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Active Safety Control of Electric Vehicle Based on the Fusion of GPS Receiver and Dynamic Sensors

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ABSTRACT: In this paper, by the fusion of GPS receiver and dynamic sensors, we design a double-layer estimator to obtain key states for active safety control system of electric vehicle. Using course angle from GPS and yaw rate from gyroscope, the first layer provides the estimation of sideslip angle and yaw angle. Utilizing the estimated sideslip angle and measured accelerations, the lateral and longitudinal velocities are estimated by the second layer. Kalman filter with disturbance accommodating technique considering the compensation of measurement delay of GPS is proposed. Estimated states are applied in two active safety controls. The former is the traction control based on slip ratio control of electric vehicle using sliding mode theory. The later is a lateral stability control system using direct yaw moment generated by in-wheel motors and active front steering.

KEY WORDS: Global positioning system, electric vehicle, Kalman filter, slip ratio control, lateral stability control.

1. Introduction

From the view of motion control, the remarkable advantages of in-wheel motors have opened a new era of active safety control of electric vehicle (EV) [1]. One of the big challenges in active safety control is how to accurately obtain the key vehicle states. Sideslip angle is mandatory for lateral stability control, and longitudinal velocity is required for slip ratio calculation in traction control on slippery road. However, reliable sensors to measure such kind of vehicle motion information are not available at affordable costs. For instance, the optical sensor produced by Corrsys-Datron is only used for sideslip angle measurement in experiments at research institutes, but it cannot be equipped in commercial vehicle. For maintaining the reasonable cost of the control system, vehicle state estimator plays a very important role. Literature review shows that vehicle state estimation using on-board dynamic sensors have been widely researched [2-4] and applied in active safety control system [5-6]. However, the measurements of dynamic sensor such as gyroscope and accelerometers are often influenced by strong noise, bias, gravity on bank road, and the wind effect is also not properly captured. The variation of estimation model's parameters like cornering stiffness which changes according to road condition is also a nontrivial problem.

Since the last decade, GPS has been a candidate for vehicle state estimation. Besides the absolute positions of vehicle, GPS receiver can provide other measurements that cannot be obtain from dynamic sensors: velocity and attitude (course angle). By using double antenna GPS receiver, sideslip angle can be calculated directly without using vehicle model [7]. This method is then applied in vehicle stability control system using braking and/or active steering [8]. However, the main disadvantage of this method is the poor update rate of GPS receiver which is often less than 50 Hz. This method is not applicable for advanced motion control of EV in which the in-wheel motor can be controlled at high frequency of 1 kHz or more. In order to provide high rate estimation, the fusion of GPS receiver with dynamic sensor has been studied. For instance, the combination of GPS receiver with gyroscope [9] or magnetometer [10] was proposed for sideslip angle estimation. In these methods, the robustness of estimation under model uncertainties and external disturbances were not deeply examined. Moreover, the time delay of data transferred from GPS receiver is another challenge.

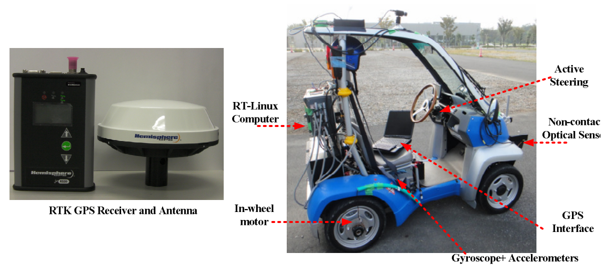


Fig. 1. Experimental EV and GPS receiver.

In this paper, a vehicle state estimator using the fusion of single antenna GPS receiver and dynamic sensors is proposed. Kalman filter is developed as the core theory of the estimator. By treating the combination of model uncertainties and external disturbances as extended states, the robustness of state estimation is improved. The time delay of data from GPS receiver is handled by the reconstruction of measurement in current time. The estimator has two layers and can provide the key states for active safety control of EV: sideslip angle and yaw angle by the first layer, longitudinal and lateral velocities by the second layer. Using sliding mode theory, traction control of in-wheel motored EV is designed with wheel slip ratio calculated from estimated longitudinal velocity. Lateral stability control system using direct yaw moment and active front steering angle is designed based on the estimation of sideslip angle. Experiments are conducted to verify the proposed estimator and active safety control systems.

