A Nonlinear Estimator Concept for Active Vehicle Suspension Control

Guido Koch*, Tobias Kloiber, Enrico Pellegrini and Boris Lohmann

Abstract—A new Kalman filter based signal estimation concept for active vehicle suspension control is presented in this paper considering the nonlinear damper characteristic of a vehicle suspension setup. The application of a multi-objective genetic optimization algorithm for the tuning of the estimator shows that three parallel Kalman filters enhance the estimation performance for the variables of interest (states, dynamic wheel load and road profile). The Kalman filter structure is validated in simulations and on a test rig for an active suspension configuration using measurements of real road profiles as disturbance input. The advantages of the concept are its low computational effort compared to Extended or Unscented Kalman filters and its good estimation accuracy despite the presence of nonlinearities in the suspension setup.

I. INTRODUCTION

Due to rising customer demands for driving comfort, the integration of controlled active and semi-active elements in modern vehicle suspension systems has increased considerably. These systems can ease the conflict of the objectives ride comfort and ride safety significantly (see e.g. [MW04], [Hro97]). In order to implement state feedback based controllers for these concepts, the vehicle’s vertical dynamic states have to be estimated from the available sensor signals because measuring all variables is unfeasible with reasonable economical effort.

Kalman filter based state estimation techniques for linear active suspension models are presented e.g. in [SCW94], [Ven93] and [YC98]. In [RH95] the nonlinear behavior of the actuator is considered in the observer design while still assuming the suspension element characteristics to be linear. Neglecting the nonlinear properties of these elements (especially the damper) for the estimator design however, leads to a degradation of the estimation quality.

One method to handle the nonlinear characteristic of the damper for the estimator design is based on [Ohs00] and [KYYN07]. The damper force is calculated from an estimate of the damper velocity and its nonlinear characteristic. The resulting force is used as an additional input signal of the estimator. This concept has been considered for semi-active suspension systems in [Lin02] and [Frö07]. Other methods for incorporating nonlinearities in the estimator design are Unscented Kalman filters [JU97] and Extended Kalman filters [ZM00]. Applications of these concepts for semi-active suspension control are presented in [FN05] and [Frö07], respectively. However, these methods are difficult to implement because of their computational complexity.

In order to study the possibility of additional disturbance feedforward control, the road profile has to be estimated because measuring it (e.g. by laser scanners in [Str08]) is very complex and expensive. In [Frö07], the estimation of the disturbance signal for suspension control applications is considered only briefly in simulations and no experimental results are given.

In this work, a Kalman filter based estimator structure enabling state feedback control of an active suspension system is developed. Besides the states, the dynamic wheel load is estimated to be used in adaptive controller structures that schedule their parametrizations according to the current driving state [Koc09], [KDL08]. Moreover, it is investigated, how accurate the road profile can be estimated with the proposed concept. The nonlinearity of the damper is taken into account by using the damper force as an additional input. Thus, the conventional Kalman filter can be used as basis for the estimator design. Applying three Kalman filters in parallel can maximize the accuracy of the estimation.

The remainder of the paper is organized as follows: In Section II the experimental setup is presented and the system and disturbance models including the main nonlinearities are introduced. Section III describes the estimator design for the active suspension system. Simulation results of the estimation performance are given in Section IV and are validated using testrig measurements for real road profiles as well as a singular excitation event in Section V.

II. TEST SETUP AND MODELLING

In the frequency range of interest (0 – 25 Hz), the vertical translatory movement of vehicle suspension systems can be described by quarter-vehicle models (Figure 1) [MW04]. The model parameters correspond to the test setup presented in Section II-B and are given in Table I. The disturbance input of the model is the vertical road displacement \( \dot{x}_g \), the control input in the active suspension case is the force of the actuator \( u(t) = F(t) \), i.e. the passive system results if \( u(t) = 0 \).

