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# A Novel Longitudinal Speed Estimator for Four-Wheel Slip in Snowy Conditions

**Dongmin Zhang [1,2], Qiang Song [1,2,*], Guanfeng Wang [1,2] and Chonghao Liu [3]**

[1] School of Mechanical Engineering, Beijing Institute of Technology, Beijing 100081, China; zhanghaorong@163.com (D.Z.); wangguanfeng2016@outlook.com (G.W.)
[2] National Engineering Laboratory for Electric Vehicles, Beijing Institute of Technology, Beijing 100081, China
[3] Automobile and Traffic Engineering, Liaoning University of Technology, Jinzhou 121001, China; qcxy_lch@lnut.edu.cn
* Correspondence: songqiang@bit.edu.cn

**Abstract:** This article proposes a novel longitudinal vehicle speed estimator for snowy roads in extreme conditions (four-wheel slip) based on low-cost wheel speed encoders and a longitudinal acceleration sensor. The tire rotation factor, η, is introduced to reduce the deviation between the rotation tire radius and the manufacturer's marked tire radius. The Local Vehicle Speed Estimator is defined to eliminate longitudinal vehicle speed estimation error. It improves the tire slip accuracy of four-wheel slip, even with a high slip rate. The final vehicle speed is estimated using two fuzzy control strategies that use vehicle speed estimates from speed encoders and a longitudinal acceleration sensor. Experimental and simulation results confirm the algorithm's validity for estimating longitudinal vehicle speed for four-wheel slip in snowy road conditions.

**Keywords:** tire rotation factor; four-wheel drive vehicle speed estimation; maximum wheel slip; snowy road; fuzzy control



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## 1. Introduction

Smart, advanced driver assistance systems have drawn considerable research attention because these active systems are essential for vehicle state estimation and control [1–3]. Numerous studies address vehicle state estimation. Vehicle speed is a key variable in wheel slip and the foundation of vehicle state estimation [4], which is used in lane change assist (LCA), emergency stop assist (ESA) and active cruise control (ACC) technologies [5]. However, vehicle speed estimation is often implemented on dry, rough surfaces to study low-slip regions, and this approach cannot easily be adapted to other surfaces, especially four-wheel, high-slip conditions, due to the special nature of the interaction between a tire and deformable ground (snow).

Studies have proposed different controllers for vehicle state estimation in various road conditions [6]. Savitski et al. integrated the speed controller with a wheel slip controller to improve vehicle mobility during acceleration and slope climbing; the study focused on a specific traction control for an electric vehicle with four individual in-wheel motors over icy roads [7]. If the slip ratio exceeds certain optimal values, force generation degrades in the lateral and longitudinal directions, reducing vehicle stability and performance [8]. The slip ratio controller in [9] achieves the desired slip ratio quickly and accurately. The controller treats longitudinal tire force as a disturbance to be rejected by the control algorithm. Longitudinal tire force is estimated utilizing a controller output observer (COO). A reduced-order sliding mode observer (RO-SMO) was developed for vehicle state estimation [10]. Its reference model accuracy is improved by considering vehicle load transfers and using a precise nonlinear tire model called "UniTire". Xu et al. proposed a novel methodology for online search of the optimal operation point. However, there is little information on the slip ratio in uncertain tire-road contact conditions mentioned in the paper [11]. The aim of [12] was to quantify the tire operating conditions during anti-lock braking system (ABS) braking in terms of longitudinal wheel slip. ABS braking tests with two subcompact passenger cars were performed on dry and wet asphalt, as well as on snow and ice surfaces. Even though these methods show great improvements, it remains difficult to obtain accurate vehicle state estimation on snowy roads. Kalman filters are conventional tire-based approaches to address these difficulties. A UKF-based longitudinal force estimation strategy was investigated in [13]. The process validity was studied using simulation and test results in slippery road conditions. Chu et al. designed an adaptive vehicle longitudinal velocity observer for the electronic stability control system [14]. The observer was designed based on fuzzy logic and the Kalman filter, and the observer's effectiveness was validated in a Carsim environment. Berntorp et al. proposed a novel approach to model-based joint wheel-slip and motion estimation of four-wheeled ground vehicles [15]. The model following control (MFC) strategy effectively employed the Rao–Blackwellized particle-filtering framework using a kinematic model. Compared with the no-control and MFC cases, the approach in [2] is a feasible method to effectively maintain vehicle stability. However, Kalman filter longitudinal speed estimation is restricted by models which rely excessively on sensors.

