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Absolute Speed Measurement of Automobile from Noisy Acceleration and Erroneous Wheel Speed Information

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Abstract

Accurate information of the absolute speed of a vehicle, when available, can be vital in simplifying the control laws of an anti-lock braking system (ABS) and auto-traction system (ATS). A current meter for measuring the speed of a vehicle is to multiply the measured wheel rotation rate to the wheel radius. The approach often includes abrupt unpredictable errors due to slip and skid of wheels and a biased error due to the steady state slip. These errors are sources of difficulty in the implementation of an ABS that is based on the absolute speed of the vehicle.

This paper describes an *accurate rule-based Kalman filtering technique* for estimating the absolute speed of a vehicle. The enhanced accuracy is achieved by employing an additional accelerometer to complement the wheel speed-based speedometer. The accelerometer measures the acceleration of the vehicle in its forward direction and may be corrupted as well by high frequency noise.

The proposed sensing technique employs the extended Kalman filter to reduce the high frequency noises in the acceleration measurement and the biased error coming from the wheel speed measurement. Furthermore, we incorporate a rule-based strategy that switches the values of the Kalman filter coefficients to compensate for abrupt nonstationary errors in the measurement. The rules are developed based on a simple set of knowledge. For example, when skid or slip occurs, the wheel speed measurement may be quite erroneous; therefore, heavier reliance on the acceleration measurements would be placed over that of the wheel speed. Simulations and laboratory model experiments were carried out to verify the proposed rule-based estimation strategy and prove that it can accurately estimate the absolute speed even when wheel slip or skid occurs.

1. Introduction

Accurate measurement of the absolute speed of a automobile allows simplification and accurate implementation of anti-lock braking control law[1]. This, in turn, helps to decrease the stopping distance of the vehicle and enhance the safety of the riders. In this paper, we presents a new technique for estimating accurately the absolute speed of the vehicles and investigate the validity of the presented *rule-based Kalman filter* type estimation strategy.

The speed sensing for vehicles can be classified into several categories, including:

(I) The contact methods in which the wheel rotation speed is measured and the speed of vehicle is obtained by multiplying the wheel radius to the wheel speed.

(II) The non-contact methods which, for example, employ reflections of optical reflection signals off the ground.

The methods in (I) are stable and used in the most vehicles[2,3]. However, these methods may include errors such as: (1) the bias error due to the steady state slip of the wheel when driving and/or the trendal change in the wheel radius due to the pressure decrease in the tire or wear of tire-surface, and (2) the abrupt impulsive error due to the slip or skip of wheels and/or dynamic tire compressions.

The non-contact methods in category(II) such as the optical-correlation method[4] and the spatial filtering method[5] can avoid the errors in the wheel speedometer. However, the optical methods require bulky and complicated mechanisms for focusing the photo-sensors and need cleaning arrangements for the optics which are inevitably oiled by rain, mud and oil.

In view of these drawbacks, the existing methods may not provide accurate measurement of the actual vehicle speed. Therefore, an alternative superior technique is proposed in this paper.

The proposed strategy is the rule-based Kalman filter which accurately estimates the absolute vehicle speed from noisy wheel speed and vehicle acceleration measurements. The undelying theory is that one can estimate the unmeasurable physical system states of interest from the knowledge of the appropriate system outputs. The relation between these physical variables can be described by a set of nonlinear ordinary differential equations and output equations. An important desirable feature required in the outputs is that the stochastic properties of the measurements errors should be independent. For the automotive application, we would also like to employ reliable and economical sensors.

We apply this basic philosophy to the problem of absolute vehicle speed measurement. The proposed output sensors to be used is the existing wheel speed-based speedometer and an additional accelerometer. We propose to estimate the absolute speed from knowing the wheel speed and the acceleration measurements which may be corrupted with noise.

The relationships between the actual acceleration, the vehicle/wheel speed and the deviation factor for the wheel radius can be described by a set of nonlinear ordinary differential state vector equations. A second set of algebraic output equations describes the acceleration measurement that is corrupted by a zero mean noise with a stochastically stationary variance, and the wheel speed measurement which is biased and impulsive, and demonstrates non-stationary property. Thus, the errors in the accelerometer and wheel-based speedometer have different stochastic properties from each other. We propose a strategy which utilizes these relationships to extract an accurate estimate of the accurate absolute vehicle speed from the noisy acceleration and erroneous wheel speed information.