2. Experimental electric vehicle

2.1. Experimental setup

A one seat micro EV named "supper capacitor COMS" is used for this research (Fig. 1). An optical sensor produced by Corrsys-Datron is installed in the front of vehicle. It can provide the measurement of sideslip angle, longitudinal velocity, and lateral velocity for comparing with the estimated values. The dynamic sensors including gyroscope and accelerometers are installed at the center of gravity of the vehicle. Encoders are used for obtaining the rotational velocity of the wheels and the steering angle. Vehicle control unit (VCU) with RT-Linux operating system is used to implement the estimation and control algorithm. The basic sampling time of the system is 1 millisecond which is the same as that of dynamic sensors. A real-time kinematic (RTK) GPS receiver, the Hemisphere R320 OmniSTAR, is used to measure the position of vehicle with the accuracy less than 1 centimeter RMS at 20 Hz update-rate. We design GPS interface software in a laptop for decoding the NMEA messages from GPS receiver, and sending the decoded data to the VCU. From the measurement of position, vehicle velocity and course angle can be obtained in real time. Two in-wheel motors are installed in the rear wheels for generating the direct yaw moment. An EPS system is used to generate active front steering and it is applicable for steer-by-wire mode.

2.2. Modeling of experimental EV

In this paper, planar bicycle model is used for estimation design (Fig. 2). In order to estimate the sideslip angle and yaw angle, the following state space model is proposed:

$$\begin{cases} \dot{x}_1 = A_1 x_1 + B_1 u_1 \\ y_1 = C_1 x_1 \end{cases} \tag{1}$$

$$x_1 = [\beta \quad \gamma \quad \psi]^T, u_1 = [\delta_f \quad N_z]^T, y_1 = [\gamma \quad \nu] \tag{2}$$

$$A_1 = \begin{bmatrix} \dfrac{-2(C_f + C_r)}{M v_x} & -1 - \dfrac{2(C_f l_f - C_r l_r)}{M v_x^2} & 0 \\ \dfrac{-2(C_f l_f - C_r l_r)}{I_z} & \dfrac{-2(C_f l_f^2 + C_r l_r^2)}{I_z v_x} & 0 \\ 0 & 1 & 0 \end{bmatrix} \tag{3}$$

$$B_1 = \begin{bmatrix} \dfrac{2C_f}{M v_x} & 0 \\ \dfrac{2C_f l_f}{I_z} & \dfrac{1}{I_z} \\ 0 & 0 \end{bmatrix} \tag{4}$$

$$C_1 = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \tag{5}$$

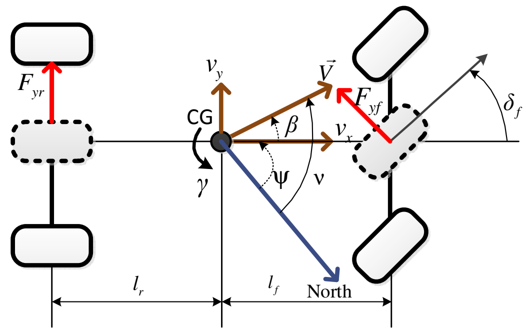


Fig. 2. Planar bicycle model of electric vehicle.

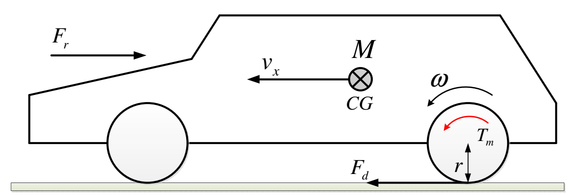


Fig. 3. One-wheel longitudinal model of electric vehicle.

Table 1 Nomenclatures.

