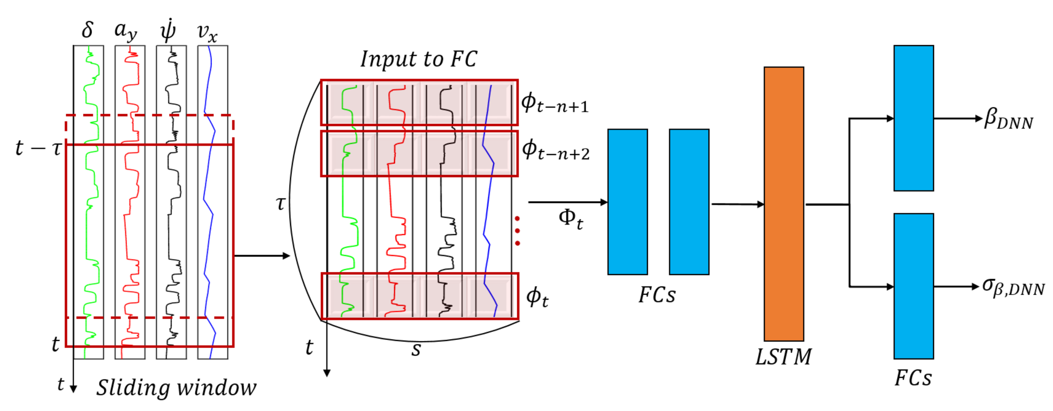
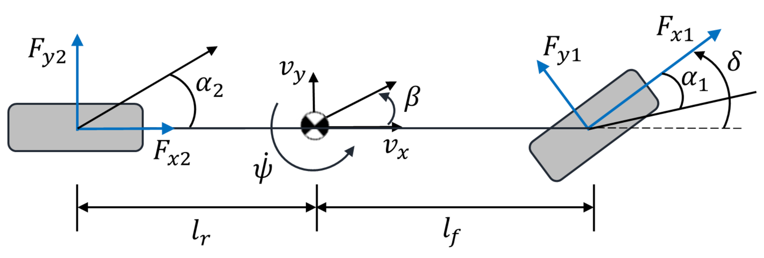


Fig. 1. Network for sideslip angle and standard deviation estimation

2. Adaptive Kalman Filters

Vehicle dynamics model

- 3-DOF bicycle model



$$m\left(\dot{v}_x - \dot{\psi} v_y\right) = F_{x1}cos(\delta) + F_{x2} - F_{y1}sin(\delta)$$
$$m\left(\dot{v}_y + \dot{\psi} v_x\right) = F_{x1}sin(\delta) + F_{y1}cos(\delta) + F_{y2}$$
$$I_z\ddot{\psi} = l_f F_{x1}sin(\delta) + l_f F_{y1}cos(\delta) - l_r F_{y2}$$

$$\dot{x} = \begin{bmatrix} \dot{v}_x \\ \dot{v}_y \\ \ddot{\psi} \\ \dot{\Delta C_1} \\ \dot{\Delta C_2} \\ \dot{F}_{x1} \\ \dot{F}_{x2} \end{bmatrix} = \begin{bmatrix} \dot{\psi} v_y + \frac{1}{m}\left(F_{x1}cos(\delta) + F_{x2} - F_{y1}sin(\delta)\right) \\ -\dot{\psi} v_x + \frac{1}{m}\left(F_{x1}sin(\delta) + F_{y1}cos(\delta) + F_{y2}\right) \\ \frac{1}{I_z}\left(l_f F_{x1}sin(\delta) + l_r F_{y1}cos(\delta) - l_r F_{y2}\right) \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

state

$$y = \begin{bmatrix} v_x \\ \dot{\psi} \\ a_x \\ a_y \end{bmatrix} = \begin{bmatrix} v_x \\ \dot{\psi} \\ \frac{1}{m}\left(F_{x1}cos(\delta) + F_{x2} - F_{y1}sin(\delta)\right) \\ \frac{1}{m}\left(F_{x1}sin(\delta) + F_{y1}cos(\delta) + F_{y2}\right) \end{bmatrix}$$

Measurement vector

Algorithm

- The **initial estimate** and its **uncertainty** are obtained from deep ensemble
- The measurement vector and noise covariance matrix are **updated**
- General EKF/UKF process
- Reliability of deep ensemble is **automatically determined** by the **uncertainty** of the estimate from deep ensemble

