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FUZZY ESTIMATION OF VEHICLE SPEED USING AN ACCELEROMETER AND WHEEL SENSORS

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ABSTRACT–The absolute longitudinal speed of a vehicle is estimated by using data from an accelerometer of the vehicle and wheel speed sensors of a standard 50-tooth antilock braking system. An intuitive solution to this problem is, "When wheel slip is low, calculate the vehicle velocity from the wheel speeds; when wheel slip is high, calculate the vehicle speed by integrating signal of the accelerometer." The speed estimator weighted with fuzzy logic is introduced to implement the above concept, which is formulated as an estimation method. And the method is improved through experiments by how to calculate speed from acceleration signal and slip ratios. It is verified experimentally to usefulness of estimation speed of a vehicle. And the experimental result shows that the estimated vehicle longitudinal speed has only a 6% worst-case error during a hard braking maneuver lasting a few seconds.

KEY WORDS : Vehicle speed, Speed estimation, Fuzzy logic, Slip ratio, ABS, Wheel speed, Accelerometer

1. INTRODUCTION

Advanced vehicle safety systems, such as CWS (Collision Warning Systems), CAS (Collision Avoidance Systems), and AHS (Automated Highway System), have recently received great attention. Objectives of CAS and AHS maintain the optimal distance from the preceding vehicle and keep the vehicle safety by controlling the brake system. In order to control the brake system optimally, the real vehicle speed and the road condition due to road-tire friction have to be estimated. By using them, the control algorithm for the safety distance has to be developed. The traction control system (TCS) as well as the anti-lock braking system (ABS) play in a critical role to CWS, CAS, and AHS. For the good performance of TCS and ABS, it is very important to estimate the vehicle speed accurately. The vehicle speed is of interest primarily because it can be used to calculate the longitudinal slip ratio between wheels and road. The Longitudinal slip ratio is related to the road-tire friction force, which of the maximum can be obtained through Magic formula tire model (Bakker *et al.*, 1989).

The higher the road-tire friction is, the less accurately the vehicle speed is estimated. With this as a momentum, several algorithms have been proposed in estimation of the vehicle speed. The vehicle speed estimator of the fuzzy logics was used (Basset *et al.*, 1997). The vehicle speed was estimated to combine the fuzzy logics and Kalman filter (Daiss and Kiencke 1995; Kobayashi etc. 1995; Song *et al.*, 2002). Neural-network method was used to estimate the vehicle speed (Oh and Song, 2002) and the tire friction with Brush tire model (Pasterkamp and Pacejka, 1996). The tire friction was estimated in consideration of the wheel load, the braking pressure and the angular velocity (Kiencke and Daiss, 1994). A 3-dimensional vehicle model, the engine speed, and the wheel angular velocity were studied to obtain the estimated the accurate road-tire friction (Bakker *et al.*, 1989; Ivanov *et al.*, 2005). The researches mentioned here, however, require excessive data to calculate the vehicle speed. And it is difficult to estimate the vehicle speed under abrupt traction or sudden braking.

Wheel speed sensors are commonly used for measuring velocities of vehicles. There are noises in wheel speed sensors due to vehicle vibration and some slippage error caused by sudden brake and abrupt traction. To estimate the vehicle speed more accurately, various sensors are recently used such as accelerometers, optical cross-correlation sensors, radar sensors, the 5th wheel sensors (Song *et al.*, 2002), and global positioning systems (Miller etc. 2001; Bevly etc. 2001). Especially, accelerometers have some merits such as small size, low

