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A robust observer based on energy-to-peak filtering in combination with neural networks for parameter varying systems and its application to vehicle roll angle estimation☆

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ABSTRACT

This paper presents a robust observer based on energy-to-peak filtering in combination with a neural network for vehicle roll angle estimation. Energy-to-peak filtering estimates the minimised error for any bounded energy disturbance. The neural network acts as a 'pseudo-sensor' to estimate a vehicle 'pseudo-roll angle', which is used as the input for the energy-to-peak-based observer. The advantages of the proposed observer are as follows. 1) It does not require GPS information to be utilised in various environments. 2) It uses information obtained from sensors that are installed in current vehicles, such as accelerometers and rate sensors. 3) It reduces computation time by avoiding the calculation of observer gain at each time sample and utilising a simplified vehicle model. 4) It considers the uncertainties in parameters of the vehicle model. 5) It reduces the effect of disturbances. Both simulation and experimental results demonstrate the effectiveness of the proposed observer.

1. Introduction

Currently, rollover accidents account for approximately 33% of all motor vehicle deaths [1]. To reduce the occurrence of this type of accident is one of the main objectives in the design of vehicle control systems [2]. Vehicle control systems that aim to improve vehicle rollover behaviour are called roll stability control (RSC) systems.

The majority of RSC systems require knowledge of vehicle roll angle to calculate lateral load transfer and properly coordinate control systems. Vehicle roll angle can be directly measured using a GPS dual-antenna. The disadvantage of this technique is that it is very costly. For this reason, vehicle roll angle should be estimated.

However, the estimation of vehicle roll angle must be performed in real time using the sensors installed on-board in current vehicles to achieve acceptable RSC controller performance [3].

In [4] and [5], GPS information was fused with information obtained from sensors installed in vehicles, such as inertial navigation system (INS) sensors, wheel speed sensors, and steering angle sensors.

The problem with using GPS is the difficulty in achieving accurate readings because of the limited visibility of satellites in both urban and forested driving environments. In [6], vehicle roll angle was estimated using information from suspension deflection sensors and a lateral accelerometer. However, this technique does not provide accurate results [7] and is very costly because the required sensors are typically not installed in vehicles.

In [8], a dynamic vehicle roll angle observer that fuses information obtained from a lateral accelerometer and gyroscope was designed. However, the drawback of this algorithm is that the estimated vehicle roll angle transient response contains a crucial error.

A common method used to fuse information from different sensors is the Kalman filter. In [7,9–11], a Kalman filter was utilised to estimate vehicle roll angle. The drawbacks of using a Kalman filter are as follows: 1) the model and measurement noises must be known, 2) the vehicle model must be precise, and 3) the gain matrix must be calculated at each time sample. If the first condition is not met, the performance of the Kalman filter may be degraded [12]. Additionally, the last condition leads to increased computation time.

To handle system uncertainties and varying parameters, a robust observer and controller must be designed. In [13–15], robust controllers were proposed to improve the lateral behaviour of a vehicle. Robust observers have also been proposed to estimate vehicle sideslip angle, [16,17] and vehicle longitudinal velocity [18]. However, there is a lack of research on the design of a robust observer related to vehicle roll angle.

The majority of previous methods use physical models for the estimation of vehicle states. However, when a model has nonlinear

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characteristics and parameters are difficult to determine, as in the case of vehicles, one potential solution is the use of artificial intelligence. In [19] and [20], vehicle sideslip angle was estimated using a neural network (NN) and adaptive neural fuzzy inference system (ANFIS). In [7], an NN was used for vehicle roll angle estimation. The problem in these methods is that sensor noise strongly affects variable estimation. In [7] and [21], integration of an ANFIS and NN with a Kalman filter was performed for estimating vehicle sideslip angle and vehicle roll angle, respectively. In these works, improved results for the ANFIS and NN were obtained when a Kalman filter was combined with previous methodologies.

Considering the aforementioned disadvantages of the Kalman filter, we focus on the development of a robust observer based on energy-to-peak filtering in combination with an NN for vehicle roll angle estimation. Energy-to-peak filtering estimates the minimised error for any bounded energy disturbance.

The design of our observer is based on the following criteria:

- To facilitate system use in all types of environments, we must not use GPS information.
- Utilise information obtained from sensors that are installed in current vehicles, such as accelerometers and rate sensors.
- Reduce computation time by avoiding the calculation of observer gain at each time sample and utilising a simplified vehicle model.
- The proposed algorithm must be usable in different road conditions.
- We must consider the uncertainties in parameters of the vehicle model.
- We must attenuate the effects of external disturbances.

The remainder of this paper is organised as follows. Section 2 describes the vehicle model used by the proposed observer. Section 3 introduces the observer architecture that is formed by an ‘NN module’ and ‘energy-to-peak filtering module’. In Section 4, simulation and experimental results are presented to verify the effectiveness of the proposed observer. Finally, our conclusions are summarised in Section 5.