A. Disturbance model

A frequently used model for the road excitation \( x_s \) approximates the power spectral density of the road profile by

\[
S_{x_s x_s}(\omega) = \frac{\alpha v}{\beta^2 v^2 + \omega^2},
\]

where \( \omega \) is the angular frequency, \( v \) is the vehicle velocity and \( \alpha, \beta \) are real parameters that characterize the road irregularities [MW04]. Assuming a Gaussian, zero mean, white noise input \( w_x(t) \) with a power spectral density of \( S_{w_x w_x} = \alpha v \) [Ven93], the disturbance model can be formulated as a first order shaping filter with a state space representation

\[
\dot{x}_g(t) = -\beta v x_g(t) + w_x(t).
\]
TABLE I
QUARTER-VEHICLE PARAMETERS OF THE TEST SETUP

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chassis mass</td>
<td>( m_c )</td>
<td>90</td>
<td>[kg]</td>
</tr>
<tr>
<td>Unsprung mass</td>
<td>( m_u )</td>
<td>24</td>
<td>[kg]</td>
</tr>
<tr>
<td>Primary spring stiffness</td>
<td>( c_c )</td>
<td>5025</td>
<td>[N/m]</td>
</tr>
<tr>
<td>Transmission ratio</td>
<td>( i_e = i_d = i )</td>
<td>0.409</td>
<td></td>
</tr>
<tr>
<td>Tire stiffness</td>
<td>( c_w )</td>
<td>149717</td>
<td>[N/m]</td>
</tr>
<tr>
<td>Tire damping</td>
<td>( d_w )</td>
<td>50</td>
<td>[Ns/m]</td>
</tr>
</tbody>
</table>

The parameters of the shaping filter have been chosen according to [Ven93] as \( \beta = 0.2 \text{ rad}^2/\text{m} \), \( \nu = 30 \text{ m/s} \) and \( \alpha \) results from the optimization routine for the covariance matrix \( \mathbf{Q} \) presented in Section III-B.

B. The quarter-vehicle testrig

At the authors’ institute a suspension testrig based on a quadricycle suspension system has been designed (Figure 1). The tire is excited vertically by a linear motor that simulates the road displacement. A second electrical linear motor is integrated between chassis and wheel mass to realize the active suspension system. The testrig is equipped with accelerometers for the vertical accelerations of chassis and wheel mass as well as a wire rope actuated position transducer that measures the suspension deflection. An incremental encoder records the vertical displacement \( x_g(t) \) and the dynamic wheel load \( F_{dy} = c_w(x_g - x_w) + d_w(x_g - x_w) \) is measured by a force sensor. The sampling time of the digital signal processing system is \( T_s = 1 \text{ msec} \).

Fig. 1. High bandwidth active quarter-vehicle suspension model (left) and quarter-vehicle testrig (right)

C. Nonlinearities of the suspension system

The main nonlinearities of the considered suspension system are the degressive force-velocity characteristic of the damper, the quadratic spring characteristic of the tire (see Figure 2), the kinematics of the suspension system as well as friction effects. While the tire spring characteristic is linearized in the operating point defined by the static load of the quarter-vehicle, the nonlinear damper characteristic is considered for the state estimation as presented in Section III-B. The measured primary spring characteristic of the suspension can be linearized in good approximation because its minor progressiveness is negligible in the operating range of the suspension deflection at the testrig.

The nonlinearities caused by the kinematics of the suspension system can be considered in the model using a transmission factor \( i_c = \frac{\Delta x_{el}}{\Delta x_{cl}} \) (with \( \Delta x_{el} \) being the relative velocity of the suspension strut in the direction of the element’s center line). The factor transforms the forces and kinematic relations at the elements (spring force \( F_{ce} = \bar{c}_e \Delta x_{cl} \), damper force \( F_{de} \)) to the corresponding quantities of the quarter-vehicle model (Figure 1), i.e. the forces acting on the center of gravity of the wheel. According to [Mat07] for the primary spring stiffness results

\[
c_c = \bar{c}_e^2 \bar{c}_e + \bar{F}_{ce} \frac{d \bar{c}_e}{d(x_c - x_w)}.
\]

The second term in (3) can be neglected in this study because it has been identified to be small. Due to the concentric configuration of the suspension strut, the transmission ratio is the same for the spring and the damper, such that \( i_c = i_d = i \) holds and for the damper force results \( F_d = i \bar{F}_d \). Dry friction effects for the movement of the chassis mass and the suspension elements are considered similarly as presented in [RH95]. These effects are neglected for the estimator design but are included in a nonlinear model of the testrig (Section II-D).

