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Longitudinal Velocity and Road Slope Estimation in Hybrid/Electric Vehicles

Development and evaluation of an adaptive Kalman filter

Master's Thesis in the International *Masters' Program*

YUNLONG GAO

Department of Applied Mechanics
Division of Vehicle Engineering and Autonomous Systems
Vehicle Dynamics
CHALMERS UNIVERSITY OF TECHNOLOGY
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ABSTRACT

An accurate and efficient method of velocity and slope estimation is presented in this thesis. An adaptive Kalman filter is proposed to deal with the over-slip wheel, which is a challenging problem during velocity estimation. The research object of this work is the hybrid/electric vehicles with electric motors.

In the adaptive Kalman filter, we control the gain matrix directly based on the over-slip flag. If all of the four wheels over-slip at the same time, the velocity results are replaced by the integration of acceleration. To reduce the integration error, the longitudinal acceleration is modified by road slope estimation results. The slope estimation is based on typical Kalman filter and the observation variable is velocity estimation result. Then, the over-slip criterion and wheel speed selection method are involved aiming to estimate velocity accurately when all the four wheels are over-slip. Besides the wheel speed and pre-estimation of velocity, the wheel torque, provided by electric motor, is also used to find out the over-slip wheels. Nevertheless, some abnormal measurements that cannot be detected by the over-slip criteria affect the accuracy of the estimation. Thus wheel speed selection is put forward to reduce the influence of measurements error as well as the calculation quantity. After selection, only one wheel speed is selected as the observation variable of Kalman filter. At last, the algorithm is verified on both high and low friction road.

Key words: longitudinal velocity, Kalman filter, over-slip, slope compensation

Contents

Preface

In this work, vehicle longitudinal velocity estimation algorithm is proposed and tested on road. On-road test is divided in two parts, one is on asphalt road, which is carried out at Tongji University, Shanghai, China; the other is on low friction road, which is carried out in Arjeplog, Sweden. This academic work is supported by the Department of Applied Mechanics, Vehicle Dynamics, Chalmers University of Technology (CTH). And this project is implemented in e-AAM, Trollhättan, Sweden. We also want to thank VINNOVA – Sweden's Innovation Agency and FKG (the Scandinavian automotive supplier association) for financially supporting this project through the FFI Vehicle Development program.

The researcher is Yunlong Gao and the project is supervised by Dr. Fredrik Bruzelius (CTH), Dr. Matthijs Klomp (e-AAM) and Dr. Lu Xiong (Tongji University). Thanks to these three supervisors, who offered the most important advice on both theoretic and practice facets, the estimation algorithm performance has improved a lot. The on-road test is carried out by the help of my co-workers Adithya Arikere, Yuan Feng and Wuxue Zhang. And I would like to thank Prof. Bengt J H Jacobson for offering me the chance to finish this work in CTH.

In addition, I appreciate the colleagues from e-AAM, such as Matthijs Klomp and Torbjörn Norlander, to help me both on working and living.

Göteborg June 2013

Yunlong Gao

Notations

Roman upper case letters

F_{zr}	Normal force on rear axle
H	Observation matrix of Kalman filter
K	Gain matrix of Kalman filter
P	Estimation error covariance matrix of Kalman filter
Q	System error covariance matrix of Kalman filter
R	Observation error covariance matrix of Kalman filter
R_r	Wheel radius
R_{ref}	Calibration results of wheel radius
T_r	Torque on rear axle

Roman lower case letters

a_x	Vehicle longitudinal acceleration
$a_{x,m}$	Measurement of vehicle longitudinal acceleration
b_f	Vehicle track (front)
b_r	Vehicle track (rear)
g	Gravity acceleration
k	Index of discrete system
k_{fl}	Element in the Kalman filter gain matrix for front left wheel
k_{fr}	Element in the Kalman filter gain matrix for front right wheel
k_{rl}	Element in the Kalman filter gain matrix for rear left wheel
k_{rr}	Element in the Kalman filter gain matrix for rear right wheel
l_f	Distance between vehicle CG and front axle
l_r	Distance between vehicle CG and rear axle
v_{GPS}	GPS measurement of vehicle velocity
v_{fl}	Measurement speed of front left wheel
v_{fr}	Measurement speed of front rear wheel
v_k	Observation noise of Kalman filter
v_{rl}	Measurement speed of rear left wheel
v_{rr}	Measurement speed of rear right wheel
v_{sel}	Selected wheel speed
v_{trans}	Wheel speed translation
v_x	Vehicle longitudinal velocity
$\hat{v}_x$	Estimation of vehicle longitudinal velocity
v_y	Vehicle lateral velocity
x	State variable of Kalman filter
y	Observation variable of Kalman filter
Δa_x	Measurement bias of accelerometer

$\Delta v_{thrshld}$	Velocity threshold value in over-slip criterion

Greek letters

Φ	System matrix of Kalman filter
Ψ	Input matrix of Kalman filter
$\Delta\alpha$	Slope threshold value in slope estimation
$\Delta\omega_{thrshld}$	Rotation speed threshold value in over-slip criteria
β	Vehicle side slip angle
$\mu_{\max}$	Road friction
τ	Sample time
ω	Wheel rotation speed
ω_{meas}	Measurement of wheel rotation speed

1 Introductions

Vehicle dynamic control systems, e.g. TCS/ABS/ESP have improved vehicle active safety distinctly (Lie A., Tingvall C., Krafft M., Kullgren A.(2005)). The performance of these control systems relies on the accuracy of vehicle states observation, one of which is the vehicle velocity. However, it needs relatively expensive sensor to measure the velocity directly. Thus, velocity estimation methods have been put forward by the help of inexpensive sensors.

According to published papers and patents, the estimation methods can mainly be divided into two kinds. One is a direct method, which uses wheel speed and vehicle body acceleration to estimate velocity directly; the other is indirect method, which estimates with vehicle model.

Jiang F., Gao Z. (2000) pointed out that the maximum wheel speed can be used as velocity estimation when braking. This method is called as Best Wheel Method. Another strategy to find the best wheel is also introduced by Liu G. (2004), such as the minimum wheel speed when traction. The best wheel method is very rapid to find out the body velocity. However, it has a large error when the best wheel is over-slip or locking. Another direct method, as introduced by Daib A., Kiencke U. (1995), is to find a reliable wheel speed first, and check the body acceleration. Then use the average weight of wheel speed and integration of acceleration to get the velocity estimation. The accuracy of this method is vulnerable because of the bias of accelerometer. Besides, the weight of each part varies in different driving scenario. As a result, it needs feedback process to update the weight. Song C.-K., Uchanski M., Hedrick J.-K.(2002) come up with the weight average method taking advantage of feedback of the accelerometer offset and wheel radius bias, or by the help of GPS. It can estimate velocity without obvious error. But it relies on the differential of wheel speed, which can cause huge noise. Kalman Filter provides a good method to find out the average weight. The weight updates in every sample time, and the estimation results could be without noise. However, the calculation quantity of this method is heavy.

As to the indirect method, Kobayashi K., Cheok K.-C., Watanabe K. (1995) used kinematic model to estimate velocity with four wheels' speed and body acceleration. This method performs well even on low friction road. While the shortage is the high demand of sensor signals, the estimation results are sensitive to the signal noise and the install location of the sensors. Bicycle model and four wheel dynamic models are also used to velocity estimation. Imsland L., Johansen T.-A., Fossen T.-I.(2006) used the dynamic model and Dugoff tire model, which offers tire force estimation, to estimate velocity. This method is not sensitive to the sensor signals; however, the estimation error caused by the modelling errors is the weakness of the method.

In conclusion, the challenges, in Table 1.1, related to estimating vehicle velocity are shown below.

Table 1.1 The problems of velocity estimation

Methods	Problems
Based on wheel speeds	The over-slip wheel, wheel radius variation
Integration of acceleration	Incorrect initial value, accelerometer bias and road

	slope
Based on vehicle/tire model	Modelling error

1.1 Aim of the Thesis

The first purpose of the project is to estimate longitudinal velocity and road slope for hybrid/electric vehicle. The estimation results are used for the slip control system. Thus, the following requirements are put forward.

a. Efficient

To achieve slip control in time, the velocity estimation should be computationally efficient and obtain velocity rapidly. The simple, but cannot be simpler method will be used.

b. Accurate

A small error of velocity estimation could cause large error in calculation of wheel slip. Taking the requirements of the slip calculation into consideration, the velocity estimation error should be within a reasonable threshold.

c. Smooth

The estimation result should be smooth, and without intense noise.

d. Robust

The algorithm will estimate the velocity on different road conditions with different hybrid/electric vehicles. Thus, it should be robust to the change of vehicle conditions and road friction.

Velocity estimation relies on wheel speeds. However, in some driving scenarios, the speed measurements of some wheels are not reliable to obtain correct vehicle velocity, such as the over-slip ones. Unfortunately, the velocity estimation is indeed needed by the traction control system when the wheels are over-slip.

Another purpose of this paper is to study if the electric motor torque can be used to improve the velocity estimation. Thus, a novel velocity estimation method is proposed in this thesis, aiming to solve the over-slip-wheel-problem. The algorithm will be developed and evaluated by simulation and on-road test. At last, a practical method of velocity estimation will be put forward.

This thesis is organized as follows. The introduction and estimation example of Kalman filter is in Chapter 2. The velocity estimation algorithm design is introduced in Chapter 3. Tests on high and low friction road are respectively explained in Chapter 4 and Chapter 5. At last, the conclusions are drawn in Chapter 6.

1.2 Former Research

Besides the velocity estimation methods mentioned above, Hsu L.-H., Chen T.-L.(2009) used non-linear observer to estimate velocity. Ouladsine M., Shraim H., Fridman L. Noura H.(2007) used a sliding model to estimation vehicle states. Qi Z.-Q, Ma Y.-F., Liu Z.-D, Li H.-J.(2010) estimated longitudinal velocity of the electric vehicle. And extended Kalman filters as well as unscented Kalman filter are also very common to obtain the longitudinal velocity. These feedback methods provide a good direction of velocity estimation.

In our previous work, Xiong L., Gao Y.,-L., Feng Y. (2012) designed an adaptive Kalman filter to solve the over-slip-wheel-problem. The algorithm can find out the over-slip wheel and estimate velocity accurately on asphalt road. However, when tested on challenging situation, for instance all the four wheels are over-slip, it cannot get satisfactory results.

2 Introduction to the Kalman Filter

Kalman filter, known as a linear estimator, is named after Prof. Rudolph E. Kalman. It has been developed a lot after the first described in technique papers by Swerling P. (1958), Kalman R.,-E. (1960) and Kalman R.,-E., Bucy P. (1961). In technology field, Kalman filter is widely used to guide, navigate and control vehicles as well as aircrafts.

Actually, the Kalman filter is an algorithm that estimates unknown variables by the help of measurements with noise. Based on prior knowledge about the noise in the estimation, the Kalman filter minimizes the mean square error of the estimation.

The concrete introduction and an estimation example of Kalman filter algorithm will be presented in this chapter.

2.1 Kalman Filter

The typical Kalman filter focuses on a discrete model of a system. For example:

$$\begin{aligned} x_k &= \Phi_{k-1} x_{k-1} + \Psi_{k-1} u_{k-1} + w_{k-1} \\ y_k &= H_k x_k + v_k \end{aligned} \tag{2.1}$$

where Φ_{k-1} and Ψ_{k-1} are, respectively, the system matrix and input matrices, w_{k-1} is process noise with zero mean multivariate normal distribution with covariance Q_k and v_k is and observation noise, which is zero mean Gauss White Noise with covariance R_k , that is

$$\begin{aligned} w_k &\sim N\left(0, Q_k\right) \\ v_k &\sim N\left(0, R_k\right) \end{aligned} \tag{2.2}$$

where Q_k and R_k are respectively system error and measurement error covariance matrix.

Then, the discrete system Kalman filter function can be written as:

$$\begin{aligned} \hat{x}_{k|k-1} &= \Phi_{k-1} \hat{x}_{k-1|k-1} + \Psi_{k-1} u_{k-1} \\ P_{k|k-1} &= \Phi_{k|k-1} P_{k-1|k-1} \Phi_{k|k-1}^T + Q_{k-1} \\ K_k &= P_{k|k-1} H_k^T \left(H_k P_{k|k-1} H_k^T + R_k \right)^{-1} \\ \hat{x}_{k|k} &= \hat{x}_{k|k-1} + K_k \left(y_k - H_k \hat{x}_{k|k-1} \right) \\ P_{k|k} &= \left(I - K_k H_k \right) P_{k|k-1} \end{aligned} \tag{2.3}$$

where $\hat{x}_{k|k}$ is the estimation results of state variable at step k , $\hat{x}_{k|k-1}$ is the pre-estimation of state at step k , $P_{k|k} = E\left\{ \left(\hat{x}_k - x_k \right) \left(\hat{x}_k - x_k \right)^T \right\}$ is the estimation error covariance matrix, H_k is the observation matrix, K_k is the Kalman filter gain matrix.

As shown in the recursive equation (2.3), Kalman filter first makes a prediction of states at time k based on the estimation results at step $k-1$, then calculate gain matrix K_k . The prediction will be updated after obtaining measurements and then get estimation results at step k . At last, the estimation error covariance matrix is calculated. As shown in Figure 2.1, the whole process is composed of two parts, one is time update, and the other is measurement update.

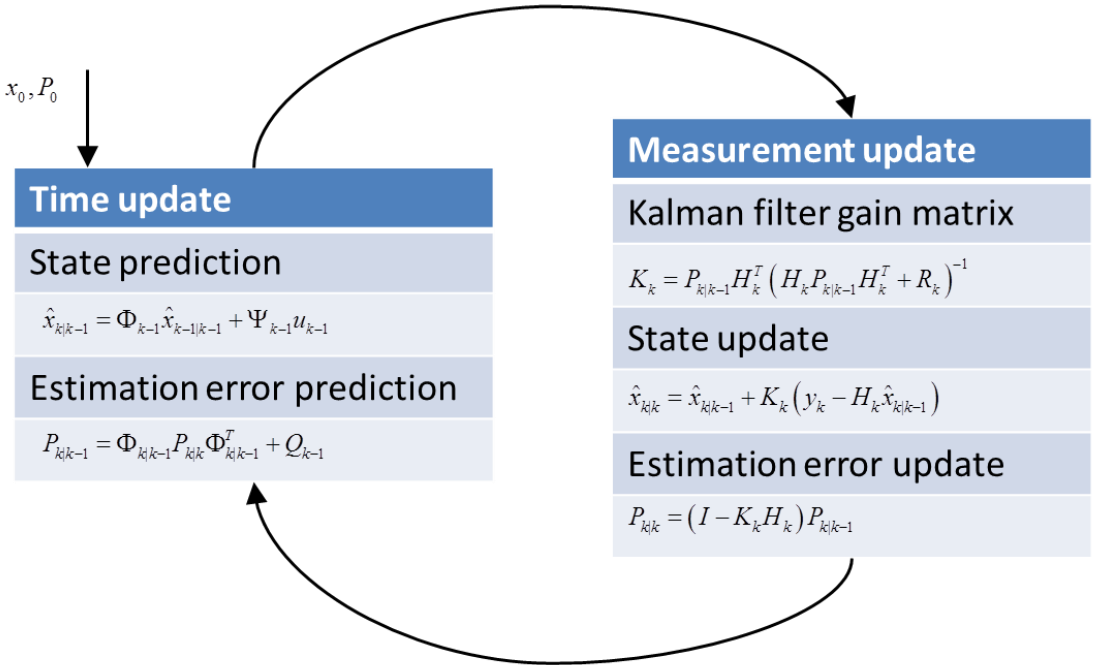


Figure 2.1 The Kalman filter process.

2.2 Estimation Example of KF

In velocity estimation, the state variable is the vehicle longitudinal velocity; the observation variables are the four wheels speed and the input is the longitudinal acceleration.

$$
\begin{aligned}
&x = v_x \\
&y = \begin{bmatrix} v_{fl} & v_{fr} & v_{rl} & v_{rr} \end{bmatrix}^T \\
&u = a_x
\end{aligned}
\tag{2.4}
$$

where v_x is the longitudinal velocity, v_{fl} , v_{fr} , v_{rl} , v_{rr} are the measurements of the four wheels speeds, a_x is longitudinal acceleration.

When the vehicle driving in straight line, the state equation can be written as,

$$\dot{x} = u + w \tag{2.5}$$

The observation equation is

$$y = Hx + v \tag{2.6}$$

where $H = \begin{bmatrix}1 & 1 & 1 & 1\end{bmatrix}^T$

Discretize the state equation and observation equation,

$$
\begin{aligned}
x_k &= x_{k-1} + \tau u_k + w_k \\
y_k &= Hx_k + v_k
\end{aligned}
\tag{2.7}
$$

where τ is the sample time of system.