Planar bicycle model (lateral motion)	
β	Sideslip angle
V	Velocity vector
v_x, v_y	Longitudinal and lateral velocity
a_x, a_y	Longitudinal and lateral acceleration
γ, ψ, ν	Yaw rate, yaw angle, and course angle
δ_f	Front steer angle
N_z	Yaw moment
C_f, C_r	Front and rear tire cornering stiffness
I_z	Yaw moment of inertia
M	Total mass of vehicle
l_f, l_r	Distance from front and rear axle to CG
F_{yf}, F_{yr}	Front and rear lateral force
On-wheel model (longitudinal motion)	
F_d	Driving force at tire-road contact path
F_r	Driving force at tire-road contact path
T_m	Motor torque
r	Wheel radius
I_ω	Wheel moment of inertia
λ	Wheel slip ratio

In this model, course angle from GPS is fused with the yaw rate from gyroscope. Course angle is the angle between velocity vector and the North direction, and it equals to yaw angle plus sideslip angle.

The lateral and longitudinal velocity can be calculated from velocity vector (obtained from GPS) and sideslip angle.

$$\begin{cases} v_x = V \cos \beta \\ v_y = V \sin \beta \end{cases} \tag{6}$$

In order to estimate the longitudinal and lateral velocity, the following state space model is established:

$$\begin{cases} \dot{x}_2 = A_2 x_2 + B_2 u_2 \\ y_2 = C_2 x_2 \end{cases} \tag{7}$$

$$x_2 = \begin{bmatrix} v_x & v_y \end{bmatrix}, u_2 = \begin{bmatrix} a_x & a_y \end{bmatrix}^T, y_2 = \begin{bmatrix} V\cos\beta & V\sin\beta \end{bmatrix} \tag{8}$$

$$A_2 = \begin{bmatrix} 0 & \gamma \\ -\gamma & 0 \end{bmatrix} \tag{9}$$

$$B_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{10}$$

$$C_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{12}$$

For the sake of simplicity, one-wheel model is used for longitudinal traction control of EV, as shown in Fig. 3. Assuming that the vehicle is accelerated, the following equations demonstrate the longitudinal motion:

$$I_\omega \dot{\omega} = T_m - rF_d \tag{13}$$

$$M\dot{v}_x = F_d - F_r \tag{14}$$

$$\lambda = \frac{r\omega - v_x}{r\omega} \tag{15}$$

3. Vehicle state estimator design

In this section, Kalman filter is developed for estimating the vehicle state using the model constructed in the previous section. To deal with the uncertainties of modeling, and the bias of sensor measurement, disturbance accommodating method is applied. The delay in measurement from GPS receiver is handled using the reconstruction of measurement in present time.

3.1. Disturbance accommodating method

Considering the discrete-time system with model uncertainties and disturbances as follows:

$$\begin{cases} x_{k+1} = \left(A_n + \Delta A\right) x_k + \left(B_n + \Delta B\right) u_k + d_k \\ y_k = \left(C_n + \Delta C\right) x_k \end{cases} \tag{16}$$

where A_n, B_n and C_n represent the nominal model; $\triangle A$, $\triangle B$, and $\triangle C$ represent the uncertainties in system modeling; d is the unknown disturbance vector. Two unknown disturbance terms can be defined as follows:

$$\begin{cases} d_{1,k} = \Delta A x_k + \Delta B u_k + d_k \\ d_{2,k} = \Delta C x_k \end{cases} \tag{17}$$

In conventional Kalman filter algorithm, the model is often constructed using the nominal parameters. Therefore, the accuracy of estimation may be degraded due to model uncertainties and external disturbances. Disturbance accommodating is a simple but effective method to solve this problem. As the first publication, the unknown disturbance terms can be augmented to be extended states in a control system based on LQR theory [11]. This idea was applied in Kalman filter design for sideslip angle estimation using GPS [12]. The unknown disturbance terms are assumed to be random walk processes with the rate n_{d_1} and n_{d_2} .

