

Optimal Sensor Configuration and Fault-Tolerant Estimation of Vehicle States

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ABSTRACT

This paper discusses observability of the vehicle states using different sensor configurations as well as fault-tolerant estimation of these states. The optimality of the sensor configurations is assessed through different observability measures and by using a 3-DOF linear vehicle model that incorporates yaw, roll and lateral motions of the vehicle. The most optimal sensor configuration is adopted and an observer is designed to estimate the states of the vehicle handling dynamics. Robustness of the observer against sensor failure is investigated. A fault-tolerant adaptive estimation algorithm is developed to mitigate any possible faults arising from the sensor failures. Effectiveness of the proposed fault-tolerant estimation scheme is demonstrated through numerical analysis and CarSim simulation.

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I. INTRODUCTION

Reliability of sensory measurements or estimated states is a major concern in automotive applications. Many advanced vehicle subsystems such as stability controllers and x-by-wire structures rely on the sensory measurements or estimated information. Noticeably, malfunction of such systems may cause unexpected consequences if not properly handled by the vehicle system. Installation of redundant sensors may help to guarantee desirable performance even with sensor failures. However, the number and type of the sensors for estimation or control purposes are important in the vehicle manufacture due to cost and performance. Thus, achieving observability and fault-tolerant estimation using a minimal and reliable sensor set is among the most important issues for the automotive suppliers and OEMs.

Literature suggests different approaches for observability analysis and determination of optimal sensor configuration.

Measuring the degree of observability is widely used to find the optimal sensor configuration. A set of sensors that results in the highest degree of observability, among all of the possible sensor sets, is considered as the optimal configuration for the system. There are some criteria to measure the degree of observability. For example, Muller and Weber [1] outlined three candidate measures including minimum eigenvalue of the observability Gramian to find the degree of observability for linear systems. Chamseddine et al. in [2] introduced two other criteria: the trace of the observability Gramian and the robust spectral norm which is the minimum singular value of the observability Gramian. In fact, these criteria are scalar numbers which provide a measure of how far the system with the current sensor configuration is from being unobservable.

Sumana and Venkateswarlu [3] used the trace of the observability Gramian and the condition number to obtain the best sensor configuration for a reactive distillation column.

The set with the maximum trace or minimum condition number was chosen as the optimal sensor configuration. Nakhaeinejad et al. [4] suggested a similar approach not only for analysis of the faults, but also for defining a guideline for model-based sensor selection for induction motors. Among all of the abovementioned methods, the condition number is more common and is frequently used in the literature [1], [5], [6]. In this paper, all of the introduced observability and sensor configuration methods are chosen and applied to determine the best sensor configuration for estimation of vehicle states. Such states are required by many automotive applications such as traction control system, ABS or other vehicle safety algorithms [7].

Despite somewhat robustness against uncertainties, these estimation methods are still sensitive to the sensor failures. Faulty sensory signals or estimation can be problematic for a closed loop control systems that rely on these estimated or sensory signals, because the controller can guide the system away from the set point, and even to instability. Therefore, a need arises to develop intelligent methods to mitigate the effects of sensor failures on the control performance.

Metallidis et al. discussed the fault detection and optimal sensor location for vehicle suspension in [8]. They presented a statistical framework to formulate the sensor location and fault detection problems as optimization problems. Kim and Lee [9] presented an analytical sensor fault detection algorithm for vertical accelerometers which are used as a part of a continuous damping control system of a vehicle. Fault detection for lateral and vertical dynamics of a vehicle was discussed in [10]. In this approach, roll dynamics and lateral load transfer are neglected.

Measured and estimated vehicle states are extensively used by many recent vehicle control and safety systems to ensure stability of the vehicle [11]-[12]. This paper studies optimal sensor configuration, sensor fault detection and fault-tolerant estimation for vehicle handling dynamics. Contents of this paper are organized as follows: Section II introduces developing a 3-DOF vehicle handling model which is used as a basis for evaluation of the sensor sets and development of the fault-tolerant estimation scheme. The model is simulated in Matlab and validated with CarSim. Section III investigates optimal sensor configuration from a finite set of sensors commonly used for vehicle control applications. Observability and optimal sensor configuration measures are described and preference of the sensor sets is quantified. Section IV discusses fault-tolerant estimation of vehicle states. Additionally, the estimation process using the Luenberger observers and LQR gain tuning is described, simulation results are provided, and performance of the estimator for the cases that one of the vehicle sensors fails is simulated and analyzed. Moreover, development of a fault-tolerant adaptive estimation algorithm to mitigate possible faults arising from sensor failures is described in this section. The reliable performance of the fault-tolerant estimation scheme is demonstrated through simulations. Finally, a conclusion is presented in Section V.

II. VEHICLE MODEL

Sufficiently accurate modeling of the vehicle dynamics is the first step in developing estimation or fault detection methods. Vehicle state observability and fault-tolerant estimation of vehicle states are herein studied using a 3-DOF vehicle model shown in Figure 1. This model represents handling dynamics of the vehicle and includes lateral acceleration (a_y), yaw rate (r) and roll rate ($\dot{\phi}$) as dominant elements that contribute to the handling performance. The majority of studies that focused on vehicle handling dynamics consider a 2-DOF vehicle model that only includes yaw and lateral motions [13], [14], [15]. However, the roll motion can significantly affect the handling dynamics due to lateral load transfer. Roll motion also affects dynamics of the steering and suspension systems [16]. Therefore, the 3-DOF model adopted in this paper can result in a better modeling accuracy which is an essential requirement for state estimation and sensor fault detection applications.

