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Vehicle State Estimation For Advanced Vehicle Motion Control Using Novel Lateral Tire Force Sensors

Kanghyun Nam, Sehoon Oh, Hiroshi Fujimoto, and Yoichi Hori

Abstract— **In this paper, new real-time methods for the lateral vehicle velocity and roll angle estimation are presented. Lateral tire forces, obtained from a multi-sensing hub (MSHub) unit, are used to estimate lateral vehicle velocity and a roll angle. In order to estimate lateral vehicle velocity, the recursive least square (RLS) algorithm is utilized based on a linear vehicle model and sensor measurements. In the roll angle estimation, the Kalman filter is designed for real-time estimation. The proposed estimation methods, RLS-based estimator and the Kalman filter, were verified by field tests on an experimental electric vehicle. Test results show that the proposed estimation methods provide better estimation performances and these methods are robust to road conditions.**

I. INTRODUCTION

Due to the increasing concerns about advanced motion control of electric vehicles with in-wheel motors, a great deal of researches on dynamics control for electric vehicles have been carried out [1]–[3]. Advanced motion control systems for electric vehicles, prevent from skidding, spinning out, and severe rolling motion, are referred to as a yaw stability control system and a roll stability control system, respectively. Compare with internal combustion engine vehicles, the electric vehicles with in-wheel motors have several advantages in the viewpoint of motion control [1], [2]. Based on these advantages of electric vehicles, a novel yaw moment control method based on the yaw moment observer (YMO) was proposed in [3] and roll stability control for safety and driver's ride quality was proposed and verified from experimental results [4]. In these stability control systems, vehicle states, e.g., yaw rate, lateral vehicle velocity, side slip angle and roll angle. etc., are required to be measured or estimated. The yaw rate can be easily measured by a cheap gyro sensor. However, in case of the lateral vehicle velocity, side slip angle, and roll angle, it is practically impossible to measure the values due to sensor cost problems. For this reason, a variety of researches on these states estimation have been carried out [6]–[10]. In [6], lateral vehicle velocity estimation algorithm was proposed using vehicle model, RLS algorithm, and Extended Kalman filter. In conventional methods (e.g., vehicle model-based method and sensor kinematics-based method), there are challenging issues such as how to compensate vehicle model uncertainties and remove numerical errors by direct integration [8]. Over the last few years, several estimation methods were proposed to estimate roll states based on vehicle dynamics model without using additional sensors (e.g., roll rate sensor) [9], [10]. In [11], several methods for roll angle estimation were discussed based on advantages and drawbacks of each method. Moreover, an approach using closed loop adaptive observer for roll angle and roll rate estimation was proposed and evaluated. In [9], a road-disturbance decoupled roll state estimator was designed, by combining the lateral model-based estimation method and vertical model-based estimation method, and evaluated by computer simulations. In other approaches [12], the Global Positioning System (GPS), which has two laterally placed GPS antennas, was used to estimate a roll angle. GPS-based estimation approaches requires satellite visibility from any location. However, the satellite visibility may be lost periodically in urban and forested driving environments and it causes inaccurate estimation. Even though the GPS devices provide a relatively accurate roll angle, it has a difficulty in vehicle applications due to the additional sensor cost.

K. Nam and S. Oh are with the Department of Electrical Engineering, Graduate School of Engineering, The University of Tokyo, Tokyo 113-8656, Japan nam@hori.k.u-tokyo.ac.jp; sehoon@hori.k.u-tokyo.ac.jp
H. Fujimoto and Y. Hori are with the Department of Advanced Energy, Graduate School of Frontier Sciences, The University of Tokyo, Chiba 153-8505, Japan fujimoto@k.u-tokyo.ac.jp; hori@k.u-tokyo.ac.jp

In this paper, novel estimation methods based on lateral tire forces, measured by a multi-sensing hub (MSHub) unit [18], are proposed to provide accurate estimates of lateral vehicle velocity and roll angle. The recursive least square (RLS) algorithm with a forgetting factor, which has been extensively utilized in the time-varying system identification [13], was used to estimate the lateral vehicle velocity. For estimating roll angle, the Kalman filter [14] was designed by using available sensor measurements and lateral vehicle velocity estimated from a RLS algorithm. The Kalman filter applications in vehicle state estimation have been widely discussed in the literature [15] and [16].

