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A Review of Research Progress on Driver's Dynamic Behavior and Driving Intentions

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Abstract

In recent years, there has been rapid development in smart vehicles and connected technology, presenting an opportunity to address traffic accidents caused by human factors. In an intelligent connected environment, comprehensive acquisition of traffic information enables the quick and accurate identification of drivers' driving intentions and behaviors. Recognizing driving intentions can be utilized to supervise drivers' anticipated actions. When a driver's predicted behavior is assessed as unsafe in the current driving environment, driving assistance systems can provide corresponding suggestions or even warnings. Furthermore, understanding and predicting drivers' driving intentions can help other traffic participants better grasp the motion status of surrounding vehicles and anticipate future traffic situations, thereby achieving safer and more efficient driving.

Keywords

Traffic Safety; Driver Behavior; Driving Intentions.

1. INTRODUCTION

Road traffic accidents are a serious issue that poses a threat to human life and property safety. According to a report released by the World Health Organization (WHO) [1], approximately 1.35 million people worldwide die from road traffic accidents each year, and the traffic accident mortality rate in developing countries is twice as high as that in developed countries. In recent years, the number of motor vehicles in China has been increasing steadily (Figure 1). According to statistics from the Traffic Management Bureau of the Chinese Ministry of Public Security, as of the end of 2022, China had a total of 415 million motor vehicles, with over 500 million licensed drivers, ranking first in the world. With the continuous growth in the number of motor vehicles, China is facing frequent and severe road traffic accidents, making the traffic safety situation increasingly critical.

Road traffic safety is influenced by the factors of "human-vehicle-road-environment," with drivers being the main factor contributing to road traffic accidents, as 90% of accidents are caused by human factors. Driving is a task that involves dynamic interactions with the driving environment, and drivers make numerous decisions and actions in response to changes in their surroundings. These decisions and actions directly or indirectly affect the behavior of other traffic participants, and incorrect decisions often lead to accidents. Understanding and recognizing drivers' behavioral intentions are crucial for traffic safety.

During the driving process, drivers' driving intentions dynamically change, and driving intentions are internal states that cannot be directly observed or measured. Therefore, they must be inferred from observable indicators or vehicle operations. Vehicle operation features are the results of interactions between drivers and vehicles, and their extraction relies on accurate sensors and data analysis algorithms. However, there may be variations in driving operation features among different vehicles and environments. This leads to poor accuracy and timeliness in identifying driving intentions based on vehicle features, limiting their practical application. Additionally, due to human heterogeneity and instability, there has been limited progress and application in addressing driving intentions from the perspective of driver characteristics.

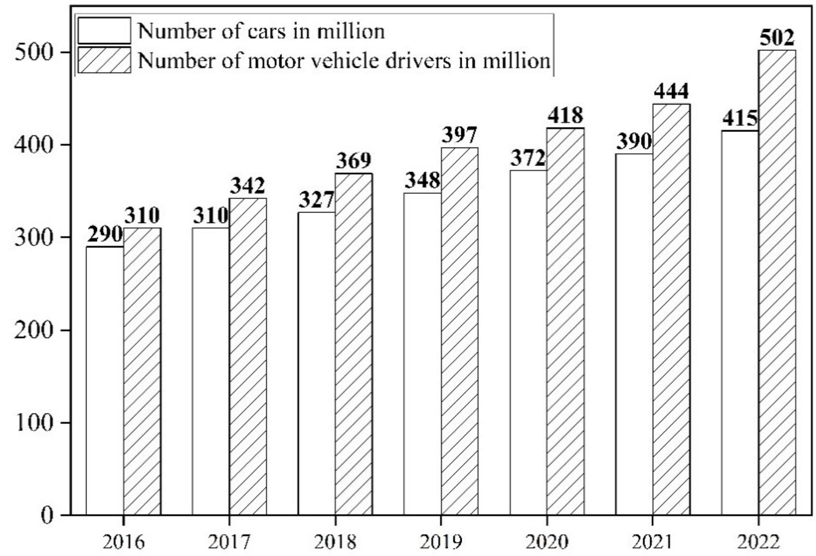

Figure 1. Statistics on the number of motor vehicles and drivers in China from 2016 to 2022

2. DRIVER'S DYNAMIC BEHAVIOR

Driver's behavior actions refer to various actions or operational behaviors taken by drivers during the driving process. These behavior actions directly affect the safety and smoothness of the driving process. Driver's dynamic behavior includes physiological features and control features. Physiological features encompass behavioral characteristics such as electroencephalography (EEG), facial expressions, eye movements, hand movements, and foot movements. Control features involve actions such as steering wheel control, brake pedal operation, and accelerator pedal operation.