Different from the above-mentioned methods, Song et al. solved the problem of estimating the longitudinal velocity of a braking vehicle using accelerometer measurements and wheel speed data from standard antilock braking wheel speed sensors [16]. Based on low-cost wheel speed encoders, a novel longitudinal speed estimator for vehicles during a cornering manoeuvre was proposed [17]. A gain-varying Kalman estimator was designed to output the lateral states of a vehicle body. The proposed estimator had a more accurate estimation of vehicle longitudinal speed during a cornering manoeuvre. Yin et al. proposed a wheel-slip control approach that ensures ESC functions normally for decentralized drive EVs [18]. This approach used the wheel rotation and chassis acceleration to estimate the maximum transmissible torque. William et al. presented a continuous slip control algorithm designed for the case in which the vehicle velocity is precisely known. The control strategy is based on both wheel slip and wheel acceleration regulation and ensures global asymptotic stability in a closed loop [19]. Li et al. presented the analysis and design of a novel traction control system (TCS) based on sliding-mode control (SMC) and the maximum transmissible torque estimation (MTTE) technique and applied it to four-wheel independent drive electric vehicles (EVs) without chassis velocity or acceleration sensors [20]. However, when all four wheels are slipping, the precision level that is available with only acceleration and wheel speed sensors is limited.

This paper aims to develop a novel longitudinal speed estimator for four-wheel drive vehicles when more than two wheels have high slip rates on snowy roads. First, a vehicle speed estimator is created to estimate vehicle speed from wheel speed by fuzzy control logic. This vehicle speed estimator based on acceleration estimates vehicle speed by integrating the acceleration variable. During four-wheel slip (especially large slip), a single fuzzy controller cannot obtain accurate vehicle speed from the wheel speed. An additional drawback is the inaccuracy of the initial vehicle speed condition from the vehicle speed estimator based on wheel speed. Consequently, it is necessary to obtain the initial vehicle speed condition. Due to the importance of judging wheel slip in the second fuzzy controller, we need relatively accurate estimation of vehicle speed. Therefore, the Local Vehicle Speed Estimator has been developed to combine two vehicle speed estimation methods, wheel speed encoders and an acceleration sensor, to obtain a more accurate estimation of vehicle speed. A weighting coefficient has been introduced to obtain a relatively accurate speed estimation by balancing the contribution between the estimated vehicle speed from the wheel encoders and acceleration sensor. The second fuzzy controller can obtain accurate vehicle speed estimation using relative slip ratio inputs. Finally, its accuracy is verified by driving experiments on split roads covered by snow. The result shows that the speed estimated by our estimator is similar to the vehicle speed obtained from a production car. The focus of this paper is longitudinal speed estimates of four-wheeled slip and in conditions of snowy road. The purpose is to obtain accurate speed estimates under snowy road and four wheels' slip condition.

## 2. Materials and Methods

### *2.1. Longitudinal Speed Estimator of Four-Wheel Drive Slipping Vehicle on Split Roads*

At a high level, the wheel rotational speeds and longitudinal acceleration are derived directly from the wheel speed encoders and the acceleration sensor after filtering the data. Then they are input to the logic controller. The estimated vehicle speed ($v_E$) is the result after calculation by the logic controller. The comparison between estimated vehicle speed and reference vehicle speed from a production car is achieved by an in-vehicle network. An overview of the strategy is shown in Figure 1.