2. System and Problem Description

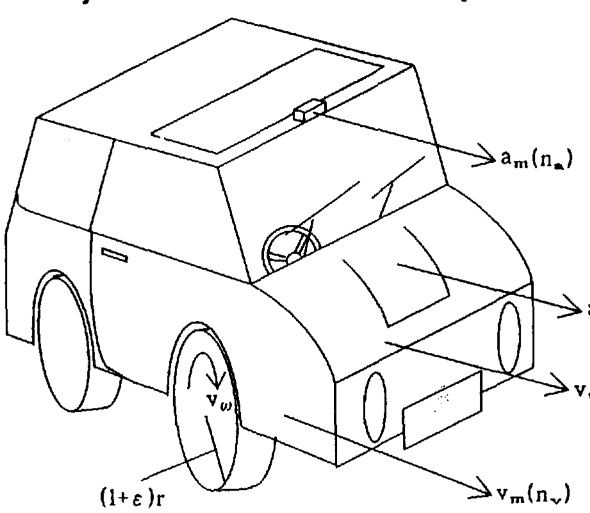


Figure 1 Speed and acceleration of a vehicle.

Figure 1 shows the vehicle moving in the forward direction. The directions of the wheel-based speedometer and accelerometer measurements are aligned in that direction of motion.

For ease of reference, we compile the definitions of variables and constants for the system below:

t :time,
τ :sampling interval of discrete measurement,
k :discrete time,
a_t :true acceleration,
a_m :measured acceleration,
v_t :true absolute speed,
v_m :speed obtained from the measured wheel speed,
v_ω :speed obtained from the wheel speed,
ω :wheel speed,
r :initial radius of wheel,
Δr :deviation of r from its initial value,
ε :rate of deviation of r,
n_v :observation noise of the speed,
n_a :observation noise of the acceleration,
ω_1 :the system noise included in the derivative of the acceleration,
ω_2 :the system noise included in the derivative of the wheel speed,
ω_3 :the system noise included in the radius change,
R_a :variance of n_a,
R_v :variance of n_v,
Q_1 :variance of ω_1,
Q_2 :variance of ω_2,
Q_3 :variance of ω_3,
P_1 :variance of the estimated value of a_t,
P_2 :variance of the estimated value of v_t,
P_3 :variance of the estimated value of ε,
θ_1; :threshold in Rule R1,
θ_2; :threshold in Rule R2,
θ_3; :threshold in Rule R3,
θ_4; :threshold in Rule R4,
$\boldsymbol{R}$:covariance matrix of the measurement noise $\{n_a, n_v\}$,
$\boldsymbol{Q}$:covariance matrix of the system noise $\{\omega_1, \omega_2, \omega_3\}$,
$\boldsymbol{P}$:covariance matrix of the estimated variable $\{a_t, v_t, \varepsilon\}$,

The estimates of $\{a_t, v_\omega, v_t, \varepsilon\}$ are represented by $\{\hat{a}_t, \hat{v}_\omega, \hat{v}_t, \hat{\varepsilon}\}$.The measurement from the wheel speed v_m is given by (initial radius r)·(measured wheel speed ω). The speed and acceleration measured involve the following errors.

(E1) The radius of the wheel that changes slowly due to wear of tire surface, change in the tire pressure and/or the change in the load of the vehicle.

(E2) Steady state slip of the wheel that occurs in the steady state driving of the vehicle.
(E3) The big abrupt and impulsive wheel slippage caused by abrupt acceleration or skid caused by quick braking action .
(E4) The speedometer errors due to vehicle vibration and offset noise.
(E5) The accelerometer errors due to large variance high frequency noise caused by vibration.
(E6) The radius of the wheel that changes abruptly due to dynamicinteraction with bumpy road/terrain.

Under the measurement system in Figure 1 and the errors above, we assume that:
(A1) The slip of (E2) is small and is proportional to the speed of the vehicle.
(A2) Noise in (E4) and (E5) are stationary Gaussian white noise with zero mean.
(A3) The accelerometer measures only the acceleration toward to the moving direction in which the vehicle's heading.

Assumption (A1) is required to model the change in the radius of wheel. Assumption (A2) is the condition necessary to apply the Kalman filtering technique. These are not restrictive conditions.

Assumption (A3) may be somewhat restrictive and is a result of employing a three-axis accelerometer. The accelerometer detects the vertical and two horizontal accelerations with different gains. One of the horizontal axis is used to detect the acceleration in the forward direction. Acceleration in a single axis between ±0.01G~±1.1G in the frequency range of DC~10Hz can be readily measured[8,9]. But when the vehicle has simultaneous forward, side and heave motions, the net acceleration toward to the moving direction can be determined from three accelerations by applying the 3-axis coupling technique. Thus, the measurement condition in Assumption (A3) can be satisfied.