D. Stochastic quarter-vehicle and testrig models

From the equations of motion and the disturbance model given in Section II-A, a state space representation of the system can be derived with the state vector

\[
x = \begin{bmatrix} x_c & \dot{x}_c & x_w & \dot{x}_w & x_g & \dot{x}_g \end{bmatrix}^T.
\]

The potential of the concept proposed in this paper is investigated using the measurement signals

\[
y = \begin{bmatrix} \dot{x}_c & \dot{x}_w & x_c - x_w \end{bmatrix}^T
\]

that represent a sensor configuration of modern production vehicles. An analysis of possible configurations with only two sensors is presented in [Friö07].

The nonlinear state equation is given by (6). The considered process noise \( \mathbf{w} \) is zero mean white Gaussian noise with covariance kernel \( E\{\mathbf{w}(t)\mathbf{w}(t')\} = \mathbf{Q} \delta(t - t') \), where \( \delta(t - t') \) denotes the Dirac delta and \( \mathbf{Q} \) is symmetric and positive definite. While \( w_{xy}(t) \) is the input of the disturbance model (Section II-A), the first four elements of \( \mathbf{w} \) represent model uncertainties.
\[ \dot{x}(t) = \begin{bmatrix} \frac{\alpha_c}{m_c} (x_c - x_c) - \frac{1}{m_c} F_d(x) + \frac{1}{m_c} u(t) \\ \frac{\alpha_w}{m_w} (x_w - x_c) + \frac{\alpha_v}{m_w} (-\beta v x_g - x_w) - \frac{\alpha_m}{m_w} (x_c - x_w) + \frac{1}{m_w} F_d(x) - \frac{1}{m_w} u(t) \\ \dot{x}_w \\ \dot{c}_w \\ \dot{m}_w \end{bmatrix} \]

\[ \begin{bmatrix} w_{x_c} \\ w_{x_w} \\ w_{x_c} \\ w_{x_w} \end{bmatrix} \]

\[ \begin{bmatrix} w_{t} \\ v_{t} \end{bmatrix} \]

The equation of the measurement signals (7) is given in discrete-time due to the discrete nature of the Kalman filter algorithm to be applied in the next Section. In (7), \( w(t) \) represents discrete-time white Gaussian measurement noise with zero mean and covariance kernel

\[ E \{ w(t)w^T(t_j) \} = \left\{ \begin{array}{ll} R & \text{for } t_i = t_j \\ 0 & \text{for } t_i \neq t_j \end{array} \right\}, \quad (8) \]

where \( R \) is symmetric and positive definite. The initial condition \( x(t_0) \) is specified by the Gaussian random variable \( x_0 \) with mean \( \mu_0 = 0 \) and covariance \( P_0 = 0 \).

An accurate testrig model, which contains all nonlinearities including the tire spring characteristic (Figure 2) and friction effects (Section II-C), is used for the parameter optimization of the Kalman filter structure (Section III-B) and the simulations presented in Section IV.

E. Controller for the active suspension system

The Kalman filter performance is tested for the active suspension system (see Sections IV and V) using a comfort oriented LQ controller. The state space model for the controller design incorporates the state vector

\[ x_c = [ \begin{array}{cccc} x_c - x_w & \dot{x}_c & x_w - x_g & \dot{x}_w \end{array} ]^T \quad (9) \]

corresponding to previous publications of the authors [KLD08, Koc09]. The new state vector \( x_c \) can be constructed from linear combinations of the observer state vector (4). A linear approximation of the damper characteristic (Figure 2) in (6) and (7) is used for the controller design. The resulting control law is

\[ u(t) = -k^T x_c, \quad (10) \]

where \( k = [-6861 -265 -174 314] \).