$$\begin{cases} d_{1,k+1} = d_{1,k} + T_s n_{d_1} \\ d_{2,k+1} = d_{2,k} + T_s n_{d_2} \end{cases} \tag{18}$$

where T_s is the fundamental sampling time. From (16) and (18), a new system with extended states is established as follows:

$$\begin{cases} \begin{bmatrix} x_{k+1} \\ d_{1,k+1} \\ d_{2,k+1} \end{bmatrix} = \begin{bmatrix} A_n & I & 0 \\ 0 & I & 0 \\ 0 & 0 & I \end{bmatrix} \begin{bmatrix} x_k \\ d_{1,k} \\ d_{2,k} \end{bmatrix} + \begin{bmatrix} B_n & 0 & 0 \\ 0 & T_s I & 0 \\ 0 & 0 & T_s I \end{bmatrix} \begin{bmatrix} u_k \\ n_{d_1} \\ n_{d_2} \end{bmatrix} \\ y = \begin{bmatrix} C_n & 0 & I \end{bmatrix} \begin{bmatrix} x_k \\ d_{1,k} \\ d_{2,k} \end{bmatrix} \end{cases} \tag{19}$$

By selecting the suitable rates of random walks and the process and measurement noise covariance matrices, the unknown terms can be estimated. This means the accuracy of state estimation using Kalman filter is improved.

3.2. Reconstruction of present measurement

Time delays consisting of few samples can be handled in Kalman filter algorithm by augmenting the state vector accordingly [13]. However, if the delay stands for a big number of samples, the size of the augmented state space system will increase considerably. Larsen proposed a well-known method based on the extrapolating the measurement to present time [14]. In this method, the size of Kalman filter is unchanged, burden in Kalman gain calculation. Recently, another method of calculating the optimal gain for robust Kalman filter with delayed measurement is proposed [15]. In this paper, the present time measurement is reconstructed from the delayed measurement and the control input stored in an N-step-storage.

A system with N-sample delay measurement is expressed as follows:

$$\begin{cases} x_{k+1} = A_n x_k + B_n u_k \\ y_k = C_n x_{k-N} \end{cases} \tag{20}$$

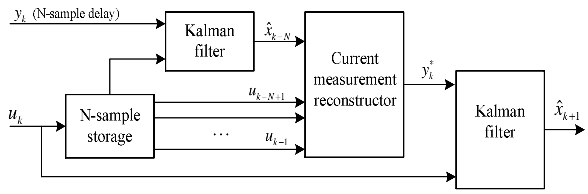


Fig. 4. Kalman filter with reconstruction of measurement in present time.

When the delayed measurement comes, it can be used to estimate the state at N samples before $\hat{x}_{k-N}$. Using this estimate, the measurement at present time can be constructed as follows:

$$\begin{cases} x^*_{k-N+1} = A_d \hat{x}_{k-N} + B_d u_{k-N} \\ x^*_{k-N+2} = A_d x^*_{k-N+1} + B_d u_{k-N+1} \\ \cdots \\ x^*_k = A_d x^*_{k-1} + B_d u_{k-1} \\ y^*_k = C_d x^*_k \end{cases} \tag{21}$$

Block diagram of Kalman filter with present time measurement reconstruction is shown in Fig. 4. The general formulation of the reconstruction is expressed as follows:

$$y^*_k = C_d \left(A_d^N \hat{x}_{k-N} + \sum_{j=1}^{N} A_d^{N-j} B_d u_{k-N+j-1} \right) \tag{22}$$

3.3. Double-layer state estimator design

In Section 2, two models are established for vehicle state estimation. Using two models, a double-layer state estimator is designed for Kalman filter. Each estimation layer is designed using the disturbance accommodating method with the reconstruction of present time measurement from GPS. The configuration of the proposed estimator is shown in Fig. 5.

As expressed in (1)-(5), the model of layer 1 is used for estimate the sideslip angle and yaw angle. The output measurement is the fusion of long sampling time course angle from GPS and with the short sampling time yaw rate. In layer 1, velocity is a time varying parameter instead of vehicle state. Therefore, it is acceptable that the velocity of non-driven wheel (obtain from encoder) is used as the approximate measurement of longitudinal velocity. In layer 1, between two consecutive updates of course angle, sideslip angle still can be estimated using only yaw rate.