In terms of physiological behavior feature detection, multiple detection devices are primarily employed. For example, Morales et al. [2] detected driver's EEG signals using TGAM devices and eye movement characteristics such as gaze amplitude and gaze duration using the JAZZ-novo head-mounted system. Feng et al. [3] used an MP150 physiological recorder to measure driver's heart rate. Huang et al. [4] utilized wearable physiological monitoring devices with various modules to obtain multiple physiological indicators of drivers, including electrocardiography (ECG), EEG, electromyography (EMG), and blood pressure data. Physiological characteristics detection using these instruments requires specific equipment and devices, as well as physical contact with the driver, which can interfere with their normal driving operations, making it challenging to apply in practical settings. Some researchers have proposed non-contact detection methods based on image recognition. Poursadeghiyan et al. [5] proposed the Viola-Jones algorithm, which utilizes driver's video images under driving simulation conditions to detect eye behaviors such as closed eyes, blink frequency, and blink duration. Ohn-Bar et al. [6] developed a vision-based real-time analysis framework algorithm using a monocular camera, enabling tracking of driver's hand motion trajectories, hand gesture prediction, and detection of abnormal events. Yin et al. [7] proposed a 2D driver pose detection method based on the

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Simple Baseline algorithm and a 3D driver pose detection method based on the DensePose algorithm, comparing and analyzing the detection results of the two algorithms using publicly available driver image datasets. Additionally, various algorithms such as OpenCV, HOG+SVM, Bi-LSTM, and MTCNN can be utilized for driver action state recognition, including yawning, mouth opening degree, head movements, eye movements, and more [8].

In terms of vehicle control behavior detection, driver behavior is primarily detected by installing onboard sensors. For example, Chai [9] obtained steering wheel data through a steering angle sensor to detect driver's steering wheel control parameters. Xu et al. [10], under natural driving conditions, measured pedal force using Forsentek sensors to capture driver's acceleration and deceleration actions. Wu et al. [11] integrated multiple onboard sensors to capture driver's actions related to accelerator pedal, brake pedal, turn signal, and steering wheel rotation. Sensor-based control behavior detection achieves higher accuracy but requires the installation of vehicle-specific sensors, which adds to the cost. Furthermore, researchers have proposed image recognition-based methods for control behavior detection. Tran et al. [12], using images captured by foot-facing cameras, employed optical flow and hidden Markov models to track foot movements and recognize driver's brake and accelerator pedal actions. Hoang Ngan Le et al. [13], based on images of drivers under natural driving conditions, introduced the MS-FRCNN deep learning algorithm to detect hand movements and accurately identify whether the driver's hands are on the steering wheel. Chen et al. [14] utilized the YOLOv5 algorithm to visually recognize driver's actions such as steering wheel control and braking operations.

3. VEHICLE DRIVING INTENT

3.1. The concept of vehicle driving intention and intention recognition

According to the theory of mind [15], intent is a mental state that represents a person's desired action to achieve a certain goal. Bratman [16] suggests that intent is an attitude that guides an individual's future actions. Pereira and Han [17] define intent as what a person wants to do soon. It can be observed that intent is an intrinsic mental attitude that precedes behavioral actions and guides them. Therefore, the vehicle driving intent of a driver can be defined as the driver's desired behavioral actions towards the vehicle soon. The term "near future" refers to the coming seconds, depending on the type of vehicle and driving scenario.

Intent recognition refers to the process of perceiving the intentions of other agents, which can be confirmed through observed behaviors or their influence on the environment. Intent prediction, on the other hand, involves inferring the intended actions of an agent based on observable features. In terms of time dimension, intent recognition confirms already occurred actions based on observable features, while intent prediction infers actions that have not yet occurred based on observable features. The recognition of driver's vehicle driving intent involves inferring their intended vehicle control actions based on observable features. Vehicle driving intent is often difficult to detect directly, but it can be inferred through analysis of vehicle control characteristics and driver's state parameter data.

