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Strategic Analysis of Dynamic Detection and Tracking Methods for Autonomous Vehicles

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Abstract: To solve the problem of perception failure due to vehicle occlusion in urban areas, this paper will review and analyze many dynamic detection and tracking methods proposed in recent years in detail. The main idea of the first representative study is to use laser beams and geometric figures for rigid matching. They are very effective in open areas, but because there is no information on the surface, the algorithm cannot work when there is occlusion. Earlier, researchers put forward a soft-assignment method by building a "four-rectangle measurement model", and it was found that probabilistic modeling is better than binary matching; now, a laser ray does not need to hit an object, and the matching probability of local sparse point clouds can be calculated. A good way to improve the efficiency of tracking is the scaled sequence algorithm. The first problem of this algorithm is that it involves a high-dimensional state search. The detection rate of severe occlusion in the KITTI dataset for the new model is higher than that of traditional methods. As shown in the above case, although this method is relatively stable in the face of missing values, it has some defects; that is, it is too sensitive to the initial prior and may be trapped in a local optimum under difficult conditions. Due to the shortcomings of the previous models, such as fixed dimensions and an inability to address all kinds of traffic flexibly, it is hoped that future research will be based on multi-scale adaptive geometric models to achieve all-weather sensing and all-conditions operation. Vehicle occlusion, Likelihood Field Model, Scaling sequence algorithm, self-motion compensation.

Keywords: Likelihood field model; Four-rectangle measurement model; Scaling sequence algorithm; Adaptive multiscale modeling

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1. Introduction

With the development of artificial intelligence and sensor technology, autonomous vehicles have gradually gone from closed-track tests to public road operation in many cities. The first need for safety in a crowded area of the city is to detect and comply with the operation of nearby moving vehicles. Due to the frequent occlusion of urban traffic, the traditional perception algorithm has serious problems; that is to say, when local features are absent, the bounding box regression of the object detector is inaccurate, and there is considerable drift. To solve the problems of vehicle detection and tracking, many studies have been carried out. First, only the grid method was studied, so grid cells were used to represent the environment. These methods have a large number of calculations and are restricted by the grid resolution; thus, they cannot meet the demand for real-time high-speed driving. Then, models based on geometric features began to be employed gradually. Among them, the "beam model" is the most typical one. The two-dimensional ray path of LiDAR is used to determine the geometric shape of the vehicle; it is very fast in an open area. The beam model has a serious defect; it determines whether a ray "hits" the surface of an object in the calculation of probabilities. That is to say, if the target vehicle is covered by other objects, the laser rays will be blocked from reaching the surface of the vehicle directly; thus, the model cannot acquire valid measurement data, and the detection and tracking function will fail. Due to the problem of perception failure in a complex urban environment, the previous methods for dynamic vehicle detection and tracking will be introduced and analyzed systematically in this paper. The purpose of the likelihood field model is to determine how probable it is that a measurement point is close to the shape of the target, and it is no longer necessary to consider only the ray-surface intersection point. Researchers have made some new applications of this idea in vehicle detection and constructed a four-rectangular vehicle measurement model to cover all visible parts of the vehicle, as well as its interior and exterior. This model can make full use of sparse 3D point cloud information; even when the target vehicle is largely occluded, it is still possible to obtain a good estimate of the vehicle's pose as long as a small number of laser points fall in the high-probability region of the likelihood field. To solve the problem of real-time computation in high-dimensional state spaces, an efficient Bayesian state estimation method called the scaling sequence algorithm has also been proposed and optimized; it is based on an "annealing" scheme and can increase the speed of state estimation. This algorithm is a multi-resolution search method that first takes a large step, then a small step, and so on; that is to say, it quickly finds an approximate location of the target and then refines it step by step to save computation. In this paper, we will present the likelihood-field-based vehicle measurement model and its optimized calculation method, introduce the whole system workflow that includes improved virtual scanning, hypothesis generation and tracker update, show experimental results on the KITTI dataset, focus on analyzing the detection performance in occlusion scenarios, and finally summarize this paper and put forward future research directions [1].

The basic task of the entire dynamic detection and tracking system for autonomous driving in complex cities is to find the position of a car accurately. Due to the instability of the old way in occlusion environments, Tongtong Chen and others have carried out a large number of studies on the likelihood field-based vehicle measurement model and optimization strategies to promote the development of this technology [2].

2. Construction of vehicle likelihood field models and algorithm performance optimization for complex occlusion scenarios

2.1. Reconstruction of the likelihood field vehicle measurement model

Traditionally, the beam model is used for vehicle detection; Petrovskaya and Thrun first mentioned in their early work that one way to find an obstacle is to determine the length of a two-dimensional laser beam, and the beam model has the advantage of very high computation speed [3]. The problem with this type of detection is that if the target vehicle is blocked by other cars or trees on the road, the laser beam cannot reach the ground for reflection, so the model does not work and cannot detect it; although a particle filter was later added to the tracking framework to estimate velocity, it also performed poorly in a complex and heavily occluded environment [4].

Therefore, scholars have been studying the basic theorems of probabilistic robotics. At the core of the above theoretical adjustment is the systematic model philosophy of probabilistic robotics. To address the uncertainty of the urban environment in the model of sensor perception more reasonably, this system will represent the uncertainty as a probability distribution and provide strong mathematical support for the quadrature measurement model [5]. Based on the work by Thrun et al. on robust Monte Carlo localisation, a new way of calculating probabilities has been introduced for the “likelihood field”, and according to Bayesian filtering theory, the likelihood field measurement model in this paper no longer needs to scan the entire outline of the vehicle; instead, it is proposed that “four rectangular boxes” (that is to say, the front, body, interior and exterior regions) be used for geometric modelling of the target vehicle [6]. The advantage of the above method is that the sparse 3D point cloud can be transformed into a four-layer rectangular model, and then matching probabilities are calculated; in the traditional direct line-of-sight method, a likelihood field-based soft assignment mechanism can be used to infer the whole position and orientation of the vehicle by maximising the probability, even when only a small number of point clouds from the partial vehicle region are available. With the recent cutting-edge research in dynamic object detection for LiDAR, a likelihood field model can be obtained from local observations to obtain the global pose, and it has shown good results in heavy urban traffic [7].

