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Review Article

Estimation of Vehicle Parameters using Kalman Filter: Review

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Abstract

Automobiles are indispensable in our modern society, and vehicle safety is consequently very important in our everyday life. In the past few decades, vehicle dynamics control systems have been developed to improve control and safety of vehicles. Vehicle dynamics control systems seek to prevent unintended vehicle behavior through active control and help drivers maintain control of their vehicles. The main function of electronic stability control is to provide enhanced stability and control not only when accelerating and braking but also when cornering and avoiding obstacles. These advanced technologies of has been developed in the pursuits of increased safety, improved performance and cost efficiency. A new method of the vehicle parameters estimation by combining GPS measurements with a vehicle dynamics model based estimator. This method presents a problem because many of the vehicle parameters maybe unknown and or change over time. Therefore, a method to identify when a correct estimator model is being used must be developed. The new estimation algorithm, which is based on using GPS in a vehicle dynamics model based estimator, is tested both in simulation and on expected data.

Keywords: *Vehicle Dynamics, Kalman Filter, GPS Data, Vehicle States, Vehicle Parameters.*

1. Introduction

The automotive industry has made significant technological progress over the last decade or so concerning active vehicle stability control, and hence improved safety, by developing and introducing microprocessor control systems. Among these controllers are systems such as the anti-lock braking system, active roll control, active front steering and electronic stability programs. Effective operation of each of these systems depends on an accurate knowledge of the vehicle states, such as velocity, lateral acceleration, yaw rate, as well as vehicle and tire side slip. Many of the estimators work only with a reduced number of states or a reduced vehicle model, such as a bicycle model. Approaches can be found that use this model for the estimation of side slip angle and yaw rate or for lateral acceleration, yaw rate and tire slip angles.

The previous methods of vehicle parameters estimation have all been limited either by gyro errors, road bank, or model accuracy. The new estimation algorithm, which is based on using GPS in a vehicle dynamics model based estimator, was tested both in simulation and on expected data. Additionally, it is shown the addition of a GPS data in sideslip estimation in the presence of a banked turn. This vehicle dynamics model based estimator using GPS measurements provides accurate and observable estimates of sideslip, yaw rate, steering angle, lateral and longitudinal acceleration, lateral and longitudinal velocity and normal loads on each tire by generating path of vehicle by using GPS data.

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2. Literature Survey

Welch and Bishop provided a practical introduction to the discrete Kalman filter. This introduction includes a description and some discussion of the basic discrete Kalman filter, a derivation, description and some discussion of the extended Kalman filter, and a relatively simple (tangible) example with real numbers & results (G. Welch *et al*, 2006).

Daily and Bevly developed a method for using global positioning system (GPS) velocity measurements to improve vehicle lateral stability control systems. GPS can be used to calculate the sideslip angle of a vehicle without knowing the vehicle model. This measurement is combined with other traditional measurements to control the lateral motion of the vehicle. Noise estimates were provided for all measurement systems to allow the sensors to be accurately represented. Additionally, a method to calculate the lateral forces at the tires was presented. They showed that the tire estimation algorithm performs well outside the linear region of the tire. Results for the controller and force calculations were shown using a nonlinear model to simulate the vehicle and the force calculations were validated with experimental measurements on a test vehicle (R. Daily *et al*, 2004).

Anderson and Bevly developed a method for estimating key vehicle states and sensor biases using Global Positioning System (GPS) and an Internal Navigation

System (INS). They used two Kalman filters, a model based filter and a Kinematic filter. These are used to integrate the INS sensors with GPS heading and velocity to provide a high update rate of the vehicle states and sensor biases. Additional key vehicle parameters, such as tire-cornering stiffness, are identified and used to correct the model based estimator. The vehicle estimated states were compared with values predicted with a theoretical model (R. Anderson *et al*, 2004).

Rodríguez and Gómez presented alternative solution to combine the data provided by different positioning sensors using a Kalman filter. The described procedure also uses an odometric estimation of the mobile position, based on the kinematic model of the agricultural vehicle. Three different implementations of the Kalman filter are described, using different sensor combinations but based on the same vehicle model (M. Rodríguez *et al*, 2009).

Bevly *et al*. developed a method of estimating vehicle sideslip by integrating inertial sensors from a stability control system with velocity information from a single antenna GPS receiver using a planar vehicle model and Kalman filters (D. M. Bevly *et al*, 2000).