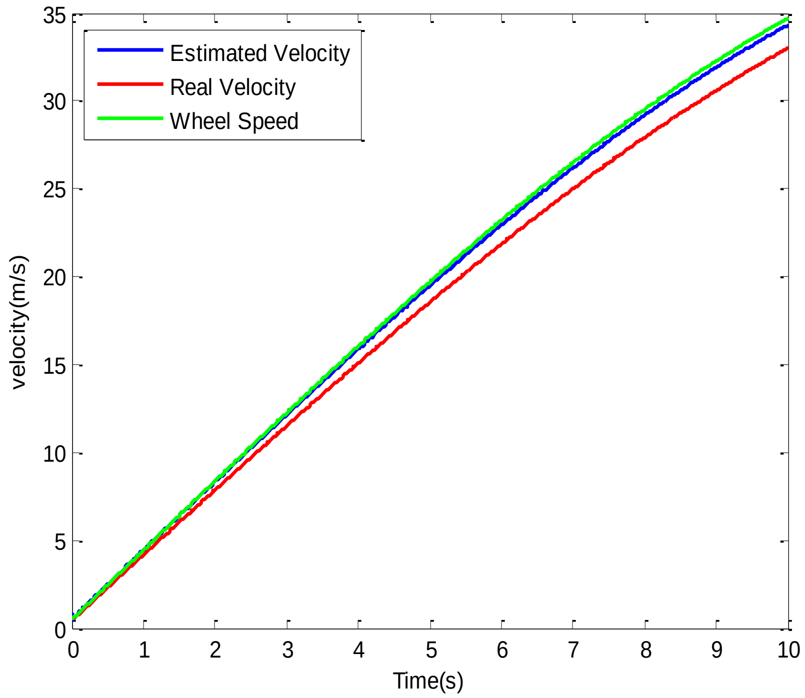
Then in the velocity estimation Kalman filter

$$\begin{aligned} \Phi &= 1 \\ \Psi &= \tau \end{aligned} \tag{2.8}$$

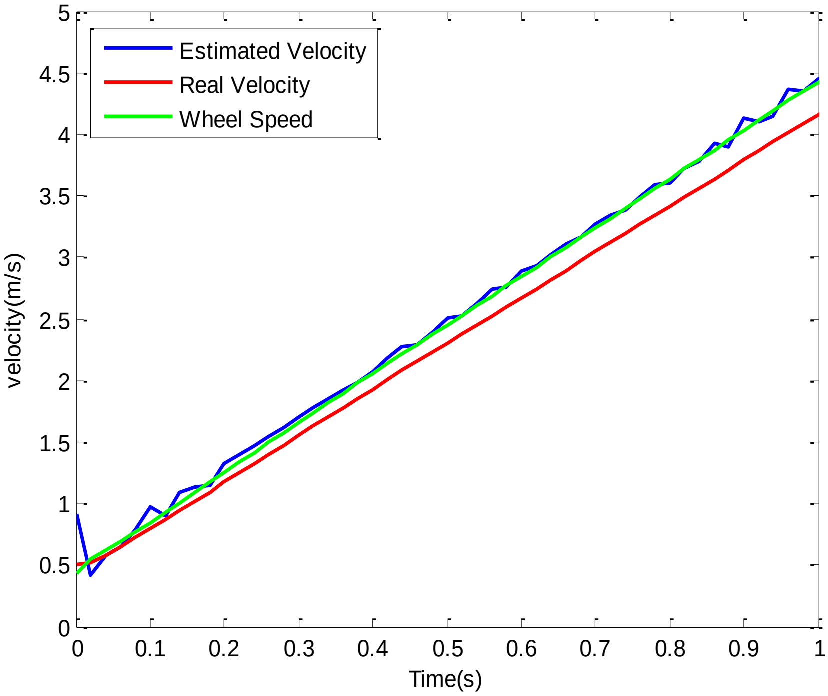
Substitute equation (2.8) to equation (2.3), and then get the velocity estimation functions

$$\begin{aligned}
\hat{x}_{k|k-1} &= \hat{x}_{k-1|k-1} + \tau a_{x,k-1} \\
P_{k|k-1} &= P_{k-1|k-1} + Q \\
K_k &= P_{k|k-1} H^T \left(H P_{k|k-1} H^T + R \right)^{-1} \\
\hat{x}_{k|k} &= \hat{x}_{k|k-1} + K_k \left(y_k - H \hat{x}_{k|k-1} \right) \\
P_{k|k} &= \left(I - K_k H \right) P_{k|k-1}
\end{aligned} \tag{2.9}$$

The covariance matrix Q and R are constant here. Thus, the Kalman filter gain matrix K will also converge to a constant after limit time period. And the value of K is decided by the matrix of Q and R. Hence, the estimation results will be directly influenced by these two covariance matrix. Aiming to get satisfactory estimation results, the value of Q and R should be decided.



(a)



(b)

Figure 2.2 Estimation results under different covariance matrix

The simulation results help to find the property covariance value. After several attempt, the Q and R are

$$R = \begin{pmatrix} 500 & 0 & 0 & 0 \\ 0 & 500 & 0 & 0 \\ 0 & 0 & 500 & 0 \\ 0 & 0 & 0 & 500 \end{pmatrix}$$
$$Q = \begin{pmatrix} 100 & 0 \\ 0 & 100 \end{pmatrix} \tag{2.10}$$

With these values, the estimation results are smooth but follow the wheel speed (we need to calibrate the wheel radius in future work), as shown in Figure 2.2 (a). However, if the values are not suitable, the estimation results will not be desired, as shown in Figure 2.2 (b), the estimation curve is not smooth.

In order to research wheel over-slip, a piece of special road is designed in simulation work. As shown in Figure 2.3, the road slip is 0.8 at first, then changes to 0.2 after 4 seconds, and recovers to 0.8 at 6 second.

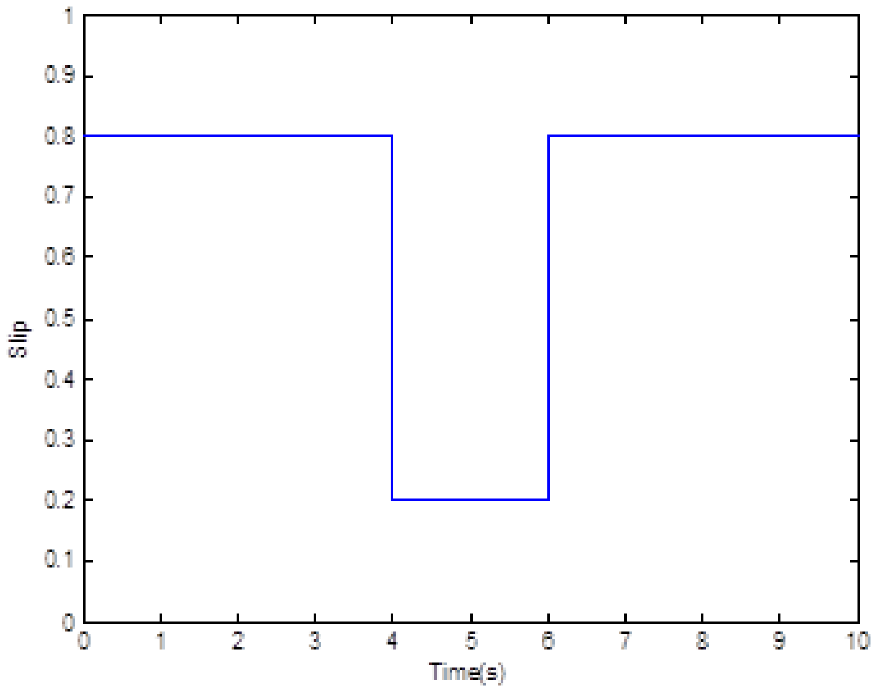
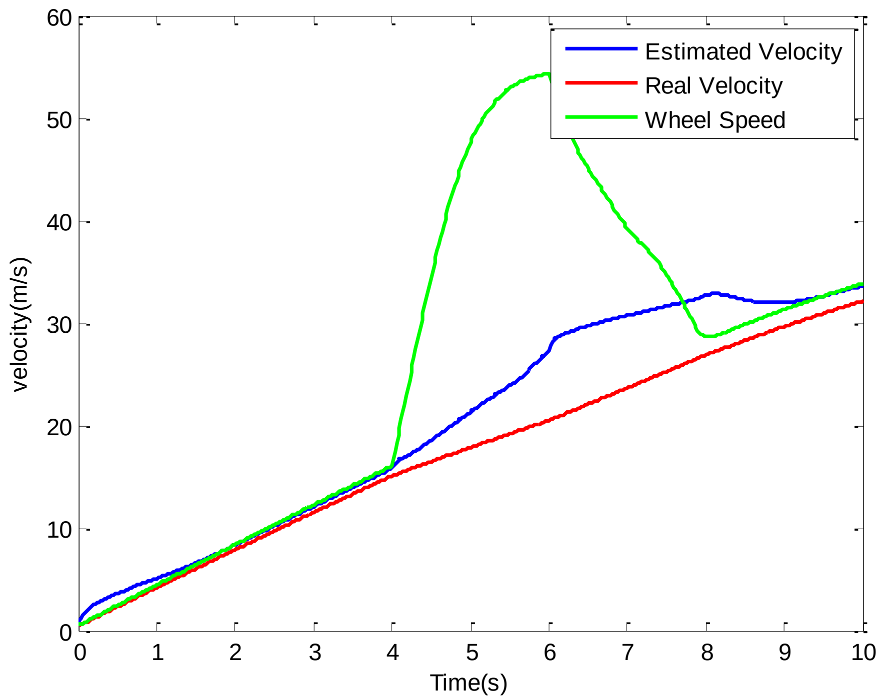
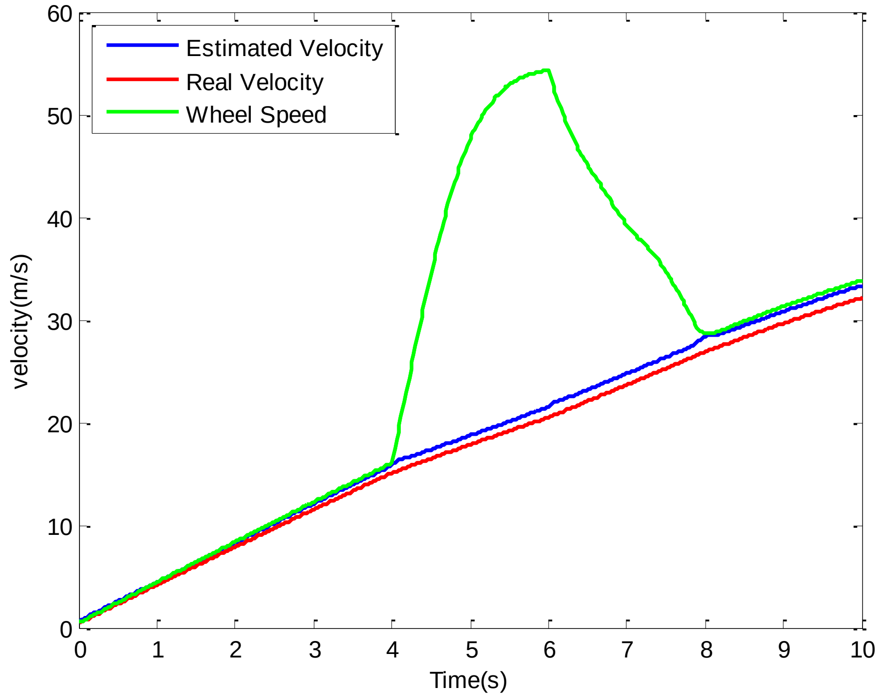


Figure 2.3 Road slip

When over slip occurs on front left wheel, the former covariance matrix values are not proper. As shown in Figure 2.4 (a), if still use former covariance, the estimation curve has an obvious error. Because the over-slip wheel speed affects the estimation results, the measurement error covariance should be changed. However, the other three wheels are still reliable; thus, it is only need to change one matrix element, the one relative to the over-slip wheel.



(a)



（b）

Figure 2.4 Simulation results when one wheel over-slip

After comparison, we choose

$$R=\begin{pmatrix}5000 & 0 & 0 & 0\\ 0 & 500 & 0 & 0\\ 0 & 0 & 500 & 0\\ 0 & 0 & 0 & 500\end{pmatrix} \qquad (2.11)$$

$$Q=\begin{pmatrix}100 & 0\\ 0 & 100\end{pmatrix}$$

In this new group of matrix, the only difference between former one is the element $R(1,1)$. It gets larger because the estimation results will less rely on the front left wheel. And the estimation results are satisfactory as shown in Figure 2.4 (b).

The typical Kalman filter can estimate longitudinal velocity accurately even if there is one wheel over-slip. However, when all the four wheels over-slip, the typical Kalman filter does not work well. To solve this problem, an adaptive Kalman filter is proposed.

Actually, the key factor of the estimation is based on the gain matrix K. K can be written as,

$$K = f(Q)\left[Hf(Q)+R\right]^{-1} \qquad (2.12)$$

where $f(.)$ is a positive correlation function.

We can see that, the larger R is, the smaller K is. That means, if the measurement error get larger, the estimation results will rely on measurement less. On the other hand, the larger Q is, the larger K is. That means, when the system error is large, the estimation results will more rely on measurements. Thus, in traditional Kalman filter, when the measurement noise is strong, then the algorithm needs a large R. But when wheel over slip occurs, there is a huge bias to represent vehicle velocity with the over-slip wheel speed; and traditional method does not work well during over-slip.

In our former work (Xiong L., Gao Y.,-L., Feng Y. (2012)), an adaptive Kalman filter can deal with the problem that all the four wheels over-slip in the same time theoretically.

However, when test on low friction road the algorithm does not work well. For instance, as shown in Figure 2.5, vehicle starts on polished ice. If all the four wheels over-slip in the same time, the velocity estimation will follow the unreliable wheel speed for a short while first, then start to estimate velocity with the integration of the acceleration. The estimation does not accurate because of the incorrect initial value of the integration.

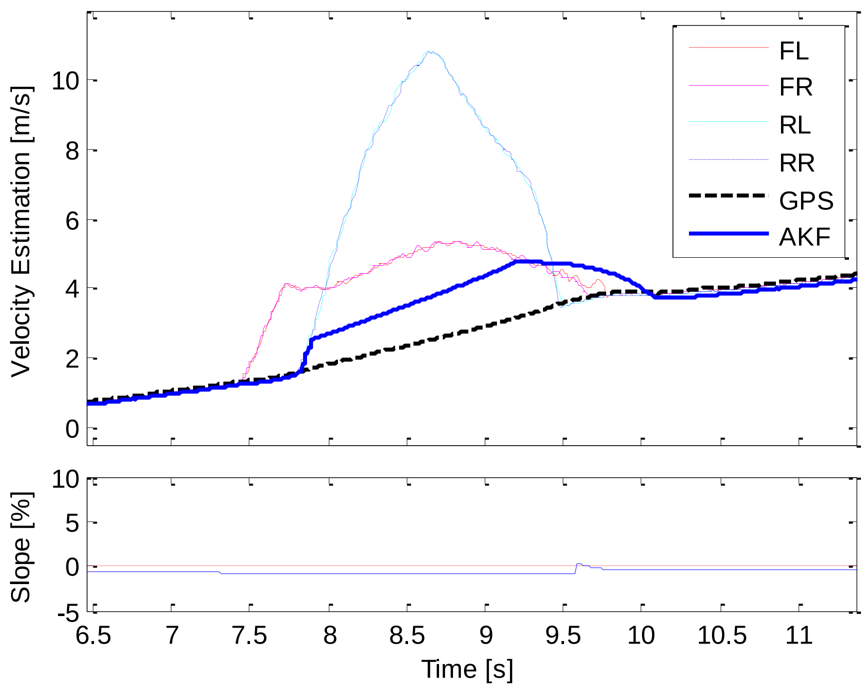


Figure 2.5 Test results when all wheels over-slip

Besides, the wheel speed measurements on low friction road have abnormal fluctuation sometimes, which also has influence on velocity estimation.

Then the flaw of the algorithm can be concluded in two points,

a. The over-slip criteria have delay to detect over-slip wheel. When all the four wheels over-slip, it will cause estimation error.

b. The lack of wheel speed selection may influence the accuracy of the algorithm.

3 Algorithm Design

As mentioned in the end of Chapter 2, the accuracy of velocity estimation could be improved in two aspects. One is to find out over-slip wheels in time, the other is wheel speed selection. Hence, the algorithm is designed based on these principles. The algorithm flow chart is shown below.

