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Proposal for Vehicle Trajectory Abstraction and Analysis Methods in Autonomous Driving

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In recent years, research and development of autonomous driving technology has been actively progressing in both the automotive and information technology industries. Not only has the evolution of advanced driver assistance systems (ADAS) been accelerated, but numerous automakers, parts suppliers, and IT companies around the world are participating in the development of fully autonomous driving (Level 4) under certain conditions, and ultimately Level 5 autonomous driving, which will enable operation in any environment. However, in order to implement and popularize autonomous driving technology in society, significant challenges must be overcome alongside technological development. One of these is "safety verification." Because the system takes over all vehicle recognition, judgment, and control functions from the human driver, it is necessary to objectively and quantitatively demonstrate safety levels equal to or even superior to those of humans.

Relying solely on traditional on-road testing is not a realistic approach to evaluating the safety of autonomous driving systems. Until now, automobile safety evaluations have focused on long-distance driving on test courses or public roads. However, statistically proving the safety of an autonomous driving system requires astronomical driving distances. This not only requires enormous time and expense, but also poses a significant risk of accidents during testing. Furthermore, dangerous situations that could lead to personal injury accidents only occur sporadically in everyday driving environments, making it impossible to cover diverse and complex traffic conditions through real-world driving alone. Therefore, verification based solely on real-world driving has physical and statistical limitations.

To overcome these challenges of real-world driving tests and advance development and evaluation efficiently and comprehensively, the "scenario-based approach" is currently mainstream. This method involves predefining various anticipated traffic situations as "scenarios" and recreating these scenarios in a virtual environment to verify the behavior of autonomous driving systems. However, if each company develops systems based solely on its own unique standards, it becomes difficult to objectively evaluate the safety of the technology and make cross-comparisons. To resolve this issue, it is essential to establish a standard evaluation method and common platform that transcends industries and countries. Against this background, the Japan Automobile Manufacturers Association (JAMA) proposed the "JAMA Framework." This framework aims to comprehensively and systematically evaluate the safety of autonomous driving systems by organizing and classifying events important to safety evaluation from an infinite number of real-world traffic environments as "scenarios." Scenarios in the JAMA framework express driving situations such as "cutting in," "departure," "acceleration," and "deceleration," as well as the vehicle's initial position, using natural language, parameters, and diagrams. This representation format has a "high level" of abstraction, making it easy for humans to intuitively understand traffic situations. However, the raw data (vehicle trajectories) obtained from simulations are huge time-series datasets that record extremely detailed physical quantities such as vehicle position (XYZ coordinates), orientation, speed, and acceleration at very short time intervals. While this is essential for detailed analysis of system behavior, its very "low level" of abstraction prevents direct comparison and verification with high-level scenarios defined by humans. In other words, a large "abstraction gap" exists between the descriptions in the JAMA framework, which serve as evaluation standards, and the simulation data that records the behavior of the autonomous driving system being verified. Existing methods have attempted to bridge this gap by using manual review or rule-based judgments with strict thresholds, but these methods have limitations in terms of efficiency and comprehensiveness. This abstraction gap poses a significant obstacle to efficiently and automatically determining whether simulation results meet specific scenario requirements and to discovering undefined, unknown, and dangerous behaviors (new candidate scenarios) from massive driving logs.

In this paper, we aim to bridge this "abstraction gap" by proposing a method for abstracting low-level vehicle trajectory data and enabling the analysis of driving behavior and situation changes. The proposed method converts trajectories, which are continuous numerical data, into meaningful, discrete "states" and represents their temporal transitions as "symbol sequences." Specifically, we implemented and evaluated the following two approaches. The first is the "equidistant grid method," which divides the relative coordinate space centered on the ego-vehicle into equidistant grids and defines states based on which grids other vehicles are located. The second is the "domain decomposition method," which segments the area around the vehicle into semantic regions such as "forward," "lateral," and "rearward," achieving abstraction that more closely matches human perception. These methods enable the seamless integration of massive amounts of data obtained from simulations and real-world driving with a structured scenario set. To verify the effectiveness of the proposed method, we conducted experiments using a pseudo dataset of tens of thousands of records generated by systematically varying parameters, as well as more realistic driving data obtained from the autonomous driving simulator AWSIM. The evaluation metrics used were scenario detection accuracy, data compression rate, and safety assessment soundness. Furthermore, to clarify the position of this research, we conducted comparative experiments with representative existing approaches. The first comparison target was a formal method using high-precision maps (Lanelet2) and signal temporal logic (STL). This method determines scenarios based on strict logical formulas, but experiments revealed that it is vulnerable to errors in map definitions (e.g., lane width settings), and even slight differences in settings from the real environment can result in false negatives. The second comparison target was a method using large-scale language models (LLMs), which have attracted attention in recent years. While LLMs excel at understanding the context of trajectory data, they face challenges in applying them to rigorous safety verification due to the computational cost of processing thousands of records and the problem of hallucination, which outputs nonexistent facts.

Experiments showed that the proposed method achieved a high compression rate, reducing the original data volume by approximately 99%. Furthermore, by appropriately setting the grid width and region definition, we were able to reduce false negatives in scenario detection to zero, demonstrating sound abstraction that prevents "overlooking danger," which is paramount in safety verification. In particular, we confirmed that using the region decomposition method (15-region model) allows for a reduction in the number of states compared to the uniform grid method without generating false negatives.Furthermore, while the existing method (STL) is a discriminative approach that determines "True/False," our proposed method has the distinct advantage of describing trajectories as symbolic sequences. This makes it possible to analyze and search for transition patterns after the fact, even for unknown behaviors that have not been defined in advance.

In conclusion, our method maintains high robustness while reducing its dependence on high-precision maps, and is capable of faster and more reliable processing than LLM. This makes it extremely effective as a technology for quickly screening dangerous scenarios from massive driving logs, significantly contributing to ensuring the safety of autonomous driving technology and improving development efficiency.