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Overview of Trajectory Prediction for Intelligent Driving Vehicles

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Abstract.. Autonomous driving technology has huge potential in improving traffic safety and traffic efficiency. Vehicle trajectory prediction is a key technology to achieve autonomous driving. This article mainly discusses some recent status quo of trajectory prediction for autonomous vehicles. This article divides trajectory prediction into three categories: based on physical models, based on maneuvering behavior, and based on interactive perception. This category is analyzed based on each method combined with the current status of relevant research. Finally, the future prospects of trajectory prediction in terms of innovation and optimization algorithms, development of vehicle-mounted sensors, vehicle model uncertainty, and vehicle-road coordination prediction are pointed out.

Keywords: Intelligent driving, Vehicle kinematics, Vehicle dynamics, Trajectory prediction

1. Introduction

The automotive industry is witnessing a shift towards electrification, intelligence, sharing and networking. These developments present an opportunity to enhance traffic safety and reduce environmental pollution. Consequently, the research community has identified smart car-related fields as a priority area. A variety of automotive organizations and research institutes are investigating the prospective applications of these technologies.

Trajectory prediction is regarded as one of the key technologies for achieving intelligent driving. It plays a crucial role in the safety, intelligence, and reliability of vehicles during autonomous driving. Smart vehicles can anticipate changes in the trajectories of surrounding vehicles by predicting their movements, allowing them to respond proactively to potential traffic scenarios over an extended period. This capability enables the planning of safe, efficient, easily controllable, and highly comfortable vehicle trajectories, ultimately providing drivers with an enhanced driving experience [1].

However, due to factors such as driver unpredictability, complex road conditions, variable environments and targets, and high speeds on highways, the problem of vehicle trajectory prediction has not been effectively resolved [2]. Uncertainty increases the error in vehicle trajectory prediction. Environmental perception uncertainty directly reduces the perception accuracy of the intelligent vehicle's perception layer. Additionally, vehicle model uncertainty affects the timeliness of the intelligent vehicle's decision-making layer, which can compromise the vehicle's safety and stability. Furthermore, driver behavior is multimodal and influenced by various environmental factors [3]. For instance, different future trajectories may emerge from a common past trajectory under different circumstances. Therefore, real-time, accurate, and reliable trajectory prediction technology can significantly reduce traffic accidents, greatly ensuring traffic safety and effectively improving traffic efficiency [4].

This paper collects and synthesizes the latest research on vehicle trajectory prediction from both domestic and international sources in recent years. Chapter 1 summarizes and analyzes trajectory prediction methods based on physical models. Chapter 2 focuses on trajectory prediction methods based on maneuver behavior. Chapter 3 reviews and analyzes trajectory prediction methods based on interactive perception. Finally, Chapter 4 concludes the paper and provides future outlooks on V2X technology and vehicle-road coordination prediction, innovation and optimization algorithms, the development of onboard sensors, and vehicle model uncertainty. This aims to provide a theoretical foundation for future research by subsequent scholars.

2. Trajectory Prediction Methods Based on Physical Models

Physical model-based methods are among the simplest models for vehicle trajectory prediction. These methods are categorized into two main types: vehicle motion models and vehicle dynamics models [5]. Physical motion models represent the vehicle as a dynamic entity governed by the laws of physics. The future motion is predicted through dynamic and kinematic models that relate control inputs (such as steering and acceleration), vehicle performance characteristics (such as weight), and external conditions (such as road friction coefficients) [6]. By leveraging these models, it is possible to predict the evolution of a vehicle's future motion, offering high computational efficiency and suitability for real-time scenarios [7]. The description and sentences of subsection. The description and sentences of subsection. The description and sentences of subsection. The description and sentences of subsection.

2.1. Vehicle Kinematic Models

The fundamental idea of any motion model is to focus primarily on aspects such as the trajectory, velocity and acceleration of an object, without considering the forces that cause the motion and factors such as mass and inertia. Thus, the simplest class of models is based on Newton's laws of motion [8].