From the estimated sideslip angle and the measurement of velocity vector from GPS receiver, measurements of longitudinal and lateral velocity are obtained using (6). However, the sampling time of these measurements depends on the update rate of GPS receiver (less than 100 Hz). In order to achieve velocity every 1 millisecond, the estimation model of layer 2 is constructed based on (7)-(12). Between two consecutive updates of velocity measurements, the lateral and longitudinal velocity can be predicted using the inputs of lateral and longitudinal accelerations.

4. Active safety controller design

In this section, we present the design of two active safety control system based on state estimator. The former is a wheel slip ratio control system (Fig. 6), and the later is a lateral stability control system (Fig. 7).

4.1. Wheel slip ratio control system

From (13), (14), and (15), a dynamic model for slip ratio control using motor torque is established as follows:

$$\dot{\lambda} = -\frac{\dot{v}_x}{v_x}\lambda + \frac{v_x}{I_\omega r \omega^2} T_m - \frac{\dot{v}_x}{v_x} - \frac{v_x}{I_\omega \omega^2} F_d \tag{23}$$

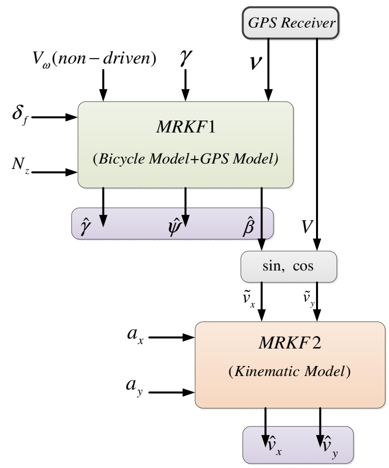


Fig. 5. Double-layer state estimator of EV.

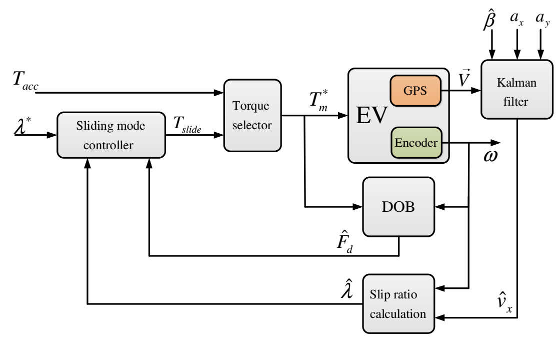


Fig. 6. Wheel slip ratio control system of EV.

Thanks to the in-wheel motor, driving force F_d can be estimated easily from disturbance observer (DOB) using motor torque and wheel velocity[16]. The slip ratio is obtained from estimated longitudinal velocity and wheel velocity. Sliding model theory is applied to design the wheel slip ratio controller. The sliding surface, reaching law, and Lyapunov function V are expressed as follows:

$$S = \left(\lambda - \lambda^*\right) \tag{24}$$

$$\dot{S} = -LS - Qsat(S) \tag{25}$$

$$V = \frac{1}{2} S^2 \tag{26}$$

$$\dot{V} = S\dot{S} = -LS^2 - QSsat(S) \tag{27}$$

In (25), L and Q are selected as positive constant. Thus, $\dot{V}$ is always negative. In other words, the stability of the control system is confirmed. A sliding mode control law is obtained as follows with the estimated slip ratio and the observation of driving force:

$$T_{slide} = \frac{I_\omega r \omega^2}{\hat{v}_x} \left[\frac{\dot{\hat{v}}_x}{\hat{v}_x}(1-\lambda) + \dot{\lambda}^* + \frac{\hat{v}_x}{I_\omega \omega^2} \hat{F}_d - LS - Qsat(S) \right] \tag{28}$$

4.2. Lateral stability control system

As shown in Fig. 7, the estimated values of sideslip angle and yaw rate are provided by Kalman filter in the double-layer state

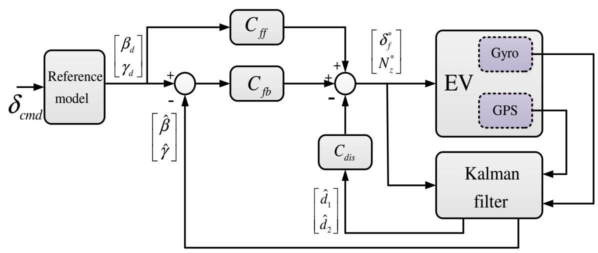


Fig. 7. Lateral stability control system of EV with disturbance accommodating in Kalman filter.