Given the above realistic conditions, we now present the Kalman filtering that is enhanced by a set of on-line design rules for an accurate estimation of the absolute vehicle speed, in spite the noisy acceleration and erroneous wheel speed measurements.

3. Estimation of the Absolute Speed

3.1 Estimation by the Extended Kalman Filter

Figure 2 shows the basic scheme of the proposed strategy to estimate the absolute speed of vehicle. The Kalman filter uses the two measurements $a_m(t)$ and $v_m(t)$ to estimate $v_t(t)$. The filter equation is determined by the physical relation between the acceleration and speed. The filter coefficient are determined by the noise information of the measurements and the estimates, i.e., the covariances of the measurement and the estimates.

The values of the covariance at the nonstational measurement conditions are not known and are determined or switch by the rule. The present estimates are used as the data for the rule firing. The details are described in the following:

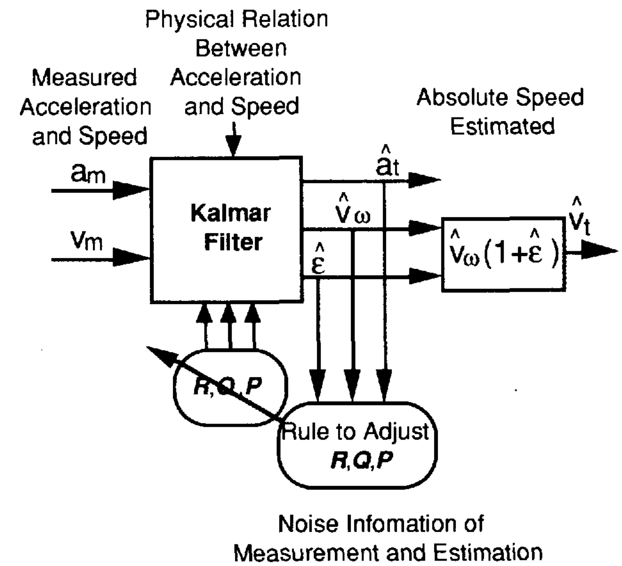


Figure 2 The basic scheme of the proposed strategy to estimate the absolute speed.

The computed vehicle speed v_ω that is based on the wheel speed ω is given by:

$$v_\omega = \omega r \qquad (1a)$$

However, since the wheel radius includes the errors asserted in Assumption (A1) and also the steady state slip of wheel, the true absolute speed of the vehicle can be modeled by the following equation:

$$v_t = \omega(r + \Delta r) = v_\omega(1+\varepsilon) \qquad (1b)$$

The measured vehicle speed based on the wheel speed is composed of the computed speed and measurement noise as follows:

$$v_m = v_\omega + n_v \qquad (1c)$$

Similarly, the measured acceleration is comprised of the actual acceleration plus measurement noise:

$$a_m = a_t + n_a \qquad (1d)$$

From Assumption (A2), n_v and n_a are zero mean white noise with normal distribution.

Let the derivative of the acceleration be defined by

$$\frac{da_t}{dt} = \omega_1,\ a_t(0)=a_{to} \qquad (1e)$$

where ω_1 represents the 'jerk' function for the vehicle forward motion. Since ω_1 is not directly measurable, it will be treated as an unknown external system disturbance or noise input.

The derivative of eq.(1b) yields

$$\frac{dv_\omega}{dt} = \frac{dv_t}{dt} - \varepsilon\frac{dv_\omega}{dt} = a_t - \varepsilon a_m + \omega_2$$

$$v_\omega(0) = v_{\omega 0} \qquad (1f)$$

where the variable ω_2 is given by

$$\omega_2 = \varepsilon n_a + \varepsilon^2 \frac{dv_\omega}{dt} \qquad (1g)$$

and will also be treated as an unknown system disturbance/noise input.

Since the deviation factor ε changes very slowly, the derivative of e can be modeled as follow:

$$\frac{d\varepsilon}{dt} = \omega_3\ ,\ \varepsilon(0) = \varepsilon_0 \qquad (1h)$$

where the variable ω_3 has the very small value and is another disturbance input. From the property of error in (E1), (E2), and Assumption (A1), ε would be a small near-constant value.