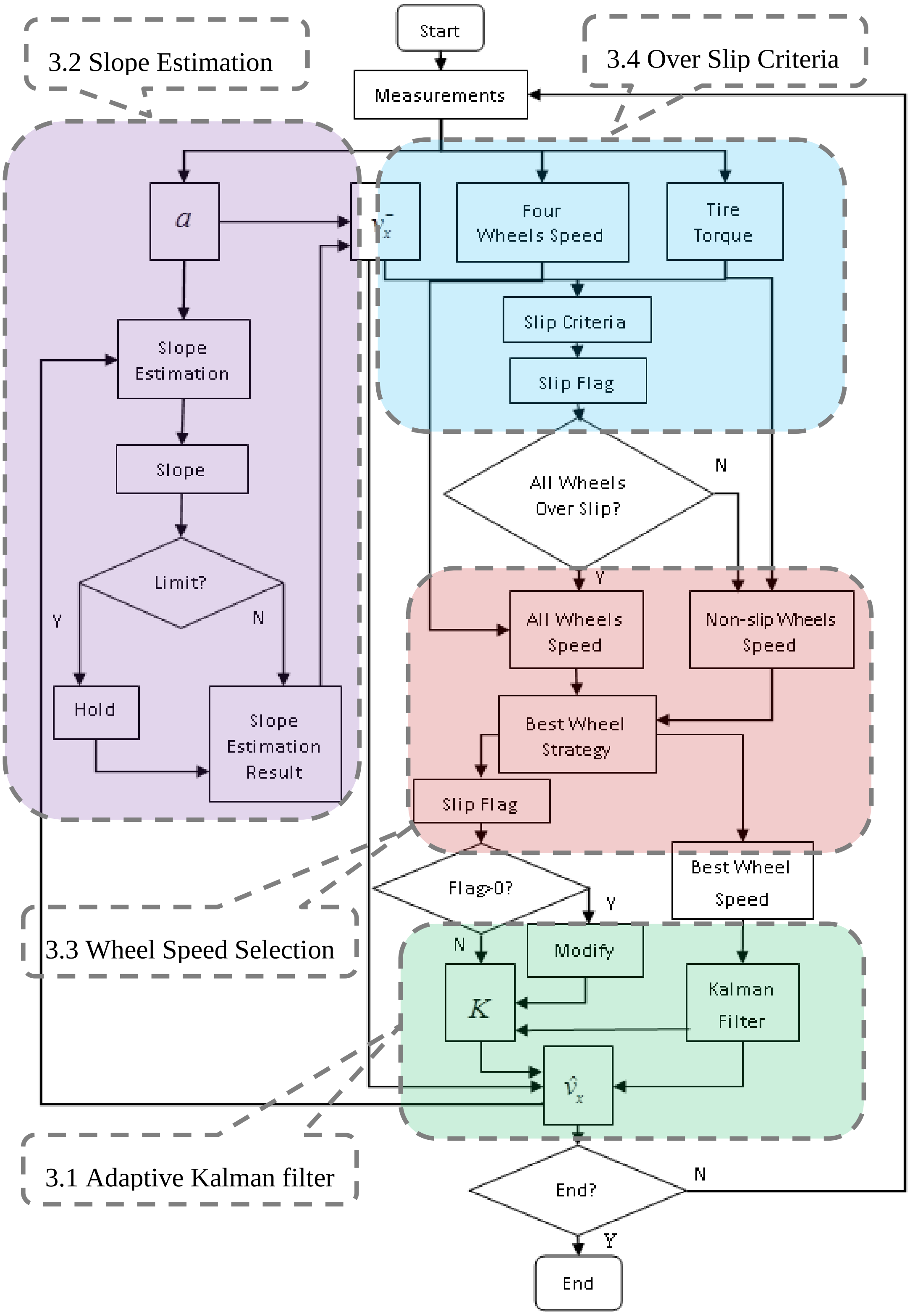


Figure 3.1 Algorithm flow chart

As shown in Figure 3.1, the algorithm is mainly composed of four parts. They are adaptive Kalman filter, slope estimation, wheel speed selection and over-slip criteria. These parts will be explained separately in follow sections.

3.1 Adaptive Kalman Filter

This adaptive Kalman filter is designed based on the typical Kalman filter. The adaptation in this method only takes the switch of gain matrix into consideration. The key point is that the gain matrix K is controlled directly in the adaptive method. And the parameters are defined as follows.

The state variable is longitudinal velocity and the observation variable is the selected wheel speed. In addition, the input is longitudinal acceleration.

$$\begin{aligned} x &= v_x \\ y &= v_{sel} \\ u &= a_x \end{aligned} \tag{3.1}$$

where v_{sel} is the selected best wheel speed multiplied by calibrated wheel radius, and the best wheel is described in Section 3.3.

The observation matrix is

$$H = 1 \tag{3.2}$$

Then equation (2.9) can be simplified to

$$\begin{aligned} \hat{x}_{k|k-1} &= \hat{x}_{k-1|k-1} + \tau a_{x,k-1} \\ P_{k|k-1} &= P_{k-1|k-1} + Q \\ K_k &= P_{k|k-1}\left(P_{k|k-1} + R\right)^{-1} \\ \hat{x}_{k|k} &= \hat{x}_{k|k-1} + K_k\left(y_k - \hat{x}_{k|k-1}\right) \\ P_{k|k} &= \left(1 - K_k\right)P_{k|k-1} \end{aligned} \tag{3.3}$$

Since only one wheel speed is chosen as observation variable, K can be written as,

$$K = k \tag{3.4}$$

As introduced in Kalman filter function, when k is small or next to zero, the measurement is less or not reliable; on the other hand, the measurements turn to be more reliable when k becomes larger.

When the selected wheel is over-slip, switch gain matrix K to zero (still, K is calculated in each Kalman filter step). That means the measurements of the slip wheels are absolutely not reliable. Thus, we do not use the over-slip wheel speed to estimate longitudinal velocity. The velocity estimation is replaced by the integration of acceleration when all wheels are over-slip.

While if not all of the four wheels are over-slip, there is no control of K, the algorithm is just the same as a typical Kalman filter.

3.2 Slope Estimation

Generally, the measurement of accelerometer is composed of both the acceleration of movement and the gravity acceleration along the road slope. As introduced above, longitudinal acceleration is a key factor in velocity estimation. Thus, the road slope compensation is necessary.

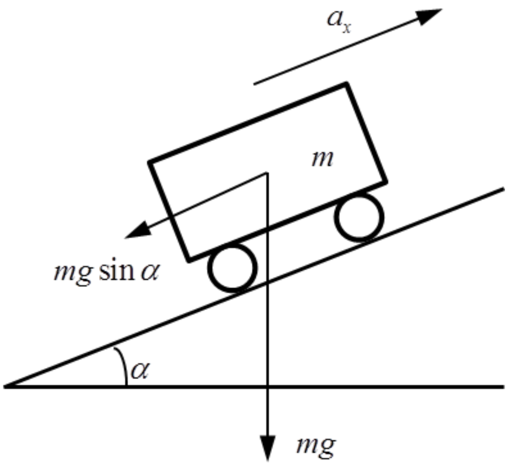


Figure 3.2 Vehicle on slope road

As shown in Figure 3.2, the measurement of accelerometer can be written as

$$a_{x,m} = a_x + g\sin\alpha \tag{3.5}$$

where $a_{x,m}$ is accelerometer measurement, a_x is vehicle longitudinal acceleration, g is gravity acceleration, α is road slope.

When driven in straight line

$$\dot{v}_x = a_x \tag{3.6}$$

Then

$$\dot{v}_x = a_{x,m} - g\sin\alpha \tag{3.7}$$

Based on equation (2.3), Kalman filter is used to estimate road slope. Choose v_x and α as state variables, and $a_{x,m}$ as the input variable.

$$\begin{aligned} x &= \begin{bmatrix} x_1 & x_2 \end{bmatrix}^T = \begin{bmatrix} v_x & \sin\alpha \end{bmatrix}^T \\ u &= a_{x,m} \end{aligned} \tag{3.8}$$

The road slope is assumed to be constant, and then the state equation is

$$\dot{x} = \begin{bmatrix} 0 & -g \\ 0 & 0 \end{bmatrix} x + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u \tag{3.9}$$

Choose the estimation result of velocity as observation variable.

$$y = \hat{v}_x \tag{3.10}$$

And the observation matrix

$$H = \begin{bmatrix} 1 & 0 \end{bmatrix} \tag{3.11}$$

Then, the observation equation is

$$\hat{y} = Hx \tag{3.12}$$

Discretize the state equation,

$$\Phi = \begin{bmatrix} 1 & -\tau g \\ 0 & 1 \end{bmatrix} \qquad \Psi = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \tag{3.13}$$

Then, substitute H, Φ, Ψ into equation (2.3) to estimate road slope.

The observation variable of slope estimation algorithm is the output of velocity estimation, and the result of slope estimation is used to fix the accelerometer measurement. Then these two algorithms are combined together. However, when all of the four wheels are over-slip at the same time on sloped road, neither wheel speeds nor acceleration is reliable. The velocity and slope estimation will be ruined at that time.

In real driving scenarios, it supposed that the road slope does not change rapidly. Thus, we set the gradient limit on the slope estimation. If the slope estimation does not meet with this criterion,

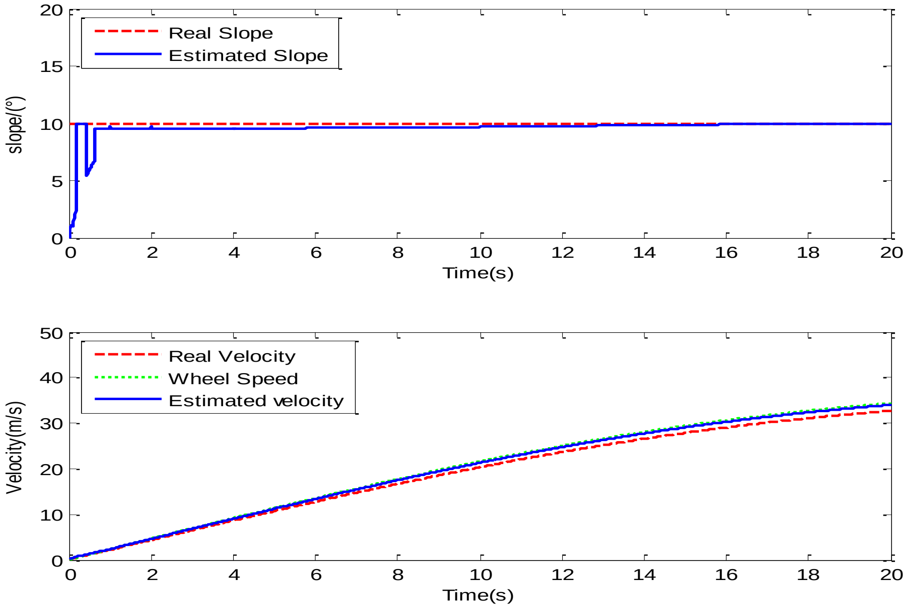
$$\left|\alpha(k) - \alpha(k-1)\right| \leq \Delta\alpha \tag{3.14}$$

Then the estimation result maintains the value obtained from last step.

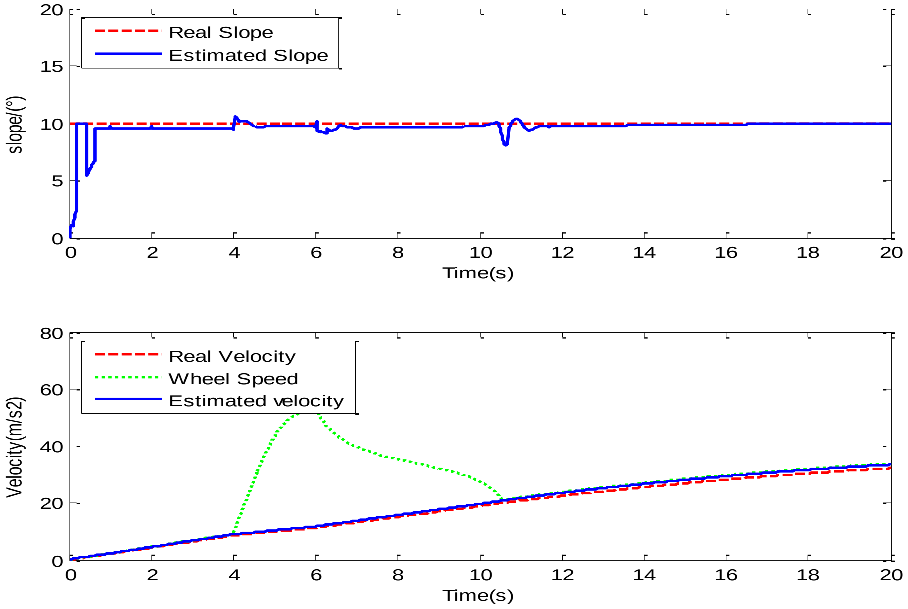
$$\alpha(k) = \alpha(k-1) \tag{3.15}$$

With this method, the estimation results are also satisfactory when all the four wheels are over-slip on constant sloped road.

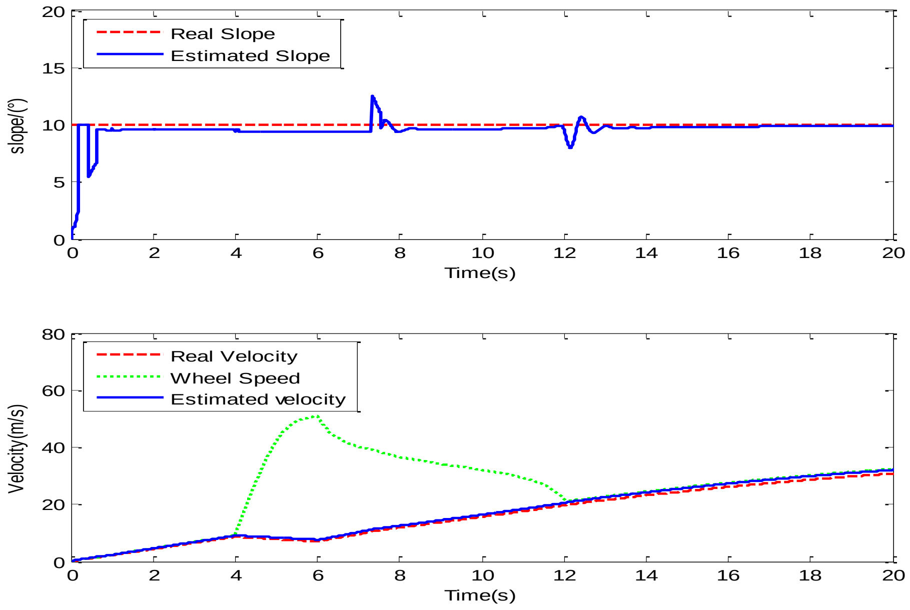
The simulation of the algorithm is carried on constant sloped road. And the driving scenarios include no wheel, one wheel and all wheels are over-slip. The simulation results are shown below.



（a）No wheel over-slip



（b）One wheel over-slip



（c）All wheels over-slip

Figure 3.3 Simulation results on constant slope road

3.3 Wheel Speed Selection

When steering, the wheel speed should be translated to the centre of gravity. Only after that the wheel speed can be used as observation variable. Take front left wheel for example,

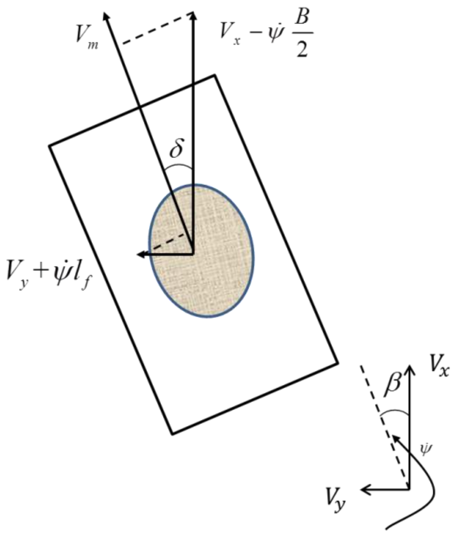


Figure 3.4 The relation between wheel speed and vehicle speed

As shown in Figure 3.4,

$$v_{fl} = \left(v_x - \dot{\psi}\frac{b_f}{2}\right)\cos\delta + \left(v_y + \dot{\psi} l_f\right)\sin\delta \tag{3.16}$$

where $\dot{\psi}$ is vehicle yaw rate, b_f is front vehicle track, l_f is the distance between front axle and gravity centre, δ is tire steer angle.

$$v_y = v_x \tan\beta \tag{3.17}$$

where β is vehicle side slip angle.