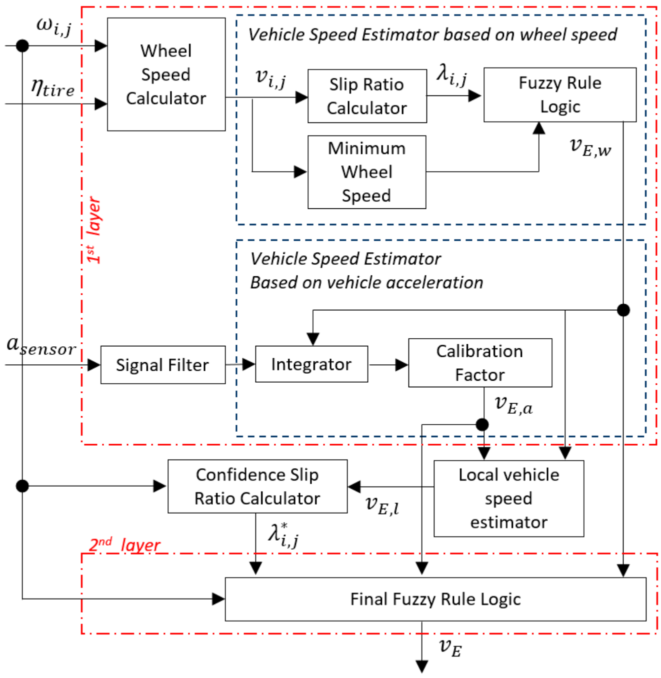


**Figure 1.** Estimator Strategy Overview.

To obtain an accurate speed estimate for vehicles with a high slip rate of two or more wheels, the vehicle network is used to handle the four wheels' speeds and longitudinal acceleration signals. Since wheel longitudinal speed is calculated from wheel angular speed, it can be easily affected by tire pressure. To enhance the efficiency of wheel longitudinal speed, it is reasonable to introduce a tire rotation factor (η) into this estimator. The controller is divided into two layers. The function of the first layer is to provide two relatively-accurate estimations of longitudinal vehicle speeds based on four wheels by a fuzzy controller and acceleration sensor by integration rather than using the final value of the fuzzy logic. These relatively-accurate speed estimates, however, are not correct for high levels of slip.

Estimating longitudinal speed based on wheel speed and estimating based on acceleration are quite different. The former is more accurate without wheel slip while the latter is better without frequent switching between acceleration and deceleration. To optimize their advantages, we propose the local vehicle speed estimator to combine the estimates of two different sensors by introducing a weighting coefficient. Then the second layer is developed as a final fuzzy controller to obtain an accurate speed estimate in extreme slip conditions.

#### 2.1.1. Wheel Rotation Speed Calibration and Result Comparison

The wheel speed signal from the wheel speed encoder is an angular speed. This angular wheel speed is determined by counting the number of ticks in each sampling period. The parameters marked on the tire, for example, 245/50 R19, indicate the width of the tire, the width-to-depth ratio and rim diameter, respectively. The actual rotating tire radius and the manufacturer's tire radius can differ because tire pressure can affect the actual rotating tire radius. By multiplying the wheel radius and the tire rotation factor (η), the wheel speeds $v_{i,j}$ can be written as follows:

$$V_{i,j} = 3.6 \cdot \omega_{ij} \cdot R_{ij} \cdot \eta.$$

There is a radius deviation between the rolling tire and the value calculated by this equation. According to the equation, the deviation is linear. To prepare the experimental vehicle and the vehicle model determined by real car calibration, the tire rotation factor is introduced in the 0–30 km/h straight acceleration driving experiments. After calculation and calibration through the proposed method, the small deviation between the vehicle speed from wheel speed and the reference vehicle speed has been eliminated.

For more generality, this experiment used a calibrated 0–30 km/h straight acceleration experimental condition. The "ref vehicle speed" signal is the vehicle speed directly obtained from the in-vehicle network, which is used as the reference vehicle speed for comparison with the vehicle speed estimated by the control logic presented in this study. The vehicle speed obtained from the wheel speed encoders after calibration is the same as the vehicle speed obtained from the in-vehicle network. In other words, it is a necessary and effective way to use calibrated method to eliminate the error caused by the tire pressure level.

#### 2.1.2. Vehicle Speed Estimator Based on Wheel Speed

The main task of this estimator is to estimate the vehicle speed by a fuzzy controller, based on a minimum wheel speed and four wheels' slip rate. Although the estimated result is not accurate in high slip conditions, it is meaningful as a reference value.

Obviously, the estimated vehicle speed based on the wheel speed encoder is a very important part. Fuzzy control logic is used to guarantee its accuracy. The key to estimating longitudinal vehicle speed accurately is the tire slip ratio. In other words, lower tire slip levels yield higher confidence levels. In the vehicle estimate, speed logic is based on wheel speed encoders and the minimum wheel speed is selected as a basic reference; then, the fuzzy logic algorithm is used to consider the effect of each slip condition. The fuzzy logic algorithm determines the confidence level based on the number of wheels that slip and each wheel's slip level. The output is a weighting coefficient to represent the influence at the minimum wheel speed to accurately estimate the vehicle's longitudinal speed.

The wheel rotation speed input signal is directly from the wheel rotational speed encoders; it is sent to and optimized by the vehicle's control unit. Signal filtering is used to avoid zero shift.

Any wheel can have the lowest speed and the lowest slip rate. The lowest wheel speed is that with the lowest slip rate among the four wheels at a certain time. The objective is to calculate the longitudinal vehicle speed based on the lowest slip rate of the four wheels

$$V_{\min} = \min\{V_{i,j}\},\ 1 \le i, j \le 2$$

There are three driving condition cases from the analysis. The first case is no wheel slip, in which the vehicle speeds calculated from each wheel speed encoder are equal to each other when the car is driving straight.

$$V_{i,j} = \text{real longitudinal vehicle speed}$$

The second case is at least one wheel slips, but the number of slipping wheels is three or fewer. Assuming the calculated vehicle speed based on the non-slipping wheel is $V_{m,m}$, then

$$V_{i,j} \ge V_{m,m} = V_{real}$$

in which, $m \ne i, j, 1 \le m, i, j \le 2$, $V_{real}$ is the real longitudinal vehicle speed.