II. VEHICLE MODEL FOR ESTIMATOR DESIGN

In this section, a three degree-of-freedom (3–DOF) yaw plane model is introduced to describe the lateral motion of electric vehicles. The yaw plane representation with independent motor torque control is shown in Fig. 1.

The governing equations for longitudinal and lateral motions are given by

$$ma_x = \sum_{i=1}^{2}(F_i^x \cos\delta_f - F_i^y \sin\delta_f) + \sum_{i=3}^{4}(F_i^x) \tag{1}$$

$$ma_y = \sum_{i=1}^{2}(F_i^x \sin\delta_f + F_i^y \cos\delta_f) + \sum_{i=3}^{4}(F_i^y) \tag{2}$$

The yaw moment balance equation with respect to point

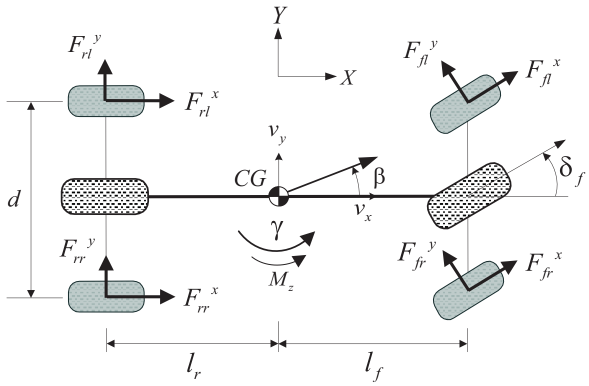

Fig. 1. 3–DOF yaw plane vehicle model

center of gravity (CG) is

$$I_z\dot{\gamma} = \sum_{i=1}^{2} l_f(F_i^x \sin\delta_f + F_i^y \cos\delta_f) - \sum_{i=3}^{4} l_r(F_i^y) + M_z \quad (3)$$

where F_i^x, F_i^y are the longitudinal and lateral tire forces at ith tire, δ_f is the steering angle, l_f and l_r are the distances between vehicle CG to front axle and rear axle, respectively, v_x, v_y are the longitudinal velocity and lateral velocity, γ is the yaw rate, I_z, m are the yaw moment of inertia and vehicle mass. And, M_z is the direct yaw moment, which is induced by the independent torque control of in-wheel motors, and it can be calculated as follows:

$$M_z = \frac{d}{2}(F_{rr}^x - F_{rl}^x) + \frac{d}{2}(F_{fr}^x - F_{fl}^x)\cos\delta_f \quad (4)$$

Here, longitudinal tire forces can be obtained from a driving force observer which is designed based on wheel dynamics [17].

The tire slip angles are calculated based on geometric derivation using wheel velocity vectors. If the velocities at wheel ground contact points are known, the tire slip angles can be easily derived geometrically and front tire slip angles are given by [5]

$$\alpha_{fl} = -\delta_f + tan^{-1}\left(\frac{v_y + \gamma l_f}{v_x - \gamma d/2}\right) \quad (5)$$

$$\alpha_{fr} = -\delta_f + tan^{-1}\left(\frac{v_y + \gamma l_f}{v_x + \gamma d/2}\right) \quad (6)$$

In usual, for the sake of design simplicity, a bicycle model is used in estimator design. Thus, the lateral and yaw rate dynamics are simplified as

$$mv_x(\dot{\beta} + \gamma) = F_f^y + F_r^y \quad (7)$$

$$I_z\dot{\gamma} = l_f F_f^y - l_r F_r^y + M_z \quad (8)$$

where β is the vehicle side slip angle, F_f^y, F_r^y are the front and rear lateral tire forces. For small tire slip angles, the lateral tire forces can be linearly approximated as follows:

$$F_f^y = -2C_f\alpha_f \approx -2C_f\left(\beta + \frac{\gamma l_f}{v_x} - \delta_f\right) \quad (9)$$

$$F_r^y = -2C_r\alpha_r \approx -2C_r\left(\beta - \frac{\gamma l_r}{v_x}\right) \quad (10)$$

where C_f, C_r are the front and rear tire cornering stiffnesses.