Discretizing the set of equations (1e), (1f) and (1h) with the sampling interval τ, and letting (1c) and (1d) to be the output equations, the above physical relationships can be compactly described by the discrete state space model

$$\boldsymbol{x}(k+1) = \boldsymbol{A}(k)\boldsymbol{x}(k) + \boldsymbol{B}(k)\boldsymbol{w}(k),\ \boldsymbol{x}(0) = \boldsymbol{x}_0$$

$$\boldsymbol{z}(k) = \boldsymbol{C}(k)\boldsymbol{x}(k) + \boldsymbol{n}(k) \qquad (2a)$$

where the vectors and matrices are defined as follows:

$$\boldsymbol{x}(k) = \begin{bmatrix} a_t(k) \\ v_\omega(k) \\ \varepsilon(k) \end{bmatrix} \qquad \boldsymbol{w}(k) = \begin{bmatrix} \omega_1(k) \\ \omega_2(k) \\ \omega_3(k) \end{bmatrix}$$

$$\boldsymbol{z}(k) = \begin{bmatrix} a_m(k) \\ v_m(k) \end{bmatrix} \qquad \boldsymbol{n}(k) = \begin{bmatrix} n_a(k) \\ n_v(k) \end{bmatrix}$$

$$\boldsymbol{A}(k) = \begin{bmatrix} 1 & 0 & 0 \\ \tau & 1 & -\tau a_m \\ 0 & 0 & 1 \end{bmatrix} \qquad \boldsymbol{B}(k) = \begin{bmatrix} \tau & 0 & 0 \\ 0.5\tau^2 & \tau & 0 \\ 0 & 0 & \tau \end{bmatrix}$$

$$\boldsymbol{C}(k) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \qquad (2b)$$

The augment state equation[6] include the radius deviation parameter ε as one of the state variables.

Let the covariance matrices of the independent system noise $[\omega_1, \omega_2, \omega_3]$ and measurement noise $[n_a, n_v]$ be defined, respectively, by

$$\boldsymbol{Q}(k) = \begin{bmatrix} Q_1 & 0 & 0 \\ 0 & Q_2 & 0 \\ 0 & 0 & Q_3 \end{bmatrix}\ ,\ \boldsymbol{R}(k) = \begin{bmatrix} R_a & 0 \\ 0 & R_v \end{bmatrix} \qquad (2c)$$

Application of the discrete Kalman filter to (2a), (2b) and (2c) yields the estimates $\hat{\boldsymbol{x}}(k)$. The

Kalman filtering algorithm is as follows:

$$\hat{\boldsymbol{x}}(k+1) = \boldsymbol{A}(k)\hat{\boldsymbol{x}}(k) + \boldsymbol{P}(k+1)\boldsymbol{C}(k+1)^T\boldsymbol{R}(k+1)^{-1}\{\boldsymbol{z}(k+1) - \boldsymbol{C}(k+1)\boldsymbol{A}(k)\hat{\boldsymbol{x}}(k)\}$$

$$\hat{\boldsymbol{x}}(0) = \hat{\boldsymbol{x}}_0 \qquad (2d)$$

where $\boldsymbol{P}(k)$ is the covariance matrix of the error between $\hat{\boldsymbol{x}}(k)$ and $\boldsymbol{x}(k)$ and is calculated by

$$\boldsymbol{P}(k) = \boldsymbol{M}(k) - \boldsymbol{M}(k)\boldsymbol{C}(k)^T[\boldsymbol{C}(k)\boldsymbol{M}(k)\boldsymbol{C}(k)^T + \boldsymbol{R}(k)]^{-1}\boldsymbol{C}(k)\boldsymbol{M}(k)$$

$$\boldsymbol{M}(k) = \boldsymbol{A}(k-1)\boldsymbol{P}(k-1)\boldsymbol{A}(k-1)^T + \boldsymbol{B}(k-1)\boldsymbol{Q}(k-1)\boldsymbol{B}(k-1)^T$$

$$\boldsymbol{P}(0) = \boldsymbol{P}_0 \qquad (2e)$$

Substitution of $\hat{v}_\omega(k)$ and $\hat{\varepsilon}(k)$ in $\hat{\boldsymbol{x}}(k) = [\hat{a}_t(k)\ \hat{v}_\omega(k)\ \hat{\varepsilon}(k)]^T$ into (1b) yields the estimate of the absolute value $\hat{v}_t(k)$. The state equation (2a) is observable if the vehicle moves. Furthermore, the measurement noises are stationary if no slip nor skid occurs. Thus the estimates $\hat{\boldsymbol{x}}(k)$ will converges to $\boldsymbol{x}(k)$ as $k \to \infty$. Under these ideal conditions, the Kalman filter can accurately estimate the accurate absolute speed in the presence of the errors mentioned in (E4) and (E5).

However, large variance non-stationary error due to slip or skid may not conveniently permit the convergence of $\boldsymbol{x}(k), \hat{\boldsymbol{x}}(k)$, because this is a situation when the Kalman filter with the fixed convariance matrices is not correctly applied.