3.2. Classification of driver's vehicle driving intention

Driver's intent classification refers to categorizing the driver's behaviors and actions into different intents. The classification of vehicle driving intent is a prerequisite for intent recognition. In terms of the timeline, vehicle driving intent can be classified into the strategic level, task level, and operational level [18]. The strategic-level intent involves top-level planning for the current driving task, such as route selection, driving strategies, destination determination, etc. It has the longest time cycle, usually in minutes or hours. The task-level vehicle driving intent is the focus of research and includes various common driving behavior

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decisions, such as going straight, changing lanes, turning, braking, etc. Due to the dynamic nature of the road environment, it is challenging to accurately determine task-level driving intent like strategic-level intent. It can only be inferred based on external temporal features. The time cycle of task-level driving intent is usually in minutes or seconds. The operational-level intent belongs to the bottom-level planning and represents the specific embodiment of the task-level intent, such as the driver's lateral and longitudinal vehicle control. The task-level intent is typically composed of a series of operational-level intents. The time cycle of operational-level intent is shorter, usually in seconds or milliseconds.

Additionally, vehicle driving intent can be classified based on the motion direction. Longitudinal and lateral are the two fundamental directions of vehicle motion. Driver's longitudinal behaviors include braking, acceleration, lane keeping, etc., while lateral behaviors include steering, lane changing, etc. Due to the complex interactions with surrounding vehicles, lateral behavior intent is usually more complex than longitudinal behavior intent. In driving, the vehicle's intent in the lateral and longitudinal directions better reflects the driver's short-term behavioral goals and is more likely to contribute to traffic accidents, thus having a greater impact on traffic safety [19].

3.3. Algorithm for Recognition of Driving Intention of Driver and Vehicle

There are three categories of research on driver's vehicle driving intent recognition and prediction based on different input parameters: vehicle control parameter-based driving intent recognition models, driver feature-based driving intent recognition models, and comprehensive models that integrate both types of parameters. Vehicle control parameters include speed, acceleration, steering wheel angle, pedal position, and turn signal status, while driver features include driver behavior actions, eye movements, and brainwave parameters.

Vehicle dynamics parameters provide direct signals and are easily collected. However, these parameters are not effective in reflecting the vehicle's driving intent before the driver takes control actions. Therefore, vehicle control parameters are often used for ongoing intent recognition rather than intent prediction before actions are taken. Driver behavior features, such as head posture and eye gaze patterns, can provide early clues about the driver's intent [20]. Studies have shown that intent models based on driver behavior features exhibit higher recognition accuracy for lane-changing intent compared to vehicle motion parameters [21]. Constructing driver intent recognition models from the driver's perspective can further improve the accuracy and lead time of driving intent recognition models.

In recent years, there has been extensive research on driver's vehicle driving intent recognition and prediction, and various models have been developed for this purpose. These models can be mainly categorized as probability models, discriminative models, rule-based models, and deep learning models.

Probability graph models, including Bayesian networks, dynamic Bayesian networks, and hidden Markov models, are commonly used in driver's vehicle driving intent recognition and prediction. For example, Leonhardt et al. [22] conducted real-world driving experiments and used head movements and gaze behavior data captured by cameras to predict lane-changing intent using Bayesian networks. Liu et al. [23] utilized the highD naturalistic driving dataset from German highways and constructed a dynamic Bayesian network model using parameters such as lateral position, lateral velocity, and lateral acceleration to predict lane-keeping, left-lane changing, and right-lane changing intents. Berndt et al. [24] employed real-world scenario data and built a Markov chain model based on vehicle operational characteristics indicators such as braking pressure, steering wheel angle, steering wheel angular velocity, and yaw rate to predict lane-changing and turning intents.

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Discriminative models mainly include support vector machines (SVM), random forests, and other models. Huang [25] used inputs such as steering angle, throttle pedal pressure, vehicle state (speed, acceleration, and yaw rate), and eye movement data to construct an SVM-based model for predicting driver's lane-changing intent, achieving an accuracy of 88.78%. Doshi et al. [26] developed a lane-changing intent model based on the relevance vector machine, with inputs including eye movement and head rotation parameters, achieving a recognition accuracy of 88.51% within 3 seconds before a lane change. Morris et al. [27] used vehicle operational characteristics such as steering wheel angle, yaw rate, and turn signal status, as well as driver eye movement features, to construct an SVM model for predicting driver's lane-changing intent, successfully detecting the intent 2-3 seconds before a lane change. Tawari et al. [28] used vehicle control parameters such as steering wheel angle, vehicle speed, brake, and throttle pedal positions, as well as driver facial features such as facial contour, eye corners, mouth corners, and nose tip, to construct a random forest-based model for predicting driver's maneuvering intent at intersections, achieving a prediction accuracy of 80% within 2 seconds.