Vehicle kinematics models mainly describe the motion of a vehicle based on its kinematic parameters (e.g., position, velocity, acceleration) without taking into account the effects of forces on the vehicle. According to whether the parameters such as velocity and acceleration are constant or not, kinematic vehicle trajectory prediction models can be classified into Constant Velocity (CV) model, Constant Acceleration (CA) model, Constant Turn Rate and Velocity (CTRV) model, Constant Turn Rate and Acceleration (CTRA) model, Constant Steering Angle and Velocity (CSAV) model, Constant Curvature and Acceleration (CCA) model, and Constant Steering Angle and Acceleration (CSA) model, etc.

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Kinematic vehicle trajectory prediction models can be categorized into kinematic models based on whether the parameters such as velocity and acceleration are constant or not as shown in Table 1:

Table 1. Kinematic model name list

Names of kinematic models	Abbreviation
Constant velocity model	CV
Constant acceleration model	CA
Constant Transverse Ratio and Velocity Model	CTRV
Constant Turn Rate and Acceleration	CTRA
Constant Steering Angle and Velocity	CSAV
Constant Curvature and Acceleration	CCA

The simplest models are CV and CA, both of which assume a linear motion of the vehicle, while CTRV and CTRA consider the variation in the Z-axis, as shown in Figure 1:

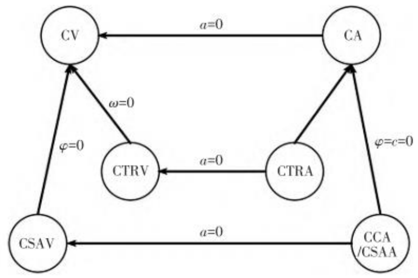

Figure 1. Relationship between the motion models

where a is the acceleration, φ is the yaw angle, c is the curvature, and ω is the yaw angular velocity. External forces such as the friction of the ground on the vehicle can be ignored using these models, thus making vehicle trajectory prediction simpler and more efficient.

Aiming at the problem of poor prediction accuracy of kinematic trajectory prediction models in the long time domain, Houenou [9] et al. proposed a trajectory prediction method combining trajectory prediction based on CTRA model and trajectory prediction based on maneuver recognition. The algorithm not only ensures the prediction accuracy for short-term trajectories, but also for long-term trajectories. Ju [10] et al. proposed a model combining Kalman filtering, kinematic modeling, and neural networks to capture the interaction effects between vehicles. Since machine learning based models can model interactions and learn nonlinear trajectory evolution from realistic data, these combined methods show better performance than single methods. Peng [11] et al. incorporated driver behavior into the CA model to improve the accuracy of position prediction and a quantitative approach based on linear quadratic regulator optimization control method was used to obtain the driver's expected control inputs and Kalman filter was used to predict the short-term motion of the vehicle but the model was only used for car tracking and lane change scenarios.

Cui [12] et al. proposed to seamlessly combine the idea of artificial intelligence with a physically-based vehicle motion model that embeds two-axis vehicle kinematics into the output layer of a deep learning trajectory prediction model to jointly predict the motion states (including position, heading, and velocity) of vehicle participants in a more accurate and kinematically feasible manner. This approach enables more accurate position and heading predictions and ensures kinematically feasible motion trajectories.

Kinematic models can all be used for trajectory prediction, and the main difference between the models is the treatment of uncertainty, which in the case of kinematic models refers to the process noise of trajectory prediction. Kalman Filter (KF) and its derivatives Unscented Kalman filters (UKF), or Particle Filter (PF) are commonly used to deal with uncertainty [13]. There are also methods to deal with uncertainty in vehicle states using normal distributions [14], as well as using Monte Carlo simulations to remove generated trajectories that exceed physical limits and reduce uncertainty [15]. In order to reduce the impact of noise and further improve the accuracy of prediction, many scholars have done a lot of research in this area, and Batz [16] and others use UKF to predict vehicle trajectories within a short prediction range. Based on the prediction results, mutual distances are calculated for each pair of vehicles, which include geometric distances, prediction uncertainty, and spatial dimensions of the vehicles. Zhang [17] et al. propose an invariant extended Kalman filter based on the Simultaneous Localization And Mapping (SLAM) algorithm (Invariant Extended Kalman Filter (In-EKF) algorithm and studied the consistency and convergence of the algorithm.

