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Leading Vehicle State Estimator for Adaptive Cruise Control and Vehicle Tracking

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Abstract

Leading vehicle states are useful and essential elements in adaptive cruise control (ACC) system, collision warning (CW) and collision avoidance (CA) system, and automated highway system (AHS). There are many approaches in ACC using Kalman filter. Mostly only distance to leading vehicle and velocity difference are estimated and used for the above systems. Applications in road vehicle in curved road need to obtain more informations such as yaw angle, steering angle which can be estimated using vision system. Since vision system is not robust to environment change, we used Kalman filter to estimate distance, velocity, yaw angle, and steering angle. Application to active tracking of target vehicle is shown.

1. Introduction

The problem of estimating nonlinear system states and parameters have over the past years attracted much attention and a number of different approaches have been proposed, including the extended Kalman filter (EKF) [2], nonlinear observers [3], and numerical solution scheme [4].

Ray described a 17 state extended Kalman filter for the estimation of tire longitudinal and lateral forces, vehicle longitudinal velocity, lateral velocity, and yaw rate. While this provides comprehensive information, and is only dependent on two vehicle parameters (vehicle mass, and vehicle yaw moment of inertia), it only achieves this at great computational expense [1].

Araki used Kalman filter to estimate preceding vehicle's driving state. A correction method of velocity and acceleration, high gain for large estimation error, is used for fast convergence to real value.

In this paper, various vehicle states are estimated using simple vehicle dynamics with less computational burden than Ray's approach [1]. Estimated vehicle states are used to track actively leading target vehicle set by criterion of application.

In the simulation environment, host vehicle has rotary laser scanning sensor / mm-wave radar which actively track target vehicle in curved road. This kind of tracking has useful advantages in advanced vehicle control. Active leading vehicle tracking may reduce false alarm in CW system, false braking in CA system, false acceleration in ACC system.

This paper is organized as follows: in section 2 single track vehicle dynamics is considered. In section 3 extended Kalman filter implementation is showed. Section 4 proposes one of applications using leading vehicle states, vehicle tracking using rotary range sensor. Simulation results and conclusions are drawn.

2. Problem Formulation

We simplified vehicle model as single track model to implement Kalman filter estimating leading vehicle states such as velocity, acceleration, etc.. Single track vehicle model assumed that vehicle drives with constant velocity and small side slip angle. This model is assumed to be valid for normal operation on highways [6].

$$\dot{x} = v\cos(\Psi + \beta) \quad (1)$$

$$\dot{y} = v\sin(\Psi + \beta) \quad (2)$$

$$\dot{\beta} + r = \frac{c_r + c_f}{mv}\beta + \frac{c_r l_r - c_f l_f}{mv^2} r + \frac{c_f}{mv}\delta_f \quad (3)$$

$$\dot{\Psi} = r \quad (4)$$

$$\dot{r} = \frac{c_r l_r - c_f l_f}{J}\beta + \frac{-(c_r l_r^2 + c_f l_f^2)}{Jv} r + \frac{c_f l_f}{J}\delta_f \quad (5)$$

From the above vehicle dynamic equation, we set up new state variables, plant model and measurement model to a Kalman filter for AICC operation.

Let plant model, measurement model, and

corresponding noise model be of the following form:

$$\dot{x} = f(x(t), t) + w(t) \quad (6)$$

$$z(t) = h(x(t), t) + \nu(t) \quad (7)$$

$$E\langle w(t) \rangle = 0 \quad (8)$$

$$E\langle w(t) w^T(s) \rangle = \delta(t-s) Q(t) \quad (9)$$

$$E\langle \nu(t) \rangle = 0 \quad (10)$$

$$E\langle \nu(t) \nu^T(s) \rangle = \delta(t-s) R(t) \quad (11)$$

where

$$x(t) = [p_x(t), p_y(t), V(t), a(t), \beta(t), \Psi(t), r(t), \delta_f(t)]^T$$

$[p_x(t), p_y(t)]$ is the relative vehicle position of a leading vehicle on host vehicle coordinate system.

$[V, a, \beta, \Psi, r, \delta_f]$ is velocity, acceleration, side slip angle, yaw rate, yaw angle, steering angle of a leading vehicle on global coordinate system.