Thus,

$$v_x = \frac{v_{fl} + \dot{\psi}\frac{b_f}{2}\cos\delta - \dot{\psi} l_f \sin\delta}{\cos\delta + \tan\beta \sin\delta} \tag{3.18}$$

The front wheel speed translation is

$$v_{fl/fr,trans} = \frac{v_{fl} \pm \dot{\psi}\frac{b_f}{2}\cos\delta - \dot{\psi} l_f \sin\delta}{\cos\delta + \tan\beta \sin\delta} \tag{3.19}$$

It is fairly complex for front wheel translation, and we suppose that the vehicle lateral speed is much smaller than the longitudinal one; the turning radius is much greater than vehicle tread, as shown in Figure 3.5.

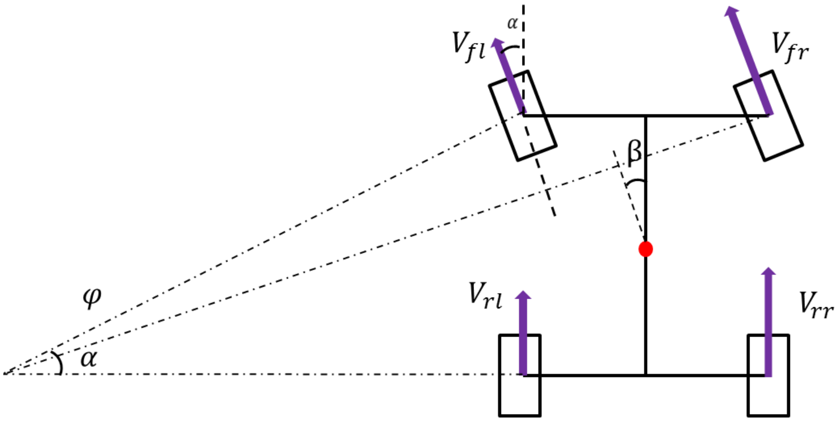
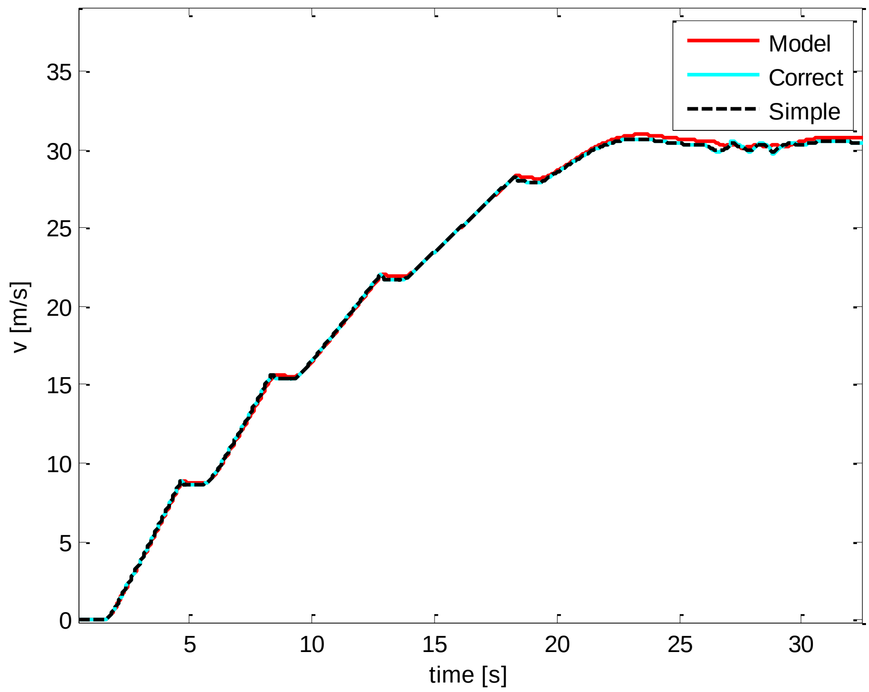


Figure 3.5   Wheel speed translation

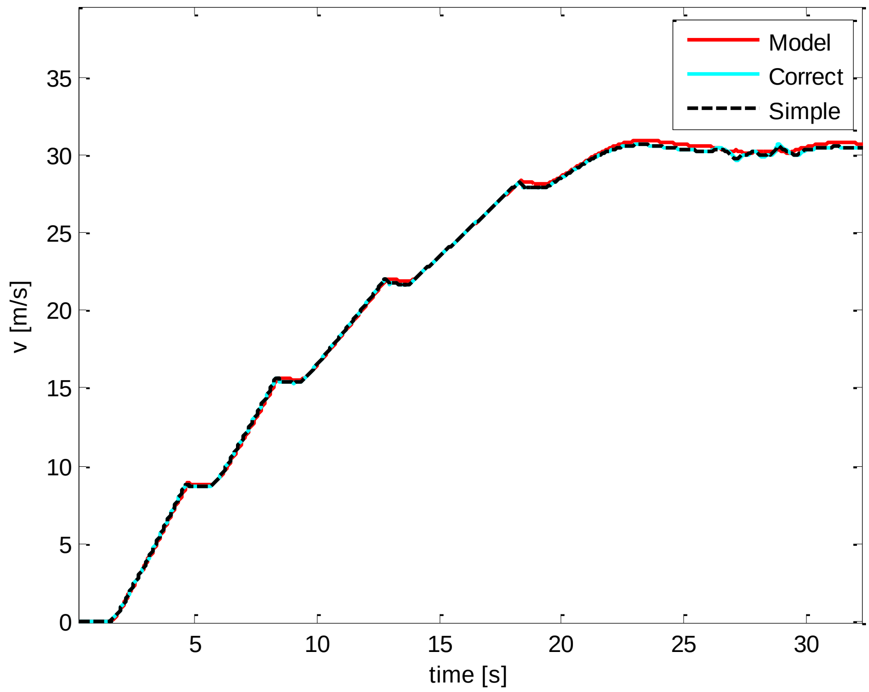
Then the front wheel translation can be written as

$$v_{fl/fr,trans} = v_f \cos\delta \pm \frac{b_f}{2}\dot{\psi} \tag{3.20}$$

Figure 3.6 shows the comparison between these two translation methods during slalom driving scenario with IPG Carmaker demo car. It can be seen that there is no obvious difference between two wheel speed curves. And both the wheels speed translation follow the reference vehicle speed.



(a) front left wheel



（b） front right wheel

Figure 3.6 Comparison between two translation methods

Hence equation (3.17) will be used to transpose wheel speed to centre of gravity.

And the rear wheel translation is

$$v_{r,trans} = v_r \pm \frac{b_r}{2}\dot{\psi} \tag{3.21}$$

where b_r is rear vehicle track.

After wheel speed translation, the Kalman filter observation variable is available. Unfortunately, there are unreliable wheel speed measurements which affect the estimation results during testing, moreover, sometimes the abnormal wheel speed cannot be detected by the over-slip criteria. Hence, before input to velocity estimation algorithm, the wheels speed translation need to be selected.

In this Algorithm, only one wheel speed is chosen as the input of Kalman filter in each sample time. At first, all the four wheels would be checked by over-slip criteria. If not all wheels are over-slip, then start to find out the abnormal measurement. If there is an obvious decrease during traction or an increase during braking, the wheel speed is abnormal and will never be selected. Then, select the maximum or minimum speed among the reliable measurements as the best wheel speed when braking or traction. If all the four wheels are over-slip, just directly choose the maximum or minimum value among the measurements. The strategy can be seen in *Table 3.1*,

Table 3.1 Best wheel strategy

Reliable wheel count	Traction	Braking
4	Minimum of 4 wheel speed	Maximum of 4 wheel speed
1~3	Minimum of reliable wheel speed	Maximum of reliable wheel speed
0	Minimum of 4 wheel speed	Maximum of 4 wheel speed

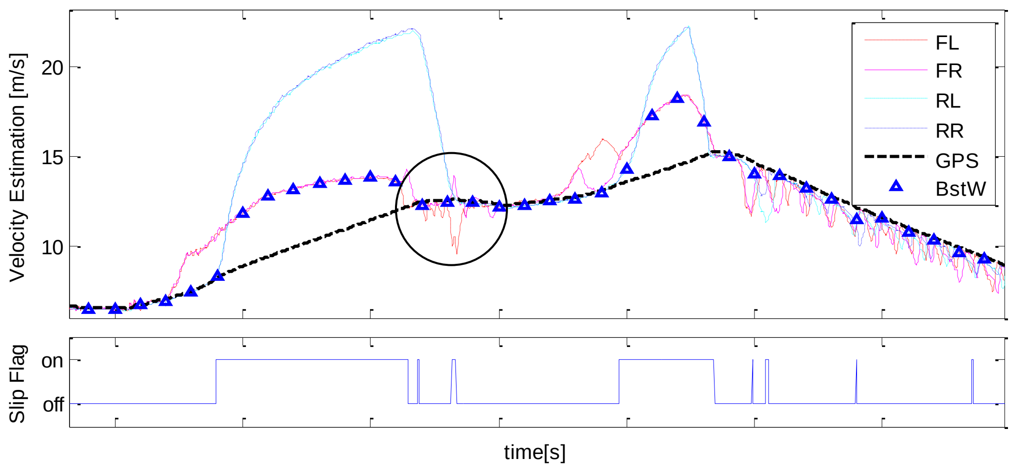


Figure 3.7 Wheel speed selection

In Figure 3.7, the triangle marked curve is the best wheel speed. It is combined with the maximum or minimum speed measurement in different time period. As to the abnormal measurement, such as the front left wheel speed in the black circle, will be removed by selection strategy. In addition, the best wheel slip flag is also selected along with wheel speed. Thus, the plot of slip flag is used to indicate the over-slip of the best wheel. Only when all wheels are over-slip, could the best wheel be over-slip.

Hence, the slip flag “on”, which means over slip occurs, indicates that all the wheels are over-slip.

Another benefit of wheel selection is that it can reduce the calculation quantity in each step before the algorithm converges.

The observation matrix of former algorithm is a 4×1 matrix, see equation (2.6). And the gain matrix is therefore a 4×4 matrix.

$$K_k = P_{k|k-1}H^T\left(HP_{k|k-1}H^T + R\right)^{-1} \tag{3.22}$$

Although the gain matrix will be a constant matrix, but unfortunately, it has to calculate the inverse of a 4×4 matrix in each step before the algorithm converges. However, if the best wheel speed is selected from 4 measurements, the observation matrix will be an element. And the gain matrix is much easier to calculate. Thus, the wheel selection also to some extent reduces the calculation quantity.

3.4 Over-slip criteria

There will be three over-slip criteria introduced in this section. They are wheel speed criterion, pre-estimation criterion and wheel torque criterion.

The aim of wheel speed criterion is to detect rapid changes in the wheel speed as an indication of over-slip. If the absolute difference between current wheel speed and the mean of former several wheel speeds, the wheel speed is decide to be over-slip.The function can be written as

$$\left|\omega(k) - \frac{1}{m}\sum_{i=k-m}^{k-1}\omega(i)\right| > \Delta\omega_{thrshld} \tag{3.23}$$

where m is the count of former steps.

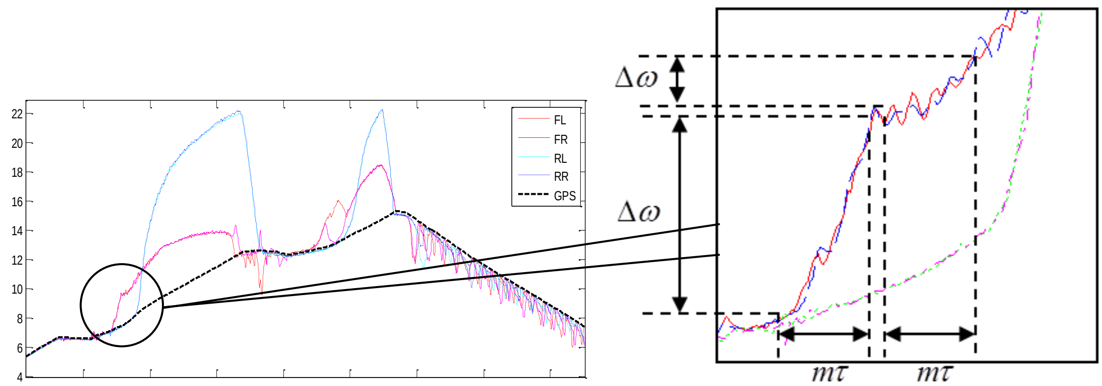


Figure 3.8 Wheel speed criteria

As shown in Figure 3.8, when the speed measurement changes rapidly, it assumed to be over-slip. However, after the beginning of over-slip, the measurement turns to be flat. Thus, the threshold should be a small value to detect all sections of over-slip. The problem is that the threshold cannot be too small; otherwise it will be ruined by the measurement noise. On the other hand, if the threshold is great, it will cause obvious delay or miss detection of over-slip. Hence, there is a compromise between the delay in slip detection and sensitivity to noise in this criterion.

Then, we have the second over-slip criterion based on the difference between the wheel speeds and the pre-estimation of the velocity. The function can be written as

$$\left|\omega(k)R_r - \hat{v}_x^-(k)\right| > \Delta v_{thrshld} \tag{3.24}$$

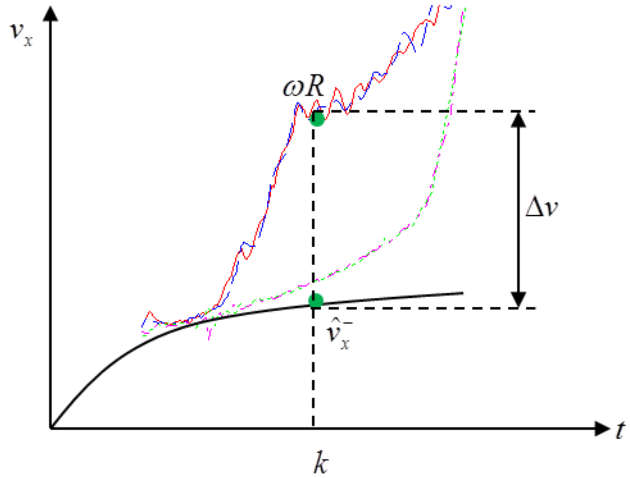


Figure 3.9 Pre-estimation criteria

To solve the problem in wheel speed criterion, the pre-estimation velocity is used to find out the over-slip wheels. As shown in Figure 3.9, even if the wheel speed turns to be flat, it is still greater than the pre-estimation value. Thus, according to this criterion, we can find the over-slip although the measurement do not change intensely. Also, the threshold here cannot be too small.

The proper threshold of the criteria can distinguish over-slip and measurement noise. Also, it causes the delay of over-slip detection, and then affects the accuracy of the velocity estimation. As shown in Figure 3.10, when all the four wheels are over-slip, the velocity estimation will be replaced by the integration of the acceleration. However, because of the delay of over-slip detection, the initial value is not correct and the estimation error is obvious.

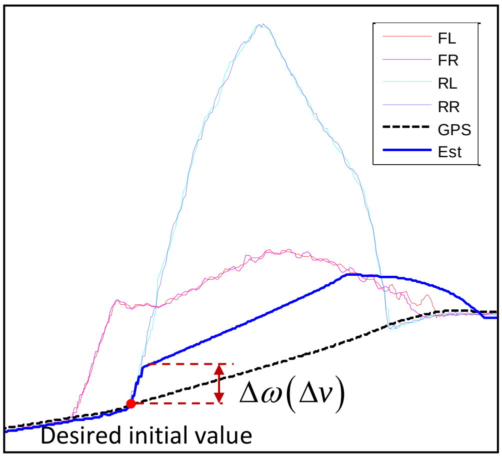


Figure 3.10 Influence of the over-slip-detection delay

On the other hand, the threshold cannot be too strict; otherwise the over-slip criteria will be affected by measurement noise. Here we will come up with the third criterion.

Generally, the wheel torque can be obtained much more accurately from an electric motor than an internal combustion engine. Hence, we take advantage of the electric motor torque to find out the over-slip wheels. When the hybrid vehicle is fully traction, the left and right wheels obtain the same torque from motor. As to the torque vectoring scenario, the wheel torque will be calculated separately from the gear box.

When the wheel torque from the motor is greater than the maximum torque that offered by the road friction, the wheel could be over-slip. Take rear axle as example, the normal force on the axle is

$$F_{zr} = \frac{l_f}{l_f + l_r} mg + \frac{h}{l_f + l_r} ma_x \tag{3.25}$$

where F_{zr} is the normal force on the rear axle, m is the total mass of the vehicle, a_x is the acceleration from the vehicle centre of gravity (CG), l_f and l_r are respectively the distance between CG and front and rear axle, h is the height of the CG (to the earth), g is the gravity acceleration.

