Kalman Filter Method Based Vehicle Mass Estimation for Automobile Suspension System

Wanmin Li, Yan Wang, Yaping Zhang and Yunzi Yang

***Abstract*—**For the issue of inconstant sprung mass caused by passengers and freight in practical application, a combination method of Kalman filter and recursive least square is adopted in this paper. With sprung mass acceleration, dynamic deflection and wheel vertical acceleration, the sprung mass velocity and wheel vertical velocity are estimated using forgetting factor based recursive least square method. Corresponding to different road grade, accuracy effected by the process noise covariance and measurement noise covariance is researched. As to the steering stability effected by sprung mass estimation, the yaw velocity using sprung mass estimation is compared to actual yaw velocity. The simulation results show that the sprung mass and the estimation can be identified precisely with process noise and measurement noise selected appropriately according to the road grade. The estimated sprung mass parameters are feasible for steering stability analysis.

***Keywords*—**Adaptive Kalman filter, recursive least square, steering stability analysis, sprung mass.

I. INTRODUCTION

IT is well recognized that vehicle mass acts as an important role in vehicle handling stability and ride comfort research. Furthermore, as to the roll over prevention control system, the vehicle mass is assumed to be an indispensable and changing parameter to predict the road-tyre contact force. In particular, reliable estimation of the vehicle mass will enable to improve the actuator performance of active suspension, and then reduce the vehicle sprung mass acceleration. Nevertheless, it has been difficult issue to obtain direct measurements of all required states, such as sprung mass and Lateral Load Transfer(LLT) coefficient[1]. In order to analyze the vehicle stability, in this paper, a vehicle mass estimator is researched and employed to judge the steering stability further[2].

As to the mass estimation issue, the estimators can be classified into estimator based on state observers, such as Kalman filters, and estimator without state observers such as polynomial chaos. [3] Considering the measurement method, this estimate algorithm could also be classified into two different ways. The sensor based direct method holds the merit that the parameters obtaining process is independent of controller design, while the model based indirect method always seem the system physics model as precondition to build the observer or obtain the unknown parameter as a by-product of a control scheme.[4] It is noted that when using sensor measurement method, the arrangements of sensors always be treated as a difficult task due to the shape and the installation location of the transducer are considerably hard to be considered together , such as the force transducer.[5][6] According to the measurable data, model based method is able to calculate and estimate the unknown parameters such as vehicle speed. In [7], the engine torque and brake torque are available over CAN bus and a carrier-phase-based GPS are adopted to estimate the wheel tire-road friction coefficients. After building the longitudinal dynamical model, the friction coefficients are obtained using different signal configurations. In [8], through housing installation and wiring, single or multi-axis accelerometers and angle rate sensors are mounted on the vehicle chassis, such that Lateral Load Transfer coefficients(LLT) are able to be estimated using state observers. Hong et al.[9] introduce an additional mass to determine the sprung mass integrated to a nonlinear model. In [10], the authors use low-frequent suspension displacement signals and suspension stiffness characteristics to estimate the center of gravity position and the vehicle mass followed a test rig validation. [11] exploits almost all parameters and derives an explicit expression without the acceleration measurement. After using the sensor data or state observer, the estimate algorithms is then designed to calculate and obtain the parameter needed. It is required to estimate the state and unknown parameters simultaneously due to the fact that all the parameters are not time in-variant. For the fast convergence and easily implement, Recursive Least Squares and Kalman Filter have been widely used in modern estimators. Wan and Nelson using the rules that the states and parameters are considered as a separate state-space formulation such that once a favorable set of estimators is found, this parameter estimator is going to be switched off. In[12], aim to the nonlinear time-invariant active suspension system, an extended Kalman filter is proposed to estimate the changing state. Then, the vehicle sprung mass, tyre dynamic deflection and suspension deflection are precisely estimated through the measured acceleration of sprung mass and unsprung mass. By building a nonlinear slide mode state estimator, the necessary information concerning estimating algorithm concludes the sprung mass absolute displacement and velocity. Pence uses polynomial chaos theory in vehicle mass estimation with reduced-order state-space models[13]. This method owns the ability that treat unknown initial states as

