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Estimation of Absolute Vehicle Speed using Fuzzy Logic Rule-Based Kalman Filter

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Abstract

Accurate knowledge on the absolute or true speed of a vehicle, if and when available, can be used to enhance advanced vehicle dynamics control systems such as anti-lock brake systems (ABS) and auto-traction systems (ATS) control schemes. Current conventional method uses wheel speed measurements to estimate the speed of the vehicle. As a result, indication of the vehicle speed becomes erroneous and, thus, unreliable when large slips occur between the wheels and terrain. This paper describes a fuzzy rule-based Kalman filtering technique which employs an additional accelerometer to complement the wheel-based speed sensor, and produce an accurate estimation of the true speed of a vehicle. We use the Kalman filters to deal with the noise and uncertainties in the speed and acceleration models, and fuzzy logic to tune the covariances and reset the initialization of the filter according to slip conditions detected and measurement-estimation condition. Experiments were conducted using an actual vehicle to verify the proposed strategy. Application of the fuzzy logic rule-based Kalman filter shows that *accurate estimates of the absolute speed can be achieved even under significant braking skid and traction slip conditions.*

Key words: fuzzy logic, rule-based Kalman filter, anti-lock braking, traction control system, absolute speed measurement, abrupt noise, high frequency noise

1. Introduction

A conventional speedometer computes and displays the speed of a vehicle by measuring the speed of wheel rotation and multiplying it with the nominal radius of the wheel. This approach works reasonably well when there is low slippage between the wheel and terrain, and when the actual radius of the wheel agrees closely with its nominal value. Under high slippage conditions, however, the wheel-based speedometer will not indicate the true speed of the vehicle.

Availability of accurate measurement of the absolute speed of a vehicle allows simplification and accurate implementation of anti-lock brake control law and auto-traction control system [1]. This, in turn, helps to enhance the safety of the occupant by improving the stopping distance and/or steeriability of the vehicle on low friction surfaces.

In this paper, we presents a new technique for estimating accurately the absolute speed of the vehicles using a fuzzy logic rule-based Kalman filter that is driven by a wheel-based speed sensor and an accelerometer. The accelerometer measures the acceleration of the vehicle in its forward direction and may be corrupted as well by high frequency noise. The proposed technique employs three Kalman filters to reduce high frequency noise in the acceleration measurement and errors coming from the wheel speed measurement.

More importantly, we incorporate a fuzzy rule-based strategy that switches the covariances of one of Kalman filters to compensate for wheel slippage. The fuzzy rules are based on understanding which sensor is more useful for updating the Kalman filter under slip conditions. In essence, 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. On the other hand, low acceleration measurement taken at low vehicle speed should not be fully trusted because of accelerator bias.

It is worth noting that speedometers for normal vehicles are generally implemented using: (I) Contact methods (such as wheel speed sensors), (II) Non-contact methods (such as optical reflection sensors). The contact methods which is used in the most vehicles [2] is economical and reliable, but may not be accurate when the wheel skids/slips. The non-contact method such as the optical-correlation method [3] and the spatial filtering method [4], on the other hand, is more accurate, but more expensive and less practical because of bulkiness, complexity, and frequent need for cleaning maintenance. Because of these drawbacks, accurate measurement of the actual vehicle speed remains a problem, which is worth investigating, in the automotive industry.

The concept of this paper is an alternative solution to the absolute speed estimation problem previously reported in [5]. In this paper, we simplify the estimation process by using three separate Kalman filters (as opposed to only one Kalman filter) and introduced fuzzy logic tuning rules (as opposed to Boolean logic). The new approach results in simpler Kalman filter implementation and smoother adaptation of the filter to produce a convergent estimate of the vehicle speed under different severe conditions.