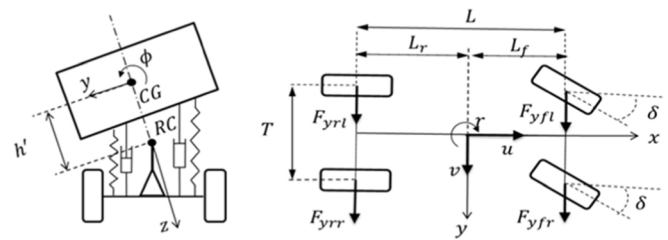


Figure 1. Vehicle model

The state-space representation of the model is formed as:

$$\dot{X} = AX + Bu \quad (1)$$

where lateral velocity (v_y), yaw rate (r), roll angle (ϕ) and roll rate ($\dot{\phi}$) are selected as the states and steering angle (δ) is the input of the system:

$$X = [v_y \ r \ \phi \ \dot{\phi}]^T \quad (2)$$

$$u = \delta \quad (3)$$

The system (A) and input (B) matrices are dependent on the geometrical and dynamic properties of the vehicle as well as characteristics of the suspension system, steering system, and tires. Considering vehicle lateral dynamics, roll dynamics, lateral load transfer, linear tire models, camber-by-roll, steering-by-roll and scrub-by-roll properties, the system and measurement matrices of the handling dynamics are formed as

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \quad (4)$$

$$a_{11} = -2 \frac{C_{af} + C_{ar}}{u.m} \quad (5)$$

$$a_{21} = -2 \frac{L_f.C_{af} - L_r.C_{ar}}{u.m} \quad (6)$$

$$a_{31} = 0 \quad (7)$$

$$a_{41} = 2 \frac{m_s h' (C_{af} + C_{ar})}{m.I_x u} \quad (8)$$

$$a_{12} = -2 \frac{L_f.C_{af} - L_r.C_{ar}}{u.m} - u \quad (9)$$

$$a_{22} = -2 \frac{L_f^2.C_{af} + L_r^2.C_{ar}}{u.I_z} \quad (10)$$

$$a_{32} = 0 \quad (11)$$

$$a_{42} = \frac{m_s h'}{m.I_x} \left(2 \frac{L_f.C_{af} - L_r.C_{ar}}{u} + u.m \right) - \frac{m_s h' u}{I_x} \quad (12)$$

$$a_{13} = \frac{2}{m} (C_{af}.K_{fSBR} + C_{ar}.K_{rSBR} + C_{yf}.K_{fCBR} + C_{yr}.K_{rCBR}) \quad (13)$$

$$a_{23} = \frac{2}{I_z} (L_f.C_{af}.K_{fSBR} - L_r.C_{ar}.K_{rSBR} + L_f.C_{yf}.K_{fCBR} - L_r.C_{yr}.K_{rCBR}) \quad (14)$$

$$a_{33} = 0 \quad (15)$$

$$a_{43} = \frac{m_s g h' - K_t}{I_x} - \frac{m_s h' (C_{af}.K_{fSBR} + C_{ar}.K_{rSBR} + C_{yf}.K_{fCBR} + C_{yr}.K_{rCBR})}{m.I_x u} \quad (16)$$

$$a_{14} = -2 \frac{C_{af}.K_{fSCBR} + C_{ar}.K_{rSCBR}}{u.m} \quad (17)$$

$$a_{24} = -2 \frac{L_f.C_{af}.K_{fSCBR} - L_r.C_{ar}.K_{rSCBR}}{u.I_z} \quad (18)$$

$$a_{34} = 1 \quad (19)$$

$$a_{44} = 2 \frac{m_s h' (C_{af}.K_{fSCBR} + C_{ar}.K_{rSCBR})}{m.I_x u} - \frac{C_t}{I_x} \quad (20)$$

$$B = \begin{bmatrix} b_{11} \\ b_{21} \\ b_{31} \\ b_{41} \end{bmatrix} = \begin{bmatrix} 2 \frac{C_{af}}{m} \\ 2 \frac{L_f.C_{af}}{I_z} \\ 0 \\ \frac{m_s h' C_{af}}{m.I_x} \end{bmatrix} \quad (21)$$

Definitions of the model parameters are provided in Definitions/Abbreviations Section.

The measurement equation for the system is also dependent on the vehicle parameters

$$Y = CX + Du \quad (22)$$

Depending on the type and locations of the vehicle sensors, the C and D matrices have different dimensions and magnitudes. For the case when lateral acceleration, yaw rate and, roll rate sensors are assumed available (i.e.

$Y = [a_y, r, \phi]^T$), the measurement matrices are

$$C = \begin{bmatrix} \frac{-2(C_{af} + C_{ar})}{u.m} & \frac{-2(L_f.C_{af} - L_r.C_{ar})}{u.m} + u & 0 & \frac{2m_s h' (C_{af} + C_{ar})}{m.I_x u} \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (23)$$

$$D = \begin{bmatrix} 2 \frac{C_{af}}{m} \\ 0 \\ 0 \end{bmatrix} \quad (24)$$

The values of the model parameters are available for commercial vehicles through standard vehicle tests from the automotive manufacture.

Accuracy of the model is validated through CarSim simulations for different maneuvers. It should be noted that the introduced model is valid for linear regions of vehicle dynamics (i.e. $a_y < 0.4g$). Moreover, the model assumes a constant or slowly-varying longitudinal velocity. This can be justified noting that the handling dynamics is much faster compared to the longitudinal dynamics and quasi-linearity of the model is satisfied.

Figure 2 illustrates simulation results for a double-lane-change maneuver at 60 *kph*. The results verify accuracy of the model despite its simplicity.