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estimation parameters and update their values recursively. It is researched that through experiment demonstration, all the system states are capable of being observed by measuring the accelerations in different place in automobile. Combining the signals originated from various sensors, more parameters can be estimated by intelligent method. In [14], the genetic algorithm is integrated with maximum likelihood estimation to figure out the nonlinear active suspension model and demonstrate the real suspension dynamic characteristics. [15] identifies the structure model parameters with neural-network weight matrix. In [16], LS method has been verified as a favorable tool to identify the semi-active suspension parameters based on a ADAMS 3 DoFs model. For the purpose of road grade estimation, the suspension dynamical response analysis has been regarded as an efficient manner to obtain a precision estimate results. By this method, it is necessary to modify the algorithm of sprung mass estimation and achieve significantly better performance on time various sprung mass problem dispose.

This paper combine adaptive Kalman filter with recursive least square to identify the vehicle sprung mass according to different national grade standard road grade. The sprung mass and absolute vehicle speed are precisely estimated using only the accelerometer signal and displacement sensor signals. Then, the estimation accuracy effected by the process noise covariance and measurement noise covariance is analyzed under different road grades. Using forgetting factors based recursive least square method, the sprung mass values at different time are estimated literately. In the end, the automobile stability are researched via longitudinal acceleration, lateral acceleration and sideslip angle estimate values. The proposed techniques are demonstrated using simulation method and the promotion of vehicle stability are researched.

II. 1/4 VEHICLE SUSPENSION MODEL

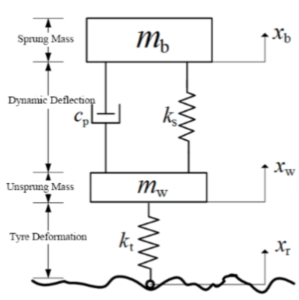


Fig. 1. 1/4 vehicle suspension model

As shown in Fig. 1, m_b and m_w denote the sprung mass and unsprung mass separately. The suspension stiffness is shown as k_s and the road elevation is presented by x_r . Then, the suspension model can be described as follows:

$$m_b \ddot{x}_b + k_s (x_b - x_w) + c_p (\dot{x}_b - \dot{x}_w) = 0 \tag{1}$$

$$m_w \ddot{x}_w + k_t (x_w - x_r) - k_s (x_b - x_w) + c_p (\dot{x}_w - \dot{x}_b) = 0 \tag{2}$$

The state variables can be selected as

$$\begin{aligned} X &= [x_b - x_w, x_w - x_r, \dot{x}_b, \dot{x}_w]^T \\ Y &= [\ddot{x}_b, \ddot{x}_w]^T \end{aligned} \tag{3}$$

Where x_b-x_w denotes the suspension dynamic deflection, x_w-x_r denotes the tyre deformation, $\dot{x}_b$ is the absolute velocity of sprung mass, $\dot{x}_w$ is the absolute velocity of automobile wheel. As to the estimator, the process noise is the random road input $w(t) = \dot{x}_r$, the measurement noise is $v(t)$. Particularity, the process and measurement noise are white Gaussian noise and irrelevant to each other. Then, the state equation and measurement can be concluded as

$$\dot{x}(t) = Ax(t) + Gw(t) \tag{4}$$

$$y(t) = Cx(t) + v(t) \tag{5}$$

where,

$$A = \begin{bmatrix} 0 & 0 & 1 & -1 \\ 0 & 0 & 0 & 1 \\ -\frac{k_s}{m_b} & 0 & -\frac{c_p}{m_b} & \frac{c_p}{m_b} \\ \frac{k_s}{m_w} & -\frac{k_t}{m_w} & \frac{c_p}{m_w} & -\frac{c_p}{m_w} \end{bmatrix}, \quad G = \begin{bmatrix} 0 \\ -1 \\ 0 \\ 0 \end{bmatrix},$$

$$C = \begin{bmatrix} -\frac{k_s}{m_b} & 0 & -\frac{c_p}{m_b} & \frac{c_p}{m_b} \\ \frac{k_s}{m_w} & -\frac{k_t}{m_w} & \frac{c_p}{m_w} & -\frac{c_p}{m_w} \end{bmatrix}$$