3.2 Rules to Adjust the Coefficient in the Kalman Filter

We would like to adjust the Kalman filter coefficient matrices $\boldsymbol{R}(k), \boldsymbol{Q}(k), \boldsymbol{P}(k)$ and smoothen the estimated variable $\hat{\varepsilon}(k)$ so that the effect of non-stationary errors due to the slip and/or skid are removed in the Kalman filtering process. We use a set of simple yet effective rules to adjust these coefficients and variables. In the following discussion the symbol* is used to represent the variances of system and observation noises under the stationary conditions.

Rule 1: Compensation of errors due to the skid or slip

Occurrence of skid or slip can be easily discriminated from the measurements and the estimates by the difference between the values $v_m(t)$ and $\hat{v}_t(t)$. In the situations when the measurement $v_m(t)$ includes very large noise, the Kalman filtering is carried out with heavy reliance on the acceleration signal and small confidence in the wheel speed signal. Such a filter is realized by decreasing the variance of the acceleration measurement and increasing the variance of the speed measurement as shown below:

(R1) IF $\left| \{ \hat{v}_t(k) - v_m(k) \} / \hat{v}_t(k) \right| > \theta_1$

THEN $R_a = 0.5 \cdot R_a^*$ and $R_v = 1000 \cdot R_v^*$

ELSE $R_a = R_a^*$ and $R_v = R_v^*$

Rule 2: Compensation of errors due to sudden acceleration or braking action

In this situation, the variance of the derivative of acceleration Q_1 should be modeled to have a large value. In addition, the sudden acceleration and/or braking action strongly influence the value $\hat{\varepsilon}$ which may change quickly in this situation. Since the change in e must be gradual in comparison with the changing speed of acceleration, we may reset Q_3 to a small value to make the response of $\hat{\varepsilon}$ slower and also reset the abruptly changed value to the old value before sharp change occurred. We thus have the following rule.

(R2) IF $\left| \{ \hat{a}_t(k) - \hat{a}_t(k-1) \} / v_t(k) \right| > \theta_2$

THEN $Q_1 = 2.0 \cdot Q_1^*$, $Q_3 = 0.00001 \cdot Q_3^*$

and $\hat{\varepsilon}(k) = \hat{\varepsilon}(k-2)$

ELSE $Q_1 = Q_1^*$ and $Q_3 = Q_3^*$

Rule 3: Low-pass filtering for smoothing ε

The errors in (E1) and (E2) cannot be compensated if the change in ε cannot be estimated with high accuracy even if the change in ε is slow. We apply a logical low-pass filtering to filter out the high frequency component. In fact, such a filtering already exists in Rule 2 (R2) above. To ensure the low-pass filtering, we introduce the more general rule below:

(R3) IF $\left| \hat{\varepsilon}(k) - \hat{\varepsilon}(k-1) \right| > \theta_3$
THEN $\hat{\varepsilon}(k) = \hat{\varepsilon}(k-2)$

Rule 4: Rule to reset the negative speed and to speed up the estimation

A vehicle moving forward cannot have a negative speed. Because of measurement noise, however, the estimated speed of a vehicle can sometimes show up as a negative value, especially when the vehicle is moving at a low speed. In such a case, we simply reset the estimated speed to be zero. At the same time, we may also speed up the estimation of Kalman filter by resetting the covariance matrix $\boldsymbol{P}(k)$ to the initial values $\boldsymbol{P}_0$.

(R4) IF $\hat{v}_t(k) < \theta_4$
THEN $\hat{v}_t(k) = 0$ and $\boldsymbol{P}(k) = \boldsymbol{P}_0$

4. Simulation and Model Experiment

We carried out simulations and experiments by using a laboratory model vehicle to examine the validity of the strategy presented in Chapter 3.

4.1 Simulation

The speed and acceleration profiles for the simulation is shown in Figure 3. The dotted curve in Figure 3(a) shows the true speed profile that represents the actual absolute speed v_t of a vehicle. Superposed on it is the solid curve which represents the measured wheel-based speed v_m, generated by adding to the true speed, a stationary random Gaussian noise with zero mean and large abrupt impulsive type noise that indicates that wheel slips and skids has taken place.

The dotted curve in Figure 3(b) shows the true acceleration a_t profile used in the simulation. The solid curve represents the measured acceleration a_m, generated by adding a stationary high frequency noise with sufficiently large variance and zero mean to the true acceleration given by the dotted curve.

