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Current Development, Comparison and Future Directions in Vehicle Trajectory Prediction

Lian Zhou, Xiaoliang Wang, Xiaolan Zhou*, Yuzhen Liu and Hao Yue

School of Computer Science and Engineering, Hunan University of Science and Technology, China, Hunan Key Laboratory for Service Computing and Novel Software Technology, China

***Corresponding Author:** Xiaolan Zhou, Hunan University of Science and Technology, Taoyuan Road, Yuhu District, Xiangtan, Hunan Province, China.

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Abstract

With the flourishing development of autonomous driving technology and the increasing demand for convenient travel experiences, more and more researchers are diving into the development of efficient and reliable autonomous driving technology. Therefore, this paper aims to explore the main technologies of vehicle trajectory prediction in autonomous driving and comprehensively review the research status of vehicle trajectory prediction in autonomous driving over the past decade. It delves into the characteristics and differences of research based on physical methods, basic machine learning methods, and deep learning methods. Next, we focus on analyzing the currently mainstream deep learning-based vehicle trajectory prediction models. We utilize open-source datasets in the autonomous driving domain, such as the Argoverse dataset and the NuScenes dataset, as well as evaluation metrics like Average Displacement Error (ADE) and Final Displacement Error (FDE), to provide a detailed exposition and analysis of the progress made with existing technologies through research and experimentation. Finally, the article points out the possible directions for future breakthroughs in this field, aiming to guide readers and researchers to overcome existing technological bottlenecks and further promote the advancement of this field.

Keywords: Autonomous Driving; Vehicle Trajectory Prediction; Physics-based Methods; Machine Learning; Deep Learning

Abbreviations

Average Displacement Error - ADE.
Final Displacement Error - FDE.
deep Monte Carlo Tree Search - deep-MCTS.
Monte Carlo Tree Search - MCTS.
Gaussian Processes - GP.
Support Vector Machines - SVM.
Bayesian Networks -BN.
Convolutional Neural Networks -CNN.
Long Short-Term Memory Networks -LSTM.
Graph Neural Networks - GNN.
Attention Mechanisms - AM.
Graph Attention Mechanism GAM.

Introduction

In practical driving scenarios, humans are recognized as the least reliable factor, contributing significantly to the frequent occurrence of traffic accidents [1]. However, in the increasingly digitized and intelligent traffic systems of today, vehicles and nearby pedestrians play crucial roles. Numerous researchers [2-6] have delved into predicting the behaviors and trajectories of agents such as vehicles and pedestrians from multiple dimensions, attempting to anticipate their future actions. With the maturation of intelligent traffic management systems, the Internet of Things, and autonomous driving technologies, accurate prediction and research on vehicle trajectories have become increasingly vital. The rapid advancement of these technologies offers new opportunities and solutions for improving traffic safety, enhancing traffic efficiency, and optimizing urban planning. Autonomous vehicles represent a key innovation in current traffic systems, aimed at reducing or eliminating traffic congestion and accidents caused by human decision-making errors or insufficient traffic information. Trajectory prediction of vehicles, as a crucial research direction and foundation, primarily relies on sensors, cameras, and various intelligent algorithms to simulate the perception capabilities of drivers, enabling real-time perception of surrounding driving environments and traffic conditions, and making accurate and reasonable predictions. This advancement fosters the development of intelligent transportation and driving safety.

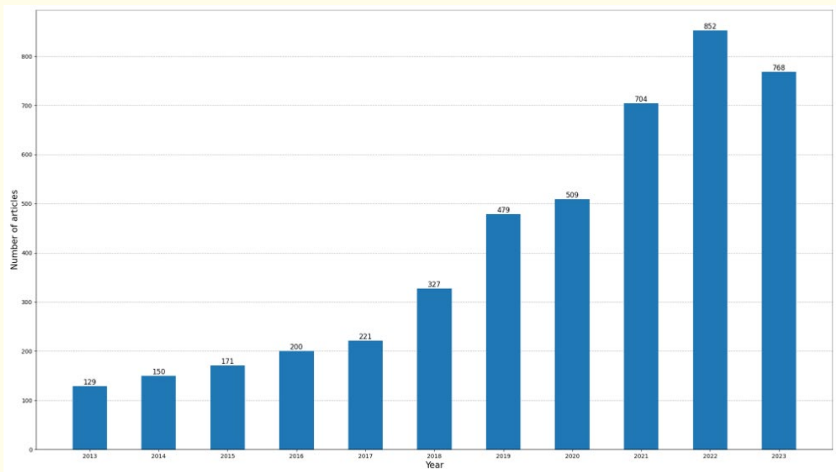

Figure 1: Displays the annual number of publications retrieved by searching the keyword 'vehicle trajectory prediction' on the Web of Science platform over the past decade. It can be observed that, with the continuous advancement and development of technology, research output on vehicle trajectory prediction has been increasing year by year, particularly reaching its peak during the period from 2021 to 2023.