Assuming that host vehicle drives with no acceleration plant model is

$$\dot{p}_x = V\cos(\Psi + \beta) - V_h + w_{p_x}$$
$$\dot{p}_y = V\sin(\Psi + \beta) + w_{p_y}$$
$$\dot{V} = a + w_V$$
$$\dot{a} = 0 + w_a$$
$$\dot{\beta} = \frac{c_r + c_f}{mV}\beta + \left(\frac{c_r l_r - c_f l_f}{mV^2} - 1\right) r + \frac{c_f}{mV}\delta_f + w_\beta$$
$$\dot{\Psi} = r + w_\Psi$$
$$\dot{r} = \frac{c_r l_r - c_f l_f}{J}\beta + \frac{-(c_r l_r^2 + c_f l_f^2)}{JV} r + \frac{c_f l_f}{J}\delta_f + w_r$$
$$\dot{\delta}_f = 0 + w_{\delta_f}$$

where V_h is host vehicle velocity.

Measurement model is

$$l_x = p_x + \nu_{l_x}$$
$$l_y = p_y + \nu_{l_y}$$

Vehicle parameters are shown in Table 1 [5].

Table 1 Simplified Vehicle Model Parameters

Parameters	Values
Mass (m)	1249 Kg
Yaw Inertia (J)	1627 Kgm^2
Distance to front axle from car COG(l_f)	1.0 m
Distance to rear axle from car COG(l_r)	1.45 m
Front cornering stiffness (C_f)	3060 Kg/rad
Rear cornering stiffness(C_r)	4437 Kg/rad

3. Kalman Filter Implementation

After discretization, Jacobian is constructed.

Plant Model: Constant Acceleration Model

$$p_{xk} = p_{xk-1} + (V_{k-1}\cos(\Psi_{k-1} + \beta_{k-1}) - V_{hk-1})T + w_p = f_1(x_{k-1}) + w_{p_x}$$

$$\frac{\partial f_1}{\partial x} = [\,1, 0, \cos(\Psi_{k-1} + \beta_{k-1})T, 0, -V_{k-1}\sin(\Psi_{k-1} + \beta_{k-1})T, -V_{k-1}\sin(\Psi_{k-1} + \beta_{k-1})T, 0, 0]$$

$$p_{yk} = p_{yk-1} + (V_{k-1}\sin(\Psi_{k-1} + \beta_{k-1}))T + w_{p_y} = f_2(x_{k-1}) + w_{p_y}$$

$$\frac{\partial f_2}{\partial x} = [\,0, 1, \sin(\Psi_{k-1} + \beta_{k-1})T, 0, V_{k-1}\cos(\Psi_{k-1} + \beta_{k-1})T, V_{k-1}\cos(\Psi_{k-1} + \beta_{k-1})T, 0, 0]$$

$$V_k = V_{k-1} + a_{k-1}T + w_V = f_3(x_{k-1}) + w_V$$

$$\frac{\partial f_3}{\partial x} = [0, 0, 1, T, 0, 0, 0, 0]$$

$$a_k = a_{k-1} + w_a = f_4(x_{k-1}) + w_a$$

$$\frac{\partial f_4}{\partial x} = [0, 0, 0, 1, 0, 0, 0, 0]$$

$$\beta_k = \beta_{k-1} + \left(\frac{c_r + c_f}{mV_{k-1}}\beta_{k-1} + \left(\frac{c_r l_r - c_f l_f}{mV_{k-1}^2} - 1\right) r_{k-1} + \frac{c_f}{mV_{k-1}}\delta_{fk-1}\right)T + w_\beta = f_5(x_{k-1}) + w_\beta$$

$$\frac{\partial f_5}{\partial x} = [\,0, 0, \partial f_5/\partial x_3, 0, 1 + \frac{c_r + c_f}{mV_{k-1}}T, 0, \left(\frac{c_r l_r - c_f l_f}{mV_{k-1}^2} - 1\right)T, \frac{c_f}{mV_{k-1}}T]$$

where

$$\frac{\partial f_5}{\partial x_3} = \left(-\frac{c_r + c_f}{mV_{k-1}^2}\beta_{k-1} - 2\left(\frac{c_r l_r - c_f l_f}{mV_{k-1}^3}\right) r_{k-1} - \frac{c_f}{mV_{k-1}^2}\delta_{fk-1}\right)T$$