At the time that the wheel begins to slip, the maximum of road friction can be written as

$$\mu_{\max} = \frac{a_x}{g} \tag{3.26}$$

Then, the maximum longitudinal force and the tire torque are

$$F_{xr\max} = F_{zr} \frac{a_x}{g} \tag{3.27}$$

$$T_{r\max} = \frac{1}{2} F_{xr\max} R_r \tag{3.28}$$

where R_r is the wheel radius. We suppose the left and right wheel gains the same torque here.

When the torque measurement is greater than $T_{r\max}$, the wheel begins to slip. With this criterion, the estimation result is better than before, as shown in Figure 3.11, the “Est” curve only uses the first two criteria above and the “Est+T” curve uses all the three criteria.

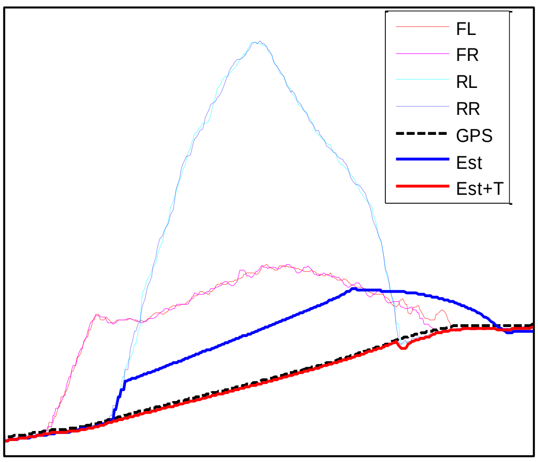


Figure 3.11 Improvement of estimation results

However, this criterion is sensitive to measurement noise because we want to find out the over-slip at the very beginning of over-slip. Hence, the wheel speed is taken into consideration to be a complement.

When the torque measurement meets with the slip criterion, if the wheel speed increases rapidly, which means the slip judgment is verified, then the wheel is decided to be over-slip; otherwise, not over-slip. That is, in a short time period after the detection of excessive torque, the increment of the wheel speed should be greater than the threshold value, see equation (3.29), and then decide the wheel is over-slip.

$$\omega(k)-\omega(k-m)>\Delta\omega_1 \tag{3.29}$$

where m is the count of former step, $\omega(k)$ and $\omega(k-m)$ are respectively the wheel speed measurements in step k and $k-m$, $\Delta\omega_1$ is the threshold value.

When recovers from over-slip, the wheel speed should decrease rapidly, see equation (3.30). After that, the over-slip ends.

$$\omega(k)-\omega(k-m)<\Delta\omega_2 \tag{3.30}$$

where $\Delta\omega_2$ is the threshold value.

The state-flow chart of this criterion is shown in Figure 3.12. The inputs are "IncreaseFlagRising", "DecreaseFlagFalling" and "delta_T" ($\Delta T = T_{meas} - T_{\max}$). The output is "flag".

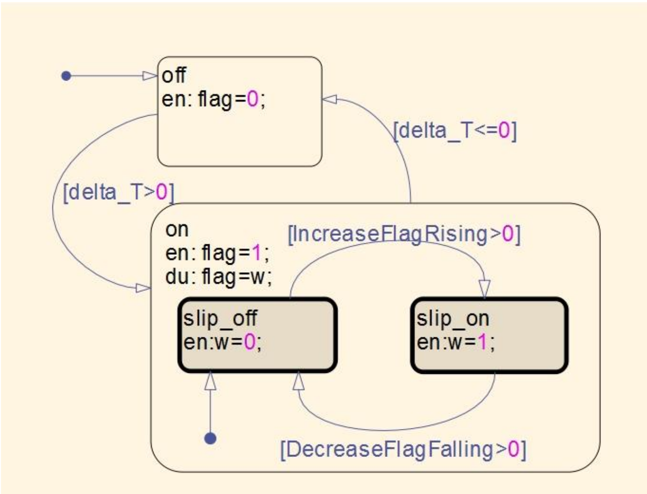


Figure 3.12 The state-flow chart of torque criterion

The example of the torque criterion is shown in Figure 3.13.

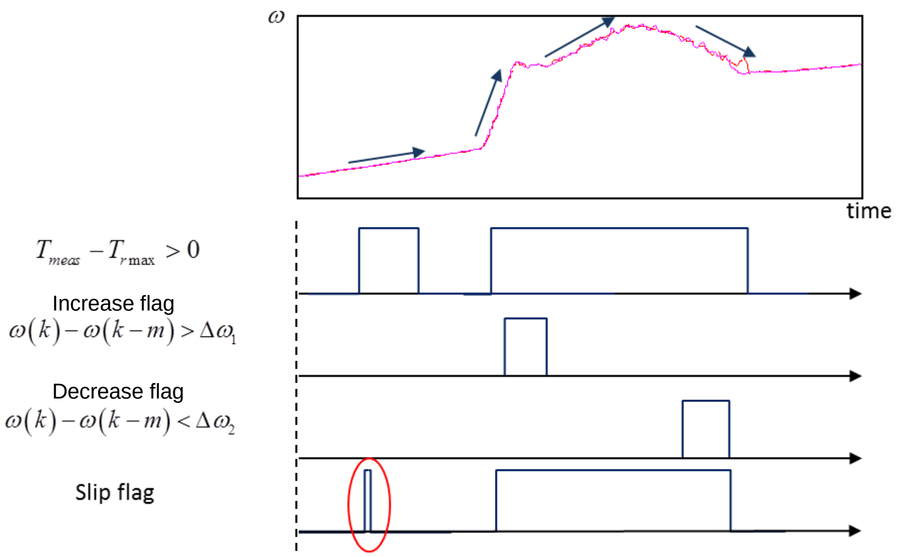


Figure 3.13 Example of the torque criteria

When the torque measurement is greater than maximum torque, but the wheel speed does not change intensely, the slip flag will rise but fall immediately. If the wheel speed measurement increases abnormally after obtaining excessive torque, the “increase flag” is activated, then begin to detect the decrease of the wheel speed. Also, the abnormal decrease will activate the “decrease flag”. At last, we find the wheel is over-slip from the rising edge of “increase flag” to the falling edge of “decrease flag”.

Obviously, there is a pulse in the slip flag, which caused by the torque measurement error. But it will not cause huge velocity estimation error.

On the other hand, when the torque measurement does not meet with the criterion, we will not check the wheel speed but decide not over-slip directly.

3.5 Parameters Calibration

The wheel speed is

$$v_i = \omega_i R_{ref}, i = fl, fr, rl, rr \tag{3.31}$$

where R_{ref} is the reference tire radius when the vehicle is driving.

The reference radius is influenced by tire pressure and other factors, thus it is not exactly a constant value. Moreover, the accelerometer is sensitive to several factors, such as temperature. And the bias of accelerometer should also be found out during velocity estimation. When influenced by the measurement bias, the vehicle acceleration can be written as

$$a_x = a_{x,m} + \Delta a_x \tag{3.32}$$

where Δa_x is the bias of the longitudinal accelerometer.

If the wheel is pure rolling when driving straight, the wheel acceleration and vehicle acceleration (modified by slope estimation) are almost the same. As shown in Figure 3.14.

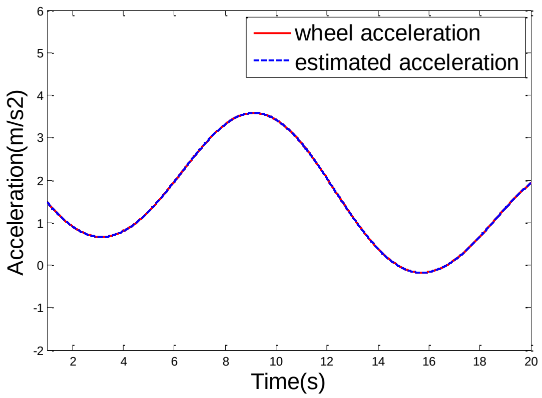


Figure 3.14 Wheel acceleration and vehicle acceleration

Thus,

$$a_x = \dot{\omega} R_{ref} \tag{3.33}$$

where ω is wheel rotation speed.

$$\dot{\omega} R_{ref} = a_{x,m} + \Delta a_x \tag{3.34}$$

Then use a Kalman filter to find the accelerometer bias and reference radius. (This method works when the road slope is known) Choose $\dot{\omega}$ as the observation variable, and the state variables are,

$$x = \begin{bmatrix} x_1 & x_2 \end{bmatrix}^T = \begin{bmatrix} \dfrac{\Delta a_x}{R_{ref}} & \dfrac{1}{R_{ref}} \end{bmatrix}^T \tag{3.35}$$

The observation variable is

$$y = \dot{\omega} \tag{3.36}$$

$$y = \begin{bmatrix} 1 & a_{x,m} \end{bmatrix} x \tag{3.37}$$

The time update of state is only relative to the system, because there is no other input,

$$\begin{bmatrix} \dfrac{\Delta a_x}{R_{ref}} \\ \dfrac{1}{R_{ref}} \end{bmatrix}_{k|k-1} = \begin{bmatrix} \dfrac{\Delta a_x}{R_{ref}} \\ \dfrac{1}{R_{ref}} \end{bmatrix}_{k-1|k-1} + w_{k-1} \tag{3.38}$$

Thus, the prediction of the state is as same as the estimation result in last step.

$$x_{k|k-1} = x_{k-1|k-1} \tag{3.39}$$

Hence the estimation equation is

$$x_{k|k} = x_{k|k-1} + K_k \left(\dot{\omega} - \begin{bmatrix} 1 & a_{x,m} \end{bmatrix} x_{k|k-1} \right) \tag{3.40}$$

The Kalman filter can estimate x_1 and x_2, the accelerometer bias and reference radius are

$$
\begin{aligned}
\Delta a_x &= \frac{x_1}{x_2} \\
R_{ref} &= \frac{1}{x_2}
\end{aligned}
\tag{3.41}
$$

On low friction road, the wheel is rather easy to be over-slip, and the on-line calibration is confronted with problems, since it is difficult to obtain the differential of the over-slip wheel speed.

Thus, the off-line radius calibration is carried out before test. The vehicle is driven to 50km/h, then coast down. The measurements of wheel speed and reference velocity are recorded during this time period.

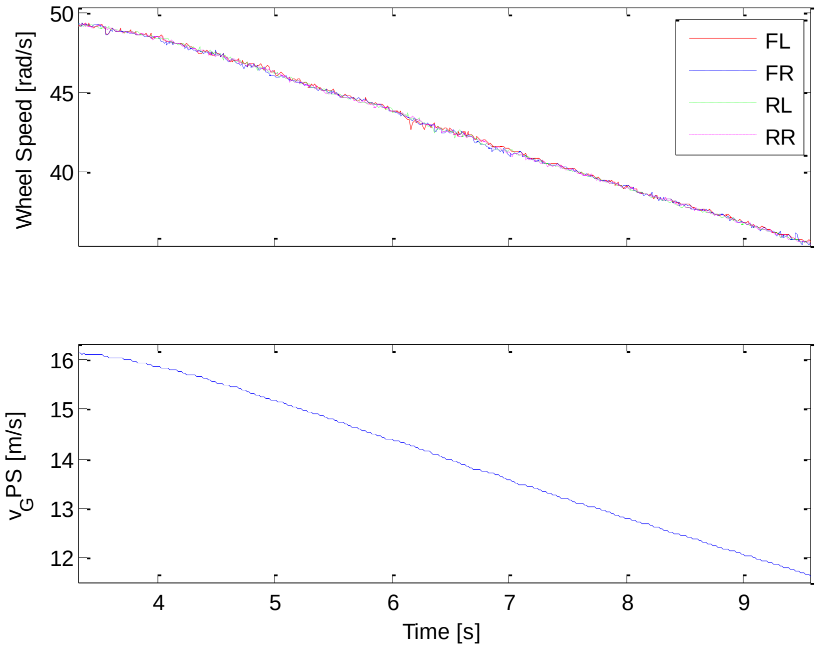


Figure 3.15 Measurements of wheel speed and velocity

Figure 3.15 is one of several groups of measurements, use "polyfit" function in MATLAB to find the linear relation between wheel speed and velocity. There is some slight constant value caused by the MATLAB function in the equation, but do not have great influence on radius calibration.

$$v_{GPS} = 0.3286\omega_{mean} - 0.0049 \tag{3.42}$$

Thus, the wheel radius is 0.3286 m based on this group of measurement. Take all groups of the measurements into consideration, the wheel radius is

$$R_{ref} = 0.3285m \tag{3.43}$$

As to the accelerometer bias, it is found out by the slope estimation algorithm off-line (most bias of the accelerometer could be detected off-line). The measurements on flat road are chosen to estimation the slope, and then calculate the mean of the slope estimation results. The average slope estimation results on flat road are shown in Table 3.2.

Table 3.2 Accelerometer bias from slope estimation results

Driving Scenario	bias value 1	bias value 2	bias value 3
Acceleration and deceleration on Ice	-0.01527	-0.01584	-0.01493
Acceleration and deceleration on Snow	-0.0182	-0.01707	-0.01690
Big Circle	-0.01530	-0.01534	-0.01534
Charge	-0.01278	-0.01473	-0.0122
Circle On Snow	-0.01706	-0.01722	-0.01698
Circle On Ice	-0.01761	-0.01692	-0.01249
Coast Down	-0.01372	-0.01244	-0.01338
Driving On Ice	-0.01026	-0.01178	-0.01109
Parking	-0.0168	-0.01665	-0.01496
Start On Ice	-0.01548	-0.01696	-0.01559
Slalom	-0.01785	-0.01704	-0.01732

Thus, the accelerometer bias is

$$\Delta a_x = -0.01525 \times 9.82 \approx -0.15 m/s^2 \tag{3.44}$$

Other parameters and some thresholds can be seen in Table 3.3.

Table 3.3 Parameters and thresholds

Notations	Description	Unit	Value
Q	system error covariance matrix of velocity estimation	-	1
R	measurement error covariance matrix of velocity estimation	-	200
$\Delta v_{thrshld}$	threshold of over-slip criterion using pre-estimation	m/s	0.4
τ	sample time	s	0.001
$\Delta\alpha$	slope rate limit	rad	0.001
$\Delta\omega_1$	Wheel speed increase threshold of	rad/s	2.4

	over-slip criterion using torque		
$\Delta\omega_2$	Wheel speed decrease threshold of over-slip criterion using torque	rad/s	-2.4
$\Delta\omega_{thrshld}$	threshold of over-slip criterion using wheel speed	rad/s	0.9

4 Test on High Friction Road

The on-road test is carried out on both high and low friction road. The high friction test is on asphalt road without steering.

4.1 Test Vehicle

The test vehicle on high friction road is an electric vehicle with four in-wheel motors, shown in Figure 4.1 and the parameters are shown in Table 4.1 .Driving torques and wheel speeds were obtained by accessing the CAN-Bus, accelerometer provided the longitudinal acceleration, and the longitudinal speed signal was obtained from the optical speed/slip angle sensor.

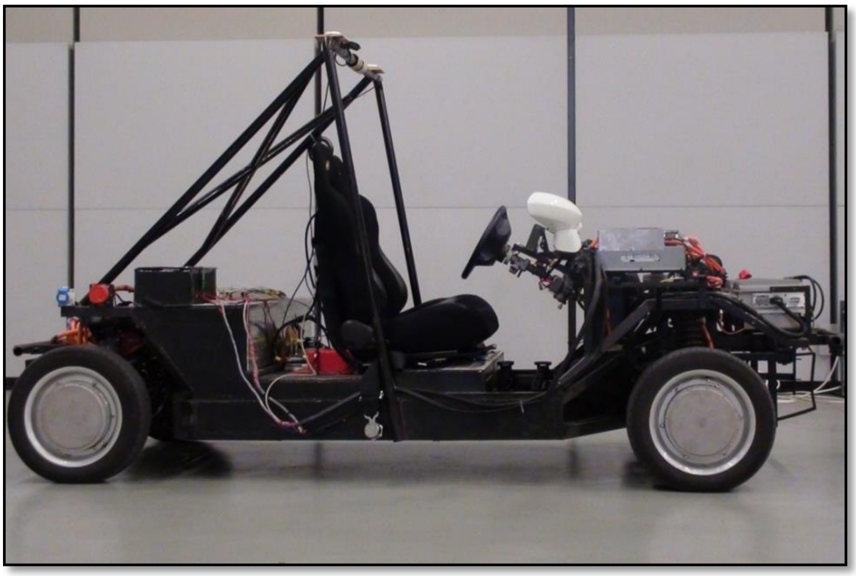


Figure 4.1 Test vehicle on high friction road

Table 4.1 Parameters of test vehicle (high friction road)

Item of vehicle	Value	Item of motor	Value
total vehicle mass	1070 [kg]	rated power	2.5 [kW]
height of the CG	380 [mm]	peak power	7.5 [kW]
CG to front axle	1080 [mm]	rated torque	55.7 [Nm]
CG to rear axle	1220 [mm]	peak torque	167 [Nm]
wheel base	2300 [mm]	max speed	1250 [rpm]
vehicle tread	1200 [mm]	rated voltage	120 [V] DC

The sensor measurements can be seen in Figure 4.2.

