Lane Changing Maneuvers for Vehicle Driving Safety

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The increasing number of vehicles has caused traffic conditions to become increasingly complicated in terms of safety. Emerging autonomous vehicles (AVs) have the potential to significantly reduce crashes. The advanced driver assistance system (ADAS) has received widespread attention. Lane keeping and lane changing are two basic driving maneuvers on highways. It is very important for ADAS technology to identify them effectively. The lane changing maneuver recognition has been used to study traffic safety for many years.

Keywords: lane changing maneuver ; acceleration ; HighD ; k-nearest neighbor classification (KNN)

1. Introduction

As the number of vehicles increases worldwide, traffic conditions are more and more complex in terms of safety. On 23 December 2005, a grave rear-end collision occurred on a highway in Beijing, China. Twenty-four people died in this collision. Forty people died in Senegal because of a traffic accident on 8 January 2023. According to the World Health Organization (WHO), approximately 1.3 million people die each year as a result of road traffic crashes. Between 20 and 50 million more people suffer non-fatal injuries, with many incurring a disability as a result of their injury.

Emerging autonomous vehicles (AVs) have the potential to significantly reduce crashes [1]. Driven by cutting-edge technologies such as sensor technology and artificial intelligence, the development of AVs has entered a new stage. There are different paths for AVs to develop. Among them, the advanced driver assistance system (ADAS) has received widespread attention. With advanced sensors and intelligent video systems, ADAS alerts the driver to potential traffic hazards or even takes over control to prevent a collision. Lane keeping and lane changing are two basic maneuvers on the road. In comparison with lane keeping maneuvers, lane changing maneuvers present more dangers and risks to traffic safety. It is also more likely for lane changing maneuvers to lead to traffic accidents. In the U.S., the percentage of fatal accidents associated with lane changing increased from 18% to 23.6% from 2005 to 2014 [2]. Traffic data in recent years also show that 23.91% of traffic accidents are caused by lane changing [3]. In order to avoid traffic accidents caused by lane changing maneuvers and improve traffic safety, it is very important for ADAS technology to effectively identify vehicles' lane changing maneuvers.

2. Lane Changing Maneuvers for Vehicle Driving Safety

Analysis of driving trajectories is one of the heated topics in the field of traffic safety. Mauriello et al. explored driving behavior on horizontal curves of two-lane rural highways based on a driving simulator experiment. Six major classes and twenty-one sub-classes were defined [4]. In addition, their study pointed out that driving trajectories are a promising surrogate measure of safety as highlighted by the correlation between the trajectories identified as dangerous and the radii of the curves. Another study analyzed driving trajectories with little lane discipline [5]. By studying lateral distance-keeping behavior, lane keeping behavior and the lateral behavior of vehicles, the research explored the non-lane-based behavior of traffic. The researchers also compared lateral clearances of various vehicle types in the study.

Lane keeping and lane changing are maneuvers that commonly happen in driving trajectories. Galante et al. studied lane keeping by analyzing the mean and standard deviation of lateral position [6]. They demonstrated several effective treatments which were strongly advised to be tested on the real road. Wonho Suh et al. developed an index related to lane keeping named Deviation of Lateral Placement (DLP) which represents a driver's steering behavior along a given section of highway [7]. The index was able to demonstrate a vehicle's overall lateral stability. Among the studies on lane changing, some researchers have used lateral position and vehicle heading angle to study lane variation [8]. They created a new ADAS system to support drivers when overtaking cyclists.

Lane changing maneuvers' recognition has been used to study traffic safety for many years. Many studies have focused on this area to test new theories, improve the accuracy of lane change identification and reduce traffic accidents. The

Gipps decision method model based on logic rules was the first to be proposed [9]. However, this model was too idealistic to be applied in practice. Researchers have optimized and improved the classical model from different aspects and built new models, such as MITSIM and CORSIM [10][11]. Other models have also been proposed by researchers. One group of researchers built an integrated lane changing model combining a sine function and a constant velocity migration function [12]. A multilevel analysis model of vehicles' longitudinal and lateral acceleration during lane change was established as well [13]. Other researchers set up a safe lane-change model based on a quintic polynomial trajectory [14].

With the development of technology, researchers used new methods to analyze lane change maneuvers. Machine learning was proven to be useful for estimating, classifying and predicting lane changing maneuvers. Using steering wheel angle and angular velocity as inputs to an HMM model, researchers developed an algorithm for recognizing lane changes [15]. Based on their method, the accuracy of lane change left (LCL), lane change right (LCR) and lane keeping (LK) classifications was 84%, 88% and 94%, respectively. Other researchers established a decision model of an autonomous lane change by analyzing the influencing factors of autonomous lane change [16]. Additionally, with the help of a support vector machine (SVM), they solved the multi-parameter and nonlinear problems. Another RVM model used 200 sensor signals [17]. It was able to classify a driver's intentions three seconds before the actual lane change occurred. With long short-term memory networks (LSTM) and deep belief networks (DBN), researchers modeled both lane keeping and lane changing [18]. Compared with the classical model, this model could accurately estimate both lane keeping and lane change maneuvers. The model had higher lane-change prediction accuracy as well. Though all these methods have achieved good results, none of them have used a distinct set of physical data as input.

Meanwhile, vehicle status data are also derived from a variety of sources. Researchers used different methods to obtain naturalistic driving data (NDD). One group of researchers developed a data collection platform called POSS-V (PKU Omni Smart Sensing - Vehicle) to collect real human driving data in urban street scenarios [19]. The POSS-V included GPS/IMU, a steering angle sensor and a panoramic camera. Other researchers made use of UAVs to collect natural driving-track data [20]. A fixed-base driving simulator was also utilized by researchers [21]. Compared with collecting data individually or using virtual data, it is more convenient and efficient to use datasets from the real world. Both NGSIM and HighD [22], two high-resolution natural vehicle-trajectory datasets, had a good effect on machine learning [23][24]. However, among the lane-changing maneuver recognition models which were based on a dataset, a distinct set of physical data was not used as the input for machine learning.

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