III. ROBUST ESTIMATION OF LATERAL VEHICLE VELOCITY

In this section, a novel method to estimate lateral vehicle velocity is introduced. The proposed method uses the lateral tire forces which are measured by a MSHub unit. The RLS algorithm was used to estimate lateral vehicle velocity in real-time. In order to design a lateral velocity estimator, the nonlinear lateral tire force equations are simplified by using following assumptions.

- The lateral tire forces are assumed to be proportional to the tire slip angles.
- It is assumed that the tire cornering stiffnesses of left and right wheels are same (i.e., $C_{fl} = C_{fr}$). In general, tire cornering stiffness is affected by weight transfer of vehicles. In contrast to engine vehicles, in-wheel-motored electric vehicles, having battery packs under the floor and driving motors attached in wheels, can lower a CG of the vehicle. This provides a less weight transfer and thereby improves the driving stability. From these features, variations in front left and right tire cornering stiffnesses due to weight transfer are neglected.

From above assumptions, the front lateral tire forces can be expressed as

$$F_{fl}^y = -C_{fl}\alpha_{fl} \approx -C_f\left(\frac{v_y + \gamma l_f}{v_x - \gamma d/2} - \delta_f\right) \quad (11)$$

$$F_{fr}^y = -C_{fr}\alpha_{fr} \approx -C_f\left(\frac{v_y + \gamma l_f}{v_x + \gamma d/2} - \delta_f\right) \quad (12)$$

By dividing (11) by (12), the lateral velocity v_y is derived as

$$v_y = \gamma l_f - \frac{\delta_f(F_{fl}^y - F_{fr}^y)}{\dfrac{F_{fl}^y}{v_x + \gamma d/2} - \dfrac{F_{fr}^y}{v_x - \gamma d/2}} \quad (13)$$

where the estimated lateral vehicle velocity is defined as a pseudo-measurement and is expressed as $\tilde{v}_y$. In section IV, this pseudo-measurement is used as a sensor measurement in roll angle estimator using a Kalman filter.

Considering that all output data and input data are determined at sample instant, v_y described in (13) can thus be formulated by the RLS algorithm.

$$y(t) = \varphi^T(t)\theta(t) \quad (14)$$

where a measured output $y(t)$, an estimated parameter $\theta(t)$, and an input regression $\varphi^T(t)$ can, respectively, be given as

$$\theta(t) = \tilde{v_y}$$

$$\varphi^T(t) = \left(\frac{F_{fl}^y}{v_x + \gamma d/2} - \frac{F_{fr}^y}{v_x - \gamma d/2}\right)$$

$$y(t) = \gamma l_f\left(\frac{F_{fl}^y}{v_x + \gamma d/2} - \frac{F_{fr}^y}{v_x - \gamma d/2}\right) - \delta_f(F_{fl}^y - F_{fr}^y)$$

The ultimate goal of the RLS algorithm is to find out parameters that minimizes the following weighted least-squares criterion [13]:

$$\hat{\theta}(t) = \arg\min_{\theta} \left\{ \sum_{k=1}^{t} \Gamma(t,k) \cdot \rho(\varepsilon) \right\} \tag{15}$$

Here, $\Gamma(t,k)$ is the weight on the prediction errors at time k, and $\rho(\varepsilon)$ is the cost function which is defined as $\rho(\varepsilon) = \frac{1}{2}\varepsilon^2$. If the prediction errors can be assumed to be Gaussian with zero mean values, the defined cost function is reasonable. The recursive process of the RLS algorithm is described as

$$\begin{aligned} \hat{\theta}(t) &= \hat{\theta}(t-1) + K(t)\left[y(t) - \varphi^T(t)\hat{\theta}(t-1)\right] \\ K(t) &= P(t-1)\varphi(t)[\lambda I + \varphi^T(t)P(t-1)\varphi(t)]^{-1} \\ P(t) &= \frac{1}{\lambda}[I - K(t)\varphi^T(t)]P(t-1) \end{aligned} \tag{16}$$

where I is the identity matrix, $\varepsilon(t)$ is the prediction error, and $K(t)$ and $P(t)$ are correction gain matrices. In order to cope with time-varying properties in a vehicle system, λ, called a forgetting factor, is used. The smaller λ is, the less weight is assigned to the older data; that is, the past data are forgotten faster. In this paper, λ around 0.995 was selected to make reasonable trade-off between tracking ability and noise sensitivity.