The pertinent conditions for simulation are summarized as follows:

[Acceleration and speed]
simulation time :40.0 s
sampling interval τ of discrete measurement :0.01 s
maximum value of ε :2.0 %
Variance Q_1^* of the derivative of the acceleration :5.14 m^2s^{-6}
Variance Q_2^* of the system noise ω_2 :$1.0 \cdot 10^{-3}$ s^{-2}
Variance Q_3^* of the system noise ω_3 :$3.0 \cdot 10^{-3}$ m^2s^{-4}

Variance R_a^* of the acceleration noise :0.80 m^2s^{-4}
Variance R_v^* of the speed noise :0.05 m^2s^{-2}
Time interval when slip occurs :3.0~6.0 s
Time interval when skid occurs :26.0~29.0 s

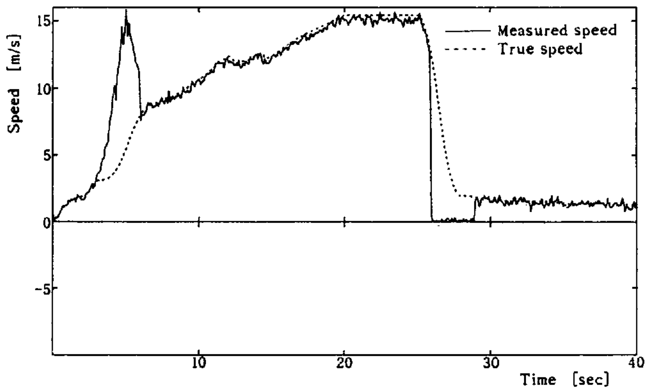
[Initial conditions for the Kalman filter]

$$P_0 = \begin{bmatrix} 1.0 & 0 & 0 \\ 0 & 1.0 & 0 \\ 0 & 0 & 1.0 \cdot 10^{-3} \end{bmatrix} \quad , x_0 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

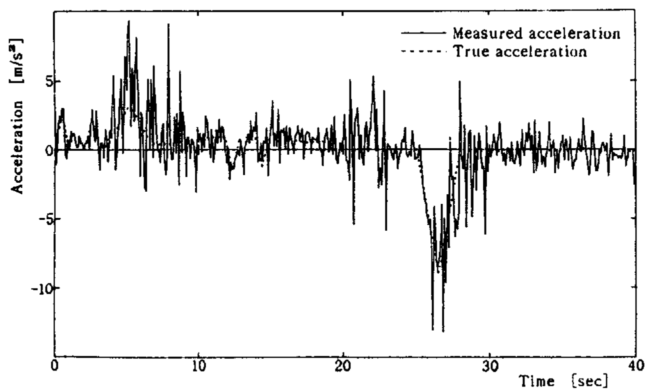
[Threshold for the rules]

$\theta_1 = 10\ \%$, $\theta_2 = 0.05\ \mathrm{ms}^{-2}$, $\theta_3 = 1.0\ \%$

$\theta_4 = 0.0\ \mathrm{ms}^{-1}$



(a) Simulated (wheel) speed with the biased error, abrupt error, and steady state noise.



(b) Simulated acceleration with the high frequency steady state noise.

Figure 3

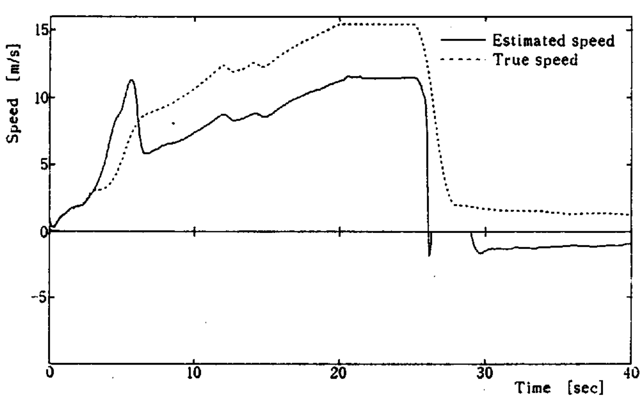


Figure 4 Estimated speed via the Kalman filter.

Figure 4 shows the absolute speed estimated only by the extended Kalman filter *without* applying the rules. The estimated absolute speed was strongly influenced by the big impulsive error due to the slip occurred during 3.0~6.0 s and the effect by the error was not compensated. This phenomena is due to the fact that the error remained in the estimation of ε.

The simulation results from the proposed rule-based Kalman filter for estimating the absolute speed under the noisy acceleration and erroneous vehicle/wheel speed measurements is shown in Figure 5. The upper part of the figure shows the absolute speed and the lower part (R1,R2,R3,R4) shows the timing when the rules were applied. The result in Figure 5 demonstrates the absolute speed estimated by Kalman filter assisted of the four rules is quite accurate even during the time interval when wheel slip occurs. Furthermore, the estimate ε converges slowly and settled down after 30 s later.