2. Vehicle model

In this study, a one degree-of-freedom vehicle model, as shown in Fig. 1, is used to describe vehicle roll motion. A detailed description of

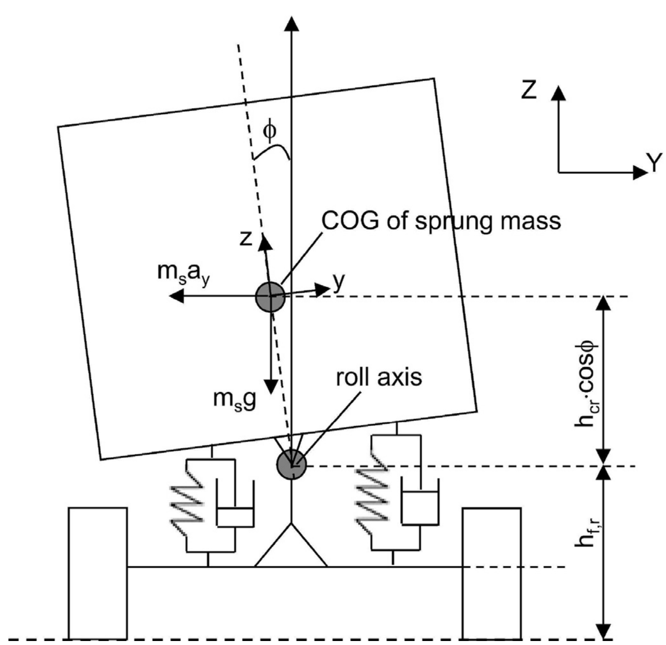

Fig. 1. Vehicle roll model.

this model can be found in [7].

A linear parameter varying (LPV) model of the vehicle roll dynamic can be represented as:

$$\dot{\mathbf{x}}_0 = (\mathbf{A_0} + \Delta\mathbf{A_0})\mathbf{x_0} + (\mathbf{B_0} + \Delta\mathbf{B_0})\mathbf{a_{ym}} + \mathbf{Hw} \tag{1}$$

$$\mathbf{y_{meas}} = \mathbf{C_0}\mathbf{x_0} + \mathbf{q}, \tag{2}$$

where $\mathbf{x}_0$ is the state vector, $[\phi, \dot{\phi}]^T$, ϕ is the vehicle roll angle, $\dot{\phi}$ is the vehicle roll rate, $\mathbf{y}_{meas}$ is the measurement vector, a_{ym} is the lateral acceleration measured by a sensor at the centre of gravity (COG) of the vehicle, $\mathbf{w}$ is the unknown and bounded external disturbance, $\mathbf{q}$ is the measurement noise, and $\Delta\mathbf{A}_0$ and $\Delta\mathbf{B}_0$ represent the system uncertainties for the matrices $\mathbf{A}_0$ and $\mathbf{B}_0$, respectively:

$$\mathbf{A_0} + \Delta\mathbf{A_0} = \begin{bmatrix} 0 & 1 \\ \frac{-(K_R + \Delta K_R)}{(I_{xx} + \Delta I_{xx})} & \frac{-(C_R + \Delta C_R)}{(I_{xx} + \Delta I_{xx})} \end{bmatrix}$$
$$\mathbf{B}_0 + \Delta\mathbf{B}_0 = \begin{bmatrix} 0 \\ \frac{(m_s + \Delta m_s)(h_{cr} + \Delta h_{cr})}{(I_{xx} + \Delta I_{xx})} \end{bmatrix} \tag{3}$$

I_{xx} is the sprung mass moment of inertia with respect to the roll axis, m_s is the sprung mass, h_{cr} is the sprung mass height about the roll axis, C_R represents the total torsional damping, K_R is the stiffness coefficient, g is the acceleration due to gravity, and ΔK_R, ΔC_R, Δh_{cr}, and Δm_s are the maximum uncertainties of K_R, C_R, h_{cr}, and m_s, respectively. $\mathbf{C_0}$ is the output matrix:

$$\mathbf{C}_0 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{4}$$

and, finally,

$$\mathbf{H} = \mathbf{I}_{2x2} \tag{5}$$

To simply analyse, the following considerations have been taken into account:

$$\frac{m + \Delta m}{n + \Delta n} = \frac{m}{n + \Delta n} + \frac{\Delta m}{n + \Delta n} \approx \frac{m}{n} + \frac{\Delta m}{n} \tag{6}$$

$$\begin{aligned}(m + \Delta m)(n + \Delta n) &= mn + m\Delta n + \Delta mn + \Delta m\Delta n \\ &\approx mn + m\Delta n + \Delta mn\end{aligned} \tag{7}$$

Then, the uncertainty matrices can be rewritten as:

$$\Delta\mathbf{A}_0 = \mathbf{E}_A \cdot \mathbf{M_A} \cdot \mathbf{F}_A \tag{8}$$

$$\Delta\mathbf{B}_0 = \mathbf{E}_B \cdot M_B \cdot \mathbf{F}_B \tag{9}$$

where

$$\mathbf{E}_A = \begin{bmatrix} 0 & 0 \\ \frac{-\Delta K_R}{I_{xx}} & \frac{-\Delta C_R}{I_{xx}} \end{bmatrix} \tag{10}$$

$$\mathbf{F}_A = \mathbf{I}_{2x2} \tag{11}$$

$$\mathbf{E}_B = \begin{bmatrix} 0 \\ \frac{\Delta m_s h_{cr} + m_s \Delta h_{cr}}{I_{xx}} \end{bmatrix} \tag{12}$$

$$\mathbf{M_A} = \begin{bmatrix} N(t) & 0 \\ 0 & N(t) \end{bmatrix} \tag{13}$$

$$\mathbf{M_B} = N(t) \tag{14}$$

$$|N(t)| \le 1 \tag{15}$$

$$\mathbf{F}_B = \mathbf{I}_{1x1} \tag{16}$$

3. Vehicle roll angle observer design

In this section, our vehicle roll angle observer is described. Fig. 2