Algorithm 1 Deep Ensemble-based Extended Kalman Filter

function Deep_EKF($\mu_{t-1}, \Sigma_{t-1}, u_t, z_t, \Phi_t$)
  $\beta_{DNN}, \sigma_{\beta_{DNN}} = f(\Phi_t)$ — Deep ensemble model (f)
  $\tilde{z}_t = \begin{pmatrix} z_t \\ \beta_{DNN} \end{pmatrix}$ — Update measurement vector (z)
  $\tilde{Q}_t = \begin{pmatrix} Q_t & 0 \\ 0 & w_\beta \sigma^2_{\beta_{DNN}} \end{pmatrix}$ — Update noise covariance matrix (Q)
  $\bar{\mu}_t = g(u_t, \mu_{t-1})$
  $\bar{\Sigma}_t = G_t \Sigma_{t-1} G_t^T + R_t$
  $K_t = \bar{\Sigma}_t H_t^T \left(H_t \bar{\Sigma}_t H_t^T + \tilde{Q}_t\right)^{-1}$
  $\mu_t = \bar{\mu}_t + K_t(\tilde{z}_t - h(\bar{\mu}_t))$
  $\Sigma_t = (I - K_t H_t)\bar{\Sigma}_t$
  return μ_t, Σ_t

General EKF process

Results

Simulation

Verification through Carsim simulator

- Training Dataset
  - Two different road conditions ($\mu = 0.3, 0.85$)

Maneuver	SWA (deg)	Velocity (kph)	frequency (Hz)	surface
Ramp steering	±120	40/60/80/100/20–120	(–)	dry asphalt (μ = 0.85)
Swept steering	$\pm40/\pm60/\pm80/\pm100$	40/60/80/100/20–120	0.2 → 0.5	dry asphalt (μ = 0.85)
Sine steering	±100	60–100	0.2/0.5	dry asphalt (μ = 0.85)
Ramp steering	±100	40/60/80/20–100	(–)	snow (μ = 0.3)
Swept steering	$\pm40/\pm60/\pm80$	40/60/80/20–100	0.2 → 0.5	snow (μ = 0.3)
Sine steering	±60	60–100	0.2/0.5	snow (μ = 0.3)

- Test Dataset
  - Includes new maneuvers and road conditions ($\mu = 0.2, 0.3, 0.5, 0.85$)

	Scenario description	Velocity (kph)	Time [s]
Scne. 1	DLC (Double Lane Change) on dry asphalt road (μ = 0.85)	120	10
Scne. 2	DLC on snowy road (μ = 0.3)	120	10
Scne. 3	Sine steering (±100 deg, 0.25 Hz) on dry asphalt road (μ = 0.85)	70 → 120 ($+1m/s^2$)	45
Scne. 4	Sine steering (±100 deg, 0.25 Hz) on snowy road (μ = 0.3)	70 → 90 ($+1m/s^2$)	45
Scne. 5	Drift to the left on new road surface (μ = 0.5)	120	15
Scne. 6	Sine steering (±100 deg, 0.25 Hz) on new road surface (μ = 0.5)	70 → 90 ($+1m/s^2$)	45
Scne. 7	Step steering (+100 deg) on new road surface (μ = 0.2)	90	15

- The maximum error improvement of the proposed method is **3.60 deg** compared to DNN only, **1.53 deg** to EKF only and **1.02 deg** to UKF only, respectively, in the sideslip angle estimation.