The third case is when all four wheels' slip.

$$V_{i,j} \geq V_{m,m} \geq V_{real}$$

in which, $m \neq i, j, 1 \leq m, i, j \leq 2$

Besides the minimum wheel speed, the wheel slip rate is the most important input variable in the fuzzy control logic,

$$\lambda_{i,j} = \frac{|\min(V_{i,j}) - V_{i,j}|}{\min(V_{i,j})}$$

in which, $1 \leq i, j \leq 2$.

To make the first-layer calculation strategy smooth, slip rates are divided into low, mid and large slip in the fuzzy control rule.

The strategy is to estimate vehicle speed on not only a high friction asphalt road but also a special (snowy) road, where the slip friction between the tire and the road is approximately 0.1 and the maximum friction is approximately 0.2. The low slip category only considers snowy road driving conditions; the slip friction between the tire and the snow surface is between 0.1 and 0.175. Mid slip considers asphalt road and snow road driving, in which the friction coefficient is between 0.1 and 0.25. The large slip condition considers friction coefficients above 0.2 [21] (Figure 2).

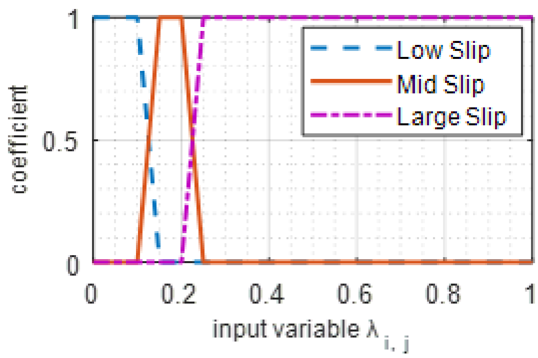


**Figure 2.** Fuzzy logic vehicle speed estimator input variables based on wheel speed.

In addition to the fuzzy logic input variables, the output variables are also important. The output variables are defined as small, mid and large rates in the fuzzy control logic, as shown in Figure 3. When a high slip rate occurs, the actual vehicle speed could be smaller than the calculated value for wheel speed, so this output variable coefficient is the inverse of the fuzzy control output variable.

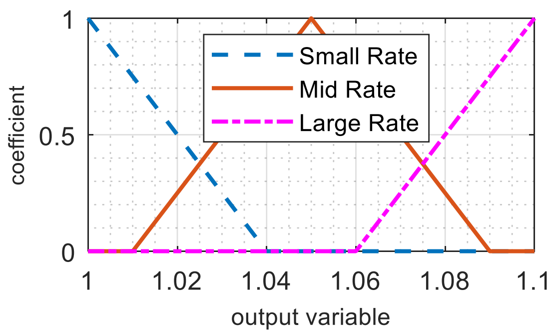


**Figure 3.** Fuzzy logic vehicle speed estimator output variables based on wheel speed.

Finally, we obtain the fuzzy logic algorithm. Fuzzy controller input variables, $\lambda_{i,j}$ are defined as the tire slip ratios, in which $i$ = 1, 2 indicate the vehicle's front and rear. Similarly,

$j = 1, 2$ indicate the vehicle's left and right sides. To use slip level to account for each input situation, the logic rules are shown in the following Table 1.

**Table 1.** Basic parameters.

| Low Slip | Mid Slip | High Slip | Output |
|---|---|---|---|
| 4 | 0 | 0 | Small Rate |
| 3 | 1 | 0 | Mid Rate |
| 2 | 1 | 1 | Mid Rate |
| 2 | 0 | 2 | Small Rate |
| 1 | 0 | 3 | Small Rate |
| 1 | 1 | 2 | Mid Rate |
| 1 | 2 | 1 | High Rate |
| 1 | 3 | 0 | High Rate |

To take the number and slip level of wheels into account based on input variables, fuzzy control logic is used to calculate the confidence level of the vehicle longitudinal speed estimated from the minimum wheel speed. The confidence level is converted to a weighting coefficient to modify the estimated value of the minimum speed, and in the case of large slip, a more accurate speed estimate is obtained.

$$\mathrm{V}_{E\_w} = \min\left(V_{i,j}\right)/\sigma$$

in which, $\sigma$ is the fuzzy logic weight.