Imsland *et al*. studied observers for nonlinear systems, and showed that the error dynamics for a nonlinear Unknown Input Observer (UIO) has the same structure as the error dynamics of a nonlinear observer without unknown inputs. This result was first used to provide synthesis inequalities for UIOs for a class of nonlinear systems, and secondly, to inspire the design of an observer for estimation of vehicle lateral velocity on banked roads (L. Imsland *et al*, 2005).

3. System Design

Scenarios

The Kalman filter is a set of mathematical equations that provides an efficient computational (recursive) means to estimate the state of a process, in a way that minimizes the mean of the squared error. The Kalman filter is very powerful in several aspects as it supports estimations of past, present, and even future states, and it can do so even when the precise nature of the modeled system is unknown.

The new estimation algorithm, which is based on using GPS in a vehicle dynamics model based estimator, was tested both in simulation and on expected data. Additionally, it is shown the addition of a GPS data in sideslip estimation in the presence of a banked turn. This vehicle dynamics model based estimator using GPS measurements provides accurate and observable estimates of sideslip, yaw rate, steering angle, lateral and longitudinal acceleration, lateral and longitudinal velocity and normal loads on each tire by generating path of the vehicle by using GPS data.

Kalman Filter

Kalman filter (KF), known as a linear estimator, is named after Prof. Rudolph E. Kalman. It has been developed a lot after the first described in technique papers by Swerling P. (1958), Kalman R. E. (1960) and Kalman R. E., Bucy P. (1961). In technology field, Kalman filter is widely used to guide, navigate and control vehicles as well as aircrafts. Actually, the Kalman filter is an algorithm that estimates unknown variables by the help of measurements with noise. The Kalman filter is a very powerful tool when it comes to controlling noisy systems. The basic idea of a Kalman filter is Noisy data in and hopefully less noisy data out. Based on prior knowledge about the noise in the estimation, the Kalman filter minimizes the mean square error of the estimation.

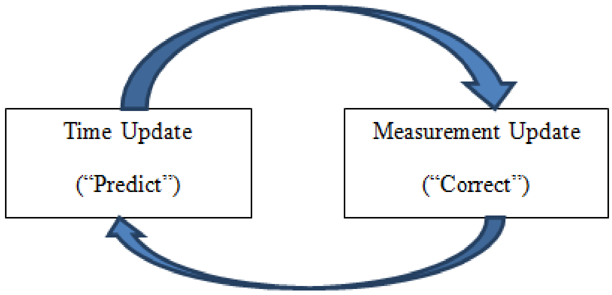

Figure 1 Discrete Kalman Filter Cycle

Theoretically the Kalman Filter is an estimator for what is called the linear-quadratic problem, which is the problem of estimating the instantaneous "state" of a linear dynamic system upset by white noise by using measurements linearly related to the state but corrupted by white noise. The resulting estimator is statistically optimal with respect to any quadratic function of estimation error (G. Welch *et al*, 2006).

The Kalman filter estimates a process by using a form of feedback control: the filter estimates the process state at some time and then obtains feedback in the form of (noisy) measurements. As such, the equations for the Kalman filter fall into two groups: time update equations and measurement update equations. The time update equations are responsible for projecting forward (in time) the current state and error covariance estimates to obtain the a priori estimates for the next time step. The measurement update equations are responsible for the feedback i.e. for incorporating a new measurement into the a priori estimate to obtain an improved a posteriori estimate.

Kalman Filter Estimator

Estimated vehicle parameters together with estimated sensor biases open the door to estimate vehicle states correctly even when GPS is not available. Parameterized vehicle models with properly estimated parameters can produce correct vehicle state estimates using INS sensors calibrated by the sensor bias estimates. This concept is illustrated in Figure 2. When GPS is available, represented in the left side of the figure, vehicle parameters and as well as vehicle states. When GPS is not available, the estimated vehicle parameters and sensor biases are used as inputs to the estimation process to estimate vehicle states without help of GPS measurements.

In addition, based on the estimated parameters and states, this thesis presents a new method for separating road bank and suspension roll angle using a disturbance observer and a vehicle dynamic model. While a lumped value of road bank and suspension roll can be measured using a two-antenna GPS system and the lumped value can be used to compensate the acceleration measurements, the separation of these two angles could be especially beneficial to vehicle rollover warning and avoidance systems. Since a small lumped value does not necessarily mean a small road bank angle, a vehicle may experience a significant road bank angle even though the sum of the two angles is small (D. M. Bevly *et al*, 2006).