This state space represent an traditional model of 1/4 vehicle suspension model, with which we can research the vehicle suspension property and state based observer. The next step following this part show this estimator design and performance modification.

III. KALMAN FILTER BASED SPRUNG MASS ESTIMATION

A. *Adaptive Kalman Filter design*

With discretization method implement on this 1/4 vehicle suspension system model, the discretized state space can be concluded as

$$x(k) = \boldsymbol{\Phi}(k-1)x(k-1) + \boldsymbol{\Gamma}(k-1)w(k-1) \tag{6}$$

$$y(k) = C(k)x(k) + v(k) \tag{7}$$

where $\Phi(k)$, $\Gamma(k)$ and $C(k)$ are system matrix, the covariance of discretization process noise is *Q (k) =E(w(k)wT(j))* , measurement noise is *R (k) =E(v(k)vT(j))* , *k* and *j* are discretization time.

In practical application, the measurement noise covariance R and process noise covariance Q is independent of the system state. In vehicle systems, the measurement noise covariance is always obtained through the data probability statistics and seemed as a statistical parameter in some degree. The process covariance Q, varying according to the road, originates from the road grade on which the automobile is running at a constant speed. The suitable value of Q and R are available on the basis of different road grade in the Kalman filter proposed in this paper by which the suspension state is able to be predicted exactly and the sprung mass estimation is feasible to be described this method explicitly.

As a recursive guesstimating method, Kalman filter initializes the state variables and then estimate the next state on the basis of current state. Due to the noise mixed measurement feedback, the estimate process should be integrated to an amendment process as following,

First step: Initialization

$$\hat{x}(0|0)=\hat{x}(0) \tag{8}$$

$$P(0|0)=P(0) \tag{9}$$

Second step: Time update

$$\hat{x}(k|k-1)=\boldsymbol{\Phi}(k-1)\hat{x}(k-1|k-1) \tag{10}$$

$$\begin{aligned}P(k|k-1)=&\boldsymbol{\Phi}(k-1)P(k-1|k-1)\boldsymbol{\Phi}^T(k-1)\\&+\boldsymbol{\Gamma}(k-1)Q(k-1|k-1)\boldsymbol{\Gamma}^T(k-1)\end{aligned} \tag{11}$$

Third step: Kalman Gain Matrix

$$K(k)=P(k|k-1)C^T(k)[C(k)P(k|k-1)C^T(k)+R(k)]^{-1} \tag{12}$$

Forth step: Measurement update

$$\hat{x}(k|k)=\hat{x}(k|k-1)+K(k)(y(k)-\hat{y}(k)) \tag{13}$$

$$P(k|k)=[I-K(k)C(k)]P(k|k-1) \tag{14}$$

B. Vehicle Sprung Mass Estimation

The resonant peak value is prone to shifting due to the mutative sprung mass and deteriorate the ride comfort. Recursive least square(RLS) method view the sprung mass as research object to estimate the sprung mass using the suspension system input/output data. In order to improve the online identification functionality, the RLS is transferred into a parameter recursive estimation form. This kind of estimation refers to the identification process that updated dynamic deflection and sprung mass acceleration are adopted to ament the sprung mass estimated result at the last time integrated with absolute velocity of sprung mass and wheel.