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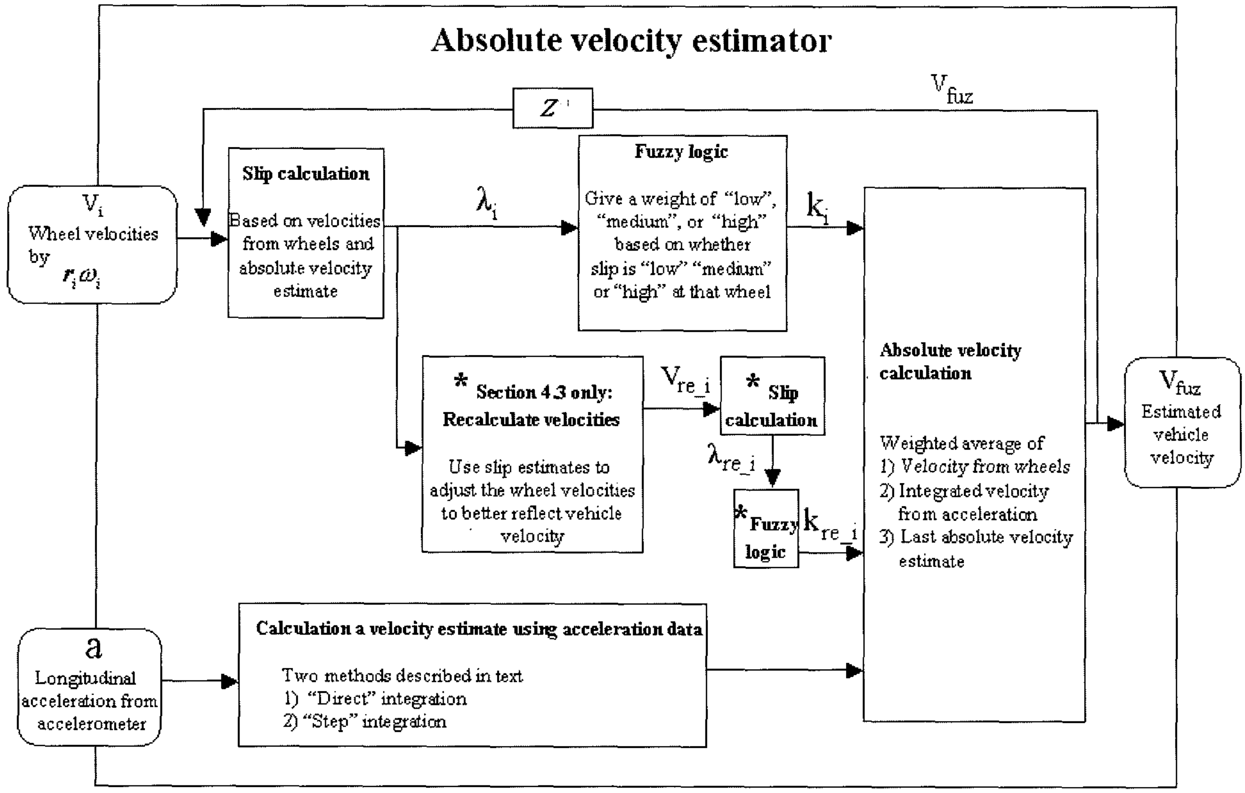


Figure 1. Schematic diagram for estimation of the vehicle speed and the slip ratios.

cost, and easy implementation. And their application with combination of wheel speed sensors were already shown in recent researches (Basset *et al.*, 1997; Daiss and Kiencke, 1995; Kobayashi *et al.*, 1995; Song *et al.*, 2002; Oh and Song, 2002; Song *et al.*, 2002).

In this paper, an accelerometer and wheel speed sensors are used to estimate the vehicle speed. An intuitive method is proposed for calculation of the vehicle speed. If the slip ratio is low, the calculation depends on the wheel speeds. Otherwise, it depends on integration of signal from the accelerometer. In the calculation, that is, time-varying weights are given to each speed from the wheel sensors and the accelerometer. This estimation method of the vehicle speed can reduce the slip effect in the wheel speed sensors and the offset effect in the accelerometer. This method is evaluated experimentally, which shows that the vehicle speed is well estimated under abrupt traction or sudden brake as well as under normal driving conditions.