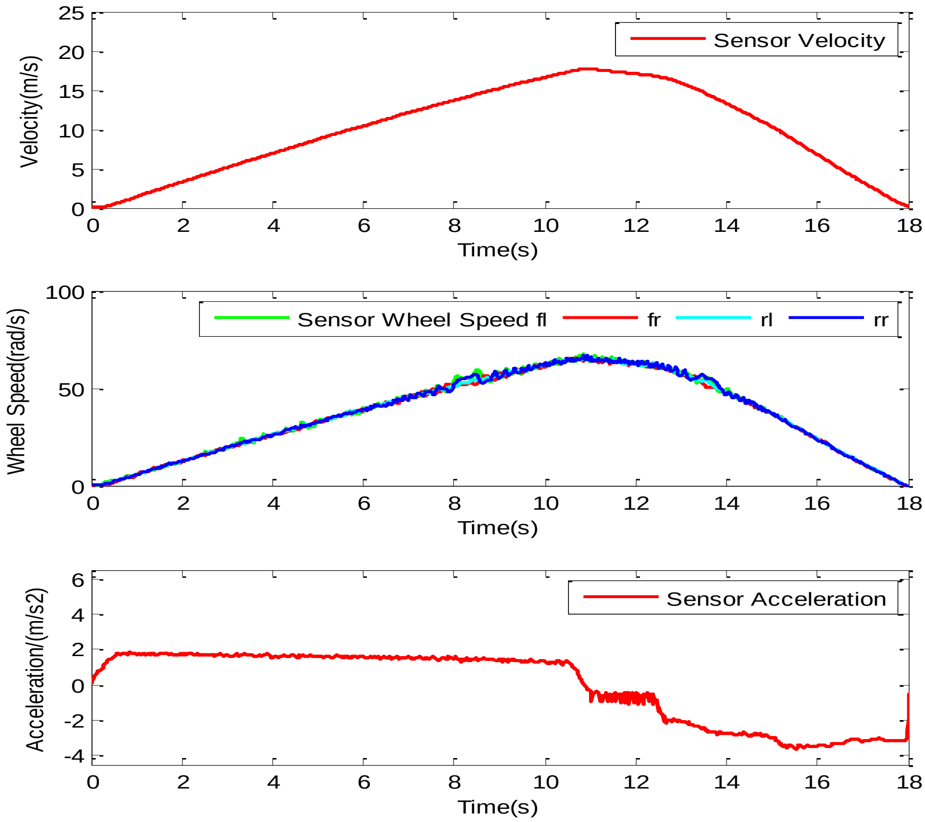


Figure 4.2   Measurements of sensors

4.2 Test on Flat Road

The driving scenarios on flat road are start from standstill as well as acceleration and deceleration.

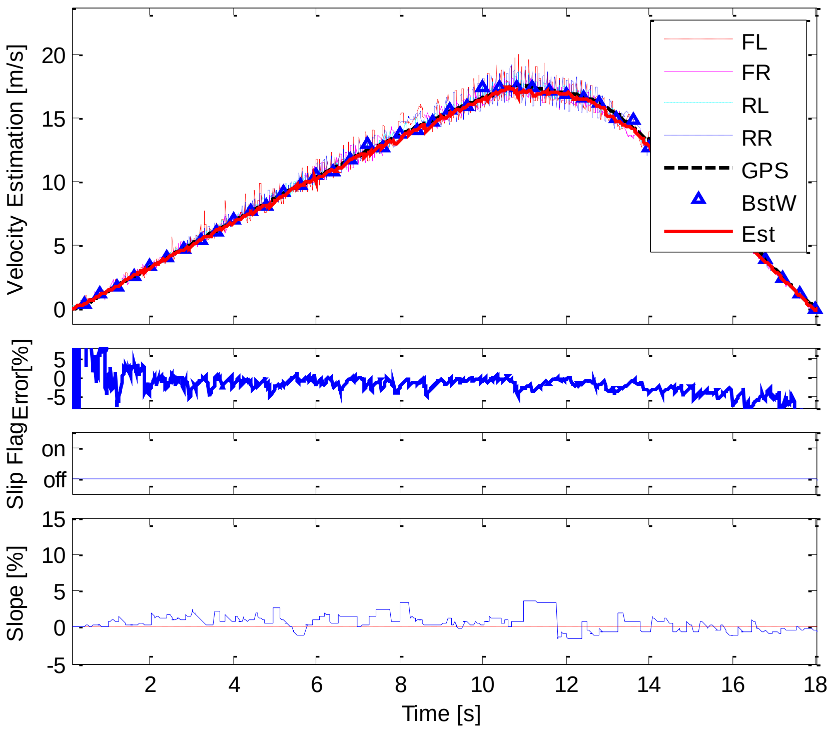


Figure 4.3   Test results of vehicle start

The vehicle is started from standstill, and the driver pushes accelerator pedal to the bottom slowly. The test results are shown in Figure 4.3, the estimation results are almost as same as GPS measurements. The error of the estimation is within ±5% when the reference measurement is not so small (greater than 2 m/s). It is satisfactory. The algorithm works well when vehicle starts. And the all the four slip flag results are “off”, for no wheel is over-slip.

In acceleration and deceleration scenario, the vehicle is accelerated to 45 km/h, then braking, coast down and accelerated again. The absolute value of acceleration is within 2 m/s^2. During this test, as shown in Figure 4.4, the velocity estimation algorithm is not influenced by acceleration and deceleration, and gets an accurate result, although the estimation error is greater than 5% in the beginning. In addition, there is no wheel over-slip.

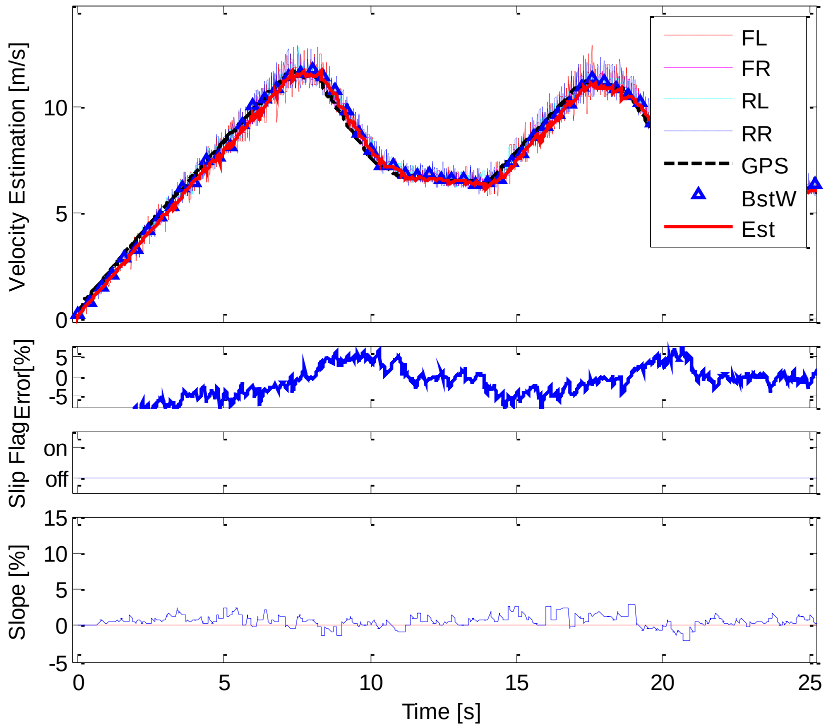


Figure 4.4 Test results of acceleration and deceleration

4.3 Test on Sloped Road

The slope road tests are including upgrade and downgrade road.

As shown in Figure 4.5, the vehicle starts on a downgrade road, then drives on flat road. The velocity estimation error is within ±5%, the result is accurate. When the vehicle is standstill on the slope, the measurement of accelerometer is used to the reference slope value. The slope estimation results get -10% on downgrade road and recover to 0 on flat road. The slope estimation is satisfactory.

Test results are shown in Figure 4.6, the vehicle starts on upgrade road and the velocity estimation error is also within ± 5%. The velocity estimation is desired because of the accurate slope compensation. In addition, no wheel is over-slip during this period.

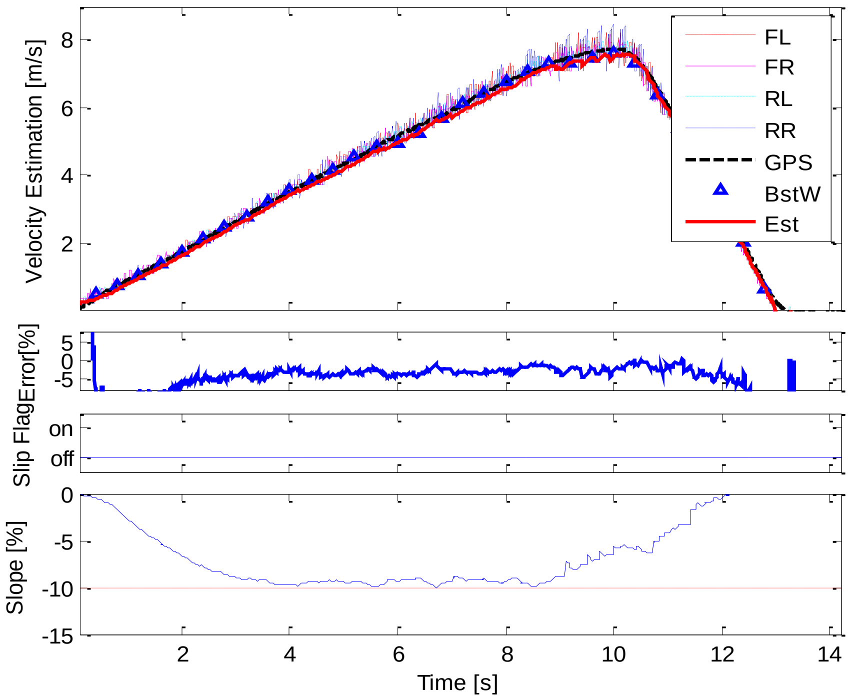


Figure 4.5 Test results on downgrade road

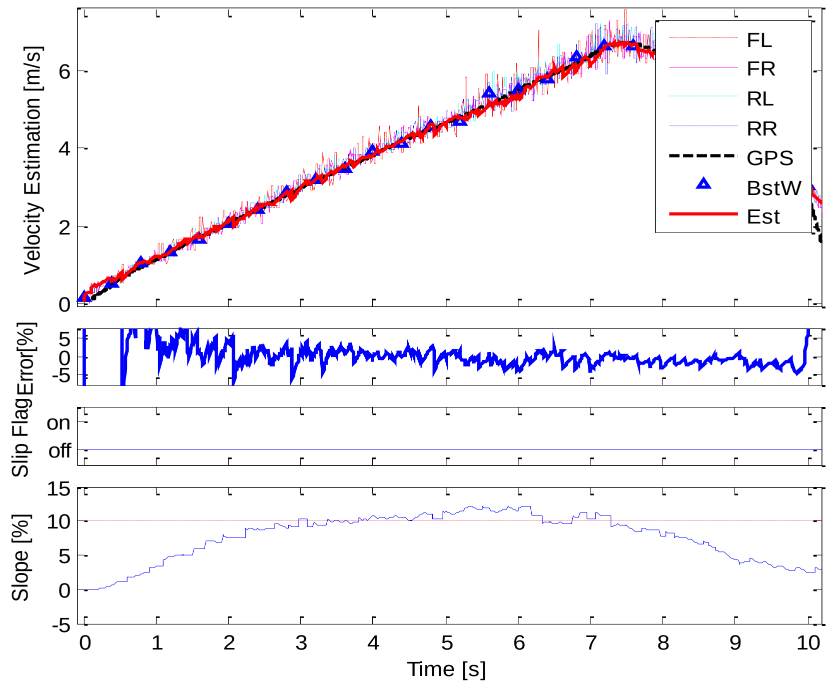


Figure 4.6 Test results on upgrade road

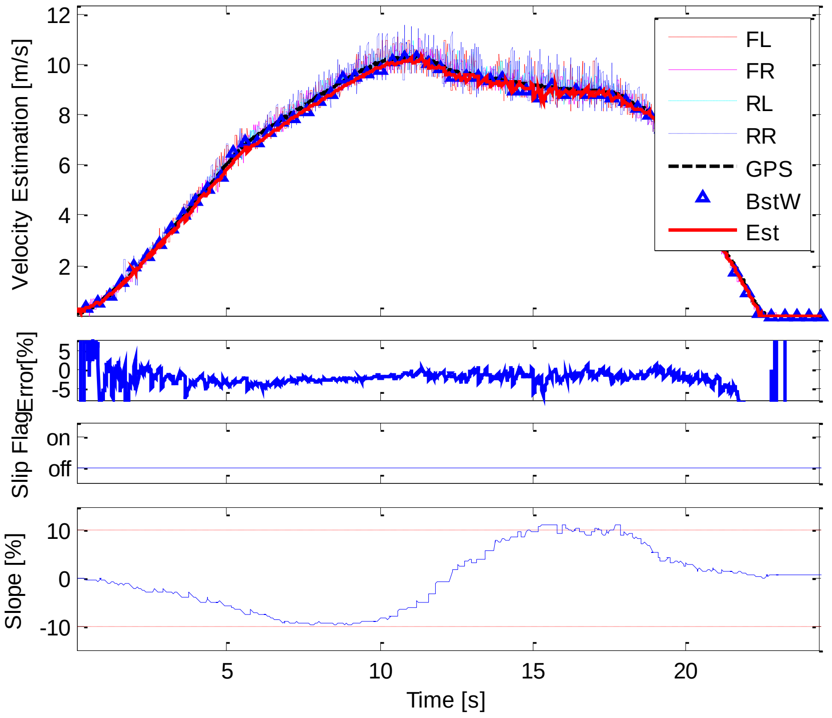


Figure 4.7   Test results on variable slope road

Figure 4.7 shows the test results on variable slope road, the U-shape road combined by upgrade and downgrade road in past test. The slope estimation algorithm performs well on variable slope road. Moreover, the velocity estimation is desired and the estimation error is within ±5% or less. In spite of there is no reference slope in the mid-part of the road, the slope estimation is proved to be accurate based on the velocity estimation.

The algorithm works well when no wheel over-slip. Then wheel slip test is carried out on upgrade road. It is easier for front axle to be over-slip when vehicle starts on upgrade road. Moreover, a piece of polished iron is paved under the front right wheel to make it over-slip.

As shown in Figure 4.8, the front right is over-slip during 1 to 4 second. The slip flag maintain to be "off" because the best wheel is not over-slip. The estimated velocity curve does not follow the over-slip wheel. But the velocity sensor has a fluctuation at the beginning of the over-slip. Thus the estimation error is greater than no wheel over-slip scenario.

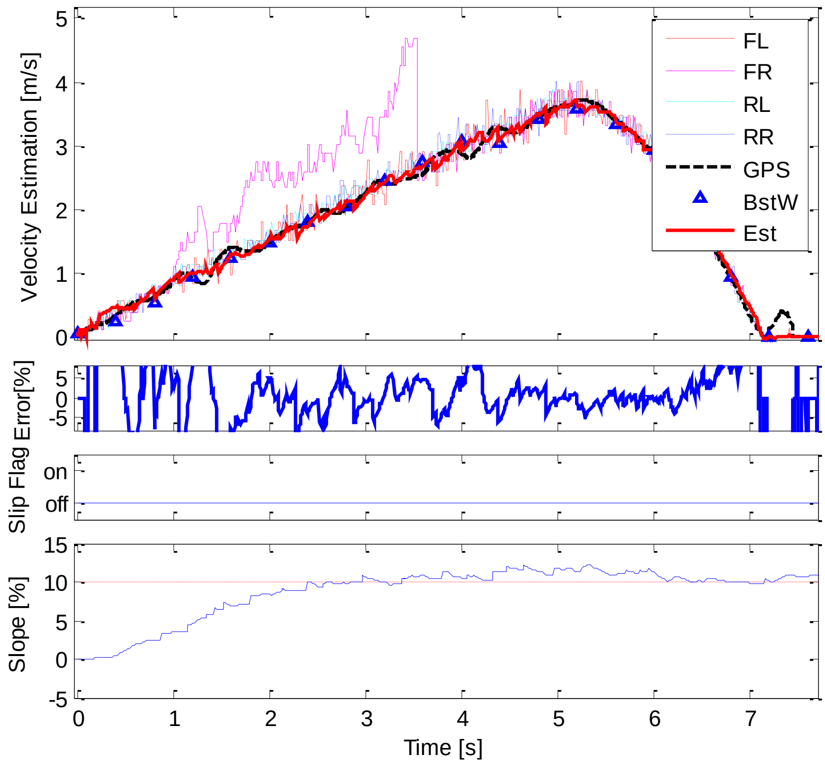


Figure 4.8 Test results when one wheel over-slip

4.4 Summary

The adaptive Kalman filter proposed in this work employs simple method instead of complex calculation. It controls Kalman filter gain matrix directly as long as wheel over-slip, which saves the adjustment work on covariance matrix.