Around the world, researchers have devoted extensive efforts and groundwork to the advancement of autonomous driving through the lenses of physics, machine learning methods, and deep learning models (as illustrated in Figure 1, depicting the annual publication volume in the field of vehicle trajectory prediction over the past decade). These endeavors have yielded a plethora of research conclusions and achievements. Against this backdrop, this paper aims to delve into the developmental trajectory of vehicle trajectory prediction. Taking cues respectively from physics, machine learning methods, and deep learning models, we systematically analyze the current research status of trajectory prediction, and compare different methods, their applicability, and potential directions for future research. Our goal is to provide valuable guidance and insights for the further advancement of this field. Additionally, we will focus on and explore the development and progress of deep learning models, which we believe hold the greatest potential. Therefore, the main contributions of this article are as follows:

1. We are grounded in the primary research methods and the current state of vehicle trajectory prediction over the past few years. By conducting comparative analyses of various methods, we aim to comprehensively understand the subtle differences and advantages, providing more effective guidance for practical applications.
2. Our focus lies in the exploration of the development of the most prominent deep learning algorithms and models in trajectory prediction. We aim to delve into their application potential and limitations in vehicle trajectory prediction from multiple dimensions.
3. We summarize the current technological bottlenecks and challenges, elucidating future research directions to facilitate breakthroughs for researchers in the field.

In the second section, we will introduce professional terminology in the field of trajectory prediction and analyze the current research status and representative works in this field from multiple dimensions. In the third section, we will compare and analyze existing technologies and methods, with a focus on introducing the achievements and differences of deep learning applied to the field of vehicle trajectory prediction. Finally, we will provide possible research directions for the future and conclusions.

Methods and Current Situation

Professional Term

- ***Multimodal Data***: Mainly refers to the dynamic data from vehicles and surrounding environments collected by various sensors (such as cameras, radar, GPS devices, etc.) according to driving needs. It can include vehicle position, speed, and acceleration, as well as information about the surrounding environment, etc.
- ***Scene Understanding and Modeling***: Refers to analyzing various elements and features in the driving environment, understanding the traffic scenes and driving conditions of vehicles, and establishing reasonable prediction and analysis models. This process is crucial for driving judgment and obstacle avoidance behaviors.
- ***Spatiotemporal Prediction***: Based on the historical trajectory information of target vehicles in actual driving scenarios (temporal dimension), and the dynamic interaction with surrounding vehicles (spatial dimension), reasonable predictions are made for target vehicles.
- ***Multimodal Trajectory Prediction***: Because of the influence of driver psychology, behavioral habits, and situations in actual driving scenarios, various driving possibilities may arise. Therefore, it is necessary to generate multiple predicted results to simulate the uncertainty in actual driving scenarios.

Current Research Status

The prediction of vehicle trajectories heavily relies on various sensors, such as cameras, radars, and GPS, among others, which can gather rich multimodal trajectory data and environmental information. These diverse sensors work together to provide comprehensive and diversified data sources for vehicle trajectory prediction. Unfortunately, the fusion and modeling of multiple types of data are challenging tasks, requiring the design of reasonable methods and models that facilitate understanding driving scene information. This facilitates the generation of multimodal trajectory predictions to simulate the uncertainty and variability of actual driving traffic scenes, thereby improving the robustness and reliability of predictions. Existing research, as illustrated in Figure 2, mainly focuses on achieving effective prediction of vehicle trajectories through methods such as physics, machine learning, and deep learning.