$$\Psi_k = \Psi_{k-1} + r_{k-1}T + w_\Psi = f_6(x_{k-1}) + w_\Psi$$

$$\frac{\partial f_6}{\partial x} = [0, 0, 0, 0, 0, 0, 1, T, 0]$$

$$r_k = r_{k-1} + \left(\frac{c_r l_r - c_f l_f}{J}\beta_{k-1} + \frac{-(c_r l_r^2 + c_f l_f^2)}{JV_{k-1}} r_{k-1} + \frac{c_f l_f}{J}\delta_{fk-1}\right)T + w_r = f_7(x_{k-1}) + w_r$$

$$\frac{\partial f_7}{\partial x} = [\,0, 0, \left(\frac{cr l_r^2 + c_f l_f^2}{JV_{k-1}^2} r_{k-1}\right)T, 0, \frac{c_r l_r - c_f l_f}{J}T, 0, 1 - \frac{c_r l_r^2 + c_f l_f^2}{JV_{k-1}}T, \frac{c_f l_f}{J}T]$$

$$\delta_{fk} = \delta_{fk-1} + w_{\delta_f} = f_8(x_{k-1}) + w_{\delta_f}$$

$$\frac{\partial f_8}{\partial x} = [0,0,0,0,0,0,0,1]$$

where T is sampling time.

Measurement Model: Range Sensor (Laser Scanning Sensor or mm-wave Radar)

$$l_{xk} = p_{xk} + \nu_{l_x} = h_1(x_k) + \nu_{l_x}$$

$$\frac{\partial h_1}{\partial x} = [1,0,0,0,0,0,0,0]$$

$$l_{yk} = p_{yk} + \nu_{l_y} = h_2(x_k) + \nu_{l_y}$$

$$\frac{\partial h_2}{\partial x} = [0,1,0,0,0,0,0,0]$$

Kalman Filter

Kalman filter recursive equations are as follows:

$$\widehat{x_{0|0}} = x_0, \quad P_{0|0} = P_0$$

for k=1,2,3...

$$F_{k-1} = \left.\frac{\partial f(x,k-1)}{\partial x}\right|_{x=\widehat{x_{k-1|k-1}}}$$

$$H_k = \left.\frac{\partial h(x,k)}{\partial x}\right|_{x=\widehat{x_{k|k-1}}}$$

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1})$$

$$P_{k|k-1} = F_{k-1}P_{k-1|k-1}F_{k-1}^T + Q$$

$$R_{ek} = R + H_k P_{k|k-1} H_k^T$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + P_{k|k-1}H_k^T R_{ek}^{-1}[h(\hat{x}_{k|k-1}) - H_k \hat{x}_{k|k-1}]$$

$$P_{k|k} = P_{k|k-1} - P_{k|k-1}H_k^T R_{ek}^{-1} H_k P_{k|k-1}$$

end

4. Application to Adaptive Cruise Control and Vehicle Tracking

Adaptive Cruise Control

ACC system is the improved version of conventional cruise control. Beside maintaining the constant vehicle speed set by driver, the headway is detected by range sensor and adjusted by automatically controlled throttle and brake system.

Most range sensor, laser scanning sensor or mm-wave radar, has small detection aperture due to cost, and difficulty in object detection and signal processing arising in the case of wide opening.

In curved road, small aperture of range sensor misses leading vehicle's lateral motion. A missing leading vehicle of situation informs ACC system of safe headway distance so that acceleration command fire to achieve desired vehicle speed. This is a disadvantage of conventional ACC system.

Active Vehicle Tracking System

Assume that range sensor has detection aperture $\theta = 20^\circ$. This sensor can detect vehicles having $\pm 10^\circ$ offsets from host vehicle.

Road shape is assumed with

$$y = \frac{k_1}{2}\left(\tanh\left(\frac{6}{k_2}x - 3\right) + 1\right)$$ where k_1, k_2 is curve ratio.

