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Application of adaptive Kalman filter in vehicle laser Doppler velocimetry

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A B S T R A C T

Due to the variation of road conditions and motor characteristics of vehicle, great root-mean-square (rms) error and outliers would be caused. Application of Kalman filter in laser Doppler velocimetry(LDV) is important to improve the velocity measurement accuracy. In this paper, the state-space model is built by using current statistical model. A strategy containing two steps is adopted to make the filter adaptive and robust. First, the acceleration variance is adaptively adjusted by using the difference of predictive observation and measured observation. Second, the outliers would be identified and the measured noise variance would be adjusted according to the orthogonal property of innovation to reduce the impaction of outliers. The laboratory rotating table experiments show that adaptive Kalman filter greatly reduces the rms error from 0.59 cm/s to 0.22 cm/s and has eliminated all the outliers. Road experiments compared with a microwave radar show that the rms error of LDV is 0.0218 m/s, and it proves that the adaptive Kalman filtering is suitable for vehicle speed signal processing.

1. Introduction

With fast development of modern technology, vehicle velocity measurement with high precision and reliability is expected, especially in the fields like long-endurance high-precision self-contained vehicle navigation, vehicle dynamic control, and vehicle speed metrology [1,2]. The traditional speedometers of vehicle include odometer, microwave radar, global positioning system (GPS), inertial navigation system (INS) and so on. However, all of these speedometers have their own disadvantages, for example, not only slide but also thermal expansion or contraction may cause great error in odometer. The beam width of microwave radar limits further improvement of accuracy. Velocity measurement error would accumulate by time in INS, and GPS is poor in autonomy [3,4]. Laser Doppler velocimetry (LDV) is one of the most precise instruments for velocity measurement based on Doppler effects of laser. Due to its advantages of high precision and resolution, LDV or LDV aided system is thought to be an effective solution to these problems [5,6]. Signal processing is key for LDV. As there are several reasons that the random error and outliers would be generated in practical applications, Kalman filter is a common method to reduce their impacts. It gives the unbiased optimal estimation and is widely used in navigation, system control, data fusion, speed and target tracking, and so on.

However, in the application of vehicle velocity measurement, traditional Kalman filter is unable to achieve satisfactory performance as it is built in linear model and non-adaptive. In order to improve the velocity measurement accuracy, study on the adaptive Kalman filter in vehicle LDV is required. Many researchers have conducted in-depth studies in related area. Wenzel [7] proposes a dual extended Kalman filter, which is formed by two Kalman filters running in parallel as a model-based vehicle velocity estimator. Papic [8] gives an approach of window width adaptation based on adaptive Doppler Kalman filter for radar systems to minimize the estimation error. Chang Guobin [9] introduces an adaptive Kalman filter algorithm with both adaptive and robust in theory, and numerical simulations are done. Bao Han [10] uses adaptive Kalman filter for integrated sensor to estimate the motion state of intelligent vehicle. Gao Siwei [11] proposes a multi-sensory joint adaptive Kalman filter through extending innovation-based adaptive estimation to estimate the motion state of the moving vehicles ahead.

In this work, the state space model is established based on the current state model, and the methods to adaptively adjust the acceleration variance and observation noise variance are given. Application and performance of adaptive Kalman filter in measuring the velocity of vehicle are researched through laboratory and road experiments.

2. Basic principle

The configuration of vehicle laser Doppler velocimetry is schematically depicted in Fig. 1. It uses a homodyne all fiber coherent Doppler

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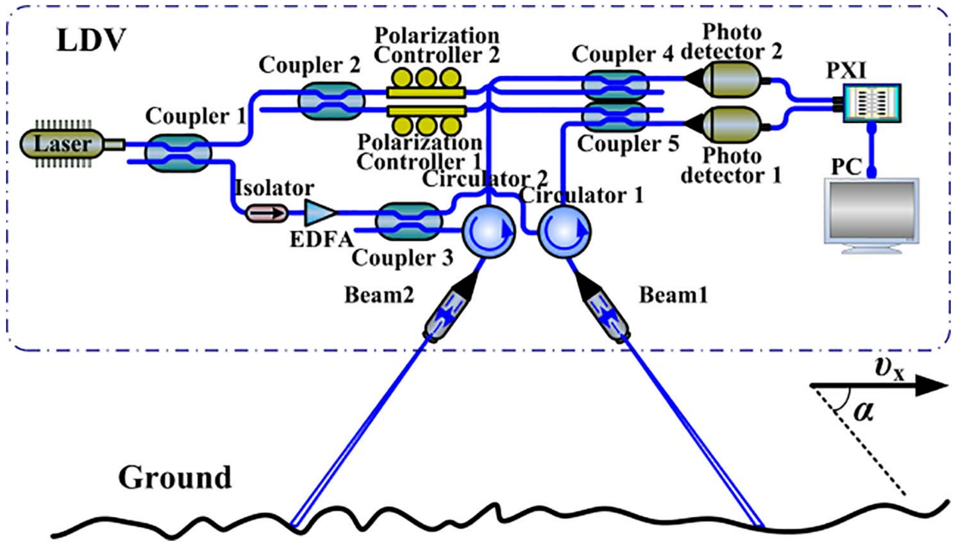