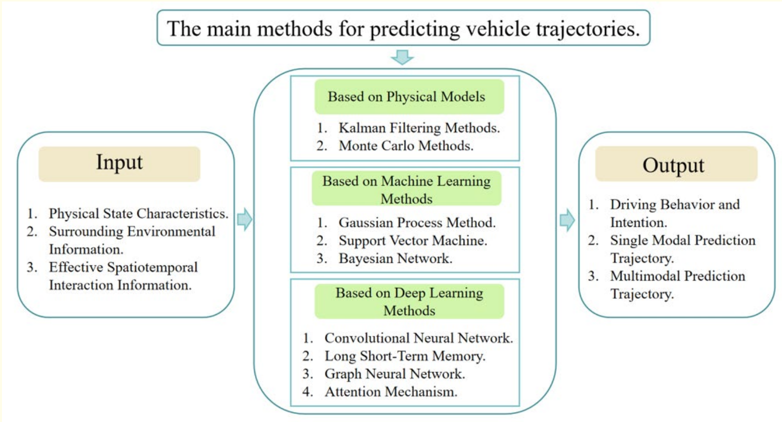

Figure 2: Methods Primarily Employed for Vehicle Trajectory Prediction.

Physics based methods

In the early days, due to limitations in experimental conditions and equipment, researchers often simulated vehicle motion based on physical state information to generate reasonable prediction results. The main approaches used to achieve effective trajectory prediction of vehicles were based on either kinematics (motion characteristics such as velocity, acceleration, and steering capability) or dynamics (dynamic properties such as mass, inertia, and friction).

In [7-9], numerous researchers have successively employed Kalman filters to introduce noise for estimating driving trajectories, which can also be considered pioneers in the field of trajectory prediction. Subsequently, the Monte Carlo method was applied to vehicle trajectory prediction, which is a numerical computing technique that solves problems through random sampling. [10] proposed a method for Deep Monte Carlo Tree Search (deep-MCTS) based on vision to enhance the driving stability and performance of autonomous vehicles. Timothy et al. [11] improved traditional methods by proposing a model-based MCTS algorithm, which effectively utilizes the future behavior of neighboring agents. From today's perspective, traditional physics-based prediction models often exhibit lower prediction accuracy and performance, mainly attributed to the models' inability to fully comprehend the physical state changes of nearby traffic participants and the complex nonlinear relationships.

Machine learning based methods

To address the aforementioned shortcomings of physics-based approaches, a plethora of machine learning-based methods have emerged. These approaches offer greater flexibility and data-driven predictions compared to their physical counterparts, particularly excelling in complex and nonlinear dynamic environments. Existing literature predominantly employs techniques such as Gaussian Processes (GP), Support Vector Machines (SVM), and Bayesian Networks (BN) in the domain of vehicle trajectory prediction.

Gaussian Processes (GP) can be applied to model the motion trajectories of vehicles or other traffic participants [12]. Gaussian Process Regression (GPR) is used to analyze data collected by static sensors to learn reasonable motion states. GP not only provide trajectory prediction results but also offer uncertainty information associated with the predictions. Liu et al. [13] combined a driving intent estimation model with a GP model in an integrated approach, improving both prediction accuracy and the rationality of uncertainty modeling. Support Vector Machine (SVM) is a classic algorithm commonly used in tasks such as classification and regression. Bayesian Networks (BN) have been applied to trajectory prediction to model driving intent and behaviors (e.g., acceleration, lane changing), performing well in classic machine learning-based approaches [14, 15]. Bayesian methods are separately used for lane changing and vehicle turning rule recognition and judgment [16]. A dynamic Bayesian network is designed for trajectory prediction of vehicle driving intent and operational behavior.

In summary, although machine learning methods that determine predictive distributions by mining data features have, to some extent, improved prediction accuracy and behavior recognition, bringing new development directions and ideas to the field of trajectory prediction, these methods excel in probability and maneuver strategy. They place greater emphasis on judgment of driving behavior and intent but lack the identification and understanding of actual road traffic participants.

Deep learning based methods

General methods only consider the vehicle's intrinsic physical state and simple behaviors, with limited modeling capabilities for roads and interactive behaviors. However, as the technology of deep learning becomes increasingly mature, numerous algorithms and models based on deep learning have emerged. These models have to some extent compensated for the shortcomings of traditional methods, demonstrating excellent predictive performance and a profound understanding of complex scenarios. Next, we will focus on comparing and analyzing the performance of vehicle trajectory prediction using methods such as Convolutional Neural Networks (CNN), Long Short-Term Memory Networks (LSTM), Graph Neural Networks (GNN), and Attention Mechanisms (AM) in deep learning.