estimator. The reference values are calculated from steering command and neutral steering condition using the bicycle model. Due to the fact that cornering stiffness varies according to the change of road friction coefficient, model uncertainty is a big problem of lateral stability control. In order to improve the robustness of the control system, we propose a control system with feedback-feed forward controller and disturbance rejection(12). The feed forward controller C_{ff} is simply designed using the inverse of lateral dynamics established from bicycle model. The feedback controller C_{fb} is designed such that the closed loop system has the following transfer function:

$$\begin{bmatrix} \beta \\ \gamma \end{bmatrix} = \begin{bmatrix} \dfrac{K_\beta}{s+K_\beta} & 0 \\ 0 & \dfrac{K_\gamma}{s+K_\gamma} \end{bmatrix} \begin{bmatrix} \beta^* \\ \gamma^* \end{bmatrix} \tag{29}$$

In (29), the cut-off frequency K_β and K_γ are determined by trial and error experiment to ensure the best responsibility of the sideslip angle and yaw rate in the respect of steering angle command. It is impossible to set these cut-off frequencies too high due to limitation of actuators.

In order to improve the robustness of the control system, the influence of two unknown terms that represent the model uncertainties and external disturbances must be compensated. They are estimated by using the disturbance accommodating method in Kalman filter. The disturbance rejecter is designed as the inverse of the input matrix with the respect of front steering angle and direct yaw moment.

$$C_{dis} = \begin{bmatrix} \dfrac{2C_{fn}}{Mv_x} & 0 \\ \dfrac{2C_{fn}l_f}{I_z} & \dfrac{1}{I_z} \end{bmatrix}^{-1} \tag{30}$$

The command signals generated by the proposed controller are expressed as follows:

$$\begin{bmatrix} \delta_f^* \\ N_z^* \end{bmatrix} = C_{ff} \begin{bmatrix} \beta^* \\ \gamma^* \end{bmatrix} + C_{fb} \begin{bmatrix} \beta^* - \hat{\beta} \\ \gamma^* - \hat{\gamma} \end{bmatrix} - C_{dis} \begin{bmatrix} \hat{d}_1 \\ \hat{d}_2 \end{bmatrix} \tag{31}$$

5. Verification of the proposed active safety system

In this section, simulation and experimental results are demonstrated to verify the proposed active safety control system.

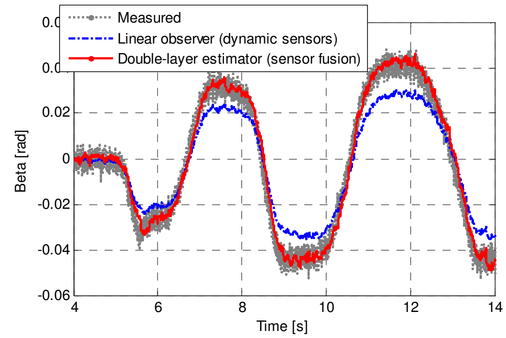


Fig. 8. Sideslip angle estimation results.

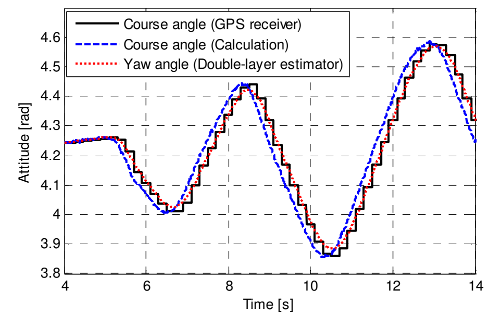


Fig. 9. Yaw angle estimation results.