Fig. 1. Diagram of vehicle laser Doppler velocimetry.

lidar, in which a narrow linewidth laser with long coherent distance serves transmitted signal and local oscillator (LO) signal. Each signal is divided into two parts by a coupler to form a Mach-Zehnder interferometer. The transmitted signals are emitted to the ground with a certain inclination angle, and the returned signals received by antennas are shifted in frequency due to the Doppler effect produced by the relative motion. The received signals and the LO signals are combined at the photodetectors, then high-speed data acquisition (eg. PXI, PCI extensions for instrumentation) system and frequency abstraction algorithm are applied to obtain the Doppler frequency. The relative velocity of the vehicle with respect to the laser wavelength λ, obeys the relationship

$$v = \lambda(f_{d1}-f_{d2})/(4\cos\theta), \tag{1}$$

where f_{d1} and f_{d2} is the Doppler frequency of beam 1 and beam 2 respectively, and θ, complement of beam pointing angle α, is the angle between the line of sight and the velocity ahead.

3. Adaptive Kalman filter

3.1. State space model

As the movement of vehicle may be very complex and temporary high intensity maneuvers may occur, state space model becomes important to improve the performance of Kalman filter. In this work, current statistical model (CSM) is applied, which describes the random vehicle acceleration as a modified Rayleigh-Markov process and is sensitive to the maneuvers [8]. Then the movement of vehicle can be expressed as

$$\dot{v}(t) = \bar{a}(t) + a(t) \tag{2}$$

$$\dot{a}(t) = -\alpha\cdot a(t) + w(t) \tag{3}$$

where $\dot{v}(t)$ is the acceleration of vehicle. $\bar{a}(t)$ is the average of the acceleration and is constant in one sampling period. $a(t)$ is zero-mean acceleration noise. α is maneuvering frequency. $w(t)$ is zero-mean white noise, and its variance is $\sigma_w^2 = 2\alpha\sigma_a^2$, where σ_a^2 is the variance of acceleration. Assuming that T is sampling interval, the state space model of Kalman filter after discretization can be written as

$$X(k+1) = \Phi\cdot X(k) + U\cdot\bar{a}(k) + W(k) \tag{4}$$

$$Y(k) = H\cdot X(k) + e(k) \tag{5}$$

where

$X(k) = \begin{bmatrix} \dot{v}(k) \\ v(k) \end{bmatrix}$, and it is the state vector.

$\Phi = \begin{bmatrix} 1 & [1-e^{-\alpha T}]/\alpha \\ 0 & e^{-\alpha T} \end{bmatrix}$, and it is the state transfer matrix.

$U = [T-[1-e^{-\alpha T}]/\alpha \quad 1-e^{-\alpha T}]$, and it is the input control matrix.

$H = [1 \quad 0]$, and it is the measurement matrix.

$W(k)$ is the zero-mean state noise, and its variance is $Q(k)$, which can be expressed as

$$Q(k) = 2\alpha\cdot \sigma_a^2 \begin{bmatrix} (4e^{-\alpha T}-3-e^{-2\alpha T}+2\alpha T)/(2\alpha^3) & (e^{-2\alpha T}+1-2e^{-\alpha T})/(2\alpha^2) \\ (e^{-2\alpha T}+1-2e^{-\alpha T})/(2\alpha^2) & (1-e^{-2\alpha T})/(2\alpha) \end{bmatrix}.$$

$Y(k)$ is the measured matrix.

$e(k)$ is zero-mean measurement noise, and its variance is $R(k)$.

The Kalman filtering equations are given by:

$$\begin{cases} X(k+1\,|k) = \Phi X(k\,|k) + U\bar{a}(k) \\ X(k+1\,|k+1) = X(k+1\,|k) + K[Y(k+1)-HX(k+1\,|k)] \\ K = P(k+1\,|k)H^T[HP(k+1\,|k)H^T + R(k+1)]^{-1} \\ P(k+1\,|k) = \Phi P(k\,|k)\Phi^T + Q(k) \\ P(k+1\,|k+1) = P(k+1\,|k)(I-KH) \end{cases} \tag{6}$$

where K is the filter gain matrix, $P(k+1\,|k)$ is the state predicting covariance matrix, and $P(k+1\,|k+1)$ is the new state covariance matrix.

Maneuvering frequency α is important, and many researches on it have been done. However, most of them are in theory and difficult to put into practical applications, and the results of some researches show that adaptive adjustment of α would easily cause instability and divergence. So in CSM, α is usually determined by experience, and it is better in the range from 0 to 1.

3.2. Adaptive adjustment of acceleration variance

In this state space model, σ_a^2 is a time-dependent parameter and has great impact on the performance of the filter. If it is set as a constant, large tracking error would be generated. According to the characteristics of maneuvers, it is thought in the traditional adaptive method that σ_a^2 follows the modified Rayleigh distribution and is in a range between σ_{min}^2 and σ_{max}^2, where σ_{min}^2 and σ_{max}^2 represents the minimum and maximum of σ_a^2 respectively [12]. It does well when there are strong maneuvers, but it costs a loss of filter performance when the maneuvers