Although the suspension roll and road bank angle have similar influences on the roll and roll rate measurements, they play very different roles in the vehicle dynamics. While the road bank angle can be treated as a disturbance or unknown input to the vehicle, the suspension roll angle is a state resulting from the road bank angle and other inputs, governed by vehicle dynamics. This implies that a parameterized vehicle dynamic model could conceivably be used to separate the suspension roll and road bank angles. A dynamic vehicle model includes suspension roll as a state and road bank as a disturbance.

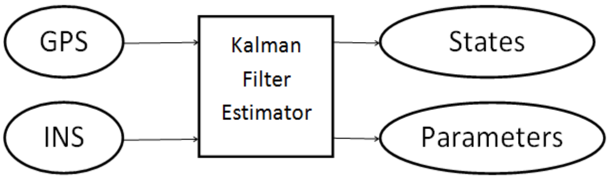

Figure 2 Estimation with GPS Availability

The disturbance observer is then implemented using the measurements of the sideslip angle, yaw rate, roll rate, and total roll angle which is the sum of road bank and suspension roll angles and other vehicle parameters from the GPS/INS system which then used to control stability of vehicles (C. McMillan, 1994).

Vehicle State and Parameters Estimation

This paper investigates the use of several GPS sensor configurations and levels of vehicle dynamics modeling fidelity in the estimation of vehicle states including sideslip angle. The vehicle yaw information is obtained from a two-antenna GPS system that not only eliminates issues of drift in attitude estimation but also provides a measurement of the roll angle. Using a two-antenna GPS system, this thesis consider the influence of road grade, bank angle, and suspension roll on GPS-based vehicle sideslip and longitudinal velocity estimates derived from a vehicle dynamics model and Kalman filter. The combined system fuses a road grade estimate derived from GPS velocity and the roll information from the two-antenna system with an appropriate roll center model of the vehicle since the two antennas are placed laterally. Comparisons with a calibrated vehicle model show excellent correlation and the relative constancy of the sensor bias estimates demonstrates that no significant dynamics are ignored. From a practical standpoint, this paper also describes a number of refinements to calibrate sensitivity variation and cross-coupling of inertial sensors (B. Hofmann-Wellenhof *et al*, 1993).

The accurate estimates of the vehicle states are available at a level previously unavailable and these estimates yield a new opportunity to estimate key vehicle parameters, such as vehicle mass, tire cornering stiffness, under steer gradient, roll stiffness, and roll damping coefficient. Once vehicle parameters are precisely estimated, parameterized vehicle dynamics models with properly estimated parameters can be used for a wide variety of applications including highway automation, vehicle stability control, and rollover prevention systems. Aiming to provide parameter estimates precisely enough to be used for most vehicle dynamics and control problems, this paper investigates vehicle parameter estimation schemes.

4. Vehicle Modeling

The subject "Vehicle Dynamics" concerned with the movements of vehicles on a road surface. Dynamic behavior is determined by the forces impulse on the vehicle from the tires, gravity and aerodynamics. The vehicle dynamics simulation based on ten differential equations which are simultaneously solved. The program requires (δ, BF_f , BF_r, and u) the inputs of steer angle, brake force front, brake force rear, and longitudinal or forward velocity. There ten differential equations provide the parameters required to accurately describe the vehicle position, velocity and orientation in 3-D space. For single mass representation, the vehicle is treated as a mass concentrated at its center of gravity as seen in figure 3.

On board, the vehicle motions are defined in reference to the right-hand orthogonal coordinate system i.e. the vehicle fixed coordinate system has the coordinates at center of gravity (CG) and travels with vehicle. By SAE convention the coordinates x is forward and on the longitudinal plane of symmetry, y is lateral out the right side of vehicle, z is downward with respect to the vehicle, P is roll velocity about the x axis, q is pitch velocity about y axis, and r is yaw velocity about z axis.

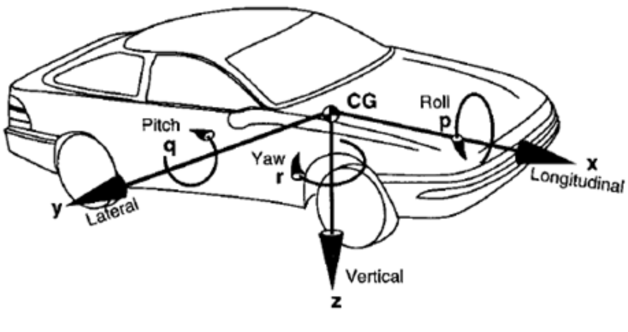

Figure 3 SAE Vehicle Axis System

The differential equations are simultaneously solved yielding the equations 1-10

Once the Above differential equations are solved for they can be used to calculate the speed and side slip angles.