Influenced by image and visual technologies, a significant amount of work [18-20] utilizes captured video features for feasibility prediction. In [2, 21], raster images and physical state information are generated based on trajectory data as model inputs, and CNN is employed to extract environmental information from raster images. This approach enhances the model's understanding of environmental information but is often constrained by the high computational cost required by image technologies and the inability to understand and model nuanced features. In [22], the introduction of LSTM accurately predicts longitudinal (such as acceleration, deceleration, etc.) and lateral (such as turning, lane-changing, etc.) motion variations on highways. [23] provides a reasonable interpretation by combining LSTM with AM to analyze the historical trajectory of the target vehicle and the interaction with nearby vehicles, demonstrating that STA-LSTM can effectively identify fine-grained channel switching behaviors. Subsequently, researchers found that graphs can effectively simulate social interaction behaviors in real driving scenarios, sparking interest in the application of GNN in vehicle trajectory prediction. PGP [24] utilizes a graph encoder to encode the target vehicle and the map into a directed lane graph to simulate effective interaction between the target vehicle and the lane [25-27]. All combine CNN with GNN to jointly consider the social interaction of predicting vehicle and surrounding neighboring vehicle environmental information, resulting in good predictive performance. The emergence of [28] introduces attention mechanisms into the field of vehicle trajectory prediction, enhancing the model's focus on key information in driving scenarios and thereby predicting future vehicle behaviors more accurately. LApred [29] designs a lane attention module to find candidate lanes that the target vehicle may follow, facilitating lane keeping and accurate prediction for the agent. K. Zhang et al. [30] proposes an attention-based interaction-aware model (AI-TP), where the model constructs a graph attention mechanism (GAM) to explicitly extract the most attention-worthy interactions to improve model performance and prediction speed.

To some extent, deep learning-based methods have improved prediction accuracy and robustness in vehicle trajectory prediction. However, these methods still face some challenges. For example, how to address the issues of high computational cost and difficulty in deployment on terminal devices, as well as how to select the most feasible route among multimodal predicted trajectories, remains worthy of further exploration.

Comparison and Analysis

In this section, we will compare the differences between various models based on deep learning methods. We will demonstrate their performance evaluation on large-scale autonomous driving public datasets, such as the Argoverse dataset and the NuScenes dataset. This will provide researchers with options for selecting suitable models for further study.

Dataset

NuScenes[31]: This dataset is a large-scale open-source dataset for the field of autonomous driving, collected and developed by the team at Motional in 2019. It consists of data collected from 6 cameras, 1 LiDAR, and 5 mmWave radars, capturing a total of 1000 real driving scenes in both Boston and Singapore. Currently, the dataset is widely used in areas such as autonomous driving and 3D object detection.

Argoverse[32]: The dataset has been released in two versions, collecting real driving scene information from six cities in the United States. It includes a vast amount of high-resolution videos, LiDAR data, vehicle status information, and HD map data, covering various complex scenarios such as city roads and traffic conditions. Its purpose is to provide authentic and effective scene data for fields like 3D object tracking and motion prediction.

Performance metrics

Average Displacement Error (ADE): The ADE calculates the Euclidean distance between each sampled point in the predicted trajectory of the target vehicle and the actual driving sampled points, and averaged the distance errors of all sampled points. It reflects the overall predictive performance of the model on average for each sampled point. The specific expression is shown in Formula (1).

$$ADE_K = \frac{1}{H} min_{k=1}^{K} \sum_{h=1}^{H} ||Y_{h,(k)}^{pred} - Y_h^{true}||^2 \qquad (1)$$

Final Displacement Error (FDE): The FDE calculates the Euclidean distance between the predicted endpoint position of the target vehicle's trajectory and the actual endpoint position of its travel. It reflects the predictive performance of the final position point of the model. The specific expression can be seen in Formula (2).

$$FDE_K = min_{k=1}^{K} ||Y_{h,(k)}^{pred} - Y_h^{true}||^2 \qquad (2)$$

In the above two evaluation metrics, $Y_{h,(k)}^{pred}$ represents the predicted position of the target agent's k sample at time point h, while Y_h^{true} represents the actual position of the target agent at time point h. K and H represent the number of predicted modes and future time steps, respectively.

Performance evaluation

In this section, we will start by briefly comparing the main methods mentioned above, as shown in Table 1, which provides a comparison of the advantages and disadvantages of major methods in the field of vehicle trajectory prediction. Each method has its own advantages and disadvantages, and in practical applications, we should choose the appropriate model and reasoning based on the actual situation.