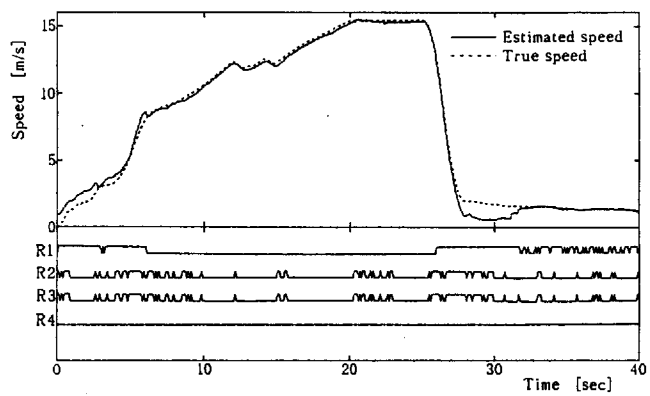


Figure 5 Estimated speed via the proposed method. Kalman filtering with assist of the four rules constructed by the simple knowledge.

4.2 Model Experiment

Actual experiments were carried out by using the laboratory experimental model system shown in Figure 6. The vehicle was set at the end of the arm whose the other end could rotate around the vertical pole fixed. The movement vehicle was restricted on the circle trajectory on the horizontal plane. The vehicle was driven by a DC motor and

decelerated by the electromagnetic brake. The wheel-based vehicle speed v_m was measured by the tacho-generator T_B set to the radius of the wheel and the true/actual absolute speed v_t was *determined by the tacho-generator* T_A *which* measured the revolutional speed of the arm. Further the acceleration was calculated by numerical differentiation of the true absolute speed.
Experimental parameters of the system in Figure 6 are listed as follows:

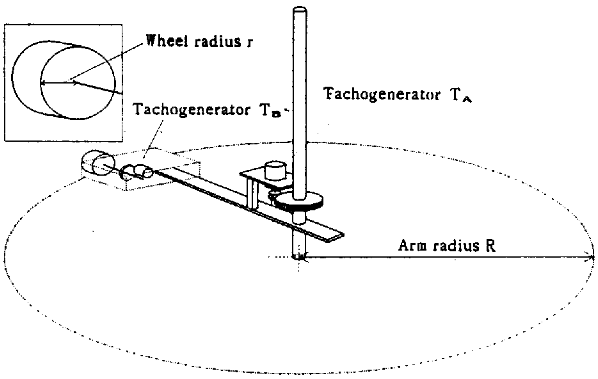


Figure 6 Experimental system.

Load to the wheel	:6.96 N
Length of arm L	:0.623 m
Radius of wheel r	:0.0302 m
Experimental time	:14.4 s
Sampling interval τ	:0.0144 s

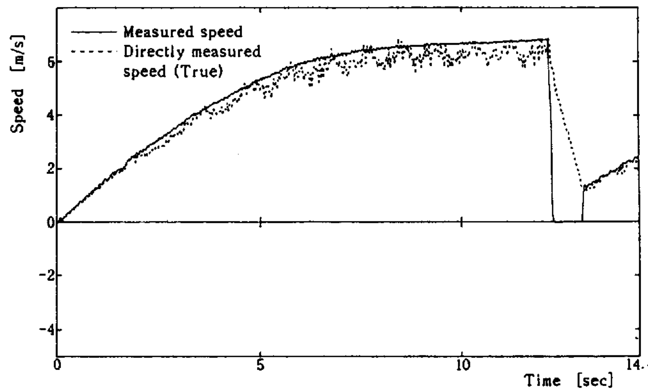
Coveriance matrices of system noise and observation noise in the steady state driving were set to

$$\boldsymbol{Q}=\begin{bmatrix}1.0 & 0 & 0\\ 0 & 1\cdot10^{-3} & 0\\ 0 & 0 & 3\cdot10^{-3}\end{bmatrix},\boldsymbol{R}=\begin{bmatrix}0.4 & 0\\ 0 & 0.1\end{bmatrix}$$

