

Detection of Unintended Acceleration in Longitudinal Car Following

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ABSTRACT

This paper presents a model-based approach to detect unintended acceleration (UA) as well as other vehicle problems. A diagnostic system is formulated by detecting several specific vehicle events such as acceleration peaks and gear shifting. Mathematical models are created for these events based on simulation data and the final diagnostic conclusion is drawn from the voting result of all these models. The detection algorithm is validated using independent data sets obtained from Matlab/Simulink. A three dimensional vehicle model is built to implement traffic simulation. Vehicle problems and drivers' reactions are simulated and added during the process. Sensor noise is also considered and corresponding filters are designed and applied. The results show that the fault diagnostic system is successful in detecting UA.

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1. INTRODUCTION

Vehicle safety is always a major concern of the automobile industry. Among all kinds of vehicle issues, unintended acceleration has become one of the most complained-about problems in recent history. According to the National Highway Traffic Safety Administration (NHTSA), "Unintended Acceleration" refers to the occurrence of any degree of acceleration that the vehicle driver did not purposely cause to occur. It was often reported to be accompanied by ineffective brakes [1].

There have been unintended acceleration complaints among different automobile manufacturers for many years. Owners of Audi cars reported a much higher-than-usual occurrence of unintended acceleration in the 1980s. However, Audi and other vehicles manufactured at that time had relatively few electronics systems and used mechanical throttle control. NHTSA had attributed the cause of Audi's problems to drivers' misapplication [2].

In contrast to traditional simple and straightforward mechanical control systems, an increasing number of electronic systems have been added to automobiles in the past 25 years. One of the most popular systems is the electronic throttle control system (ETC). At this time, many drivers reported experiencing UA problems, which could have been caused by software or other electronic failure. In 2010 the National Aeronautics and Space Administration (NASA) conducted an investigation into the potential vulnerabilities of the electronics in the Toyota ETC. The final report said no evidence of Toyota ETC being a plausible cause of UA was found. NHTSA also conducted several investigations into the cause of UA. Its analysis

indicated that the most likely cause was pedal misapplication. However, there was still a possibility that the accidents resulted from vehicle problems [3].

To prevent accidents caused by vehicle problems and drivers' misapplication, a new detection system is needed to perform the inherently complex task of identifying real-time, abnormal vehicle behavior. Research efforts have been devoted to detecting abnormal vehicle events. Schmidt et al. [4] built a framework to enable vehicles to communicate with other vehicles in the vicinity, using Vehicular Ad-Hoc Networks. Vehicles were classified as trustworthy, untrustworthy or neutral in regards to traffic safety. Sang et al. [5] identified abnormal behavior by performing video-based detection and creating an information chain of tracked vehicles. Bouttefroy et al. [6] introduced a paradigm for abnormal behavior detection, relying on the integration of contextual information in Markov random fields. This technique models the local density of object feature vector and leads to simple and sophisticated criterion for behavior classification. Chen et al. [7] presented an approach to detect potential ECU application software abnormal behavior based on the Mahalanobis Distance, the Mahalanobis-Taguchi System and vehicle driving data playback capability with a simulator.

Besides these approaches, one plausible scheme to better understand and detect abnormal driving situations is to utilize the existing driving data. Vehicle data such as velocity, acceleration, and throttle/brake position form an n-dimensional space. Each Point in this space can be regarded as a vehicle state. The goal of distinguishing between abnormal vehicle behaviors and normal behaviors can be accomplished by finding the boundary between their regions in this n-dimensional space or its transformation.

However, collection of data for abnormal behaviors is a very expensive, time-consuming and even dangerous task. No accurate data is available for UA since this problem only occurs occasionally and no one has drawn a final conclusion about the cause of UA. Without the help of abnormal behavior data, predicting an accurate boundary is very complicated. One possible error is shown in [Figure 1](#). Since collected data for normal behavior does not cover the whole space of normal behavior, this leads to wrong predictions of the boundary and some vehicle status are therefore misclassified. What is more important is that the detection system cannot be validated without abnormal behavior data.

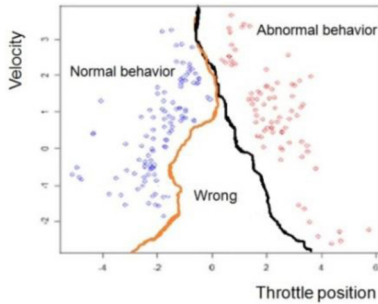


Figure 1. Misclassification of vehicle events

This paper proposes a model-based approach to collect the data for abnormal vehicle behavior and detect UA. It uses a logical description of driver behavior in conjunction with a vehicle dynamic model to capture vehicle-driver interaction on the road. [Figure 2](#) shows the flowchart of the process. First, a three-dimensional vehicle model was built in Simulink. Then, possible causes of vehicle problems, such as UA, were simulated and added to the traffic simulation. Finally, simulation data was randomly divided into two parts. One part was used to create mathematical models to predict the boundary between normal and abnormal behavior by detecting acceleration peaks and gear shifting. The other part was used for model validation.