2. Problem Description

2.1. Definition

For ease of reference, definitions of variables and parameters for the system model is given below:
t:time,τ:sampling interval of discrete measurement
k:discrete time index
a_t:true acceleration of vehicle
a_m:measured acceleration of vehicle (accelerometer)
a_w:wheel acceleration (transposed to linear speed)
v_t:true or absolute speed of vehicle
v_m:measured wheel speed times nominal wheel radius
v_w:actual wheel speed
n_{am}:observation noise of the acceleration
n_{vm}:observation noise of the wheel speed
n_t:observation noise of measured speed
w_{at}:system noise of the vehicle jerk $d(a_t)/dt$
w_{aw}:system noise of the wheel jerk $d(a_w)/dt$
w_{vw}:system noise of wheel speed change
w_{vt}:system noise of the speed
S_t:effect of slip/ skid in observation equation
R:covariance of n_t,Q:covariance of w_{vt}
P:covariance of $v_t - \hat{v}_t$
Estimates of $\{a_t, a_w, v_w, v_t\}$ will be represented by $\{\hat{a}_t, \hat{a}_w, \hat{v}_w, \hat{v}_t\}$. Traction slip and brake skid can be defined by

$$\lambda = \frac{v_w - v_t}{\max(v_w, v_t)} \tag{1}$$

where

$$v_w = \begin{cases} v_t/(1-\lambda) & \textit{traction slip condition} \\ v_t \cdot (1+\lambda) & \textit{brake slip condition} \end{cases} \tag{2}$$

2.2. Measurement Inaccuracies

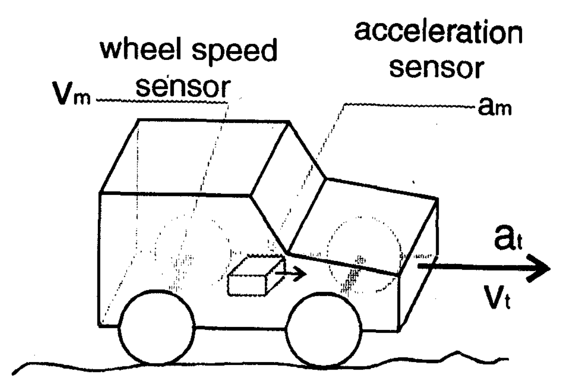

Figure 1: Measurement of speed and acceleration and speed.

Figure 1 shows the vehicle moving in the forward direction. The direction of the wheel-based speed sensor and accelerometer measurements are aligned in that direction of motion.
The wheel-based vehicle speed is obtained by multiplying the wheel rotation speed with the normal radius. Error in the speed and acceleration measurements (v_m and a_m) may be introduced by:

(E1) Accelerometer noise due to large variance high frequency noise caused by vibration.
(E2) Speedometer noise due to vehicle vibration.
(E3) Large abruptive and impulsive wheel slippage caused by abrupt acceleration, skid caused by quick braking action, and sudden encounter with low friction surface.
(E4) Radius of the wheel changing abruptly due to dynamic interaction with bumpy road/terrain.
(E5) Small but fixed variation in the wheel because of tire wear, change in tire pressure and/or change in load of the vehicle.
(E6) Normal slip condition of the wheel that occurs in the steady state driving of the vehicle.

2.3. Normal driving conditions

We assume that the following are true under normal driving conditions:

(A1) The normal slip of (E2) is small.
(A2) Noise in (E4) and (E5) are stationary Gaussian white noise with zero mean.

2.4. Problem Statement

The value of λ depends on v_m and v_t, which are the results of wheel and vehicle dynamics involving engine torque, brake torque, and wheel-terrain interactions. These dynamics are complex and cannot be easily predicted by computer simulation with high accuracy. Given all of the above conditions, our goal is to use the noisy and at times erratic measurements v_m and a_m to estimate the absolute vehicle speed v_t as accurately as possible.

3. Estimation of the Absolute Speed

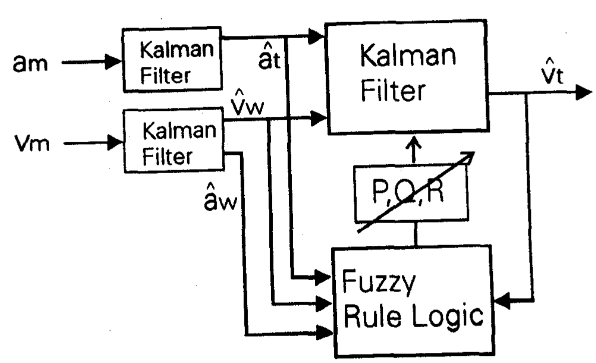

Figure 2:The Basic structure of the proposed method.