The main advantages of a proposed estimation method are summarized in three points. First, it is robust against variations in vehicle parameters and tire-road conditions. This is certified that (13) does not involve varying parameters. Second, a proposed method can be easily realized without much additional cost: MSHub units (see [18]), including rolling bearings used to support wheels of the vehicle, can measure the loads applied to the rolling bearing. In many conventional vehicles, wheel hub units with built-in active ABS sensors (i.e., wheel velocity sensor) were equipped. Comparing MSHub units with wheel hub units which are currently used in vehicles, MSHub units have almost the same mechanical structure except for rolling elements in a pair of rows and is capable of being constructed at a low cost. Therefore, accurate lateral tire force measurements using MSHub units can be realized without much additional cost. Finally, a proposed recursive algorithm is very simple and can be easily implemented in real-time. Moreover, the estimated lateral vehicle velocity can be used to identify cornering stiffness in (9) and (10).

IV. ROLL ANGLE ESTIMATION FOR ROLL STABILITY CONTROL

The vehicle roll motion generally occurs as a result of lateral motion by steering maneuver and road disturbances. In contrast to conventional engine vehicles, electric vehicles with in-wheel motors show a low ratio of sprung mass over unsprung mass due to in-wheel motors installed in each wheel. This implies that ride quality can be deteriorated. In order to avoid deterioration in ride quality, the suspension stiffness was selected as a smaller value. It indicates that the roll motion easily occurs. Thus, the roll stability control system is required and accurate roll angle estimation has to be carried out before control design. In this section, a roll angle estimation method, which uses sensor kinematic relationships and a linear roll model, is introduced.

A. Roll Dynamics and Sensor Kinematics

This section introduces roll dynamics for estimator design. Fig. 2 shows the two-dimensional roll dynamics for electric vehicles with in-wheel motors. In order to model the roll dynamics, the following assumptions are made:

- The location of the roll axis is assumed constant in a height of roll center (RC) parallel to the ground and the lateral and vertical movements of RC due to the asymmetric suspension geometry are not considered.
- The pitching and bouncing motion of sprung mass are neglected.
- A small roll angle is assumed such that $sin\phi \approx \phi$ and $cos\phi \approx 1$.
- The effect of road bank angle is not considered in this study.

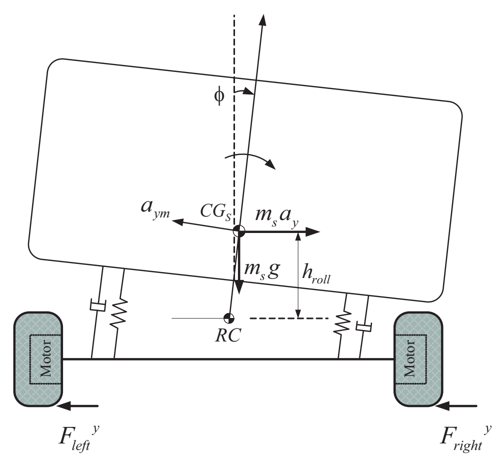

Fig. 2. Two-dimensional roll dynamics for an electric vehicle

The two-dimensional roll dynamic equation and the kinematic relationships of the lateral acceleration of CG, a_y, and a sensor measurement, a_{ym}, are expressed as

$$I_x\ddot{\phi} + C_{roll}\dot{\phi} + K_{roll}\phi = m_s(a_{ym})h_{roll} \tag{17}$$

$$a_{ym} = \dot{v_y} + \gamma v_x + g\phi \tag{18}$$

$$a_y = \dot{v_y} + \gamma v_x \tag{19}$$

where I_x is the roll moment of inertia, C_{roll}, K_{roll} are the roll damping coefficient and roll spring coefficient, m_s is the sprung mass, h_{roll} is the height of the center of sprung mass above roll center (RC), (18) is the sensor kinematics of a lateral acceleration sensor including roll angle effect. In (17), the roll moment acting on sprung mass, caused by lateral motion, can be explained by lateral inertial force and gravity force of sprung mass.