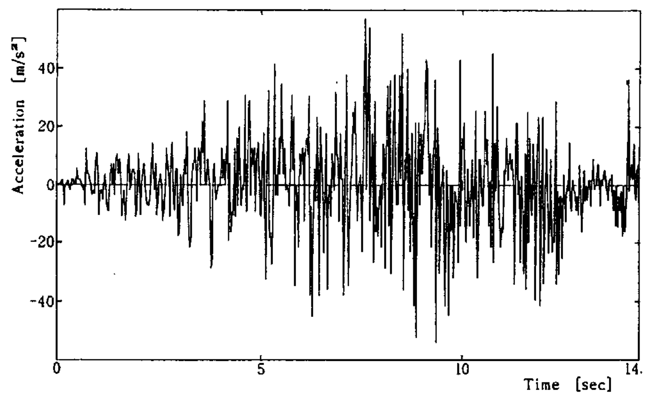
The initial value of the covariance matrix $\boldsymbol{P}_0$ was same as that in the simulation and the thresholds of the rules were

$\theta_1 = 5.0\ \%$, $\theta_2 = 0.06\ \mathrm{ms}^{-2}$, $\theta_3 = 0.3\ \%$
$\theta_4 = 0.0\ \mathrm{ms}^{-1}$

Figure 7(a) shows the speed. The solid curve is the absolute speed v_m measured by wheel speed by using the tacho-generator T_B.
The dotted curve is the absolute speed v_t determined by the revolutional speed of the arm measured by the tacho-generator T_A. When disacceleroating, the wheel was locked and $v_m = 0$, indicating that large impulsive-type errors has occurred. The acceleration a_m was very noisy as shown in Figure 7(b). The noise level was more ten times righter than the signal level.



(a) Measured (wheel) speed when the wheel has the steady state slip and lock when breaking.
Figure 7



(b) Measured acceleration when the wheel has the steady state slip and lock when breaking.
Figure 7

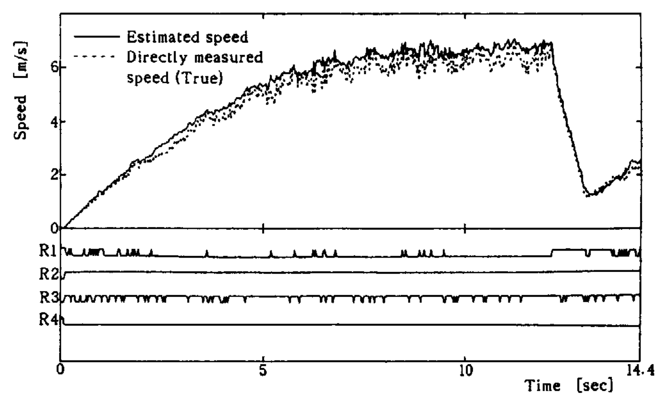


Figure 8 Estimated absolute speed by the proposed method.

Figure 8 shows the estimated absolute speed $\hat{v}_t$ (solid curve) generated from the results of the extended Kalman filter with the rules, and the true absolute speed v_t as measured directly by the tacho-generator T_A. The results demonstrated accurate estimation, even in the time interval when the wheel was locked at about the 12th second into the experiment. The noises in the acceleration was also filtered out cleanly.

4.3 Supplementary Explanation

In the above simulations and model experiments, the parameters in the rules and those in the Kalman filtering were not sensitive. The constants of 0.5 or 1000 in R1, the constants 2.0 or 0.00001 in R2, thresholds $\theta_1, \theta_2, \theta_3, \theta_4$ and the initial value of the Kalman filtering $\boldsymbol{P}_0$ are not always required to be set as exactly as prescribed. Similar results were obtained even if those parameters were 5 times greater or less than those set here. This fact means that the method does not require the fine-tuning of the parameters, and may be considered to be quite robust.

5. Conclusions

This paper presents a new speedometer method for generating an accurate estimate of the absolute speed of a vehicle from the noisy acceleration and erroneous wheel speed. The acceleration measurements may be corrupted by high frequency noise with large variance and the erroneous wheel speed measurement may include bias error due to steady state slip and the big abrupt impulsive error due to wheel slip or skid. The method based on the Kalman filtering was applied to a state variable model that relates the wheel speed, the absolute speed, the acceleration and the changes in the wheel radius. When big abrupt and non-stationary error due to slip or skid occurred, the coefficients of Kalman filter were switched to other values to reduce the estimation errors in the Kalman filtering. The validity of the method was examined and verified by computer simulations and actual laboratory model experiments. Both the simulation and experiment demonstrated the accurate estimated absolute speed even in the time interval when the slip and/or skid occurred. Furthermore, the noise in the acceleration was also cleanly filtered out. Because the *rule-based Kalman filter strategy* provides the accurate absolute speed, especially when slip and/or skid occurred, the strategy can be effectively applied to generate reference speed which can be used for anti-lock braking as well as auto-traction control systems.

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