Figure 2 shows the basic scheme of the proposed strategy for estimating the absolute speed of vehicle consisting of two steady state Kalman filter that complement Fuzzy Logic-based Kalman filter (FLKF).

3.1. Kalman Filtering of Sensor

The first Kalman filter is based on the premise that the acceleration of the vehicle can be modeled by:

$$\dot{a}_t(t) = w_{at}$$
$$a_m(t) = a_t(t) + n_{am} \tag{3}$$

where w_{at} is the random "noise" input that shapes the acceleration of the vehicle and n_{at} is the measurement noise from the accelerometer.

Similarly the second KF is based on the model describing acceleration and speed of the wheel:

$$\begin{bmatrix} \dot{a}_w(t) \\ \dot{v}_w(t) \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} a_w(t) \\ v_w(t) \end{bmatrix} + \begin{bmatrix} w_{aw} \\ w_{vw} \end{bmatrix}$$
$$v_m(t) = \begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} a_w(t) \\ v_w(t) \end{bmatrix} + n_{vm} \tag{4}$$

where w_{aw} and w_{vw} represents abrupt changes in a_w and v_w, and n_{vm} is the wheel speed sensor noise. The covariances of there noise can be experimentally determined.

We assume that (3) and (4) are statistically time-invariant. Hence, standard discrete-time KF can be readily designed and implemented to produce discrete-time estimates $\hat{a}_t(k)$,$\hat{a}_w(k)$,$\hat{v}_w(k)$ of the accelerations and velocity. Since the formulation is well known [5, 8], details of DTKF will not be shown here, for the sake of brevity.

3.2. Kalman Filter Estimation of Vehicle Speed

The dynamics of the vehicle speed can be described the following equation.

$$\dot{v}_t(t) = a_t(t) \tag{5}$$

From (2), the wheel speed v_w can be related to the vehicle speed v_t via

$$v_w(t) = v_t(t) + S_t(t) \tag{6}$$

$$\text{where } S_t(t) = \begin{cases} \lambda v_w(t) & \text{traction slip} \\ \lambda v_t(t) & \text{brake slip} \end{cases}$$

represent the effect of slip or skid variations. The output relationship will be affected drastically by large changes in the slip λ.

To formulate a Kalman filter for estimating v_t, we substitute the estimates $\hat{a}_t$ and $\hat{v}_m$ into (5) and (6) and obtain the approximate dynamic model:

$$\dot{v}_t = \hat{a}_t + w_{vt}(t)$$
$$\hat{v}_w(t) = v_t(t) + n_t(t) \tag{7}$$

where $n_t(t) = S_t(t) + n_{vt}(t)$, and w_{vt} account for discrepancies due to the approximation. We will treat w_{vt} and n_t as "system noise" and "measurement noise", respectively. Furthermore, we assume that they are zero-mean independent Gaussian noise with covariances given by $Q(t)$ and $R(t)$, respectively.

Application of discrete-time Kalman filter to (7) yields the estimates $\hat{v}_t$ as follows (referred to as vehicle speed Kalman filter):

$$\hat{v}_t(k+1) = \hat{v}_t(k) +$$
$$\tau\hat{a}_t(k) + P(k+1)R^{-1}(k+1)\{\hat{v}_m(k+1) - \hat{v}_t(k)\}$$
$$\hat{v}_t(0) = \hat{v}_0 \tag{8}$$

where $P(k)$ is the covariance of the error between and $\hat{v}_t(k)$ and $v_t(k)$ which is calculated from

$$P(k) = M(k) - \frac{M^2(k)}{M(k) + R(k)}$$
$$P(0) = P_0$$
$$M(k) = P(k-1) + \tau^2 Q(k-1) \tag{9}$$

Under normal driving conditions (assumptions (A1) and (A2)), the Kalman filter (8) and (9) can accurately estimate the absolute speed in the presence of the errors mentioned in (E1) and (E2). The estimates $\hat{v}_t(k)$ will converges very closely to $v_t(k)$ as $k \to \infty$, under appropriate choice of constant covariances P, Q and R.