B. Kalman Filter Design for Roll Angle Estimation

In this section, a roll angle estimation method, based on sensor measurements and roll dynamics, is proposed. The Kalman filter was applied to estimate a roll angle and to remove sensor measurement noises. The process of roll angle estimation is divided into two steps. First, the lateral vehicle velocity estimation is conducted described in section III. Second, this estimated lateral vehicle velocity is used to estimate roll angle in a Kalman filter. The estimated v_y from (16) is considered as a pseudo-measurement $\tilde{v}_y$, and thereby (18) can be rewritten as follows:

$$\dot{\tilde{v}}_y = a_{ym} - \gamma v_x - g\phi \tag{20}$$

From yaw dynamics model, lateral acceleration sensor kinematics, and roll dynamics model, the state space equations for Kalman filter design are obtained as

$$\begin{aligned} \dot{x} &= Ax + Bu + w \\ y &= Cx + v \end{aligned} \tag{21}$$

where

$$x = [\ \tilde{v}_y \quad \gamma \quad \phi \quad \dot{\phi} \quad F_f^y \quad F_r^y\ ]^T, \quad u = [\ a_{ym} \quad M_z\ ]^T,$$

$$y = [\ \tilde{v}_y \quad \gamma \quad F_f^y \quad F_r^y\ ]^T$$

$$A = \begin{bmatrix} 0 & -v_x & -g & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{l_f}{I_z} & \frac{-l_r}{I_z} \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & -\frac{K_{roll}}{I_x} & -\frac{C_{roll}}{I_x} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix},$$

$$B = \begin{bmatrix} 1 & 0 \\ 0 & \frac{1}{I_z} \\ 0 & 0 \\ \frac{m_s h_{roll}}{I_x} & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

It is noted that the system described by (21) could be completely observable by using $\tilde{v}_y$ in (20) as a sensor measurement.

For implementation on an experimental electric vehicle, (21) is discretized as follows:

$$\begin{aligned} x[k+1] &= G[k]x[k] + H[k]u[k] + w[k] \\ y[k] &= C[k]x[k] + v[k] \end{aligned} \tag{22}$$

where

$$\begin{aligned} G[k] &= e^{AT_s}, \quad H[k] = \int_0^{T_s} e^{A\tau} B d_\tau \\ C[k] &= C, \quad T_s : \text{Sampling time} \end{aligned}$$

where $w[k]$ and $v[k]$ are the process noise and measurement noise, k is the time step. It is assumed that the process and measurement noise are zero-mean Gaussian processes, and the covariance matrices are given as follows:

$$Q_w = E(w[k]w[k]^T) > 0, \quad R_v = E(v[k]v[k]^T) \gg 0 \tag{23}$$

The extent of Kalman filter bandwidth and its susceptibility to sensor measurement noises totally depend on its covariance matrix of process noise Q_w, which represents the level of confidence placed in the accuracy of the observer model, and the covariance matrix of measurement noise R_v, which represents the level of confidence placed in the accuracy of the sensor measurements. These values are used to tune the filter characteristics including an accuracy and a response, and it was experimentally determined by using sensor measurements. In this paper, the covariance matrices of process noise and measurement noise are selected as follows:

$$Q_w = \text{diag}[Q_{\tilde{v}_y}, Q_\gamma, Q_\phi, Q_{\dot{\phi}}, Q_{F_f^y}, Q_{F_r^y}] \tag{24}$$

$$R_v = \text{diag}[R_{\tilde{v}_y}, R_\gamma, R_{F_f^y}, R_{F_r^y}] \tag{25}$$

In principle, the covariance matrices are not necessarily diagonal. However, treating the noise covariance matrix as a diagonal matrix (i.e., individual noise components are not cross-correlated) is advantageous since it reduces computation time. In selection of covariance matrices, it should be noted that the less noise in sensor measurements compared to the uncertainty in dynamics model, the more the states will be adapted to follow sensor measurements. Since the new measurements for lateral tire forces is much more accurate than the prior estimates, we put the high uncertainty on states (i.e., lateral tire forces). The states (e.g., roll angle and roll rate) are modeled using reliable vehicle roll dynamics. Therefore, the process noises are relatively small. The suitable process noise variances for other states (e.g., lateral vehicle velocity and yaw rate) are selected based on comparison to the corresponding measurement noise variances. The noise variances of three sensor measurements are determined from statistical data analysis using Matlab software.

