Analysis of Following Vehicles' Driving Patterns

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Despite the potential benefits of autonomous vehicles (AVs) of reducing human driver errors and enhancing traffic safety, a comprehensive evaluation of recent AV collision data reveals a concerning trend of rear-end collisions caused by following vehicles. Developing a methodology that identifies the relationship between driving patterns and the risk of collision between leading and following vehicles using spectral analysis can address this issue. Specifically, a process is proposed for computing three indices: reaction time, stimulus compliance index, and collision-risk aversion index. These indices consistently produced reliable results under various traffic conditions. The findings align with existing research on the driving patterns of following vehicles. Given the consistency and robustness of these indices, they can be effectively utilized in advanced driver assistance systems or incorporated into AVs to assess the likelihood of collision risk posed by following vehicles and develop safer driving strategies accordingly.

sustainable traffic management | autonomous vehicle | driving behavior | car following

1. Introduction

According to the National Highway Traffic Safety Administration (NHTSA), rear-end collision is the most frequent type of crash among motorized users [1]. Almost 30% of all car accidents in the U.S. are rear-end collisions, with nearly 2.5 million being reported every year. These collisions typically occur when the preceding car suddenly decelerates or when the following car accelerates more rapidly than the preceding car. Drivers' inattention, unintentional close following due to misjudgment of the required deceleration, and deliberate aggressive close following are the main factors contributing to rear-end collisions [2]. Significant research has been conducted to improve drivers' ability to prevent such accidents by integrating collision warning systems or advanced driver assistance systems (ADASs) onboard vehicles [3][4].

Autonomous vehicles (AVs) are expected to cause a paradigm shift in road traffic safety. However, according to Tesla's annual report, about 830,000 vehicles have been sold in the United States since 2015, when vehicles equipped with the Autopilot function began to be sold, and a total of 35 traffic accidents have occurred. Despite the potential of AVs to eliminate human driver errors and enhance traffic safety, a comprehensive evaluation of recent AV collision data indicates that modern AVs are prone to rear-end collisions with following vehicles.

Generally, it is unrealistic to expect all conventional vehicles (CVs) to be converted into AVs within a few days. If the transition from a fleet of CVs to a fleet of AVs occurs over a long period, AVs must make proper decisions in safety-critical situations by interacting with the surrounding CVs for sustainable traffic management. Accidents involving AVs often occur because of their failure to respond reasonably to the behaviors of surrounding CVs. Therefore, a firm understanding of the collision risk posed by CVs is essential for AVs to make safe driving decisions.

The collision risk in a certain traffic situation is calculated using safety surrogate measures (SSMs), which rely on microscopic traffic variables such as an individual vehicle's speed, acceleration, time headway, and space headway [5]. However, most SSMs are highly dependent on mathematical models based on physical dynamics, which can limit their accuracy because they estimate collision risk based on the assumption of constant vehicle velocity. Additionally, these measures do not consider the driving-pattern data collected from vehicles. To reduce the occurrence of rear-end collisions, it is crucial to continuously analyze the driving behaviors of surrounding vehicles and activate preventive or protective measures accordingly.

2. Spectral Analysis Techniques in Following Vehicles' Driving Patterns

There are several ways to abstract and model real traffic events depending on the level of aggregation. Macroscopic traffic flow models describe collective vehicle dynamics in terms of aggregate traffic variables such as density, flow, and speed using fluid dynamics models [6]. Microscopic traffic flow models, on the other hand, describe the dynamics of individual vehicles and their interactions using car-following models and cellular automata models [7][8]. Mesoscopic traffic flow models describe microscopic vehicle dynamics as functions of macroscopic fields using gas kinetics models [9]. Among the three modeling approaches, microscopic traffic flow models are becoming increasingly important owing to the widespread use of ADASs, such as adaptive cruise control (ACC), infrastructure-to-vehicle (I2V) and vehicle-to-vehicle (V2V) communications, and other applications of intelligent transport systems (ITSs). Additionally, the deployment of AVs in smart mobility services is becoming increasingly common worldwide [10].