III. Estimator Design

Since the Kalman filter [Kal60] is able to infer the state of a stochastically disturbed linear system in an optimal manner, it is selected as a basis for the estimation task at hand. In the following Section a short overview on the Kalman filter algorithm is given first and subsequently the estimator design for the quarter-vehicle system is presented including the handling of the nonlinearity.

A. Kalman filter

Let the system state \( x \in \mathbb{R}^n \) be modeled by the linear stochastic differential equation

\[ \dot{x}(t) = Ax(t) + Bu(t) + w(t), \quad (11) \]

where \( u \in \mathbb{R}^p \) is the deterministic control input and \( w \in \mathbb{R}^q \) is a zero mean white Gaussian noise process with covariance kernel according to Section II-D. The initial condition \( x(t_0) \) is specified by the Gaussian random variable \( x_0 \) with mean \( \mu_0 \) and covariance \( P_0 \). Assuming that a first order hold is applied for the control input, (11) can be represented equivalently by the stochastic difference equation

\[ x(t_i) = \Phi(T_i)x(t_{i-1}) + B_d u(t_{i-1}) + w_d(t_i), \quad (12) \]

where \( \Phi(t) = \exp(A t) \) denotes the state transition matrix and \( B_d = A^{-1}(\Phi(T_i) - I) B \) the discrete-time input matrix [May79]. The system noise \( w_d \) is a discrete-time white Gaussian process with mean zero and covariance kernel

\[ E \{ w_d(t_i)w_d^T(t_j) \} = Q_d = \int_0^{T_i} \Phi(t)Q\Phi^T(t) dt, \quad (13) \]

\[ E \{ w_d(t_i)w_d^T(t_j) \} = 0, \quad t_i \neq t_j. \]

Moreover, let the discrete-time measurement process \( y \in \mathbb{R}^q \) be modeled by

\[ y(t_i) = Cx(t_i) + v(t_i), \quad (14) \]

with \( C \in \mathbb{R}^{q \times n} \) a constant matrix and \( v \in \mathbb{R}^q \) a zero mean discrete-time white Gaussian noise with covariance kernel given by (8). Additionally, \( x(t_i) \), \( w \) and \( v \) are assumed to be stochastically independent of each other.

The Kalman filter recursively determines the mean \( \hat{x}(t_i) \) and the covariance \( P(t_i) \) of the state vector \( x(t_i) \) at each sampling instant \( t_i \), conditioned on the entire history of measurements taken. The calculation comprises two steps: According to [May79], in the time update the two conditional moments are propagated forward from the point \( t_{i-1} \) just after the measurement \( y_m(t_i-1) \) has been processed to the time \( t_i \) just before the measurement \( y_m(t_i) \) becomes available as

\[ \dot{\hat{x}}(t_i) = \Phi(T_i)\hat{x}(t_{i-1}) + B_d u(t_{i-1}). \quad (15) \]

\[ P(t_i) = \Phi(T_i)P(t_{i-1})\Phi^T(T_i) + Q_d. \quad (16) \]
The measurement update incorporates the measurement $y_m(t_i)$ by means of

$$L(t_i) = P(t-i)C^T [CP(t-i)C^T + R]^{-1},$$  \hspace{1cm} (17)$$

$$\hat{x}(t_i) = \hat{x}(t_i^-) + L(t_i)[y_m(t_i) - C\hat{x}(t_i^-)],$$  \hspace{1cm} (18)$$

$$P(t_i^+) = P(t_i^-) - L(t_i)CP(t_i^-),$$  \hspace{1cm} (19)$$

where $L(t_i)$ is the Kalman filter gain [May79]. Under the assumptions made, the conditional mean $\hat{x}(t_i^-)$ can be shown to be the optimal state estimate. The conditional covariance $P(t_i^+)$ of the state vector $x(t_i^+)$ simultaneously characterizes the covariance of the error which results from using $\hat{x}(t_i^-)$ as estimate [May79].