Since kinematic models are simpler compared to kinetic models, kinematic model-based trajectory prediction is relatively common in the application area of vehicle trajectory prediction [18].

2.2. Vehicle Dynamics Models

The vehicle dynamics model focuses on the vehicle motion subjected to various external forces, such as longitudinal and lateral tire forces, and road inclination angles. It is based on the Lagrange equations to calculate the parameters of vehicle motion. In this process, the uncertainty in the vehicle dynamics model mainly involves the model error [19] and the various external forces acting on the vehicle.

Due to the high computational efficiency of simple models, two-degree-of-freedom vehicle dynamics models are usually used to model vehicle dynamics in order to ensure the vehicle dynamics characteristics and real-time performance. In addition, there are some other vehicle dynamics models, such as 7-degree of freedom and 8-degree of freedom models [20], but with the increase of the degree of freedom, the more accurate their models are, but with the increase of complexity and computation, which will make the real-time performance worse.

For vehicle dynamics model trajectory prediction, the problem of uncertainty in vehicle trajectory prediction due to errors in on-board sensors has been investigated by using Gaussian distribution method to build Gaussian process for vehicle trajectories and iteratively obtaining the trajectory information of the vehicle by using the KF method [21]. Wang [22] and his team proposed a new method for predicting the trajectory of vehicles at intersections. The method integrates the vehicle dynamics and the estimation of the driver's future motivation, and utilizes a dual KF algorithm consisting of yaw angle KF and position KF to estimate the current vehicle state. At the same time, the desired trajectory is determined based on the road geometry information and the driving behavior of a particular driver. In order to solve the problem of poor trajectory prediction of intelligent vehicles in complex dynamic environments, Zhang [23] et al. proposed a dynamic trajectory planning algorithm for driver assistance systems based on vehicle steady-state dynamics. The algorithm improves trajectory planning in highly dynamic environments by establishing a "search space", evaluating each trajectory generated by the generator, and selecting the best trajectory under the optimal conditions. Brännström [24] et al. utilized a linear bicycle model to predict the trajectories of the main vehicle and obstacles over a future period of time. trajectories over a period of time. They proposed a decision-making method for estimating how the driver of the primary vehicle steers and accelerates and decelerates to avoid collisions.

Tu [25] et al. built a maple intersection collision warning system and used three simple KF filters to predict the trajectories of local and neighboring vehicles. Wenzel [26] et al. used EKF to predict future vehicle trajectories by introducing a complex model of vehicle tires (which involves vehicle inertial parameters such as vehicle stiffness). However, since most systems are nonlinear in practice, it is difficult to apply the KF method to nonlinear systems. In addition to the KF method, the Monte Carlo method, which is also applicable to trajectory prediction based on vehicle dynamics models, is a tool used to approximate computational distributions. It generates a set of possible future trajectories by randomly sampling the input variables of the evolutionary model. Considering the topology of the road, weights can be applied to the generated trajectories to penalize those that do not meet the road layout constraints [27]. Typically, the sampled input data includes the acceleration and steering angle of the vehicle. Monte Carlo simulations can be used to predict vehicle trajectories, either for a known current state or for a current state with uncertainty estimated by a filtering algorithm.

Considering the driver reaction time and the time required for the vehicle dynamics to take effect, a 2 s time period is selected as the prediction level, which is also the most commonly used time range in real-time collision warning systems [28]. Since the dynamics model provides more references of vehicle parameters compared to the kinematic model, the trajectory prediction based on the dynamics model is more accurate, but how to ensure the timeliness needs more in-depth research.