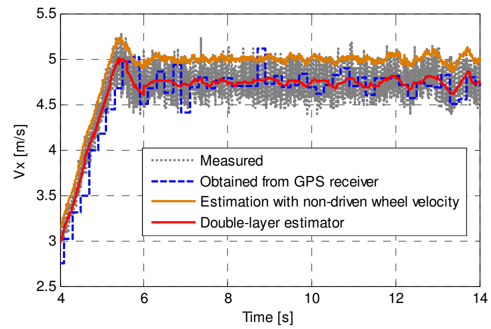


Fig. 10. Longitudinal velocity estimation results.

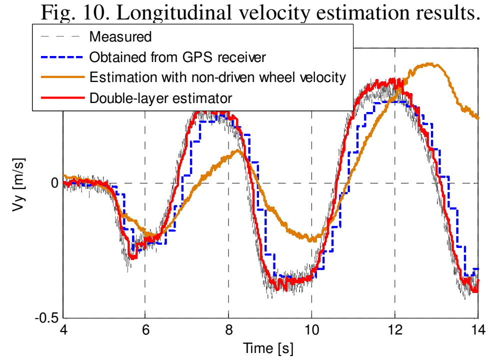


Fig. 11. Lateral velocity estimation results.

5.1. Verification of double-layer state estimator

In order to simulate the conventional GPS receiver, measurements from Hemisphere R320 are sampled at 200 millisecond (or 5 Hz update rate) and the time delay is set as 100 millisecond.

Results of sideslip angle estimation are shown in Fig. 8. Another sideslip angle estimation method using dynamic sensors

Fig. 12. Traction control on slippery road.

is performed for comparison. This method was proposed based on linear observer using the measurement of yaw rate and lateral acceleration(2). The cornering stiffness of the EV according to road condition in this experiment are $C_f \approx C_r \approx 7000$ [N/rad]. We intentionally design each estimation model with the nominal cornering stiffness $C_{fn} = C_{rn} = 10{,}000$ [N/rad]. This means a considerable model error is introduced to each estimator. Fig. 8 shows that the linear observer using dynamic sensors is sensitive to model error. In contrast, by using the fusion of GPS and gyroscope with proposed Kalman filter algorithm, sideslip angle can be estimated with much smaller estimation error. The advantages of the proposed sensor fusion method is vehicle attitude can be estimated, as shown in Fig. 9. The course angle obtained from GPS receiver is delayed and its sampling time is 200 milliseconds. For comparison, calculated course angle at 1 millisecond is obtained using measured sideslip angle and estimated yaw angle. Using the proposed estimator, the time delay is handled and yaw angle is estimated at high rate (every 1 millisecond).

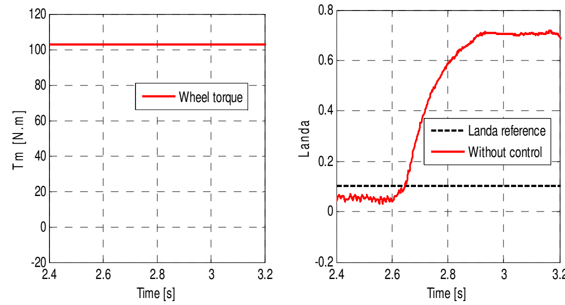
The estimation results of longitudinal and lateral velocity are shown in Fig. 10 and Fig. 11, respectively. Based on kinematic relationship, a Kalman filter is designed for estimating vehicle velocity(3). According to this method, the non-driven wheel's velocity is used as the approximate measurement of EV's longitudinal velocity while longitudinal and lateral accelerations are inputs. Using this method, estimated longitudinal velocity is almost closed to the measured value. However, under the measurement noise and the influence of roll motion to lateral motion, the estimation error of lateral velocity increases considerably. Using the proposed double-layer estimator, the time delay of measurements from GPS receiver is handled, and both longitudinal and lateral velocity are estimated with high accuracy.

5.2. Verification of wheel slip ratio control system

The low friction sheets covered with water is placed on the test course to simulate the slippery road (Fig. 12). The driver accelerates the vehicle from a starting point near by the low friction sheets. Because the vehicle motion is straight in this test, it is necessary to show the results of only one wheel (the rear left, for instance). In case of without control, the motor torque is kept constant as the driver's command (Fig. 13 (a)). As the results, the wheel slip ratio increase considerably (Fig. 13 (b)) and the slip occurs. When the proposed slip ratio control based on sliding mode theory is applied, motor torque is controlled and reduced in the low friction sheets as shown in Fig. 14 (a). Wheel slip ratio follows the reference value of 0.1 (Fig. 14 (b)) and safety traction of EV is achieved.