However, the Kalman filter will not converge as readily (1) when abruptive and/or large skid or slip occurs (2) when undesired bias in accelerator signal becomes a dominant factor at low speed, and/or (3) when signal-to-noise ratios in speed measurement become unacceptably low. For the estimate $\hat{v}_t(k)$ to converge the true speed $v_t(k)$ in the optimal sense of Kalman filtering, the covariances $P(k)$, $Q(k)$ and $R(k)$ must be carefully chosen and adjusted. We address there problems through the use of fuzzy logic as follows.

3.3. Fuzzy Rule for Adjusting the Coefficients of the Vehicle Speed Kalman Filter

The covariances will be adjusted according to the following simple rules based on understanding of the slip/skid phenomena and limitation of the sensors. By choosing $P(k)$, $Q(k)$ and $R(k)$ appropriately, the effect of error due to the slip and/or skid and sensor inaccuracies are removed by the Kalman filtering process. The fuzzy rules are as follows:

Tuning of R to handle skid or slip conditions.

Occurrence of skid or slip can be easily discriminated from the measurements and the estimates by the difference between $\hat{v}_w$ and $\hat{v}_t$ and also between $\hat{a}_w$ and $\hat{a}_t$. In the situations when the measurement $|\hat{v}_w - \hat{v}_t|$ and $|\hat{a}_w - \hat{a}_t|$ have large values, the Kalman filtering (8) and (9) is carried out with heavier reliance on the acceleration signal and smaller confidence in the wheel speed signal. For example, this basic idea can be described by the following fuzzy rules:

if $\lvert\hat{v}_w - \hat{v}_t\rvert$ is S and $\lvert\hat{a}_w - \hat{a}_t\rvert$ is S *then* R is S
if $\lvert\hat{v}_w - \hat{v}_t\rvert$ is S and $\lvert\hat{a}_w - \hat{a}_t\rvert$ is M *then* R is M
if $\lvert\hat{v}_w - \hat{v}_t\rvert$ is S and $\lvert\hat{a}_w - \hat{a}_t\rvert$ is L *then* R is L
if $\lvert\hat{v}_w - \hat{v}_t\rvert$ is M and $\lvert\hat{a}_w - \hat{a}_t\rvert$ is S *then* R is M
if $\lvert\hat{v}_w - \hat{v}_t\rvert$ is M and $\lvert\hat{a}_w - \hat{a}_t\rvert$ is M *then* R is L
if $\lvert\hat{v}_w - \hat{v}_t\rvert$ is M and $\lvert\hat{a}_w - \hat{a}_t\rvert$ is L *then* R is L
if $\lvert\hat{v}_w - \hat{v}_t\rvert$ is L and $\lvert\hat{a}_w - \hat{a}_t\rvert$ is S *then* R is M
if $\lvert\hat{v}_w - \hat{v}_t\rvert$ is L and $\lvert\hat{a}_t - \hat{a}_t\rvert$ is M *then* R is L
if $\lvert\hat{v}_w - \hat{v}_t\rvert$ is L and $\lvert\hat{a}_t - \hat{a}_t\rvert$ is L *then* R is L

where S,M and L generically denote small, medium and large fuzzy values in each of the fuzzy variable domain.

Tuning of Q to accommodate offset of accelerometer.
When a vehicle speed is slow, acceleration sensor output may not accurate because of low signal to noise ratio and bias offset. In such a case, Kalman filtering is carried out with heavy reliance on the wheel speed and small confidence in the acceleration signal. For example, the fuzzy rules:

if $\hat{v}_m$ is Small and $\lvert\hat{a}_t\rvert$ is Small *then* Q is Large
if $\hat{v}_m$ is Large and $\lvert\hat{a}_t\rvert$ is Small *then* Q is Small
if $\lvert\hat{a}_t\rvert$ is Large *then* Q is Small

where Small and Large are fuzzy values defined for each of the fuzzy variables.