B. Application to the quarter-vehicle system

As the suspension model in (6) and (7) contains the nonlinear damper characteristic, the standard Kalman filter algorithm cannot be applied directly. Obviously, the equations (6) and (7) can be decomposed in a linear and a nonlinear part according to

$$\dot{x}(t) = Ax(t) + bF(t) + b_2F_d(x(t)) + w(t),$$  \hspace{1cm} (20)$$

$$y(t) = Cx(t) + dF(t) + d_2F_d(x(t)) + v(t).$$  \hspace{1cm} (21)$$

Considering the damper force as fictitious input signal as proposed by [Ohs00] and [KYYN07], one can define an augmented input vector $u(t) = [F(t) F_d(t)]^T$ with associated matrices $B_u = [b b_2]$ and $D_u = [d d_2]$. The resulting linear system representation serves as basis for the Kalman filter design. Since the damper force is unknown, an estimate is generated using the estimated damper velocity from the previous sampling instant and the damper characteristic displayed in Figure 2. This value is fed back into the state estimator resulting in the Kalman filter structure depicted in Figure 3. Additionally, first order lowpass filters with a cutoff frequency of $f_{LP} = 60\,\text{Hz}$ are used for the measurement signals $y_m$ as well as the actuator force $F(t)$ in order to reduce the high frequency measurement noise resulting from the power electronics at the testrig.

The tuning of the Kalman filter is accomplished by varying the diagonal entries of the covariance matrices $Q$ and $R$, while all other elements are fixed at zero. In order to achieve the best possible estimation performance, a numerical optimization algorithm is employed to determine appropriate covariance values. Measurements of a real road profile, being passed with a vehicle velocity of $50 \,\text{km/h}$, serve as road excitation. The measurement noise used in the simulation has been derived from sensor signals recorded at the testrig. For the tuning process the passive nonlinear testrig model (Section II-D) is considered. To quantify the estimation accuracy of an arbitrary signal $z(t_i)$ in a time set $T = \{t_0, t_1, \ldots, t_N\}$ with equidistant $t_i$ the performance measure

$$\Gamma_z = 1 - \frac{\sqrt{\frac{1}{N} \sum_{n=1}^{N} (z(t_n) - \hat{z}(t_n))^2}}{\sqrt{\frac{1}{N} \sum_{n=1}^{N} z^2(t_n)}} = 1 - \Xi_z$$  \hspace{1cm} (22)$$

is introduced, where $\hat{z}(t_i)$ denotes the estimated value of $z(t_i)$. Corresponding to the variables of primary interest (Section II), the objective function to be minimized is chosen as

$$J(\eta) = \left[ \Xi_{\dot{x}_w - x_w} \quad \Xi_{x_w - x_g} \quad \Xi_{\dot{x}_c} \quad \Xi_{x_c} \quad \Xi_{F_{dyn}} \right]^T,$$  \hspace{1cm} (23)$$

where $\Xi_z = \Xi_z(\eta)$ is defined as in (22) and $\eta$ is a vector containing the diagonal elements of $Q$ and $R$. Moreover, a constraint is introduced, which compares the actual estimation error of each state variable with its theoretical standard deviation $\sigma_i(t_i^-) = \sqrt{P_{ii}(t_i^-)}$. Since the error process $e(t_i^-)$ is Gaussian and has zero mean [May79], we demand according to [ZM00] that 68.3% of the error values are within the interval $[-\sigma_i(t_i^-), \sigma_i(t_i^-)]$.