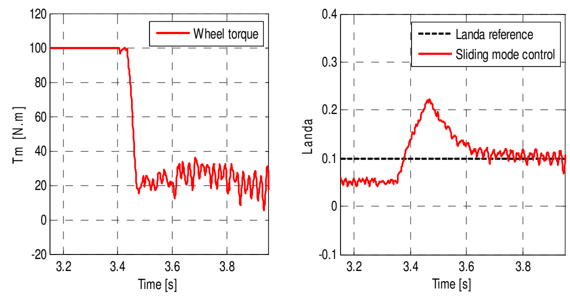
5.3. Verification of lateral stability control system

Cornering tests are conducted on high friction road at the speed of 20 kph. In this test, steer-by-wire mode is performed such that the steering angle is generated by control program and



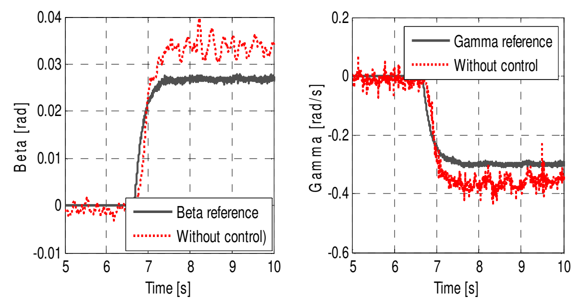
(a) Wheel torque (b) Slip ratio

Fig. 13. Longitudinal motion on slippery road (without control).



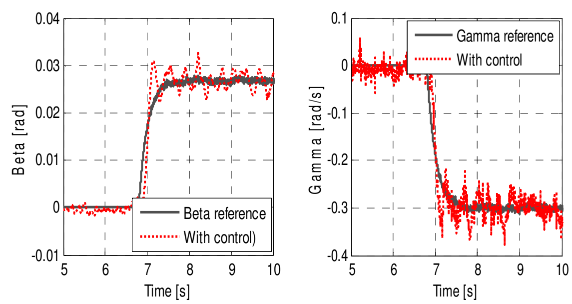
(a) Wheel torque (b) Slip ratio

Fig. 14. Longitudinal motion on slippery road (with control).



(a) Sideslip angle (b) Yaw rate

Fig. 15. Lateral motion of EV (without control).



(a) Sideslip angle (b) Yaw rate

Fig. 16. Lateral motion of EV (without control).

there is no need to handle the EV by the driver. In case of without control, both sideslip angle and yaw rate increase over their reference values (Fig. 15 (a) and (b)). When the proposed lateral stability control is applied, the controlled variables can track with the reference values, as shown in Fig. 16 (a) and (b). This means that the proposed control system can improve the stability of EV.

6. Conclusion

In this paper, a framework of active safety control of EV based on the fusion of single antenna GPS receiver and dynamic sensors is proposed. Kalman filter is developed as the core theory of sensor fusion. In order to deal with model uncertainties and external disturbances, disturbance accommodating method is applied in Kalman filter to enhance the robustness of estimation. The time delay of GPS receiver is handled by the reconstruction of measurement in current time applied in Kalman filter. Using the development in Kalman filter, a double-layer state estimator is proposed to provide key states for active safety system of EV: sideslip angle, yaw angle, longitudinal velocity, and lateral velocity. Experiments are conducted to verify the effectiveness of the proposal in comparison with other estimation methods using dynamic sensors. Thanks to the estimated states from double-layer estimator, two active safety control systems are designed. The former is wheel slip ratio control system with slip ratio calculation through estimated longitudinal velocity. The later is lateral stability control system with estimated sideslip angle.

In future works, the lost of a source of sensors (GPS or a dynamic sensor) will be considered. The change of GPS receiver accuracy due to the number of satellites in view is another nontrivial problem to solve.

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