#### 2.1.3. Vehicle Speed Estimator Based on Vehicle Acceleration

The longitudinal vehicle speed $v_{E,a}$ is obtained after low pass filtering of the acceleration integration and a linear calibration in the "vehicle speed estimator based on acceleration" controller. Although it has drawbacks in low vehicle acceleration during vehicle driving start and drastic changes in acceleration, the estimation can benefit in certain other cases based on the wheel speed encoders. We use this estimated vehicle speed to supplement the estimate based on the wheel encoder speeds in the first layer.

To accurately estimate longitudinal speed in extreme slip conditions, it is necessary to compensate for the errors of the vehicle speed estimator based on the wheel speed algorithm. However, there may be limits for practical application.

$$\mathrm{V}_{i,j} \geq \mathrm{V}_{m,m} \geq \text{real longitudinal vehicle speed}$$

Another acceleration sensor is introduced. Fortunately, its low-cost and stable characteristics bring no extra challenges to the automotive application. One drawback, though, is the lack of output precision during low acceleration. Since speed is derived from integrating the acceleration, noise can be amplified during the calculation process.

Its inherent advantage in output precision is better than the vehicle speed estimator based on wheel speed, prompting its usage in high-level slip. This method is adopted as another reference in the first layer.

In the vehicle speed estimator, signal shift is eliminated after filtering the acceleration signal from sensors. Then, a small step iterative integration method is added to integrate the acceleration signal with initial vehicle speed obtained from the estimated vehicle speed based on wheel speeds.

$$V'_{E,a} = \int_{time}^{time+step} a_{sensor}\, dt + \mathrm{V}_{time}$$

Although compensation has been performed to obtain an integration result, there are still flaws due to the presence of noise and accuracy of the acceleration sensor. Therefore, a linear compensation method is adopted.

$$V_{E,a} = V'_{E,a} \cdot \text{calibration\_coefficent}$$

### 2.1.4. Local Vehicle Speed Estimator and Confidence Slip Ratio Calculator

As mentioned above, the first-layer vehicle speed estimate objective is a relatively-accurate estimate of vehicle speed. Furthermore, there are estimates of longitudinal vehicle speed based on wheel encoder speeds and the acceleration sensor in the first layer. They estimate accurate longitudinal vehicle speeds in certain situations but are inaccurate in other situations. In the case of low wheel slip and correct tire diameter calibration, the wheel encoder speed estimate is accurate. In the case of mild acceleration and large wheel slip, the estimate based on vehicle acceleration is more accurate than the wheel encoder speed estimate. The basic concept of an estimator strategy is to optimize the confidence level between each vehicle speed estimate based on wheel encoder speeds and the vehicle acceleration sensor. It is also the reason that the estimated vehicle speed based on wheel speed and the acceleration sensor are in the first layer.

Moreover, it is difficult to calculate longitudinal vehicle speed based on certain wheel encoder speeds for large slips, which is a disadvantage of estimating vehicle speed based on wheel encoder speed. Although it is not sufficiently accurate, it is beneficial for use as a reference value to compare with the estimated longitudinal vehicle speed based on vehicle acceleration, and then apply corrections based on the confidence level.

The local vehicle speed estimator is introduced before the second layer to balance the two longitudinal speed estimates using a weighting coefficient matrix, to provide the most accurate speed possible. Then, slip rate is calculated with the help of the confidence slip ratio calculator, which provides input variables to the final fuzzy algorithm. The estimated vehicle speed ($V_{E,l}$) is given by

$$v_{E,l} = W_{local} \cdot V_{E,w} + (1 - W_{local}) \cdot V_{E,a}$$

A specific confidence factor value is selected based on an experiment to obtain the relatively-accurate vehicle speed estimate $v_{E,I}$. The purpose of $v_{E,I}$ is to re-calculate a higher-confidence slip rate for the four wheels, $\lambda^*_{i,j}$. This factor is a more accurate four-wheel slip rate to balance the confidence between the estimated vehicle speed calculated based on wheel encoder speeds and vehicle acceleration. $W_{local}$ is weight factor defined in "local vehicle speed estimator".

### 2.1.5. Final Fuzzy Logic Algorithm

Both the Kalman filter and the fuzzy control algorithm can satisfy the accuracy requirement with the application of speed sensors. However, longitudinal speed estimation using the Kalman filter is restricted by its linearization and sensor information-based models. The combination of speed and acceleration sensors does not provide good estimates in single wheel slip cases, let alone high slip level conditions.