To adequately assess the research progress in existing deep learning methods in the field of vehicle trajectory prediction from multiple dimensions, this paper employs the ADE and FDE metrics to evaluate performance, aiming to accurately assess the accuracy and effectiveness of models in trajectory prediction. All result data are sourced from publicly available papers on the internet, as shown specifically in Tables 2 and 3. From the data in the tables, it can be observed that with the increasing maturity of deep learning technology, the experimental errors of prediction models have been decreasing year by year. This can be primarily attributed to the rapid maturation of existing technologies and the high-speed development of computational resources.

Methods	***Advantages***	***Disadvantages***
Physical Methods	-Solid theoretical foundation and strong interpretability.	- Modeling complex traffic environments is difficult.
	-Generally, training does not require a large number of datasets.	- Accurate modeling of the system is required in advance.
	- Applicable to problems with clear physical models.	-Professional knowledge is required to design suitable physical models.
Machine Learning Methods	-Capable of handling complex nonlinear relationships.	-A large amount of data is required for training.
	- To a certain extent, it has generalization ability.	-Sensitive to data quality and feature selection.
	-It can automatically learn feature representations.	- It is difficult to explain the working principle inside the model.
Deep Learning Methods	- Capable of handling large-scale data.	- High demand for computing resources.
	-There are multiple types of methods and models to choose from.	- High technical requirements for data preprocessing and model tuning.
	-Suitable for handling complex relationships in traffic scenarios.	- A large amount of data is needed to train the model.

Table 1: Comparative analysis of the main methods in the field of vehicle trajectory prediction.

Model	$ADE_{k=6}$	$FDE_{k=6}$	$FDE_{k=1}$
MTPLA[33]	0.99	1.71	4.31
THOMAS[34]	0.94	1.44	3.59
TNT[35]	0.73	1.29	-
Lapred[29]	0.71	1.44	3.29
FRM[36]	0.68	0.99	-
HiVT[37]	0.66	0.96	-
LAformer[38]	0.64	0.92	-

Table 2: Prediction Performance Based on the Argoverse Dataset.

Model	$ADE_{k=5}$	$ADE_{k=10}$	$FDE_{k=1}$
MTP[21]	2.22	4.83	10.36
CoverNet[2]	1.96	1.48	9.26
LaPred[29]	1.53	1.12	8.12
GOHOME[39]	1.42	1.15	6.99
THOMAS[34]	1.33	1.04	6.71
PGP[24]	1.30	1.00	-
FRM[36]	1.18	0.88	6.59

Table 3: Prediction Performance Based on the NuScenes Dataset.

Future research directions

In this section, we delve primarily into various analyses and considerations based on the aforementioned performance evaluations and practical scenarios. We aim to explore potential technological breakthroughs for future autonomous vehicles, to provide valuable guidance and references for subsequent researchers in their practical development and application endeavors.

Interactive modeling: In real driving conditions, vehicles not only need to follow their own driving situations but also pay attention to the changes in surrounding environmental information. The model should also consider effective interactions between the target vehicle and other traffic participants in real-world scenarios to accurately assess changes in nearby traffic participants, thereby enhancing the safety and predictive accuracy of the driving system.

Generalization and adaptability: Vehicle trajectory prediction models need to have good generalization capabilities to adapt to actual complex environments and driving behaviors. Current research also needs to further improve the generalization performance of the model to address differences in rules between different cities, driving cultures, and countries.

Ad hoc decision-making: In reality, there are often sudden events with a certain probability, such as pedestrians crossing the road or sudden dangers ahead. This requires the model to make reasonable responses to newly emerging situations in a very short time. Future researches can focus on developing predictive models and decision algorithms that can respond quickly and adapt to emergent situations.

Conclusion

In this article, we first review the rapid development and current status of the field of vehicle trajectory prediction over the past decade. We systematically discuss methods and models based on physics, machine learning, and deep learning. Additionally, we analyze the commonalities and differences among numerous literature. We also introduce two important performance evaluation metrics in trajectory prediction, namely ADE and FDE. Furthermore, we analyze the existing technological advancements in the field of deep learning, based on the NuScenes and Argoverse datasets. Finally, we delve into future research directions and potential breakthroughs in this field, providing references and insights for researchers.

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