Here, make a transformation on equation (2),

$$m_{\mathrm{b}}\ddot{x}_{\mathrm{b}}+c_{\mathrm{p}}\left(\dot{x}_{\mathrm{b}}-\dot{x}_{\mathrm{w}}\right)=-k_{\mathrm{s}}\left(x_{\mathrm{b}}-x_{\mathrm{w}}\right) \tag{15}$$

For arithmetic simplification, the estimated parameter vector and information vector can be identified as,

$$\theta=[\,m_{\mathrm{b}}\quad c_{\mathrm{p}}\,]^T \tag{16}$$

$$\varphi(t)=[\ddot{x}_b\quad \dot{x}_b-\dot{x}_w] \tag{17}$$

$$y(t)=-k_s(x_b-x_w) \tag{18}$$

Then, the equation(15) can be rewritten as,

$$y(t)=\phi^T(t)\theta \tag{19}$$

With the increase of collected data, the recursive gain matrix will be smaller and the $\hat{\theta}_{LS}(t)$ amend effect will be impaired. In order to overcome data saturation in recursive process and realize real-time tracking, a forgetting factor is introduced in this equation,

$$J=\sum_{i=1}^{L}\lambda^{L-i}[\mathrm{y(i)}\text{-}\hat{\theta}^T\phi(i)]^2 \qquad y(t)=\phi^T(t)\theta \tag{20}$$

Where0.9<λ<1 is forgetting factors. Then, the estimation of parameter vector is

$$\hat{\theta}_{LS}(t)=\left(\sum_{i=1}^{L}\lambda^{L-i}\phi(i)\phi^T(i)\right)\left(\sum_{i=1}^{L}\lambda^{L-i}\phi(i)y(i)\right) \tag{21}$$

here θ can be obtained through revursive method,

$$\hat{\theta}_{LS}(t)=\hat{\theta}_{LS}(t-1)+\mathrm{L}(t)[\mathrm{y}(t)-\phi^T(t)\hat{\theta}_{LS}(t-1)] \tag{22}$$

$$\mathrm{L}(t)=\frac{F(t)\phi(t)}{\lambda+\phi^T(t)F(t-1)\phi(t)} \tag{23}$$

$$\mathrm{F}(t)=\frac{1}{\lambda}[1-\mathrm{L}(t)\phi^T(t)][\mathrm{F}(t\text{-}1)] \tag{24}$$

Using recursive least square with forgetting factor, the different weighting coefficients arising from forgetting factors, are imposed on these data and used to improve the performance of Least Square method.

IV. VEHICLE STEERING STABILITY ANALYSIS

Considering the important role that sprung mass plays in vehicle steering stability analysis, the issue of steering sensitivity analysis should be covered. Here, according to the 2DoF of automobile steering model, the formulations regards to steering wheel input and yaw velocity output are derived as

$$\begin{aligned} &(k_1+k_2)\beta+\frac{1}{u}(ak_1\text{-}bk_2)w_r-k_2\delta=m(\dot{v}+uw_r) \\ &(ak_1\text{-}bk_2)\beta+\frac{1}{u}(a^2k_1+b^2k_2)w_r-ak_1\delta=I_z\dot{w}_r \end{aligned} \tag{25}$$

where k_1 and k_2 are sideslip angle stiffness of front and rear axle, u is the velocity of automobile, a and b are the position center of gravity between wheels, δ denotes the steering angle, $\dot{v}$ denotes the lateral acceleration, u denotes the longitudinal velocity, w_r denotes the yaw velocity, I_z denotes the momentum of inertia around vertical axis.