The optimization problem is solved by means of the NSGA-II, a multiobjective genetic algorithm proposed by Deb et al. in [DPAM00]. The results obtained from analyzing the received Pareto front are depicted in Figure 4. The dashed line shows the performance measure $\Gamma$ of the configuration, which minimizes the Euclidean norm $||J||$ and thus is the best compromise. The dotted line represents the maximum $\Gamma$-value of each single quantity, individually determined over all configurations contained in the Pareto front. From the curves the conflict regarding the estimation performance of each signal becomes clear. One might argue that this contradicts the optimality of the Kalman filter, but it has to be noted, that this optimality is based on the assumption, that the physical system is exactly modeled by the Kalman filter equations, a premise which is not met in the case at hand. The conflict motivates the use of multiple parallel Kalman filters of the presented type, each of them supplying the signals, that are estimated with maximum quality. As illustrated by the solid line in Figure 4, three Kalman filters are sufficient to achieve the maximum possible accuracy. The first one
provides the signals $\dot{x}_c$, $x_w - x_g$ and $F_{dyn}$, the second one $\dot{x}_w$ and $x_c - x_w$ and the third one is necessary only for the estimation of the road excitation $x_g$.

A robustness analysis in [Frö07] has shown that the main influence on the estimation performance is a deviation of the chassis mass $m_c$ from its nominal value. In order to consider this, the concept can be extended by a mass estimation [Frö07], which however is not within the scope of this paper.

IV. Simulation Results

The nonlinear testrig model (Section II-D) is used to analyze the performance of the estimator structure before its validation at the testrig is presented in Section V. Three different signals are used as excitations: Two of them are measurements of real road profiles, which have been recorded by a vehicle equipped with laser scanners and accelerometers to compensate for the test vehicle’s chassis movements. These profiles are passed with the velocities $v_{1,1} = 50 \text{km/h}$ (profile 1) and $v_{1,2} = 30 \text{km/h}$ (profile 2), respectively. The other test-signal is a singular disturbance event (bump) which is frequently used in literature (e.g. in [MW04]) to test the performance of suspension systems. It is represented by

$$x_g(t) = h \left( 1 - \cos \left( \frac{2\pi v_b t}{L} \right) \right)$$

with $h = 0.04 \text{m}$, $v_b = 10 \text{km/h}$ and $L = 0.5 \text{m}$. The parameters have been chosen according to the testrig specifications.

The simulations confirm the performance of the estimator structure based on three parallel Kalman filters (Table II). In order to ensure comparability with the measurement results presented in the next Section, the measured disturbance signals $x_g(t)$ of the testrig have been used for the simulations because the original road profile signals are slightly changed due to the dynamic behavior of the lower testrig actuator. The largest estimation errors occur for the road profile ($\Gamma_{x_g} = 0.26$).

V. Experimental Results

The experimental results at the quarter-vehicle testrig are summarized in Figure 5 and visualized in Figure 6 where Figure 6 a) to f) correspond to road profile 1 and Figure 6 g), h) present the response to the excitation with the singular disturbance event formulated in (24). The performance achieved in measurements and simulations is given in Table II for all three excitation signals. The estimations are compared to the corresponding reference signals which are gained from measurement data. The reference signals for chassis and wheel velocity are calculated offline from the corresponding acceleration signals by integration and fourth order high pass forward backward filtering (Butterworth filter with cutoff frequency $f_{bp1} = 0.4 \text{Hz}$) to achieve zero-phase deviation and eliminate drifts. The reference signal for the tire deflection is gained from the measured dynamic wheel load and the nonlinear tire stiffness characteristic depicted in Figure 2, which is possible because the tire did not loose ground contact in the measurements. The small tire damping is neglected for the calculation of the reference signal.

The estimation performance is remarkable for most of the state signals. A slight performance degradation compared to the simulation results occurs for the tire deflection estimation ($\Gamma_{x_w - x_g} = 0.67$) and the dynamic wheel load ($\Gamma_{F_{dyn}} = 0.68$), respectively. In comparison, Venhovens [Ven93] achieves results of $\Gamma_{x_c} = 0.67$ and $\Gamma_{F_{dyn}} = 0.77$ in a linear simulation with a conventional Kalman filter. Using a computationally more complex Unscented Kalman filter, Fröhlich gives measurement results of $\Gamma_{F_{dyn}} = 0.73$, $\Gamma_{x_c} = 0.86$ in [FN05], which is similar to the performance achieved by the proposed estimator structure.