Resetting P and bounding $\hat{v}_t$ to improve estimation convergence.
A vehicle moving forward cannot have a negative speed. Measurement noise, however, may occasionally produce negative speed estimates, especially when the vehicle is moving at low speed. In this low signal to noise situation, 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 P to the initial values P_0.

$$if\ \hat{v}_t < 0\ then\ \hat{v}_t = 0 \text{ and } P = P_0$$

4. Experimental Results

4.1. Experimental Procedures

We verified the strategy described above by conducting a series of experiments using an actual rear drive vehicle (SKYLINE GTS by Nissan Corp.). The speed of vehicle was monitored by two wheel based speed sensors; one is mounted in one of the front wheels and the other is one of the rear.
The accelerometer was set on the center of rear stabilizer. The accelerometer was piezo-resistive type sensor (ICSensors Model 3145-002) whose output range is ±2G, frequency range is DC∼220Hz, sensitivity is 100mV/G, resonance frequency is 1.12kHz and transverse sensitivity is 1.0±%Span.
In the experiments, locking of wheels was effected by using the parking brake to induce brake skid condition. Traction slip condition was generated by flooring the acceleration pedal. The rear wheel wheel-based speed measurement v_m, which contains errors described in (E1) through (E6).
To produce a reference for comparison, the true speed v_t of vehicle was calculated from the front wheel speed sensor. Note that front wheels will not skid when the parking brake is applied. Nor will it slip when acceleration pedal is applied excessively. Thus, using the front wheel to generate a speed reference v_t is valid under the test procedure described.
The parameters of the experimental system are determined to be:
Sampling interval of A/D conversion : 0.0025 sec

1st Kalman Filter
Covariance of initial estimated error $\hat{a}_t$: 1
Covariance of the system noise w_{at} : 4300
Covariance of the acceleration noise n_{am}: 11
Covariance of the speed noise n_{vm}: 0.005

2nd Kalman Filter
Covariance of initial estimated error $\hat{a}_w$: 1
Covariance of initial estimated error $\hat{v}_w$: 1
Covariance of the system noise w_{aw} : 100
Covariance of the system noise w_{vw} : 0.01
Covariance of the speed sensor noise n_{vm}: 0.05

3rd Kalman Filter
Variance of initial estimated error v_t: P_0=1
Normal covariance of for system noise w_{vt}:Q = 0.05
Normal covariance of for measurement output n_t:R = 0.05

4.2. Experimental results

Experiments were carried out with the vehicle running over a flat road. Extremely promising experimental results were obtained. We present four illustrative experiments to demonstrate the effectively of the proposed FLKF. They are:

(Expt.1) Normal Acceleration and Deceleration.(Fig.3)
(Expt.2) Traction Slip via Full Throttling.(Fig.4)
(Expt.3) Brake Skid via Sudden Braking.(Fig.5)
(Expt.4) Traction Slip followed by Brake Skid.(Fig.6)

Figure (3) through (6) display four similar sets of subplots for comparison there experiments. Subplots (a) in Figure(3) through (6) show the measured accelerations (a_m) which clearly contain high frequency sensor noise. Subplots (c) shows the result of the first KF output ($\hat{a}_t$) where significant sensor noise have been removed, in all the cases.
Similarly, subplot(b) shows the measured wheel speed (v_m) which also contain high frequency sensor noise. Subplots (d) and (e) show the smooth results of the second KF outputs ($\hat{v}_w$) and ($\hat{a}_w$), respectively.
Subplots(f) shows the results ($\hat{v}_t$) of the vehicle speed FLKF along with the measured reference v_t. We also include v_m for comparison. Examination of subplots (f) for all the four cases show that the FLKF produces excellent estimates of the true speed in spite of the drastic dynamic slip and skid, and poor signal-to-noise sensor information. Subplots(g) and (h) shows how the FL tuning rules came into effect by adjusting the covariances P, Q and R to accommodate the drastic wheel slip/skid dynamics and discriminate against unreliable sensor information.