The proposed algorithm is aimed at longitudinal speed estimation on snowy surfaces. This estimator has two layers: the first layer calculates a relatively-accurate value, while the second layer consider slip rate and the number of slipping wheels using fuzzy logic. The basic idea is to introduce a confidence coefficient to judge conditions. If the number of slipping wheels is less than two, it directs toward the wheel speed-based estimator, otherwise, toward the vehicle accelerometer-based estimator.

Thus, we obtain the final estimate of longitudinal vehicle speed $v_E$ in the second layer, which is believed accurate in the large and multiple-wheel slip conditions considered in this paper. To balance the estimates of vehicle speed ($v_{E,w}$, $v_{E,a}$) in final fuzzy logic algorithm, the final estimated longitudinal vehicle speed is optimized for the highest confidence level.

To achieve the logic algorithm, the final fuzzy logic approach begins by defining Slip and No Slip as input variables. For a No Slip condition, the slip ratio, monitored by the slip ratio calculator, is less than 0.1. Slip ratios larger than 0.1 indicate wheel slip on a snowy road. The weighting coefficient definition for the vehicle speed estimate of slipping wheels is shown in Figure 4.

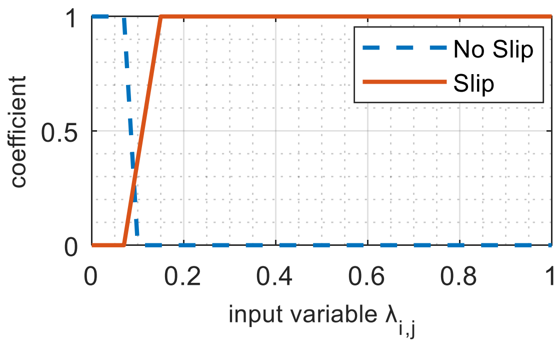


**Figure 4.** Final fuzzy logic algorithm input variables.

Estimated longitudinal speed based on wheel sensor speeds becomes less accurate during the experiment, and fuzzy control is adopted when more than two wheels' slip. Moreover, if four wheels slip simultaneously, the algorithm performance will decline rapidly because of inaccurate input. However, after calibration, the longitudinal speed estimate from the wheel sensor speed remains accurate without wheel slip. According to the findings above, the output variable definition for zero to four slipping wheels is shown in Figure 5.

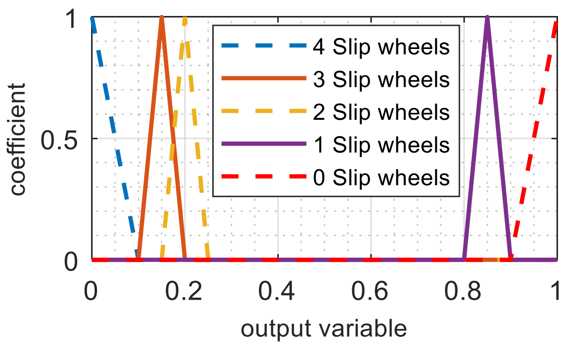


**Figure 5.** Final fuzzy logic algorithm output variables.

Although simple estimation of $v_{E,l}$ from the local vehicle speed estimator is not sufficiently accurate, it can still judge the slip condition for the final fuzzy control logic.

The confidence coefficients of $V_{E\_w}$ and $V_{E\_a}$ are different depending on how many wheels slip. The basic rule is that the more wheels' slip, the higher the confidence of estimating the vehicle speed from the acceleration sensor. The lower the number of slipping wheels, the higher the confidence of estimating vehicle speed from the wheel encoder speeds is. The fuzzy control logic algorithm is shown in Figure 6.

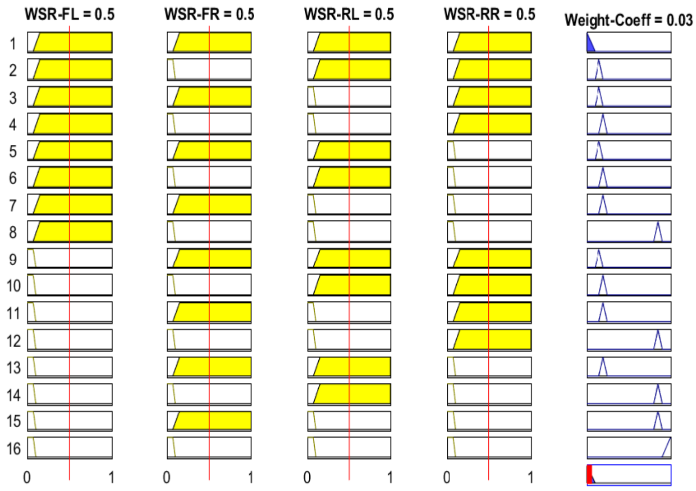


**Figure 6.** Final fuzzy logic algorithm.

## 3. Results and Discussion

### *3.1. Experimental Condition*

For estimator accuracy verification, a 4WD production vehicle with in-vehicle network is prepared to complete experiments on a split road. The signals of the four wheels' speed, longitudinal acceleration and steering angle are obtained from the in-vehicle network. The basic parameters of this production vehicle are shown in Table 2.