The advantages and disadvantages of these models in the aspect of modeling are also indicated. The advantage of the linear model is the simple approximation of the real vehicle.

$$\frac{dr}{dt} = \frac{[(F_{ylf} + F_{yrf})a - (F_{yrr} + F_{yrl})b + (F_{xlf} - F_{xrf} + F_{xlr} - F_{xrr})(\frac{5.2}{2})]}{I_{yy}}$$ (1) Yaw Equation,

$$\frac{dv}{dt} = \frac{(F_{ylf} + F_{yrf} + F_{yrl} + F_{yrr}) - u.r - cg(-((K-(w_f + w_r)(cg))\Phi + C.\Phi + (F_{ylf} + F_{yrf} + F_{yrl} + F_{yrr})}{I_{yy}}$$ (2) Lateral Velocity Equation,

$$\frac{dx}{dt} = u.\cos(\Psi) - v.\sin(\Psi)$$ (3)X Coordinate of Center of Gravity,

$$\frac{dy}{dt} = v.\cos(\Psi) + u.\sin(\Psi)$$ (4)Y Coordinate of Center of Gravity,

$$\frac{d\Phi}{dt} = \dot{\Phi}$$ (5) Roll Angle velocity,

$$\frac{d\dot{\Phi}}{dt} = \frac{-((K-(w_f + w_r)cg)\Phi + C.\dot{\Phi}) + (F_{ylf} + F_{yrf} + F_{yrl} + F_{yrr})cg}{I_{xx}}$$ (6)Angular Velocity about Roll Axis,

$$\frac{du}{dt} = \frac{F_x + v.r}{m}$$ (7) Longitudinal Velocity,

$$\frac{d\theta}{dt} = \dot{\theta}$$ (8) Pitch Angle velocity,

$$\frac{d\dot{\theta}}{dt} = \frac{-(BF_f + BF_r)cg - K\theta - C\dot{\theta}}{I_{yy}}$$ (9) Angular Velocity about Pitch Axis,

$$\frac{d\Psi}{dt} = r$$ (10) Heading Angle,

The model works properly with the regular operating conditions such as small steering angles and low lateral acceleration. The main disadvantage of nonlinear model is the difficulty to couple it with a linear driver models represented as transfer functions. Depending on the problem, the right model may save the cost associated with computation and design of the efficient controllers (R. Anderson *et al*, 2004).

Two important states of the vehicle affecting the path following control are the lateral position and head angle of the vehicle. A linear bicycle model provides sufficient feedback for the driver to maintain the vehicle following a path. The increased complexity arising from the nonlinearity of the vehicle model raises difficulties in the modeling and enlarges the computational time. Moreover, most of passenger cars have the rollover thresholds significantly greater than 1.0g, while light trucks, vans and SUVs threshold range from 0.8 to 1.2g and for that of a heavy load truck lies well below 0.5g (R. Daily *et al*, 2004).

5. Discussion

In this paper it is assumed that there exists a measurement of GPS data of the path followed by the vehicle on the test track which then will be used by the observer. Since there is no sensor to measure the lateral velocity, this state is estimated by integrating the estimated lateral velocity change. Therefore the velocity change rate is required to be estimated accurate in order to avoid errors due to noise when integrating.

The objective of the research leads to the vehicle dynamics model where the vehicle dynamics equations are mainly considered. The model assumes that there is a minor roll effect on driving a vehicle so that it can be neglected at the benefit of a much simplified directional model. Also, the yaw rate is the time derivative of the yaw angle (Ψ). Yaw angle is experienced when the vehicle is taking turn. A yaw rate sensor, also called gyro-meter, measures the angular velocity of the chassis along its vertical axis. Accurate information about the yaw rate is for many reasons very important and modern cars have therefore often a yaw-rate sensor. **T**he roll angle also needed to compensate the lateral acceleration sensor. The roll is not possible to measure, and very few vehicles are equipped with a roll rate sensor, so the estimation has to entirely be based on the vehicle dynamics estimator model. Pitch angle is the angle between the vehicle X-axis and ground plane and is denoted by θ. If the vehicle changes its longitudinal velocity the chassis will pitch. It occurs at the acceleration or braking of the vehicle. By the same reasons as for the roll angle, the pitch angle will affect the load transfer which is used by the tire model.

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