2. SPEED ESTIMATION WITH FUZZY WEIGHTS

The slip ratio $\lambda_i(t)$ ($i = 1, 2, 3, 4$) in a vehicle with 4 wheels can be defined as the following equation.

$$\lambda_i(t) = \frac{v_i(t) - v(t)}{\max(v_i(t),\ v(t))},\ v_i(t) = r_i\omega_i(t) \tag{1}$$

Here, $v(t)$ is the vehicle speed, and $\omega_i(t)$ is the angular speed of the wheels, and r_i is the radii of the tires. The wheel speed, $v_i(t)$, is somewhat accurate and steady under normal driving conditions. And, the slip ratio is also steady and small. In this case, the wheel speed can be represented with the vehicle speeds as follows:

$$v_i(t) = v(t) + n_i(t) \tag{2}$$

where $n_i(t)$ is the measurement noise including the wheel slip error. When abrupt traction or sudden brake happens, the above equation (2) is no longer valid due to excessive slip ratio.

To solve such a problem, an accelerometer is introduced.

$$a(t) = \dot{v}(t) + n_p(t) \tag{3}$$

Here, $\dot{v}(t)$ is acceleration of the vehicle, $a(t)$ is acceleration signal, and $n_p(t)$ is process noise. The acceleration signal has high frequency noise due to vehicle vibration, offset due to road slope, the voltage bias, and so on. A Butterworth filter is introduced to reduce such noises from acceleration signal. But the offset is low frequency noise, which remains in the acceleration signal. If the initial speed, v_o of vehicle is known, the current speed from the acceleration signal can be computed by direct integration as the following equation:

$$v_a[k] = v_o + \sum_{j=1}^{k} a[j] \cdot \Delta t \tag{4}$$

where Δt is the measured time interval and is assigned to 5 ms. $v_a[k]$ is the calculated speed from the acceleration signal at $k \cdot \Delta t$, and $a[j]$ is the measured acceleration signal at $j \cdot \Delta t$.

This paper considers a vehicle, whose two front wheels ($i = 1, 2$) are operated to brake. And the ABS valves, transmitting hydraulic pressure from the master cylinder to two rear wheels ($i = 3, 4$), are closed. The two rear wheels roll freely regardless of braking pressure. Such a vehicle can give severe braking condition to the two front wheels in experiments. Hereafter, an estimation algorithm of the vehicle speed is evolved from the two front wheel speeds.

The vehicle speed is estimated using the speed from acceleration and wheel speeds. It is desirable that the estimation makes the effects of $n_i(t)$ and $n_p(t)$ minimized. This paper introduced weighting factors to the wheel speeds and the speed from accelerometer. And, the weights are determined by a fuzzy rule using slip ratios.

$$\hat{v}[k] = \frac{\sum_{i=1}^{2} k_i v_i[k] + k_a v_a[k] + k_v \hat{v}[k-1]}{\sum_{i=1}^{2} k_i + k_a + k_v} \tag{5}$$

Here, $\hat{v}[k]$ is the estimated speed. $k_i(i = 1, 2)$, k_a and k_v are the weighting factors corresponding to the wheel speeds, the speed from accelerometer, and the estimated speed, respectively. The slip ratios, $\hat{\lambda}_i[k]$ of each wheel can be calculated from the speed estimated at the previous cycle for the real time processing.

$$\hat{\lambda}_i[k] = \frac{v_i[k] - \hat{v}[k-1]}{\max(v_i[k], \hat{v}[k-1])} \tag{6}$$

Figure 1 shows the schematic diagram for estimation of the vehicle speed and slip ratios of each wheel.

The weighting factors, k_v and k_a, are fixed to certain values. The fuzzy logic calculates only the weight, k_i using the slip ratios. For fuzzyfication of $\hat{\lambda}_i[k]$, this paper introduces five linguistic variables, as shown in Figure 2. They are severe braking, normal braking, no braking/traction, normal traction, and severe traction. The

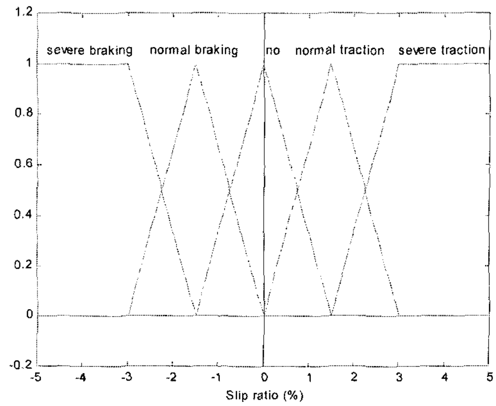


Figure 2. Fuzzyfication of wheel slip data.