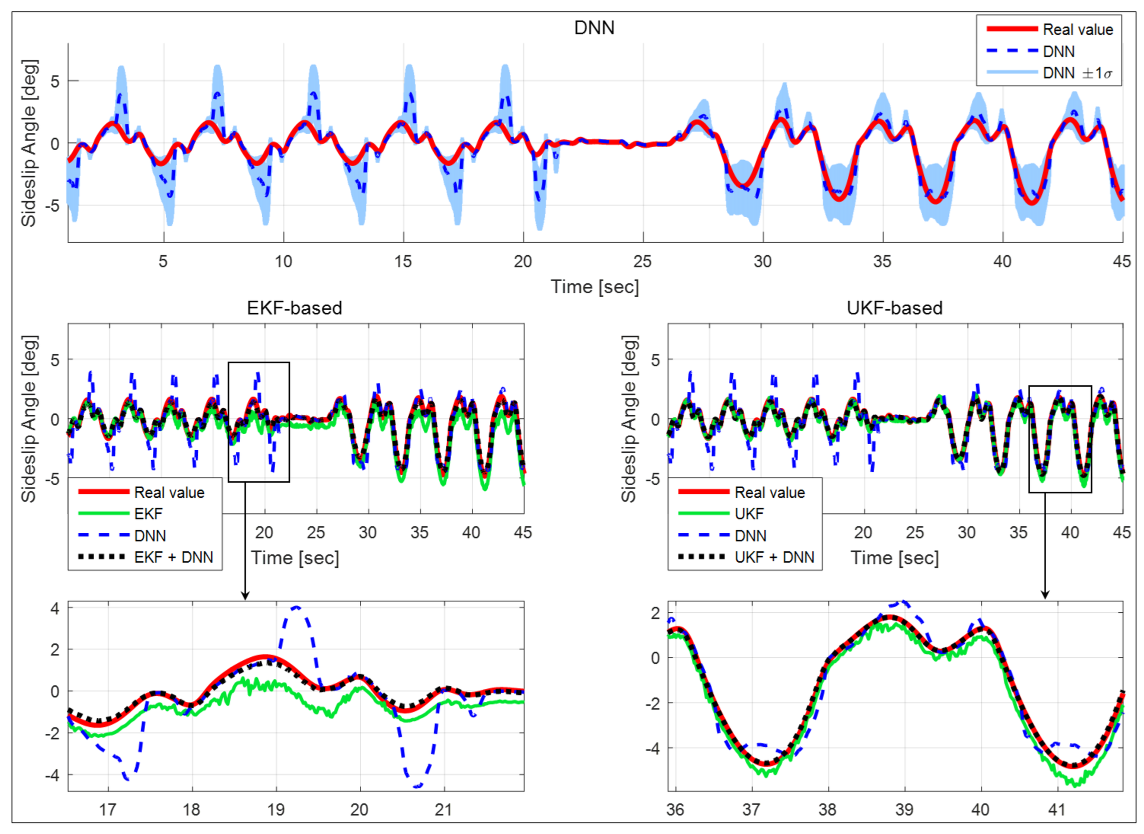


Fig. 3. Simulation results for test scenario 4

Experiment

Verification through the test vehicle equipped with an optical sensor

- The maximum error improvement of the proposed method is **0.36 deg** compared to DNN only, **1.01 deg** to EKF only and **1.16 deg** to UKF only, respectively, in the sideslip angle estimation.

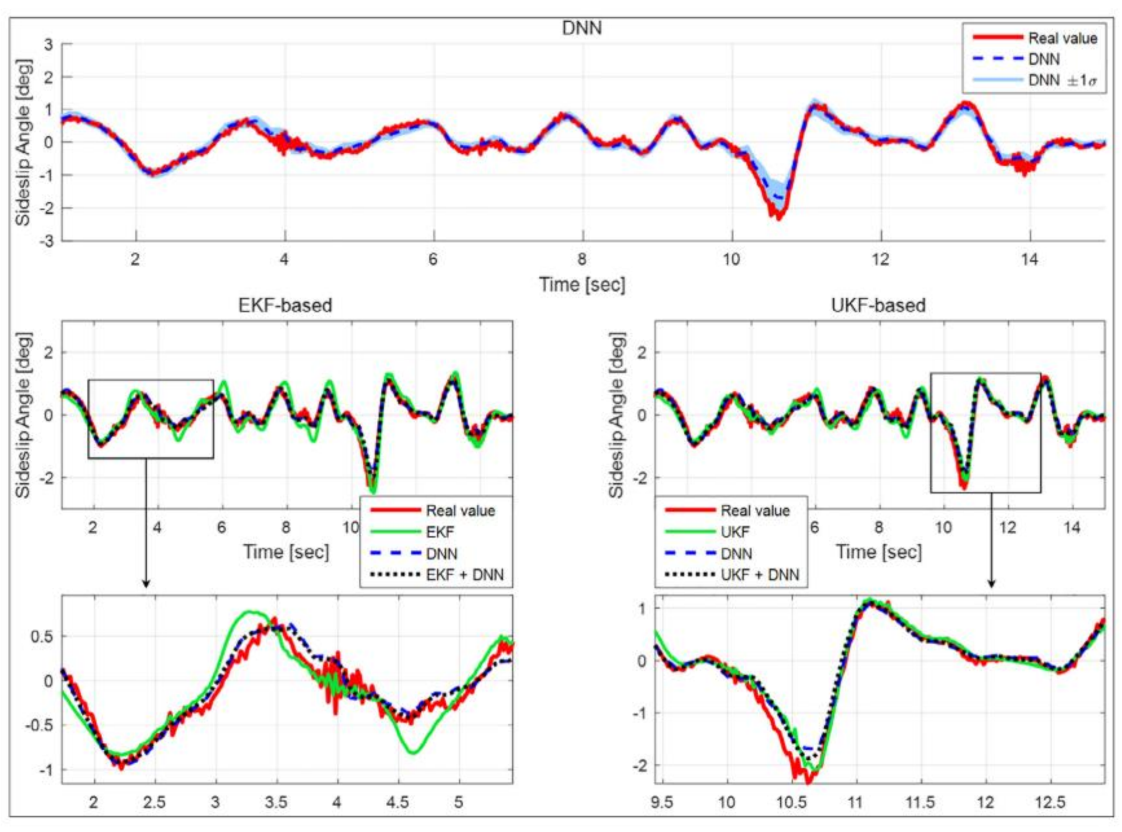


Fig. 4. Experimental results for test scenario 2