According to the transient response of yaw velocity derived from automobile theory, the response time is of importance. Affected by the estimate value of sprung mass, there should be a different response result. In this research, the attention is focused on the transient response result due to different running velocity. It is well known that the parameter steering sensitivity assigns a position of special importance in vehicle engineering research. The stability factor represented by sideslip angle stiffness and the distance between front and rear axles and gravity center reflects the transient response characteristics. The positive stability factor stands for the steering radius prone to increase. While, the negative factor shows the decrease steering radius tendency, which means an instable running condition. In this research, the angular steady-state gain of the yaw is consist of the yaw velocity and steering angle input. For simplicity purpose, when the steering angle is seemed to be the same in a comparative group, the yaw velocity would be the single and convenient assessment criteria to figure out the difference between the comparative results. In this paper, considering the importance of the steering sensitivity and same steering angle input, we extract the yaw velocity under real vehicle sprung mass and estimated sprung mass to valid the estimated effect.

V. Design Example

In this section, the proposed adaptive Kalman filter is used to estimate the sprung mass. As mentioned earlier, following this estimator, the steering stability is shown by comparative study at different speeds. The structure parameter values are listed in Table 1.

In the simulation process, the road simulation is assumed as the elevation of ISO road grade in time domain. Some researchers found that the tyre vibration and sprung mass vibration are collected by the accelerometer with 2% precision. In reasonable transducer range, the vibration amplitude of the tyre and sprung mass will be amplified along with increasing road grade, as well as the measurement noise covariance. For the reason that the velocity is selected as the input of suspension model, the Q and R values in Kalman filter algorithm are able to be obtained ahead under different road grade, according to the ISO road grade. Thus, the Kalman filter measurment covariance R and process covariance Q and R are shown in table 2.

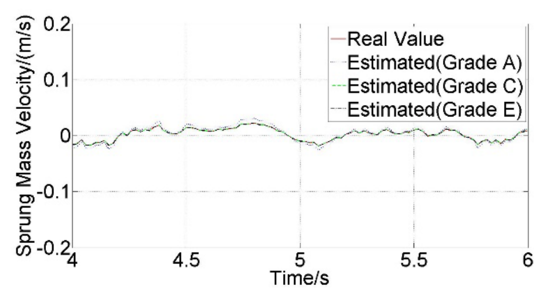
Table. 1. Automobile Suspension Parameter

Parameter	Meaning	Value
m_b	Sprung Mass	260kg
m_w	Unsprung Mass	40kg
k_s	Suspension Stiffness	16000 N/m
k_t	Tyre Stiffness	183000 N/m
I_z	Momentum of Inertia	3885kgm^2
a	Distance Value	1.463m
b	Distance Value	1.585m
k_1	Front Sideslip Stiffness	-62618N/rad
k_2	Rear Sideslip Stiffness	-110185N/rad
u	Velocity	-

Table 2. ISO Road Grade Based R and Q Value.

Road grade	R	Q
A	2.1×10-7	0.0035
B	8.4×10^{-7}	0.014
C	3.4×10^{-6}	0.056
D	1.4×10^{-5}	0.224
E	5.6×10-5	0.896
F	2.2×10-4	3.584
G	8.8×10^{-4}	14.34
H	3.5×10^{-3}	57.34

Employing aforementioned Kalman filter method, we selected the value Q and R on grade C road condition with simulation, the estimated values are shown in Fig. 2. Besides, value Q and R on the road of grade E and grade A are seemed as the comparative operation condition. The estimated errors of sprung mass and tyre velocity are shown in Fig. 3



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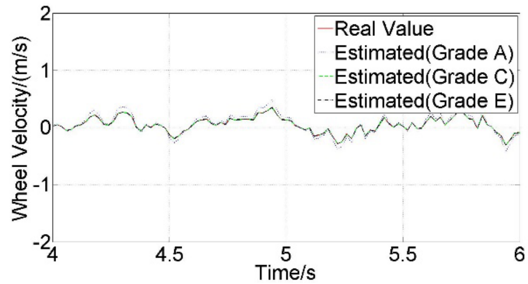

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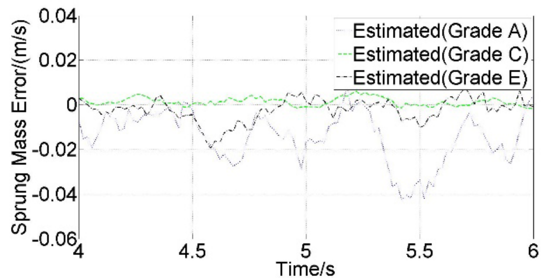
Fig. 2. Estimated Resaults on Road Grade C. a) Sprung mass velocity estimation. b) Wheel velocity estimation.