Based on considering only the physical motion information of the vehicle and completely ignoring the development and evolution of the surrounding traffic environment, the physical model has large limitations. The vehicle is affected by the behavior of the surrounding vehicles and various uncertainties during the actual driving process, and this physics-based motion prediction method is limited to be effective for short-term prediction, and performs relatively poorly for long-term prediction [29]. According to the physics-based model, the trajectory prediction error will accumulate over time, which will eventually lead to a large prediction error that cannot meet the needs of intelligent vehicle decision-making and control.

3. Trajectory Prediction Model Based on Maneuvering Behavior

Physics-based trajectory prediction models are able to make accurate predictions in the short term with vehicle motion models. On the contrary, the trajectory prediction model based on maneuvering behavior can predict vehicle trajectories in the long term.

Behavioral intent-based vehicle trajectory prediction methods consider the vehicle as an independent entity and take into account the driver's operational behavior. Based on the driver's behavioral intentions (e.g., lane change, U-turn, steering) estimated by the prediction model, the corresponding future trajectories of the vehicle are generated. The method first predicts possible driver behavioral intentions and then inputs the most probable behavioral intentions into the vehicle trajectory prediction model. This approach effectively reduces the prediction error and extends the prediction time domain (from 3 to 5 seconds).

Some of the more widely used driving intention recognition algorithms are Hidden Markov Model (HMM), Support Vector Machion (SVM) and Recurrent Neural Network (RNN), Bayesian Network (BN), etc. After recognizing the driving intention of the vehicle, alternative predicted trajectories are calculated and a cost function is established for trajectory prediction.

3.1. Hidden Markov Model

Qiao [30] et al. abstracted trajectories as a series of discrete motions and used HMM to predict the trajectories of moving objects. Schlechtriemen [31] et al. proposed a plain Bayesian-based vehicle action prediction method, which is capable of predicting a more accurate target vehicle behavior by 2.2s. HMM is effective for segmentation and classification of driving actions due to the ability of the HMM model to capture spatio-temporal variations in vehicle trajectories. Morris [32] et al. used HMM to probabilistically encode the spatio-temporal dynamics of the activity and discover new behaviors through periodic retraining for long-term monitoring.

Since the HMM is designed as a probabilistic graphical model, making it easier to directly understand the relationships between nodes, it has the advantage of handling dynamic data and temporal pattern recognition. However, HMM assumes that the transfer between states is Markovian, which may not always hold true in real driving scenarios.

3.2. Support Vector Machine

Aoude [33] et al. used feature variables such as distance to the intersection, speed, and steering wheel angle to determine the driving behavior of a traffic vehicle while passing through an intersection by combining an intent predictor of SVM with an effective threat assessor using a fast detecting stochastic tree. Kim [34] proposed a target vehicle prediction method based on dynamic occupancy grid graphs considering vehicle motion, using time streaming and SVM cascade algorithm to categorize the occupancy grid graph into two types: upper and lower layers. The role of the upper grid is to predict whether the target vehicle can safely enter the driving area of the auto-vehicle or not, while the lower grid utilizes SVM to make decisions. For the classification problem of driving intention, SVM can handle the nonlinear decision boundary well by kernel trick. However, training and testing SVM on large-scale datasets may be time-consuming compared to other algorithms.

3.3. Recurrent Neural Network

Motion prediction can be viewed as a time series regression or classification problem. Recurrent Neural Networks (RNN) are the main reason for the significant advances in sequence modeling and generation techniques. They have shown promising results in several areas such as natural language processing and speech recognition. In literature [35], an artificial neural network (NN) based algorithm was developed which uses collected real data vehicle data to train a neural network to predict the next state of the vehicle for a given speed and steering angle. Zyner [36] et al. used a Long Short Term Memory (LSTM) based RNN to predict the driver's intention when a vehicle enters an intersection. The model learns by fusing position, heading, and speed from data collected by the self-vehicle. RNNs are naturally suited for processing sequential data and can capture the time dependence of driving behavior well. However, when dealing with long sequences, RNNs may face the problem of gradient vanishing or gradient explosion.