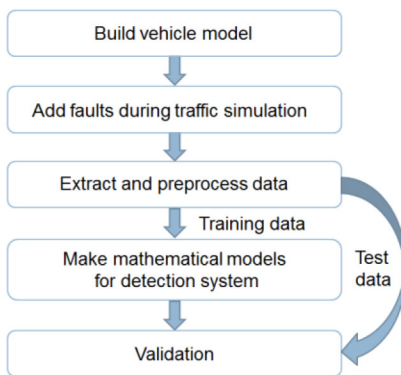


Figure 2. Flowchart of the process

The rest of this paper is organized as follows. [Section 2](#) describes the vehicle dynamic model. The process of traffic simulation is introduced in [Section 3](#). The details of the fault detection algorithm are discussed in [Section 4](#). Final test results are presented in [section 5](#). [Section 6](#) summarizes the detection system and outlines a few topics for future research.

2. VEHICLE DYNAMIC MODEL

2.1. Powertrain

A three dimensional automatic front-wheel drive (FWD) vehicle model was built in Simulink. The model contains basic powertrain components including engine, torque converter, gearbox, differential gear, and brake, as shown in [Figure 3](#). Front wheels use disc brakes and rear wheels use drum brakes. Independent rear suspension is applied. The car is assumed to use symmetric camber angles and toe angles so that it can move along a straight line when the steering angle is zero. The reason for choosing automatic transmissions is that, based on reports, UA most often happens with automatic vehicles.

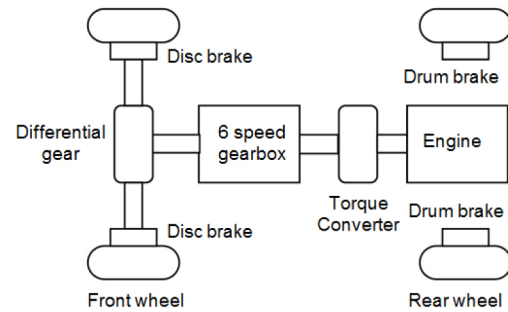


Figure 3. Powertrain model

2.2. Vehicle Dynamics

In this study, a Society of Automobile Engineers (SAE) standard coordinate system is used. The positive x axis points forward, the positive y axis points to the right and the positive z axis points down [8]. Positive rotations are determined by the right-hand rule for these axes, as shown in [Figure 4](#). The longitudinal, lateral and yaw movement of a vehicle is described by

$$\begin{cases} m(a_x - V_y\omega) = \sum_i FX_i - F_{drag} - F_{slope} \\ m(a_y + V_x\omega) = \sum_i FY_i \\ I_z\alpha_z = \sum_{i=1,2} FY_i L_f - \sum_{i=3,4} FY_i L_r + (FX_1 - FX_2) \frac{TW_f}{2} \\ \quad + (FX_3 - FX_4) \frac{TW_r}{2} + \sum_{i=1:4} M_{zi} \end{cases} \quad (1)$$

where F_{drag} is the aerodynamic drag force, F_{slope} is the force caused by the slope of the road, L_f and L_r are the distance from CoG to the front and rear axles, TW_f and TW_r are the front and rear track width, and M_z is the tire aligning moment. The longitudinal and lateral wheel forces are calculated as:

$$\begin{cases} FX_i = \sum_i F_{xi} \cos \delta_i - \sum_i F_{yi} \sin \delta_i \\ FY_i = \sum_i F_{xi} \sin \delta_i + \sum_i F_{yi} \cos \delta_i \end{cases} \quad (2)$$

where F_{xi} and F_{yi} are longitudinal and lateral tire forces, which are determined from the tires normal forces, and δ_i is the steering angle. The rolling resistance is contained in F_{xi} .