Rule-based models for vehicle driving intent prediction mainly establish rules to relate vehicle operational features to driver state changes. For example, Bocklisch et al. [29] conducted real-world driving experiments, captured driver's head movements and vehicle control characteristics using cameras and sensors, and predicted driver's lane-changing intent using an adaptive fuzzy pattern classification rule, achieving real-time recognition of driver's lane-changing intent 7 seconds before the lane change. Lee et al. [30] formulated grammar-structured rules based on driver's gaze, driving speed, steering angle, and other vector sequences to construct a driver intent recognition method, achieving detection accuracies of 70.5%, 75.0%, and 80.8% for driving intents (lane changing and turning) within 2.0s, 1.5s, and 1.0s, respectively. Xu et al. [31] recognized driver's braking intent based on the driver's brake pedal actions, using fuzzy inference rules and learning vector quantization methods, to achieve intent recognition.

In recent years, deep learning has rapidly developed and has been widely used in driver's vehicle driving intent recognition. Research often relies on building neural network models, with at least two hidden layers, for intent recognition. For example, Li et al. [32] constructed a model for recognizing driver's left-lane changing and right-lane changing intents based on a recurrent neural network (RNN), achieving an intent recognition accuracy of 96%. Zhang et al. [33] proposed a long short-term memory (LSTM) network framework based on the vehicle's trajectory to predict overtaking behavior intentions of rear vehicles. Jain et al. [34] combined RNN and LSTM networks, integrating internal and external vehicle features to predict driving intent based on partial time contexts. Guo et al. [35] introduced an attention mechanism into an LSTM-based model for driver's lane-changing intent recognition, achieving a recognition accuracy of 98.3% within 3 seconds before a lane change.

Discriminative models are more suitable for binary classification recognition of driver's driving intent. Probability graph models achieve higher detection accuracy in multiple intent recognition tasks. Rule-based models for vehicle driving intent prediction mainly rely on vehicle dynamics parameters as inputs, while deep learning models can utilize various parameters compared to other prediction models, often achieving higher prediction performance.

3.4. Evaluation of Intent Recognition Algorithms

Driver-vehicle trajectory prediction models for detecting driver's intent can be evaluated based on two aspects: detection accuracy and prediction horizon [36]. Existing models for driver-vehicle trajectory prediction are essentially classifiers, and therefore, detection accuracy is commonly assessed using metrics such as prediction accuracy, error rate, precision, and recall [37]. Dogan constructed three models for driver-vehicle intent recognition: recurrent neural

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networks, feedforward neural networks, and support vector machines. These models were compared based on prediction accuracy, error rate, precision, and recall.

The prediction horizon refers to the number of future time steps in advance for which intent can be predicted. A superior intent prediction model is capable of predicting further into the future. However, as the prediction horizon increases, the prediction accuracy gradually decreases. Therefore, an excellent driver-vehicle intent prediction model needs to maintain good prediction accuracy while ensuring a certain prediction horizon. Kumar et al. [38] developed an SVM-based vehicle intent prediction model that achieved an 80% recognition accuracy within a prediction horizon of 1.3 seconds. Gong et al. [39] constructed a radial basis neural model for vehicle intent prediction, achieving a recognition accuracy of 95.22% within a prediction horizon of 3 seconds. Leonhardt et al. [40] developed an ANN-based vehicle intent prediction model that reached a recognition accuracy of 98.3% within a prediction horizon of 2 seconds. Ju and Bi [41] designed a vehicle intent prediction model capable of recognizing intent 0.6 seconds before braking with an accuracy of 83%. Existing driver-vehicle intent detection models often achieve high accuracy within a prediction horizon of 2-3 seconds.

4. CONCLUSION

In summary, existing research on driver's vehicle driving intent tends to be relatively static, typically relying on historical data to build models for intent recognition and prediction. Moreover, intent prediction models often rely heavily on vehicle dynamics parameters, resulting in poor accuracy and timeliness in driving intent recognition. Studies that utilize driver behavior features as inputs often require specialized experimental equipment, limiting their applicability in real-world driving scenarios. Deep learning algorithms based on computer vision recognition, with their diverse input parameters and strong generalization capabilities, have gradually become the mainstream research approach for driver's vehicle driving intent. The recognition of driver's driving intent is still in the research stage, focusing on observable features of the driver. It provides theoretical and technical references for the design of intelligent driving assistance systems, aiming to reduce traffic accidents and enhance driving comfort.

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