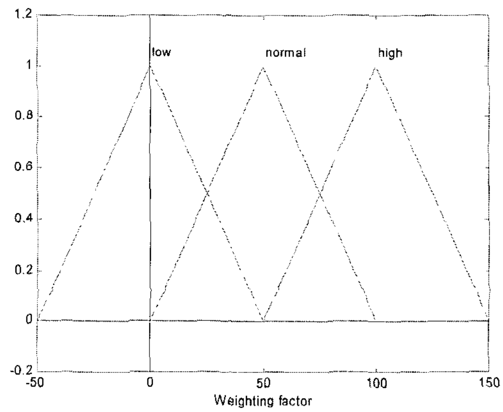


Figure 3. Defuzzyfication to obtain weighting factors.

weighting factors are derived from the five linguistic variables with a defuzzyfication rule in Figure 3, which are low, normal, and high. The defuzzyfication rule is summarized as follows:

If a wheel slip is Severe Braking,
then its weighting factors are Low;
else if Normal Braking, then Normal; (7)
else if No Braking/Traction, then High;
else if Normal Traction, then Normal;
else Severe Traction, then Low.

3. EXPERIMENTS OF SPEED ESTIMATION

All results in the paper were calculated using experimental data from straight-line braking maneuvers using a rear wheel drive test vehicle. The left front wheel speed signal and the accelerometer signal were the main sensors used for the velocity estimates. In addition to the accelerometer and wheel speed sensor, the vehicle was outfitted with a fifth wheel to provide a ground velocity reference. The bicycle-like wheel was mounted from a

Figure 4. The fifth wheel attached on the vehicle.

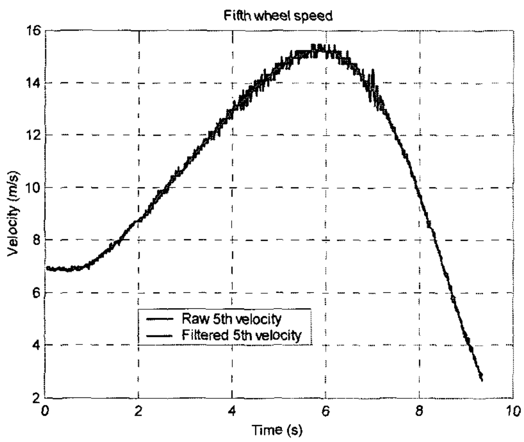
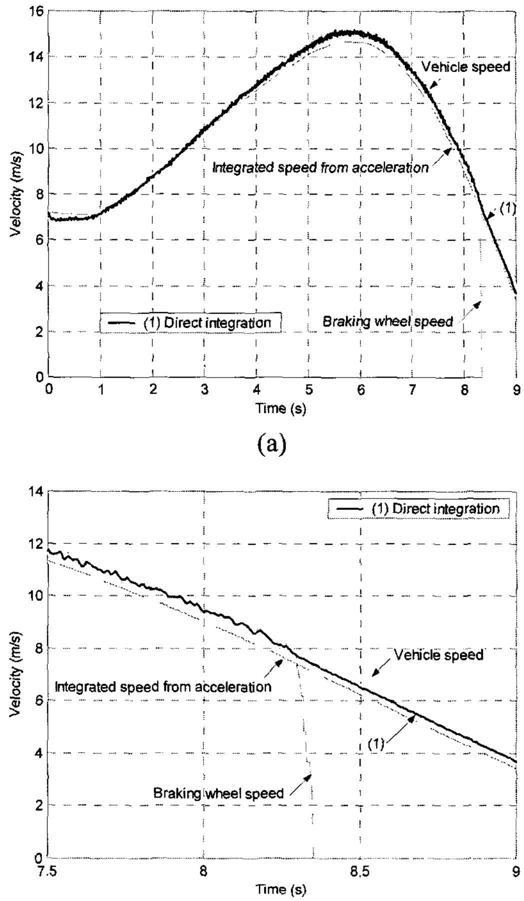


Figure 5. A filtered signal of the fifth wheel speed.