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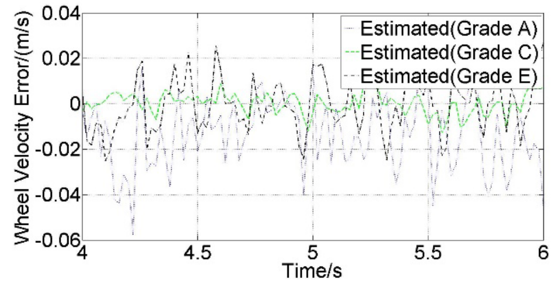

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Fig. 3. Estimated Parameter Error on Road Grade C. a) Sprung mass velocity estimation error. b) Wheel velocity estimation error.

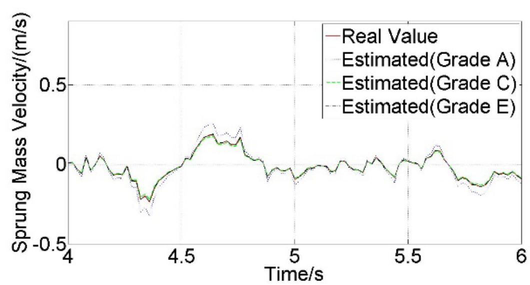
For the observation convenience, the data ranged from 4s to 6s are captured in Fig. 2. The red curve denotes the real sprung mass and tyre velocity value in road grade C. The other curve denote Q and R value in different road grade.

The sprung mass and tyre velocity errors in these three different conditions are counted in table 3.

Table 3. Estimated Sprung mass and wheel velocity error

estimated error	estimated parameter (m/s^2)	Road Grade C R & Q	Road Grade E R & Q	Road Grade A R & Q
Maximum error	Sprung mass velocity	0.003	0.006	0.026
	wheel velocity	0.013	0.014	0.032
Average error	Sprung mass velocity	1.03×10^{-3}	3.2×10^{-3}	0.012
	wheel velocity	8.7×10^{-3}	9.1×10^{-3}	0.011

Stimulated on the road grade E, estimated sprung mass and wheel velocity can be calculated by the corresponding Q and R value in Fig 4. Here, the other two different road grade, C and A are seemed as control group. Fig. 5 shows the sprung mass and wheel velocity estimated variance.



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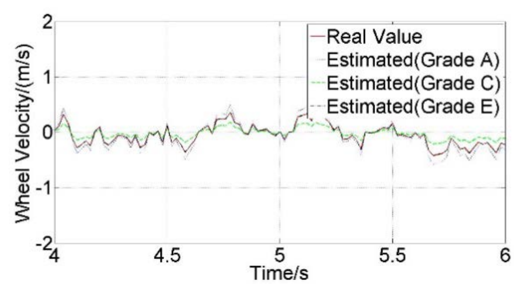

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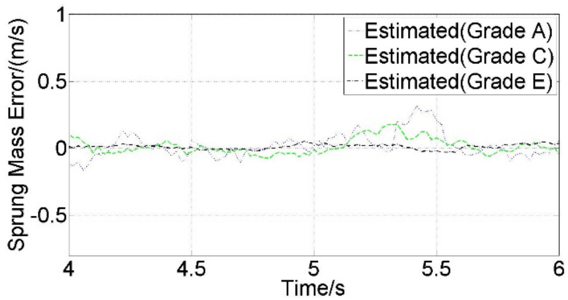
Fig. 4. Estimated Resaults on Road Grade E. a) Sprung mass velocity estimation. b) Wheel velocity estimation.