5. Conclusions

This paper describes a new method for generating an accurate estimate of the absolute speed of a vehicle from noisy acceleration and erroneous wheel speed information. The method uses two simple Kalman filters and one fuzzy logic rule-based KF to handle abrupt wheel skid and slip, and poor signal-to-noise sensor data. The validity of the method verified by experiments using data from an actual vehicle. The experiments demonstrates that accurate estimate of the vehicle absolute speed can be obtained even under heavy slip and skid condition, and corrupted sensor noise. Based on the results obtained we conclude that FLKF provide a simple and effective mean to estimate the absolute speed of vehicle, without resorting to complicated dynamics analysis. Further work and experiments are being carried out to refine the concept and technique for all wheel drive vehicles.

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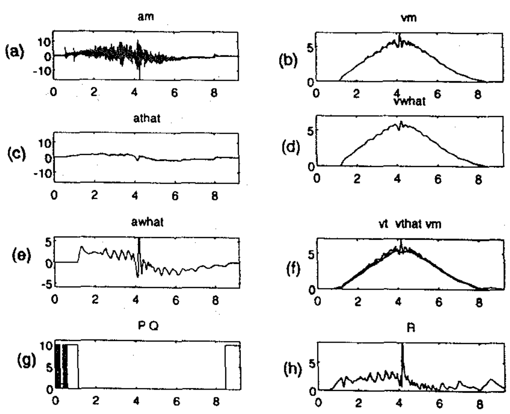

Figure 3 Normal Acceleration and Deceleration.

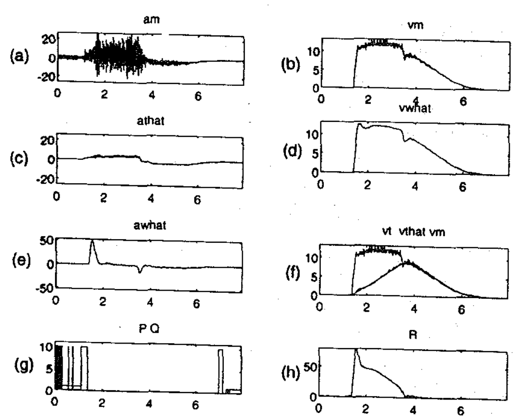

Figure 4 Traction Slip via Full Throttling.

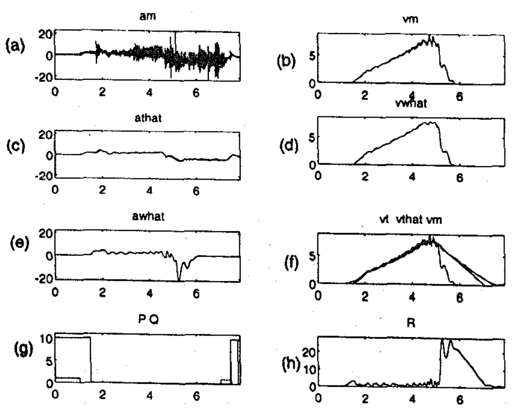

Figure 5 Brake Skid via Sudden Braking.

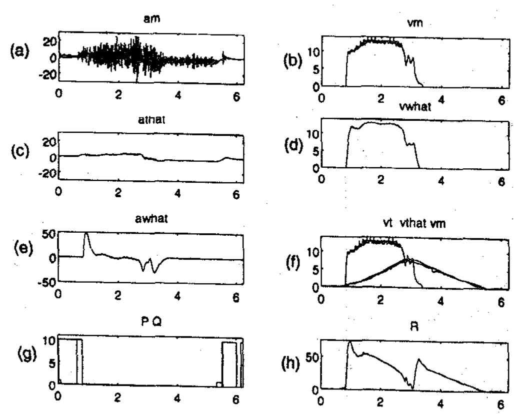

Figure 6 Traction Slip followed by Brake Skid.