**Table 2.** Basic parameters.

| No. | Parameter | Values |
|---|---|---|
| 1 | Vehicle weight | 2205 (kg) |
| 2 | Wheelbase | 2866 (mm) |
| 3 | Front wheelbase | 1594 (mm) |
| 4 | Rear wheelbase | 1622 (mm) |
| 5 | Tire radius | 245/45R19 |
| 6 | Length of the car | 4717 (mm) |
| 7 | Width of the car | 1891 (mm) |
| 8 | Height of the car | 1689 (mm) |
| 9 | Track | 1568 (mm) |

The accuracy is verified by experiments driving on the split road, which is covered by snow and asphalt; the road condition is shown in Figure 7.

**Figure 7.** Snowy road driving experiment.

Conventional studies mainly use experiments on dry or wet roads, but we use a split road covered by snow and asphalt. An acceleration test on a split road is necessary to simulate the entire range of behaviour from no-slip to entire-slip. The purpose is to verify our estimator using real and poor conditions. Meanwhile, the adaptability of the estimator to different conditions is verified from no slip to four-wheel slip.

### 3.2. Experimental Result and Discussion

The vehicle is accelerated at full throttle from 0 km/h to 30 km/h, holding the steering wheel in the centre. Then, we obtain the proposed controller input variables from the test car's in-vehicle network. These include the rotation speed of the four wheels collected by the wheel encoders, as shown in Figure 8. The longitudinal acceleration obtained from the acceleration sensor is shown in Figure 9.

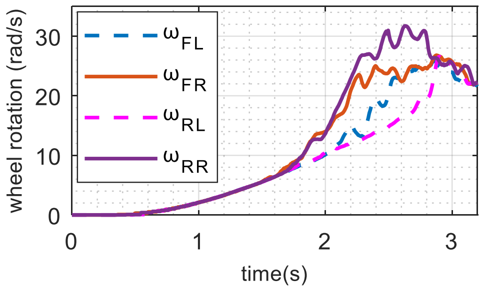


**Figure 8.** Wheel rotation speed controller input variables.

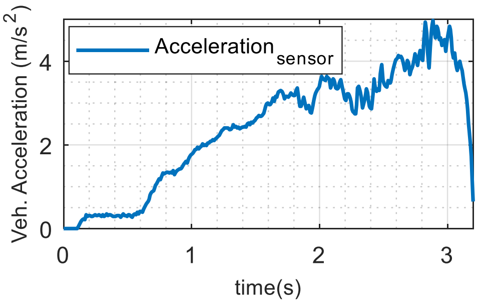


**Figure 9.** Longitudinal acceleration controller input variable.

Left side wheel speeds are much slower than right side speeds after 1.7 s, but their speed change is smoother, which means the left two wheels slip later and more gently than the right wheels. This is because the left two tires are located on the asphalt road, while right tires contact the snowy road. The left rear wheel rotates smoothly before 2.8 s without dramatic change, indicating no slip on this wheel until 2.8 s. While the left front wheel has no slip before 2.1 s, the other two wheels slip at 1.7 s.

The longitudinal acceleration signal not only provides a reference for the integrated speed value but also verifies the slip condition determined by the speed sensors. For example, the longitudinal acceleration changed dramatically due to the loss of traction force at 1.7 s when the vehicle slipped.

Although the wheel rotation speed input variables originate from different encoders, there is nearly no wheel slip from 0 to approximately 1.7 s, two wheels slip from 1.7 s to 2.1 s, three wheels slip from 2.1 to 2.8 s and four wheels slip from 2.8 s to 3.2 s. These cases are divided into four parts for further analysis: no wheel slip, two-wheel slip, three-wheel slip and four-wheel slip. The calculated calibrated sensor-based wheel speeds used as the output speeds from the controller are shown in Figure 10.