The estimated road disturbance signal is high pass forward filtered (first order, cutoff frequency $f_{bp2} = 0.1 \text{Hz}$) to eliminate a slow drift but its estimation performance is still not comparable to the other signals. Notice that if the estimation of the road excitation is discarded, two parallel Kalman filters are sufficient for the estimation of the states and the dynamic wheel load with the presented accuracy, which reduces the computational load and facilitates the implementation of the concept. The estimator performance can be further increased if additional shielding actions are taken for the measurement signals, which are affected by noise of the testrig’s power electronics.

The simple state feedback controller used for the experiments achieves a comfort gain of up to 27% which is defined using the rms-value of the passive system as a reference for the active suspension system performance

$$C_g = 1 - \frac{||X_{c,act}||_{rms}}{||X_{c,pass}||_{rms}}$$

(25)

The rms- and peak values of the dynamic wheel load do not significantly exceed the values of the passive system such that ride safety is still guaranteed.

<table>
<thead>
<tr>
<th></th>
<th>profile 1 meas</th>
<th>profile 1 sim</th>
<th>profile 2 meas</th>
<th>profile 2 sim</th>
<th>bump meas</th>
<th>bump sim</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Gamma_{x_g - x_c}$</td>
<td>0.98</td>
<td>0.98</td>
<td>0.97</td>
<td>0.97</td>
<td>0.93</td>
<td>0.95</td>
</tr>
<tr>
<td>$\Gamma_{x_c}$</td>
<td>0.94</td>
<td>0.93</td>
<td>0.87</td>
<td>0.88</td>
<td>0.91</td>
<td>0.92</td>
</tr>
<tr>
<td>$\Gamma_{x_w - x_g}$</td>
<td>0.67</td>
<td>0.82</td>
<td>0.57</td>
<td>0.76</td>
<td>0.73</td>
<td>0.72</td>
</tr>
<tr>
<td>$\Gamma_{x_c}$</td>
<td>0.85</td>
<td>0.87</td>
<td>0.81</td>
<td>0.85</td>
<td>0.89</td>
<td>0.89</td>
</tr>
<tr>
<td>$\Gamma_{F_{dyn}}$</td>
<td>0.68</td>
<td>0.82</td>
<td>0.59</td>
<td>0.81</td>
<td>0.78</td>
<td>0.84</td>
</tr>
<tr>
<td>$\Gamma_{x_w}$</td>
<td>0.23</td>
<td>0.26</td>
<td>-0.33</td>
<td>-0.08</td>
<td>-0.65</td>
<td>0.76</td>
</tr>
<tr>
<td>$\Gamma_{x_c - x_w}$</td>
<td>0.75</td>
<td>0.80</td>
<td>0.63</td>
<td>0.84</td>
<td>0.88</td>
<td>0.86</td>
</tr>
<tr>
<td>$C_g$</td>
<td>17</td>
<td>19</td>
<td>12</td>
<td>5</td>
<td>27</td>
<td>24</td>
</tr>
</tbody>
</table>

Fig. 5. Comparison of estimator performance for profile 1.
VI. CONCLUSION

An estimator structure for active vehicle suspension control incorporating three parallel Kalman filters has been presented. The estimator takes into account the nonlinear damper characteristic by considering the damper force as an additional input. Thus, the conventional Kalman filter algorithm can be used and computational effort is kept small. The results are analyzed in simulation and are validated using an active suspension configuration on a quarter-vehicle testrig. The estimation performance can be significantly increased compared to a single Kalman filter. Future work will involve the integration of the estimator in an adaptive controller structure and a comparison with output feedback controllers without state estimation. A possible extension of the Kalman filter concept is the estimation of the vehicle mass in order to ensure robustness.

REFERENCES