Range sensor is assumed to be rotary, so that range sensor is controlled to track leading target vehicle. Rotation(ϕ) range of sensor is constrained between $-\theta/2$ and $+\theta/2$ so that direct front view part from the vehicle can be visible in any case of situation. Rotation angle θ can be obtained with negligible error range if we use stepping motor to control rotary part. Kalman filter discussed in section 3 can be used if measurement model changed in the following form:

$$l_{xk} = p_{xk}\cos\theta - p_{yk}\sin\theta + \nu_{l_x} = h_1(x_k) + \nu_{l_x}$$

$$\frac{\partial h_1}{\partial x} = [\cos\theta, -\sin\theta, 0,0,0,0,0,0]$$

$$l_{yk} = p_{xk}\sin\theta + p_{yk}\cos\theta + \nu_{l_y} = h_2(x_k) + \nu_{l_y}$$

$$\frac{\partial h_2}{\partial x} = [\sin\theta, \cos\theta, 0,0,0,0,0,0]$$

Simulation Results

Figure 1 shows the estimation results of vehicle speed and acceleration. Vehicle acceleration command is applied fictitiously. Since Kalman filter assumed that constant velocity model, acceleration estimation has some settling time although velocity estimation shows good result, which is good enough to be applied in ACC, CW/CA system.

Figure 2 shows the estimation results of vehicle side slip angle, yaw angle, and steering angle. Although steering angle and slide slip angle shows delayed response, yaw angle estimation result is smooth and reliable so that it can be used to fusion vision data to obtain road geometry measurement for ACC, CW/CA system.

5. Conclusions

Vehicle states, relative position, velocity, acceleration, yaw angle, and steering angle are estimated using extended Kalman filter with simplified single track vehicle dynamics. Estimated vehicle states are used to track actively leading target vehicle set by criterion of application.

From the simulation environment, host vehicle has rotary laser scanning sensor / mm-wave radar which actively track target vehicle in curved road. This kind of tracking has useful advantages in advanced vehicle control. Active leading vehicle tracking may reduce false alarm in CW system, false braking in CA system, false acceleration in ACC system.

With this result, we are now research on target vehicle recognition algorithm for ACC system, CW/CA system. Moreover Kalman filter with adaptive learning algorithm applied to road vehicle is under our focus.

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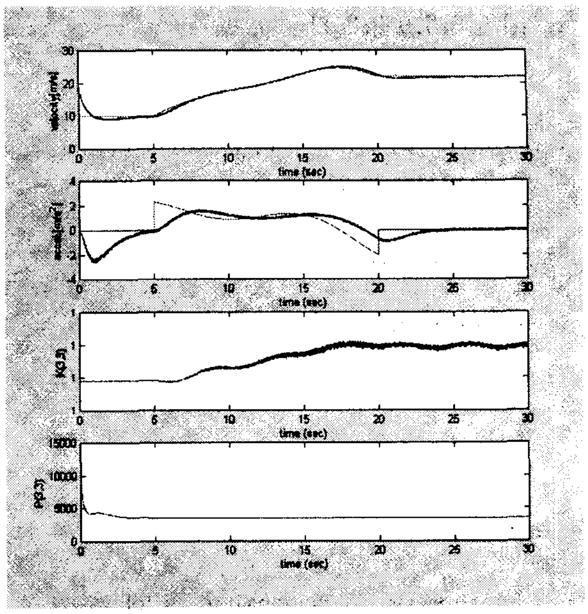

Figure 12 Vehicle Velocity and Acceleration Estimation

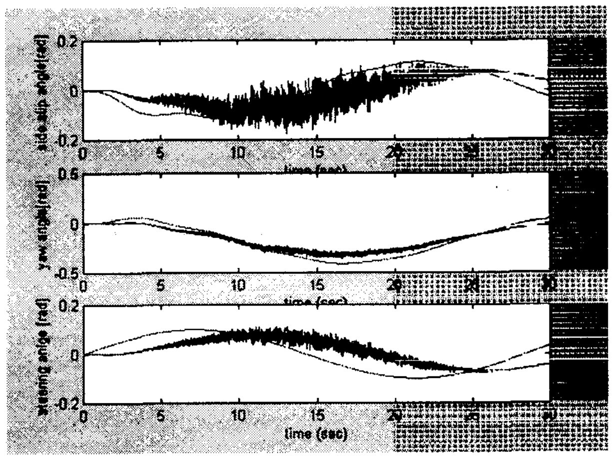

Figure 13 Estimation of side slip angle, yaw angle, and steering angle