V. EXPERIMENTAL VERIFICATION

A. Experimental Electric Vehicle

The experimental electric vehicle named "FPEV-II Kanon", shown in Fig. 3(a), was used for field tests. The "FPEV-II Kanon" has following special features.

1) In-wheel motors are mounted in each wheel. It means that we can control each wheel's torque completely and independently.
2) A MSHub unit for measuring the lateral tire forces is installed in each wheel. Fig. 3(b) shows the MSHub unit which was invented by NSK LTD. [18]

(a) (b)

Fig. 5. Experimental electric vehicle: (a) FPEV-II Kanon, (b) MSHub unit (NSK LTD.)

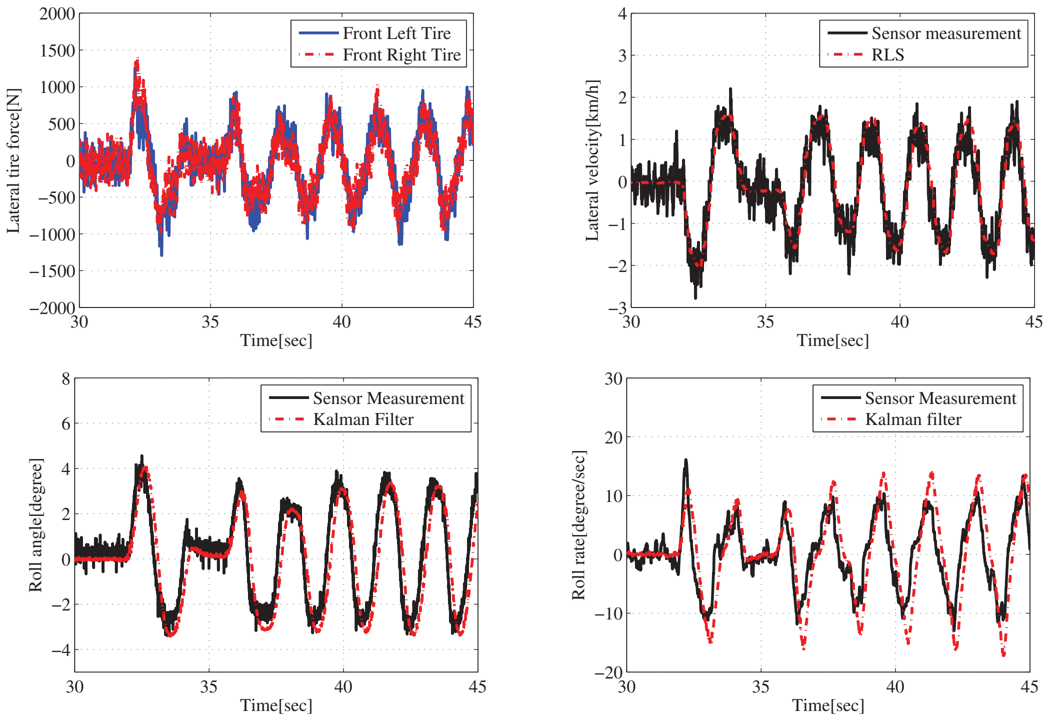

Fig. 3. Results of a field test on dry asphalt (i.e., $\mu \simeq 0.9$): (a) Measured lateral tire forces. (b) Lateral vehicle velocity. (c) Roll angle. (d) Roll rate.