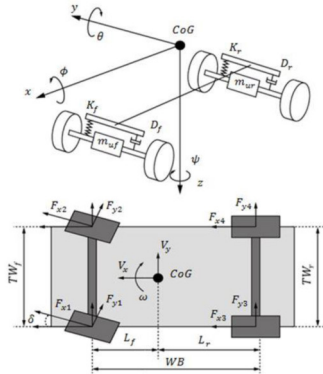


Figure 4. Vehicle dynamics

For a small roll angle ϕ and pitch angle θ , roll and pitch equations are given by:

$$\begin{aligned} (I_x + m_c d_{roll}^2) \ddot{\phi} + (D_{rollf} + D_{rollr}) \dot{\phi} + (K_{rollf} + K_{rollr}) \phi \\ = m_c g d_{roll} \sin \phi - m_c (a_y + V_x \omega) d_{roll} \cos \phi \end{aligned} \quad (3)$$

$$\begin{aligned} (I_y + m_c d_{pitch}^2) \ddot{\theta} + D_{pitch} \dot{\theta} + K_{pitch} \theta \\ = m_c g d_{pitch} \sin \theta + m_c (a_x - V_y \omega) d_{pitch} \cos \theta \end{aligned} \quad (4)$$

where d_{roll} is the length of the roll moment arm, K_{rollf} and K_{rollr} are front and rear roll stiffness, D_{rollf} and D_{rollr} are front and rear roll damping, d_{pitch} is the length of the pitch moment arm, K_{pitch} is the pitch stiffness, and D_{pitch} is the pitch damping.

The normal tire forces consist of four parts: the static vertical load F_s , the longitudinal load transfer due to acceleration F_p , the lateral load transfer due to rolling F_r and the lateral load transfer due to acceleration of the unsprung mass F_u . The tire normal force of the left front tire is given by

$$\begin{aligned} F_{z1} &= F_{s1} + F_{p1} + F_{r1} + F_{u1} \\ &= \frac{-h F_{drag} - (m_c h + m_{uf} h_{uf} + m_{ur} h_{ur}) g \sin \gamma + m g L_r \cos \gamma}{2WB} \\ &\quad - \frac{(m_c h + m_{uf} h_{uf} + m_{ur} h_{ur}) * a_x}{2WB} \\ &\quad + \frac{(a_y \cos \phi + g \sin \phi) * m_c d_{roll} * K_{rollf}}{TW_f (K_{rollf} + K_{rollr})} \\ &\quad + \frac{m_c a_y h_{uf} * \frac{L_r}{WB} + m_{uf} a_y h_{uf}}{TW_f} \end{aligned} \quad (5)$$

where m_c is the sprung mass, m_{uf} and m_{ur} are the front and rear unsprung mass, h is the height of sprung mass CoG, h_{uf} and h_{ur} are the height of front and rear unsprung mass CoGs, WB is the wheel base, and γ is the road inclination angle. The normal loads on other tires are similar. The values of some vehicle parameters are shown in Table 1.

Table 1. Vehicle parameters

m	1450 kg	h	0.5 m
TW_f	1.585 m	L_f	1.07 m
TW_r	1.575 m	L_r	1.605 m
m_{uf}	95 kg	m_{ur}	95 kg

2.3. Tire Model

Tires are one of the most important parts of vehicles and tire modelling is crucial to the accuracy of simulation. In this study, Pacejka tire model (Magic Formula) [9] is used for the calculation of tire dynamics since it has proved to be reasonably accurate and computationally fast. One critical term in the Pacejka tire model is slip ratio, which measures the difference between the rotational speed of the wheel and the translational velocity of the wheel center. To avoid singular values at low speed, slip ratio is defined as:

$$\sigma_i = \begin{cases} \frac{\omega_i r - V_{xi}}{|V_{xi}|} & |V_{xi}| > V_{threshold} \\ \frac{\omega_i r - V_{xi}}{V_{threshold} + \frac{(\omega_i r)^2}{v_{threshold}}} & |V_{xi}| < V_{threshold} \end{cases} \quad (6)$$

3. TRAFFIC SIMULATION

Traffic simulation is a relatively effective approach to capture the patterns for abnormal vehicle behaviors and analyze the effects of vehicle problems. A complete traffic simulation has three parts. First, environmental conditions are determined. Then, different kinds of vehicle faults are simulated and added to the simulation. Finally, a driver model to mimic the reaction of real drivers in this scenario is built.

3.1. Traffic Scenarios

In this study, it is assumed that drivers have specific driving patterns in certain traffic scenarios. To generate representative vehicle data that can cover the whole space of normal and abnormal behaviors, several typical traffic scenarios need to be chosen. This paper focuses on the longitudinal car following, in which drivers only control the gas pedal and brake pedal. Numerous car-following models have been developed since the 1905s. Gipps [10] proposed a behavioral car-following model based on the assumption that each driver sets the limits of his desired braking and acceleration rates. Lee et al. [11] [12] compared a few longitudinal driver models and suggested that the Gipps' model was the most promising. They also modified the Gipps' model by considering that the following driver would take time to observe the deceleration of the lead vehicle. This paper adopts Modified Gipps' model because its calculated distances between two cars are closer to the assumed safe distance, which is one car length