3.4. Bayesian Network

Ramchoun [37] et al. extended the SVM algorithm using Bayesian theory and achieved better results than right lane change (LC) in vehicle recognition. Schreier [38] et al. used causal and diagnostic evidences in BN to model all vehicles in a driving scenario, which led to the inference of high-level abstraction of the driving operation's distribution, and after trajectory planning, they can reason about the impending collision of vehicles a few seconds in advance. The BN can effectively handle uncertainty and is adaptive to the uncertainties in driving scenarios. However, it requires careful design of network structure and parameters, and relies more on expert experience.

4. Vehicle Trajectory Prediction Model Based on Interaction Perception

Physics-based motion models and predictive models based on maneuvering behavior do not model the complex interactions among traffic participants well. In order to improve the reliability of vehicle trajectory prediction, it is necessary to consider the interaction of traffic participants [39]. The interaction-aware model, in which the object of study and the surrounding vehicles are interacting entities that interact with each other, is a more realistic and complex modeling scenario than the previous two approaches. The interaction-aware vehicle trajectory prediction method considers the target vehicle and other vehicles in the traffic scenario as interacting entities with certain connections, and uses multi-vehicle historical trajectory data to generate future trajectory predictions for the target vehicle by modeling the interaction between vehicles. The interaction-aware motion model takes into account the interdependence of different vehicles in the traffic scene.

4.1. Dynamic Bayesian Network

With the introduction of artificial neural networks [40], many recent interaction-aware motion models use deep learning methods [41] and different structural forms of neural network-based deep learning algorithms have emerged. Many of the earlier researched interaction-aware algorithms used Dynamic Bayesian Network (DBN) to learn the interdependencies between multiple entities [42].

Jiang [43] et al. proposed a probabilistic vehicle trajectory prediction method based on the DBN model, which integrates driver's intention, maneuvering behavior and vehicle dynamics. By selecting the feature vectors with the highest correlation, a Gaussian mixture model-hidden Markov model was designed. Accurate long-term trajectory prediction was achieved. Li [44] et al. proposed a DBN maneuver prediction method based on multi-dimensional features, which are road structure-based features (presence of lanes and lane curvature), interaction-aware features (state of neighboring and leading vehicles), and physically-based features (vehicle dynamics), and the results showed that the method can effectively improve the performance of maneuver prediction with a prediction time of 3.75s.

The DBN algorithm effectively handles uncertainty and provides modeling of probability distributions that can represent different possibilities. However, its handling of large-scale data can be complex and has relatively high computational overhead.

4.2. Long Short-term Memory Networks

Recurrent Neural Networks (RNN) have shown good performance in sequence learning, but RNN learning suffers from the problem of gradient spreading or explosion. To compensate for this deficiency, Long Short-Term Memory (LSTM) has become a solution in recent years. LSTM adds forgetting gates to the original RNN, which makes the information in the time dimension selectable and thus enhances the learning fitting and information mining ability for long term temporal problems. As one of the most commonly used in vehicle trajectory prediction models, LSTM is a variant of RNN that can effectively overcome the gradient vanishing and gradient explosion problems existing in RNN.LSTM consists of a cellular memory storing summaries of past input sequences and a gating mechanism, which controls the flow of information between inputs, outputs, and the cellular memory. Oblivion gates use decay rate ft to produce LSTMs with long-term memory [45].