The algorithm can estimate velocity accurately on high friction road without steering. When no wheel is over-slip, the adaptive Kalman filter acts just like the typical KF. It is accurate and the velocity estimation error is small. When front right wheel is over-slip, the estimation results are not affected by the unreliable wheel speed but keep accurate and smooth. In addition, the slope estimation method works as well. By the way, the velocity and slope estimation are separated in two filters because the slope estimation is sensitive to over-slip wheels; it will be ruined when all of the four wheels are over-slip.

Then this algorithm will be tested on winter test ground, where there are roads covered by ice, snow and both. And the driving scenarios are also more challenging.

5 Test on Low Friction Road

The low friction road test is carried on the Colmis winter test ground, Arjeplog (Colmis Homepage (2013) and AAM Homepage (2013)). The driving scenarios include start on ice, acceleration and deceleration, circle on ice and snow, start on ice covered slope, driving on slope, and so on. The vehicle wheel is rather easy to be over-slip on low friction road, thus in some scenarios, the algorithm will be tested while all the four wheels over-slip, which is the most challenging situation.

5.1 Test vehicle

The test vehicle on low friction road is a modified Saab 9-5, which has an electric motor driving the rear axle and a traditional engine and manual gearbox driving the front axle. The standard sensor signals are obtained via CAN-Bus. The reference velocity is provided by an RT3000 inertial and GPS system. The picture of the vehicle is shown in Figure 5.1. The parameters of the vehicle are shown in Table 5.1.

Figure 5.1 Test vehicle (and RT 3000) on low friction road

Table 5.1 Parameters of test vehicle (low friction road)

Parameter	Value
Wheel Radius	328.5 [mm]
Steer Ratio	15.7
Front Axle to CG	1361.76 [mm]
Rear Axle CG	1475.24 [mm]
Total Mass of the Vehicle	1987 [kg]
Vehicle Track (Front/Rear)	1583/1585 [mm]

The hybrid vehicle has three driving modes, full traction, motor disconnect and torque vectoring (Hallnor M., Duringhof H.,-M., Klomp M., Arikere A. (2012)). The picture of the electric motor and its control system can be seen in Figure 5.2.

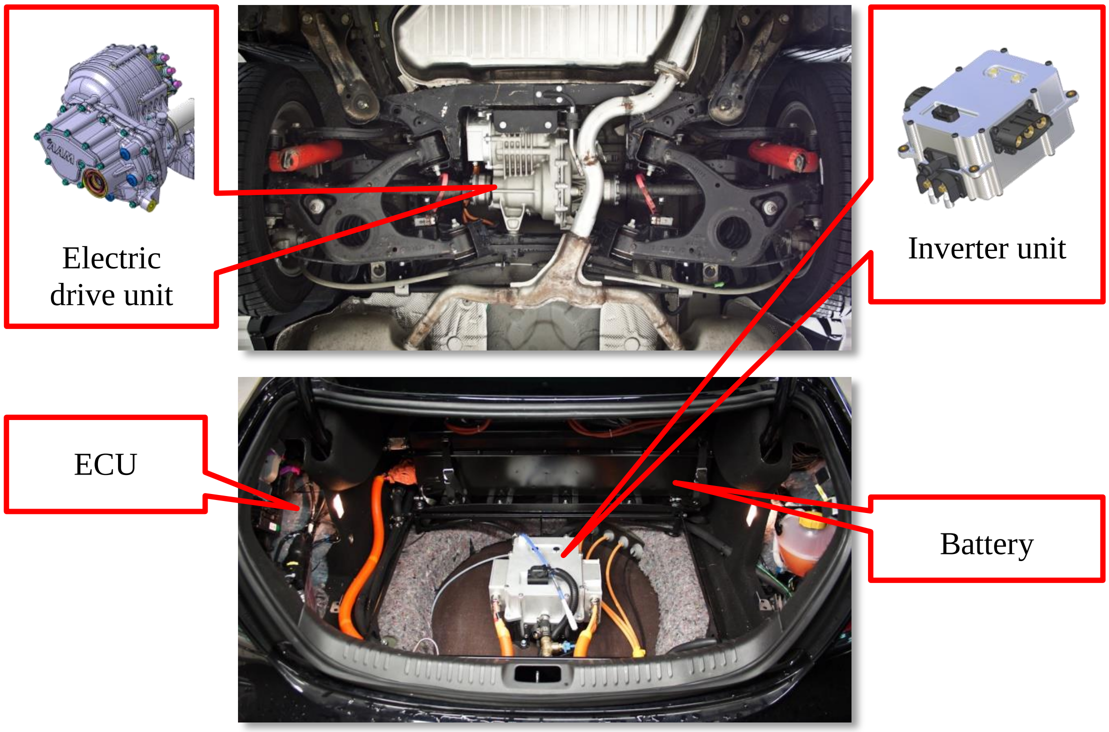


Figure 5.2 Electric drive system

The front axle is driven by a B205E 2.0T engine and the rear axle is driven by the electric motor provided by eAAM. The parameters of the combustion engine and the electric motor can be seen in Table 5.2.

Table 5.2 Parameter of engine and motor

Item of Engine	Value	Item of motor	Value
peak power	110 [kW]	peak power	50 [kW]
peak torque	240 [Nm]	peak torque	106 [Nm]
displacement	1998 [ml]	max speed	15000 [rpm]
gear box	6-speed manual	gear ratio (traction)	11.3

The sensor signals are including steering wheel angle, longitudinal acceleration, yaw rate, reference velocity as well as four wheels speeds. The sensor measurements can be seen in Figure 5.3.

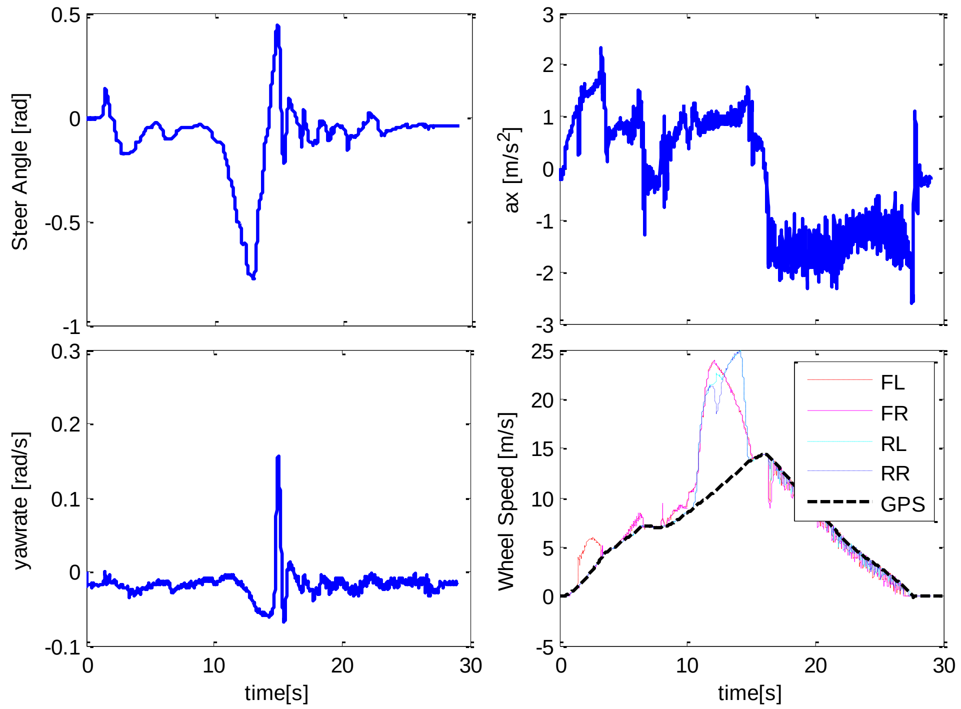


Figure 5.3 Measurements of sensor signals

5.2 Test on Flat Road

During flat road test, the vehicle is not only driven on straight line, but also in steering situation. The driving tests are including the straight line test, circle test and parking test.

5.2.1 Straight Line Test

The straight line tests mainly focuses on polished ice covered road, since these are challenging for the algorithm. The reason being on the slippery road, the algorithm is confronted with the scenario that all the four wheels over-slip at the same time. And the test results will be compared with our former estimation results, the “Gao2012” curve (Xiong L., Gao Y.,-L., Feng Y. (2012)).

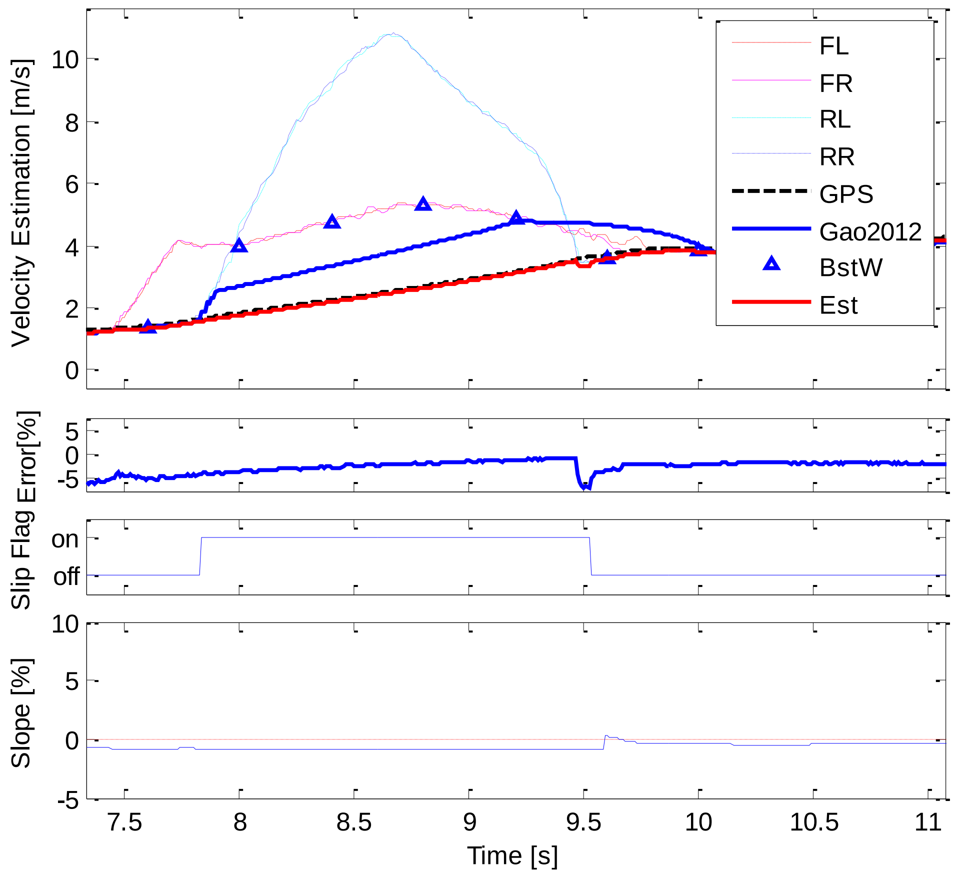


Figure 5.4   Test results of start on polished ice

As explained in Section 2.2, the former AKF algorithm has delay to detect over-slip. After added novel over-slip criterion, the current method can detect over-slip wheel in time. As shown in Figure 5.4, the slip flag turn to "on" as soon as all the wheels over-slip. The current estimation results (red curve) follow the reference velocity closely, even if all the wheels over-slip simultaneously. By the help of over-slip criteria, the algorithm starts to calculate the integration of acceleration without delay and the results are better than our former method (blue curve). It can also be seen in the error plot, the error of current method is very small.

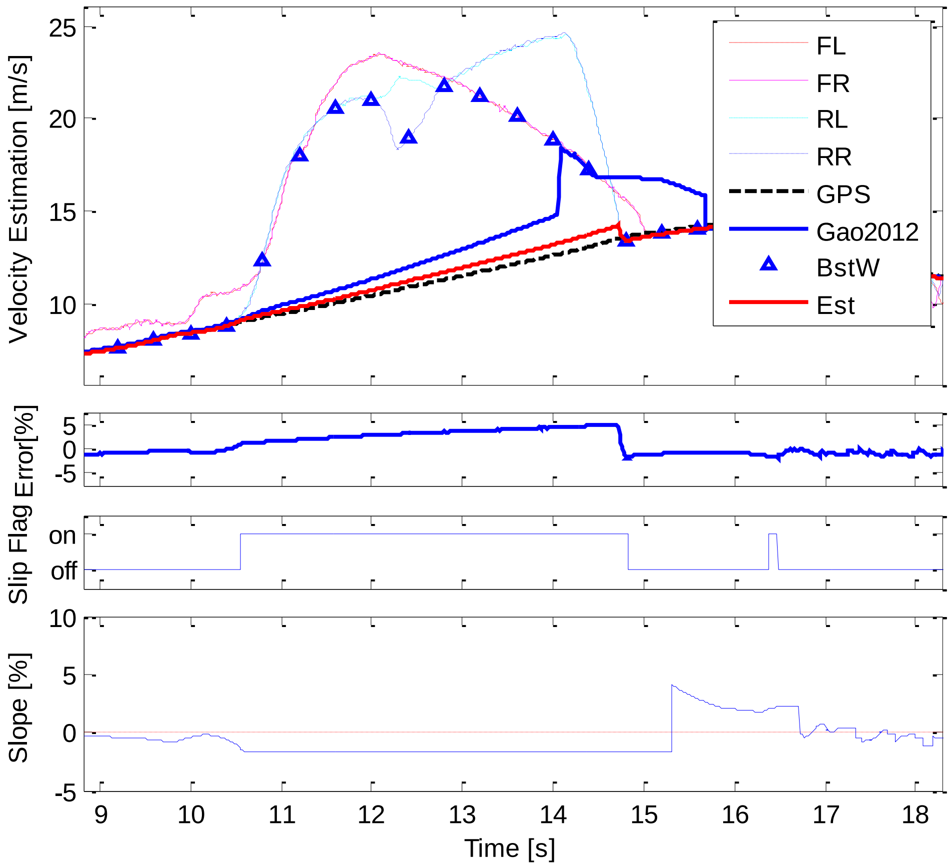


Figure 5.5 Test results of acceleration and deceleration on polished ice

See Figure 5.5, the vehicle has a challenging situation when acceleration on polished ice. All the four wheels over-slip, but the velocity estimation results are accurate during the challenging situation. There is a little over estimation in velocity because of the bias of slope estimation. However, it does not cause huge error, and the estimation error is within $\pm 5\%$.

5.2.2 Circle Test

Circle test is carried out on ice and snow covered road. The algorithm will be tested in steering scenarios and the wheel speed will be transposed to CG firstly.

When the vehicle is driven on circle road covered by ice, the wheel speed measurements have obvious fluctuation, as shown in Figure 5.6. And the abnormal measurements may have influence on velocity estimation, for instance, our former method has some bias estimation during the circle. However, the wheel speed selection can reduce the influence of the abnormal wheel speed. And the estimation results of current method are satisfactory. In addition, the four wheels are not over-slip in the same time during this test, thus the slip flag is always “off”.