(a)

(b)

Figure 6. Experimental result of estimated speed with the direct integration.

spring-loaded arm on the back of the car like Figure 4. Because the wheel did not slip, and because its radius was well known, the vehicle speed could be measured exactly. However, there was a little noise at the fifth wheel speed, and a Butterworth filter was used to reduce it.

A filtered speed was compared with its original speed in Figure 5. The filtered speed of the fifth wheel was denoted to the vehicle speed in experiments.

The means of the front wheel speed is called as braking wheel speed. Each k_i ($i = 1$, 2) is bounded in 0 and 100 by the fuzzy logic, and k_v is assigned to 100 in this experiment. Because of offset at acceleration signal, error in the speed integrated from it can increase according to the integrating time. Therefore, the weighting factors, k_a is assigned to small value of 10.

The experiments are done on wet pavement with no slope. Acceleration signal has no offset contributed by road slope. The experimental results is shown in Figure 6, where Figure 6(b) is the detail figure of Figure 6(a) between 7.5 s and 9.0 s. Due to small slip on the front wheels, the braking wheel speed is different slightly from the measured speed during normal driving condition, between 0 s and 8.3 s. However, there is an increase of error between the speed from acceleration signal and the measured speed with the passage of time.

This is due to voltage bias in acceleration signal, even though small. The small weighting factors of the acceleration signal are taken into consideration.

Since the front wheels are locked and the slip on the front wheels is big, after 8.3 s, the estimated speed approaches the speed integrated from acceleration signal.

Therefore error of the estimation speed increases more during the braking time than normal driving time.

In order to reduce the offset error involved in acceleration signal, the step integration from acceleration signal is also tried. The speed $\hat{v}_a[k]$ by the step integration is calculated as equation (8) using the previous estimated speed $\hat{v}[k-1]$.

$$\hat{v}_a[k] = \hat{v}[k-1] + a[k] \cdot \Delta t \tag{8}$$

The fuzzy speed equation (5) is modified with the step-integrated speed as the following equation.

$$\hat{v}[k] = \frac{\sum_{i=1}^{2} k_i v_i[k] + k_v \hat{v}_a[k]}{\sum_{i=1}^{2} k_i + k_v} \tag{9}$$

Figure 7 shows the estimated speed of the step integration method, which matches the measured vehicle speed better than that of the direct integration method. The estimated slip ratios are shown in Figure 8. And errors between estimated speeds and the measured speed are compared in Figure 9. When the estimated slip ratios of the braking wheels are large, the weighting factors of the wheels are made to be small. And consequently, $\hat{v}_a[k]$ is weighted more than the speeds of slipping wheels. From experiment results the step integration method is superior to the direct integration method. However, the offset error of acceleration signal has an effect on the speed estimation during braking condition with severe slip. Enhancement of the estimation method is needed to reduce the offset error.

4. ENHANCEMENT OF SPEED ESTIMATION

In order to improve the two previous methods, the slip ratios are introduced to estimate the wheel speeds, $v_{\lambda\_i}[k]$ during braking or traction.

$$v_{\lambda\_i}[k] = \frac{v_i[k]}{1 + \hat{\lambda}_i[k]}, \ \textit{when braking,}$$

$$v_{\lambda\_i}[k] = (1 - \hat{\lambda}_i[k]) \cdot v_i[k], \ \textit{when traction} \tag{10}$$

The speed estimator of the direct integration equation (5) is modified as the following equation:

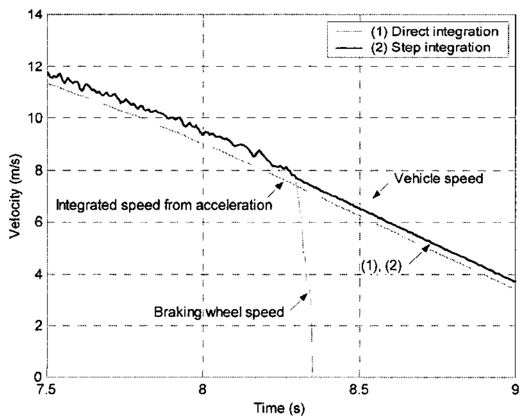


Figure 7. Experimental result of estimated speed with the step integration.

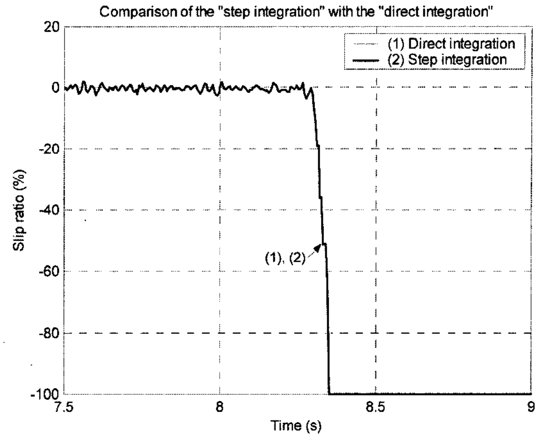


Figure 8. Estimated slip ratios.

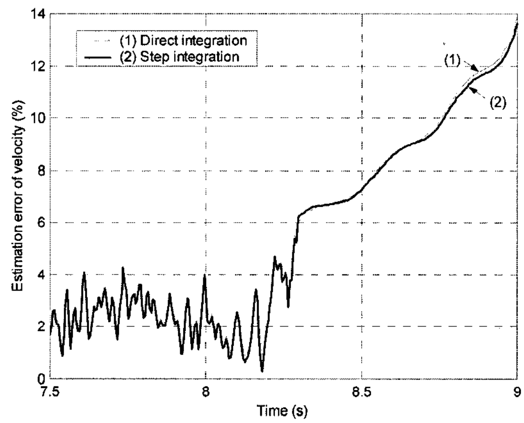


Figure 9. Errors of estimation speeds.

$$\hat{v}[k] = \frac{\sum_{i=1}^{2} (k_i v_i[k] + k_{\lambda\_i} v_{\lambda\_i}[k]) + k_a v_a[k] + k_v \hat{v}[k-1]}{\sum_{i=1}^{2} (k_i + k_{\lambda\_i}) + k_a + k_v} \tag{11}$$

where k_{λ_i} (i =1, 2) are new weighting factors. They are also calculated from fuzzy logic with slip ratio equation (6) by replacing $v_i[k]$ with $v_{\lambda\_i}[k]$. The speed estimator of the step integration (9) is also modified as the following equation.

$$\hat{v}[k] = \frac{\sum_{i=1}^{2} (k_i v_i[k] + k_{\lambda\_i} v_{\lambda\_i}[k]) + k_v \hat{v}_a[k]}{\sum_{i=1}^{2} (k_i + k_{\lambda\_i}) + k_v} \tag{12}$$

The experimental results of the two modified methods are shown in Figure 10. The two estimated speeds are

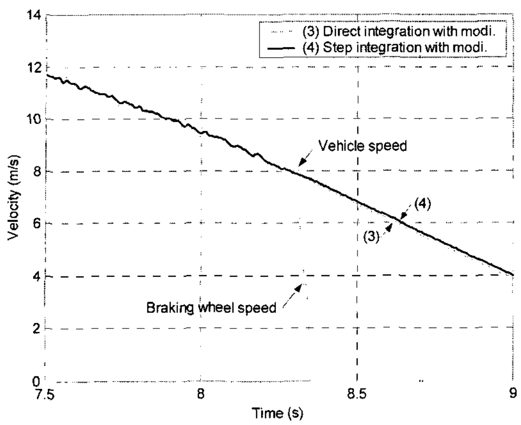


Figure 10. Estimated speeds in the modified methods.