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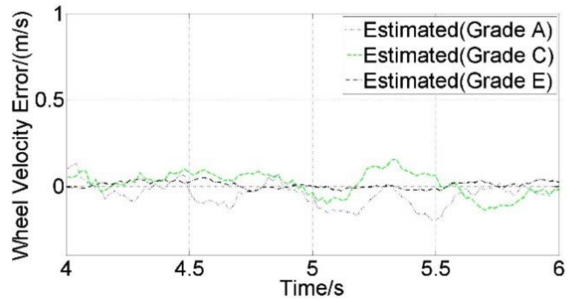

(b)

Fig. 5. Estimated Parameter Error on Road Grade C. a) Sprung mass velocity estimation error. b) Wheel velocity estimation error.

For the observation convenience, the simulation data ranged from 4s to 6s are captured in Fig. 5. The red curve denotes the sprung mass and tyre mass velocity real value. The estimated sprung mass describes the estimated error apparently on road grade C and road grade A using value Q and R.

The estimated error values of sprung mass and wheel velocity are counted shown in Table 4. Though the sprung mass and unsprung mass are selected as the estimation aim, the sprung mass and suspension dynamic deflection also can be conducted in the authors team former research. As described before, due to reason that different parameter R and Q are chosen, in different rows, the max error and average error are listed corresponding to sprung mass and unsprung mass.

Table 4. Estimated error values of sprung mass and wheel velocity

estimated error	estimated parameter (m/s^2)	Road Grade C R & Q	Road Grade E R & Q	Road Grade A R & Q
maximum error	Sprung mass velocity	0.003	0.018	0.41
	wheel velocity	0.08	0.19	0.42
average error	Sprung mass velocity	1.02×10^{-3}	0.008	0.13
	wheel velocity	1.9×10^{-3}	4.6×10^{-3}	9.3×10^{-3}

According to the simulation analysis, it is shown that a high accuracy observation result is able to be obtained with Kalman filter algorithm applied on velocity of sprung mass and wheel estimation. Through selecting corresponding road grade value, the filter performance is reinforced and the blindness of process covariance and measurement covariance can be avoided.

Forgetting based recursive least square sprung mass estimating simulation result is shown in Fig. 6. Due to the measurement noise, the estimated curve fluctuate around the real value. The initial sprung mass is 260kg added to 450kg after 1.5 seconds. The estimated curve matches the real sprung mass after 0.4s. Reducing the sprung mass to 350kg, the estimated curve match the real curve. Actually, in the former research of our group, the departure of real curve and estimated value especially in the period between 1.2s to 2s and 3s to 4s really have impact on the performance research in the other fields with regard to vehicle research. Fortunately, the deviation between real value and estimated value show similar output result corresponding to stability and brake research. On the other hand, the difference between estimation and real remind us that there still have room to grow.