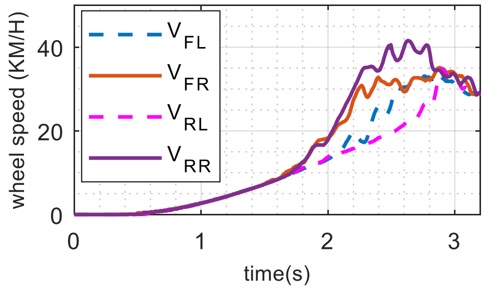


**Figure 10.** Controller output of wheel speed.

To compare and validate the estimated vehicle speed, we collect the longitudinal vehicle speed from the in-vehicle network and define the signal as Ref.Vehicle Speed. Meanwhile, we obtain the estimated longitudinal vehicle speed though the estimator and define it as Est.Vehicle Speed. The comparison between the controller-estimated vehicle speed and the reference vehicle speed from the production vehicle is shown in Figure 11. The smooth curves show that the controller-estimated longitudinal speed is similar to the reference vehicle speed.

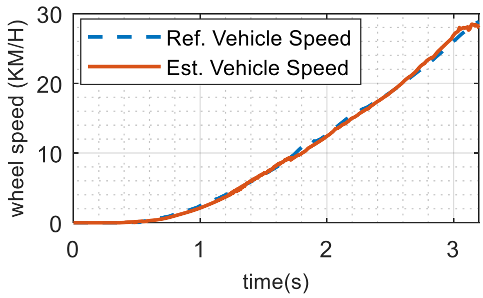


**Figure 11.** Controller-estimated speed and reference vehicle speed from the production vehicle.

To verify the performance of the proposed controller, the error rate is calculated from the estimated speed and the reference speed, as shown in Figure 12.

$$\delta = \frac{v_{est} - v_{ref}}{v_{ref}} \cdot 100\%$$

in which $\delta$ : *error rate*, $v_{est}$: estimated longitudinal speed, and $v_{ref}$: reference vehicle speed.

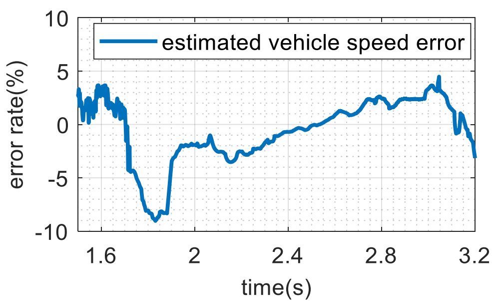


**Figure 12.** Estimated vehicle speed error rate.

Because this estimator is mainly designed to address high slip levels, we focus on vehicle speeds from 1.5 s to 3.2 s to study the error rate with obvious slip (Figure 12). The largest absolute error rate is below 9%. There are four experimental conditions categorized by the number of slipping wheels, as shown in Table 3 below.

**Table 3.** Experimental conditions.

| Time Domain | Slip Condition | Error Rate |
|---|---|---|
| 0–1.7 s | No slip | - |
| 1.7–2.1 s | 2 wheels slip | −8.974~−1.042% |
| 2.1–2.8 s | 3 wheels slip | −3.496~2.578% |
| 2.8–3.2 s | 4 wheels slip | 2.625~4.321% |

The proposed estimator focuses on the high slip level condition, as supported by the error rates shown in Table 3. The largest error rate is approximately 9% in the second condition (two slipping wheels). The third condition (three slipping wheels) benefits most, with an error rate below 3.5%. The last condition is slightly higher but still below 4.321%.

## 4. Conclusions

This study introduced a longitudinal vehicle speed estimator for four-wheel slipping conditions on a split snowy road based on wheel encoder speeds and an acceleration sensor using a fuzzy control algorithm.

In the estimator, the estimated longitudinal vehicle speed is calculated in the first layer based on wheel encoder speeds and an acceleration sensor separately. Then, the local vehicle speed estimator is employed to address the inaccurately estimated vehicle speed and tire slip ratio. Afterwards, the final estimated vehicle speed is calculated by subsequent fuzzy control strategies with speed encoders and acceleration sensors.

Different from the longitudinal vehicle speed estimation under normal road conditions through the Kalman filter algorithm, this paper emphasizes the speed estimation of four-wheels' slip under snowy road conditions. Instead of validating four wheels' slip condition by dangerous drift driving, researchers in this experiment drove on the artificial split snowy road at full throttle until the four wheels' slip, avoiding accidents and obtaining special requirement validation condition.

Finally, the algorithm accuracy is verified by the experiment of vehicle driving on the artificial split road covered with snow and asphalt. The results demonstrate that the vehicle speed estimated by the proposed estimator is closer to that obtained from the production vehicle. Furthermore, the proposed controller focuses on the high-slip-level condition, generating more benefits when three or four wheels are slipping, with an error rate lower than 4.321%.

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