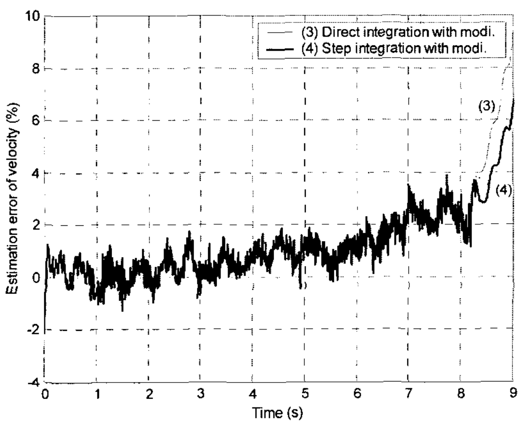


Figure 11. Errors of the estimated speeds in the modified methods.

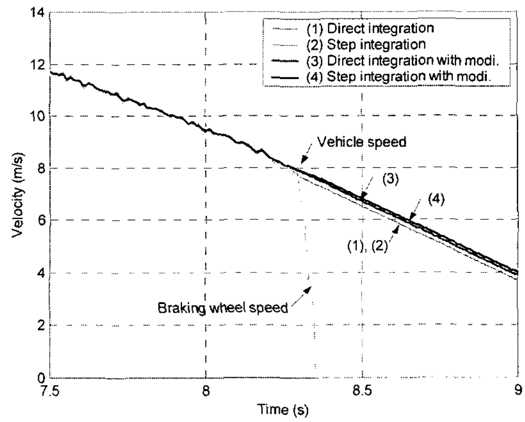


Figure 12. Comparison of the estimation speeds.

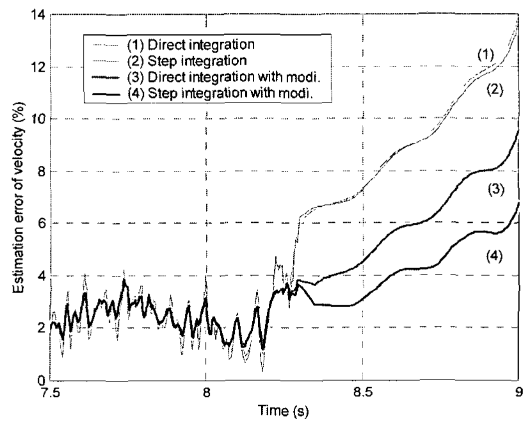


Figure 13. Comparison of errors in the estimation speeds.

similar during normal driving condition with small slip, between 0 s and 8.3 s. During braking condition with severe slip, however, the step integration with modified velocities gives experimental result better than the direct integration with modified velocities in comparison with errors shown in Figure 11.

Moreover, the estimated speed from the modified step integration is more similar with the measured speed during braking than normal driving. And the error of the estimated speed is lower than 6% during a hard braking maneuver lasting three seconds.

All the experimental results are plotted in Figure 12 and 13. Comparison of the results indicates that the step integration with modified velocities is the best result. And the direct integration with modified velocities gives result better than the step integration with modified velocities at the start of braking condition. This indicates that the offset of acceleration signal has an effect on estimation speed.

5. CONCLUSION

The fuzzy logic was applied to estimate the vehicle speed using an accelerometer and wheel speed sensors. In order to reduce offset noise in acceleration signal and slip effect in wheel speeds, four methods of speed estimation had been proposed by intuition. This algorithm had been verified experimentally. And the step integration with modified velocities provided good estimation of vehicle speed, less than 6% worst-case error of estimated speed during a hard braking maneuver lasting a few seconds. We expect, in practical application, that the vehicle speed can be more accurately using four wheel sensors instead of only front wheels.

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