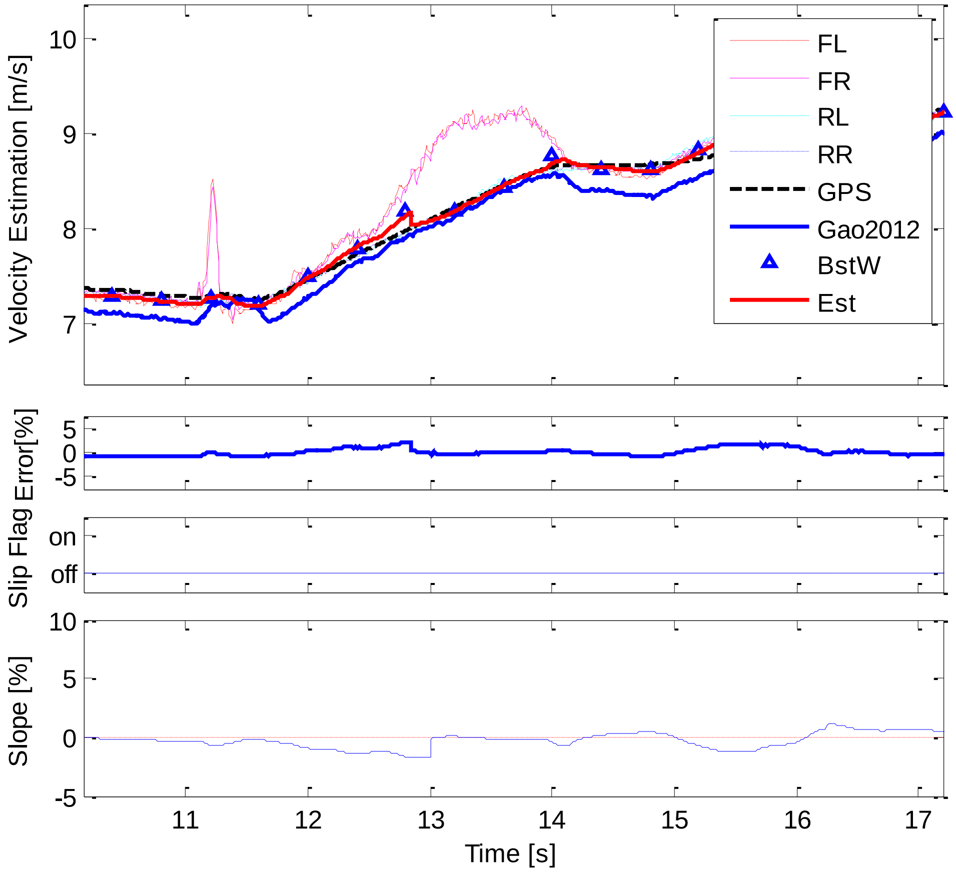


Figure 5.6 Test results of circle on ice

When driven on snow, the vehicle does not face with very challenging situation. In spite of there is some noise in wheel speed measurement, it can be treated as Gauss White Noise and has no serious influence on velocity estimation. See Figure 5.7, both the former work and the current method work well in this test. And the estimation error is within $\pm 5\%$.

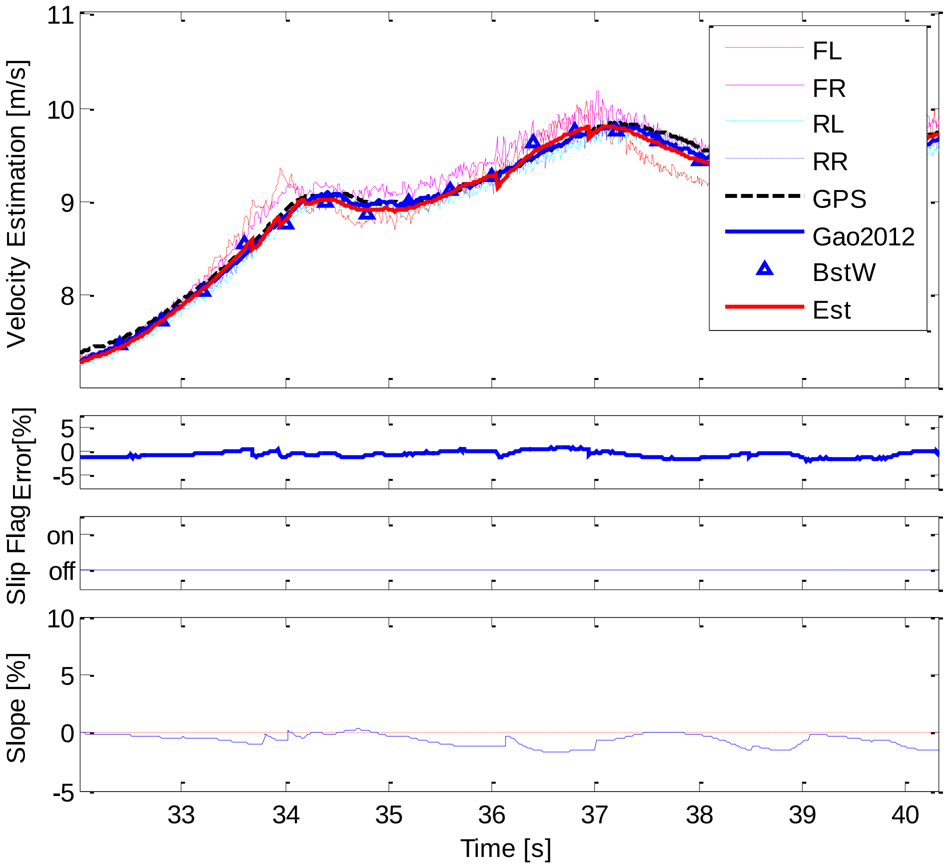


Figure 5.7 Test results of circle on snow

5.2.3 Parking Test

The parking test driving scenario is moving forward with steering, then moving backward to the parking position.

The challenge of this test is that the wheel speed sensor cannot indicate the direction of the measurement. That means, whether the vehicle moves backward, the wheel speed measurements are always the absolute value of the wheel speed. It can be seen in Figure 5.8.

Fortunately, the electric motor on the rear axle can point out the direction of wheel speed. Thus, the measurement of motor speed is used to detect the reverse movement of the vehicle. With the help of motor speed, the velocity estimation follows the GPS measurement closely, especially when vehicle is moving backward.

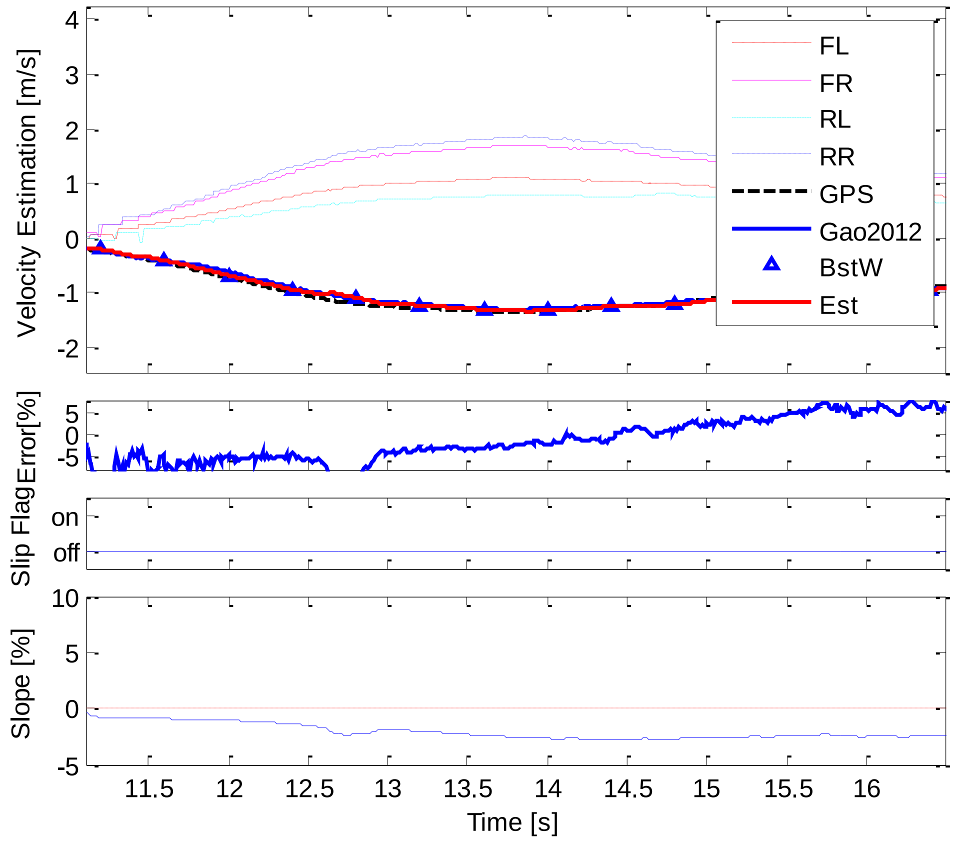


Figure 5.8 Test results of parking

5.3 Test on Slope Road

The slope test is carried out on standard 10% slope. In this test, the slope roads are covered by polished ice. And the driving scenarios are start on slope as well as driving on slope.

As shown in *Figure 5.9*, the vehicle starts on 10% slope road. The wheels are over-slip intensely at the beginning of this test. However, the wheel selection method finds out the best wheel speed. The slip flag indicates there are only a short while that all the wheels are over-slip, and the best wheel curve is quite smooth even if some wheels are over-slip. In spite of the delay of slope estimation, the velocity estimation results are desired.

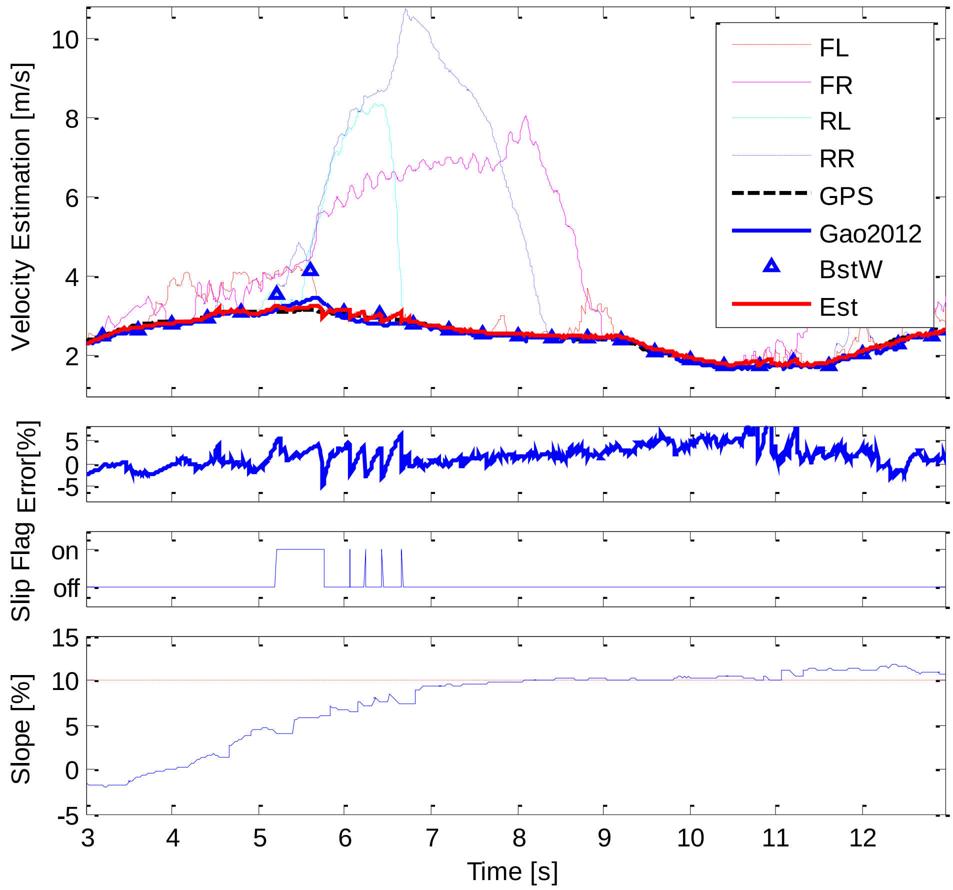


Figure 5.9 Test results of start on 10% slope

The driving scenario of test on 10% slope is that the vehicle starts on flat asphalt road, then drives on the 10% slope after gets 15km/h speed.

When the vehicle is driven on ice covered slope road, the front wheels are quite easy to be over-slip, as shown in Figure 5.10, but the rear wheels are not over-slip so seriously as front ones. Thus the selected wheel is not over-slip during this test and the slip flag is always “off” from the beginning to the end. It is just like no wheel over slip occurs after wheel speed selection.

The former method estimation curve is closer to the reference velocity than current one. But the estimation error of current method is quite small, within ±5%. Thus, the estimation results are satisfactory in this test.

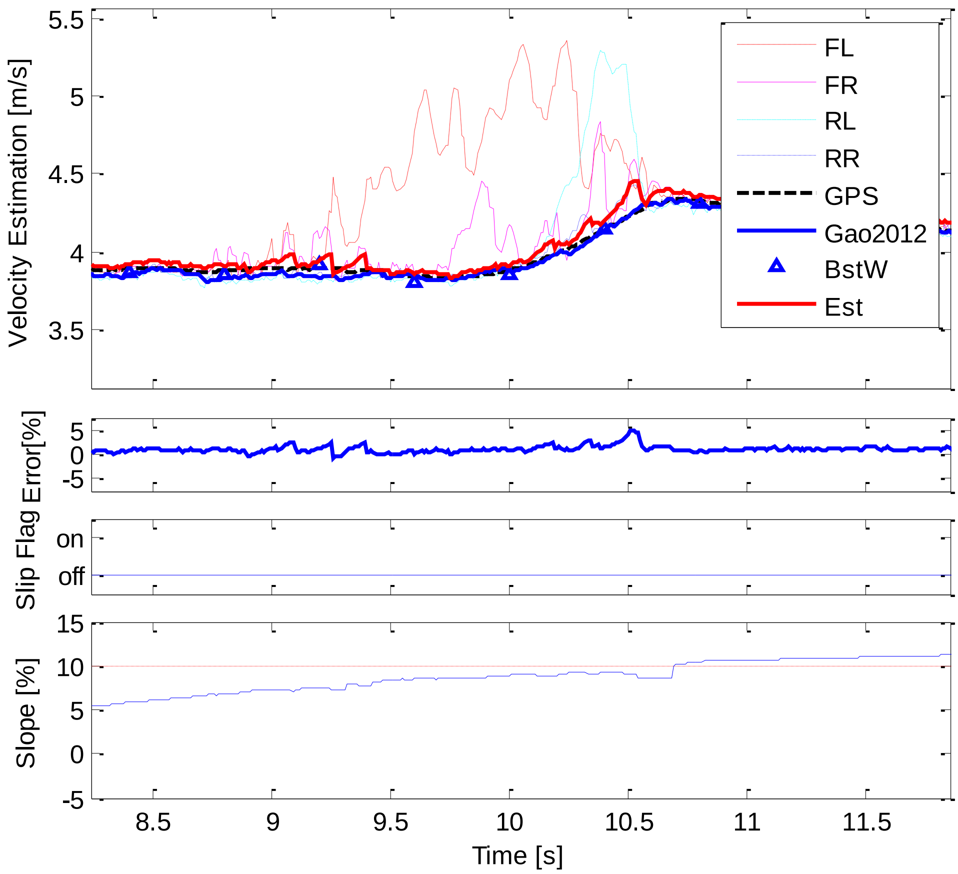


Figure 5.10 Test results of driving on 10% slope

5.4 Summary

The former method (Xiong L., Gao Y.-L., Feng Y.(2012)) cannot estimate longitudinal velocity accurately on slippery road. The drawback the algorithm is the delay to detect over-slip and lack of wheel speed selection. But they are not exposed on high friction road test.

However, in low friction test, these flaws affect the estimation results obviously. Thus, the additional over-slip criterion is proposed. And the novel criterion can find out the over-slip wheels in time. Moreover, the wheel selection is added into the algorithm to reduce the influence of the abnormal measurements as well as the calculation quantity.

The new method can estimate velocity more accurately than the former one, especially when all the wheels are over-slip in the same time. After verified by the tests, the algorithm works well on winter test ground.

6 Conclusion and Recommendation for Further Research

This paper presents a method to estimation longitudinal velocity and road slope when wheels are over-slip. The algorithm is designed based on simulation work, and tested on both high and low friction road. As the driving scenarios become more and more challenging, the flaws of the former algorithm come out. Hence, the novel over-slip criterion and wheel speed selection method is proposed to improve the algorithm.

The main points of this paper is

a. The adaptive Kalman filter

When wheel over slip occurs, the method controls gain matrix directly and efficiently. Different from typical Kalman filter, this adaptive method does not focus on covariance matrix, but on gain matrix. It can reduce the influence of the over-slip wheels significantly.

b. The novel over-slip criteria

Besides the wheel speed criterion and pre-estimation criterion, the third criterion is come up with based on the wheel torque, which can be obtained accurately from electric motor. This criterion can detect the over-slip wheels without delay but sensitive to measurement noise, thus wheel speed is used to verify the over-slip judgment. And the criterion is both in time and accurate.

c. Wheel speed selection

The velocity estimation accuracy is affected by wheel speed measurements. Some abnormal measurements can cause the estimation error but cannot be detected by over-slip criteria. Thus, wheel speed selection is added into the algorithm to improve the observation variable of the Kalman filter. On the other hand, the wheel speed selection can to some extend reduce the calculation quantity of the algorithm.

The next step of this work could be

a. Take more use of wheel torque to improve the accuracy of the velocity estimation, as well as wheel slip estimation.
b. When the four wheels torque are different, the over-slip criteria need to be used on individual wheel instead of the vehicle. And the wheel speed selection strategy also needs to update.
c. Wheel radius is a variable, which could be estimated on line.

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