Emphasis on interaction-aware modeling has been a trend in recent years. Yu [46] et al. proposed a dynamic and static context-aware attentional network (DSCAN) for vehicle trajectory prediction, which utilizes an attentional mechanism to dynamically model inter-vehicle interaction information, and feature embedding learning to augment the constraining effect of the static environment. Gupta [47] et al. proposed the Social GAN, whose generator consists of an LSTM-based encoder, a context pooling module, and an LSTM-based decoder, which also uses LSTM for its discriminator. However, GANs have a drawback. Implementing the Nash equilibrium is challenging and takes a lot of time. Woo [48] et al. proposed a method for predicting the trajectories of neighboring traffic participants using an LSTM network, whose goal is to take into account the relationship between the self-vehicle and the surrounding vehicles.

Song [49] et al. combined MLP with RNN for the purpose of extracting features from input trajectories or traffic scene context. Jean [50] et al. extracted traffic participant state features based on LSTM by treating trajectories as a sequence of states [51]. Andra et al. combined LSTM and convolutional neural network (CNN) to model heterogeneous road agent interaction. Altché [52] et al. proposed the use of LSTM network to predict the road trajectories of surrounding vehicles. The method performs consistent trajectory prediction through a Long Short-Term Memory (LSTM) neural network, enabling the prediction of future longitudinal and lateral trajectories of vehicles on the highway. Kim [53] et al. proposed a probabilistic LSTM-based vehicle trajectory prediction method, which employs a large amount of trajectory data obtained from processing sensor measurements during long-term driving. The LSTM is trained to learn the complex dynamics of surrounding vehicle motion and predict its future location. The experimental results demonstrate that the method is more effective in predicting the motion trajectories of surrounding vehicles.

In addition, the Transformer architecture has achieved very good results in the field of natural language processing due to its demonstrated ability in context learning and sequential prediction [54].The Transformer architecture is inspired by the encoder-decoder architecture of RNNs, which introduces an attention mechanism. Scholar Khandelwal [55] used Transformer to extract state features from traffic participants, proposing a recursive graph-based attention approach for trajectory prediction.

Also used as neural networks are Convolutional Neural Networks (CNN) and Graph Neural Networks (GNN). Cui [56] et al. encoded each actor's environment as raster images and used them as inputs to a Deep Convolutional Network (DCNN) to automatically acquire features relevant to the task. Casas [57] et al. used CNNs to detect actors and compute their initial state, and then used GNNs to iteratively update the character state through a message-passing process.

While neural networks can be trained for end-to-end learning to reduce the need for manual feature engineering. However, according to the research related to deep learning [58-67], learning-based method can be overfitted for small samples of data, and the training time can be long, requiring significant computational resources.

Conclusion

As autonomous driving technology advances, traditional trajectory prediction algorithms are unable to meet the growing demand for anticipating intricate traffic scenarios. This paper presents a synthesis of the recent developments in vehicle trajectory prediction, outlining the key prediction algorithms that have emerged. Consequently, the following aspects of automatic driving trajectory prediction warrant further investigation:

(1) Regarding innovation and optimization algorithms, it is evident that a single trajectory prediction algorithm is inherently flawed and deficient. Consequently, the fusion of multiple prediction algorithms is a general trend that will likely continue in the future.

(2) In the development of vehicle sensors, it is necessary to predict the vehicle trajectory. This requires information such as the vehicle's position, speed, heading, etc. The self-driving vehicle obtains this information through the vehicle, which is equipped with a variety of sensors for measurement. Therefore, it is important to consider how to improve the sensing accuracy of the sensor, as this will be a key consideration in the future. Additionally, reducing the cost of the sensor is also an urgent need to solve the key technical problems.

(3) The uncertainty of vehicle models will have an impact on trajectory prediction. Complex dynamic environments exhibit nonlinearities along with sensor measurement delays, sensor errors, unknown external disturbances, and noise. These features may cause vehicle model uncertainty, which in turn leads to delays in the trajectory prediction signal. Therefore, the timeliness problem of the intelligent vehicle prediction system can be improved by investigating Kalman filtering and its optimization algorithm to deal with the uncertainty of the vehicle model.

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