Microscopic models are used to describe the behavior of individual vehicles with three primary actions: acceleration, deceleration, and steering. The collective behavior of individual vehicles results in a macroscopic traffic flow. Microscopic models can be classified into two categories: car-following and lane-changing models. Car-following models describe the longitudinal dynamics of individual vehicles, such as acceleration and deceleration, based on the movement of the preceding vehicle in the same lane. On the other hand, lane-changing models do not include the steering-induced lateral dynamics of individual vehicles but rather describe lane-changing decisions and related actions. It is assumed that the lane-changing maneuver occurs instantaneously. Therefore, the present study, which proposes an assessment methodology for driving patterns and rear-end collision risk in certain time intervals, does not consider lane-changing behaviors.

The first car-following models were proposed in the 1950s by Reuschel [11] and Pipes [12]. Since then, many variants have been developed. The Gazis–Herman–Rothery (GHR) model explains the relationship between two vehicles based on stimuli, response, and sensitivity [13]. The model captures many essential features at the qualitative level and provides a framework for mathematical stability analysis. However, it cannot properly describe the traffic phenomena in the free-flow state. Gipps developed a behavioral car-following model in which a driver alters his/her speed to reach the desired speed or safely follows the leader [14]. Measurement models have been proposed to explain the desire of a driver to maintain the minimum space headway [15]. Existing car-following models have been developed under the assumption that two vehicles must adhere to one of the minimum safety requirements, such as minimum safety distance, minimum reaction time, and minimum deceleration rate. Recently, research on a car-following model that reflects the driving behavior of an automated vehicle has been conducted. Y. Zhou et al. developed a methodology to adjust the car-following behavior of connected and automated vehicles (CAVs) using V2X communication [16], and W. Kontar et al. developed a model to predict car-following behaviors of AVs. They proposed a logistic classifier coupled with a convoluted multivariate Gaussian process (MGP) [17]. However, these models have the limitation that they cannot describe risky situations that do not follow the basic assumption of the minimum safety requirements. To develop ADASs and AVs that can operate correctly in real traffic situations, a robust tool to describe rare events, such as near-collision and collision events, is needed. Yajie Zou et al. developed a coupled hidden Markov model (CHMM) that can explain the intra-heterogeneity of individual drivers [18], and Jon Ander Ruiz Colmenares et al. conducted research to derive driving behavior that causes motion sickness using machine learning techniques [19]. Yuchuan Du et al. developed a deep reinforcement learning technique that enables autonomous vehicles to perform comfortable and energy-efficient speed control on rough pavement [20]. SSMs are crucial to representing the contributing factors and failure mechanisms that lead to road collisions because it is challenging to collect data on such rare events. Although historical collision data are available, they do not include near-collision data, which are also critical to improving safety. Several SSMs have been developed to estimate collision risk in car-following situations, including the time-to-collision (TTC) method developed by Hayward [21], which estimates the risk of collision between two consecutive vehicles. However, TTC has limitations in representing the collision risk under various traffic conditions. Modified TTC methods have been proposed, and stopping distance-based SSMs, such as the stopping distance index (SDI), stopping headway distance (SHD), and the crash index (CI), have high sensitivity but still do not fully reflect human reaction behavior [22].

Driving behavior models only explain overall behavior but have limitations in that they cannot explain the risky driving behavior required by AVs for decision making. On the other hand, collision-risk models, including SSMs, cannot identify potential risky driving tendencies because they calculate risk according to the relationship between two vehicles at a specific point in time. Therefore, a methodology that can identify the potential risky driving tendency of a following vehicle is needed by AVs for safe decision making. This risky driving tendency can be derived from the response change of the following vehicle according to the stimulus of the leading vehicle, and the study proposes a methodology to analyze the relative speed wave appearing as the response of the following vehicle using spectral analysis.

Spectral analysis is used to transform temporal variance information into frequency variance information, thereby providing insights into the periodicity and dominant frequencies of a time series. Abdüsselam Altunkaynak et al. predicted hourly significant wave height using spectral analysis-based models [23], and Wuan Wang et al. applied spectral analysis to identify drivers' behaviors before and after the start of distracted driving [24]. This technique has also been applied to the field of traffic analysis, where it can reveal information regarding the distribution characteristics of the frequency components and provide valuable information for developing traffic forecasting models.

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