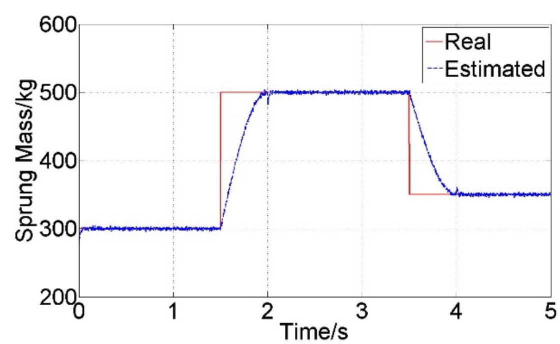

Fig. 6. Automobile Sprung Estimation

Corresponding to the steering stability, the steering wheel input is set to be 10 degree. Using online sprung mass estimation, the identified mass is adopted in Simulink model to compare with real sprung mass simulation result. Here, the automobile yaw velocity is selected as the index to substitute for the steering sensitivity. In Fig. 7 and Fig. 8, with the yaw velocity at speed of 30km/h and 70km/h, the steering input ranges from -20 degree to 20 degree. It is shown explicitly that though the input changes sharply, the sprung mass estimation is able to precisely obtain and the steering stability is capable of following the real curve. This property is of importance due to the control requirements that the online identified value should track the real value fast and accurate. From the estimation result, even the steering angle input changes from -20° to 20° suddenly, the yaw velocity using estimated mass is able to follow up the yaw velocity using real mass. It is shown that the estimated sprung mass is accurate and the employment of this term in steering stability analysis is feasible.

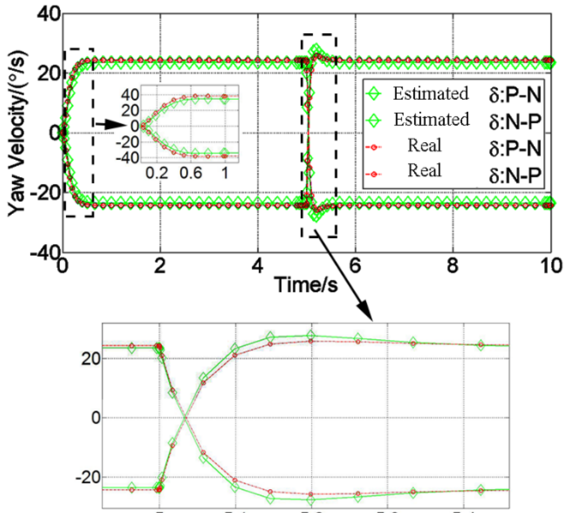

Fig. 7. Steering Stability Analysis at Speed 30km/h

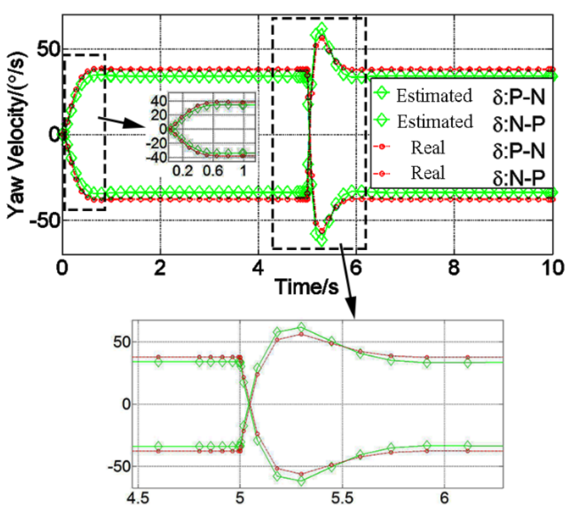

Fig. 8. Steering Stability Analysis at Speed 70km/h

VI. Conclusion

Considering the easily changing characteristic of vehicle sprung mass which influence the suspension response seriously, the combination of Kalman filter and recursive least square method are proposed to estimate the sprung mass. Employing the sprung mass vibration acceleration, wheel acceleration, and suspension dynamic deflection signals, Kalman filter algorithm estimate the sprung mass and wheel absolute velocity. The precision reducing issue, due to the fact that measurement noise covariance and process noise covariance are not able to fit road grade the vehicle running on, is considered in the estimation process. Then, recursive least square method is adopted to sprung mass value prediction. Considering the steering stability effected by sprung mass estimation, the yaw velocity under different longitudinal velocity is compared using simulation method. It is shown that estimated mass influence the transient and steady response of yaw velocity apparently. With proposed estimation method, the yaw velocity of estimation is able to track the actual yaw velocity rapidly and the actual value of sprung mass is precisely estimated. It is also reflected that the maximum deviation exists at the input changed moment, while in the steady state, the error is prone to zero. The transient state owns considerable short settling time and peak time and fast response rate.

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