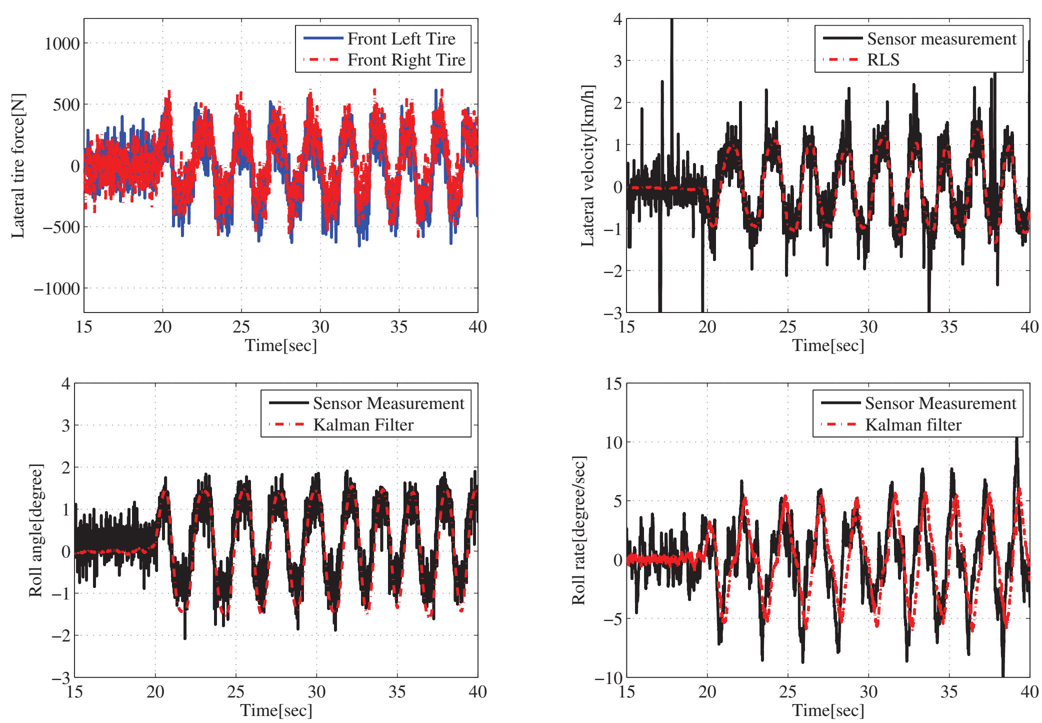

Fig. 4. Results of a field test on a slippery road (i.e., $\mu \simeq 0.3$): (a) Measured lateral tire forces. (b) Lateral vehicle velocity. (c) Roll angle. (d) Roll rate.

B. Experimental Result

The proposed estimation method was implemented in an experimental electric vehicle shown in Fig. 3(a). In order to evaluate estimation results of proposed estimators, a non-contact optical sensor, Correvit (Corrsys–Datron), is used for accurate measurements of lateral vehicle velocity and longitudinal vehicle velocity. Moreover, the vertical potentiometers and a roll rate sensor were used to accurately measure the roll angle and roll rate, respectively. The random steering test on dry asphalt was conducted and a field test on a slippery road was also carried out to verify the robustness to road conditions.

Fig. 4 shows experimental results for the random steering test at a vehicle speed of 50 km/h on dry asphalt. Fig. 4(a)–(d) present the measured lateral tire forces and estimates of the lateral vehicle velocity, a roll angle, and a roll rate as well as sensor measurements ,respectively. As shown in Fig. 4(b), estimated lateral vehicle velocity from RLS algorithm well follows the trend of measured lateral vehicle velocity. It can be also seen that the estimated roll angle and roll rate correctly follow the actual values with small errors. Similarly, the result, shown in Fig. 5 , obtained from a field test on a slippery road shows the small estimation errors. This implies that the proposed estimation methods provide robustness to road conditions.

VI. CONCLUSIONS AND FUTURE WORKS

A novel estimation method is proposed to accurately estimate the lateral vehicle velocity and roll angle. The RLS algorithm with a forgetting factor and a Kalman filter were used in estimator design. Estimation performances and robustness of proposed estimators were discussed and evaluated by field tests on dry asphalt and a slippery road. It was shown that the estimation method utilizing lateral tire forces could provide improved estimation of the vehicle lateral vehicle velocity and roll angle. From experimental results of proposed estimators, it is anticipated that lateral tire forces, can be accurately measured by a MSHub unit, will provide practical solutions to challenging issues in vehicle state estimation. Future studies will aim to design advanced motion control systems for electric vehicles based on proposed estimation methods and to apply the cost-effective MSHub units to vehicle stability control system.

VII. ACKNOWLEDGMENTS

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