2.2. Algorithm acceleration and state optimization strategies

The model of the likelihood field is theoretically free from occlusion, but it is too computationally intensive. To improve the speed of computation for the autonomous driving system, which must respond within milliseconds, two optimizations have been made to the algorithm.

Probability calculations in the likelihood field have a large number of complicated exponential and distance operations. At the beginning of the system, frequently used mathematical formulas can be pre-calculated and stored as high-precision offline data tables; then, to get the probability values in real time, only a simple memory lookup is needed. Engineering optimization has increased the overall speed of computation by about 4.5 times compared with real-time calculation and reduced the computational load on the onboard computer significantly; therefore, this way of trading computational efficiency for data preprocessing has also been widely used in recent research on point cloud perception. For example, a small encoder can be used to reduce the amount of data that needs to be transmitted from the car’s sensors in real time, so all the original point cloud data do not have to be transferred [8].

A full-space global optimum search would be too far-reaching; it is not easy to find a needle in a haystack. Therefore, when the algorithm first searches for a potential vehicle, it has a loose matching criterion (that is to say, it is a rough search with a high threshold); after the system finds a target in a certain area with a high probability, it will gradually lower the criterion (reduce the threshold) and perform a local, high-precision pose alignment. In other words, it is a “coarse-to-fine” method that can be both fast in terms of search speed and very accurate for final localization, thus supporting continuous tracking.

3. Dynamic vehicle detection and tracking system

Tongtong Chen and others have built a very stable single-frame pose estimation model, and based on this model, a whole dynamic vehicle detection and tracking system has been constructed according to the temporal tracking framework.

3.1. Improved virtual scan and hypothesis generation

Data preprocessing and the extraction of the Region of Interest (ROI) need to be carried out for the tracking system. In the construction of an occupancy grid in traditional virtual scanning technology, it is often the case that occluded unknown regions are either ignored or marked as unobstructed. It is suitable for an open area, but due to the large number of vehicles at this busy intersection, continuous observation of the obscured vehicle is not feasible.

To solve the above problem, the improved virtual scanning method has changed the logic of global uniform processing and carries out separate clustering and analysis on each object in the scan image. A spatiotemporal difference mechanism is used in the system to accurately align the radar images of the previous frame with those in the current frame based on the own GPS and inertial navigation data of the autonomous vehicle, remove static background elements, and if a point cloud cluster shows a large spatial displacement, it will be promptly marked as a “suspected vehicle” and trigger the likelihood field model for pose verification. According to the latest research results on dynamic vehicle detection in road scenes, this method is based on prior pose estimation and dynamic differentiation to filter out interference from leaves and pedestrians and reduce the false positive rate of the system to a certain extent [9].

3.2. Tracker updates and self-motion compensation

The main problem in the target-tracking stage is how to track a moving object over a long period stably. The first type of algorithm that the researchers have been studying is the very efficient Bayesian estimator called “Scaling Series” [10]. It was first designed for overseas adaptation in terms of touch feedback for robotic arms, and it already has good support for all kinds of data distributions.

It does not change much if it is different. After a large number of alterations, it has been successfully employed in the area of vehicle tracking for autonomous driving. The first addition was the self-motion compensation function. Autonomous driving is not only about sensing objects in the external environment but also about moving the car at a high speed. Self-motion compensation is to subtract the vehicle’s own motion data, such as vibrations due to acceleration and deceleration, and angular velocity produced during turns at intersections, from the relative motion; thus, the system does not have a change in its own coordinate system and only contains the absolute motion trajectory of the target vehicle in the global coordinate system. Chen Fu and others have found that to guarantee the accuracy of tracking in a highly dynamic environment, strict spatio-temporal synchronization and self-motion compensation need to be carried out; at the start of a traffic light change or during a complex turn at an intersection, it can be observed that [11].

4. Technical challenges and development

Although dynamic vehicle detection and tracking algorithms based on likelihood field models have achieved some success in solving the problem of vehicle occlusion and reached a detection rate of up to 65% in experiments, autonomous driving perception systems still have many technical problems that need to be solved before they can be deployed on a large scale in open urban roads.

First of all, there is a problem of computation time and real-time demands. Although the previous research has presented lookup table methods and improved scaling sequence algorithms to accelerate highfrequency computation and search in high-dimensional state spaces, keeping the response time in the millisecond range on the limited onboard computing platform is still a serious engineering problem due to the increasing congestion in urban traffic. Second, the main bottleneck of the current system is that it has fixed geometric dimensions for the models; Secondly, the core problem of the current system is the fixed size of the models, and as a result, the evaluation framework for 3D multi-object tracking is also relatively unchanged. Although the basic Bayesian framework can handle occlusion, it cannot adaptively adjust according to different vehicle sizes and performs poorly in mixed-traffic conditions. Therefore, in order to achieve all-scenario perception, a 3D tracking benchmark with good generalization ability needs to be constructed [12]. Although the existing quadrilateral measurement model can use sparse point clouds for local pose estimation, fixed-size models are not very suitable for the complex reality of mixed traffic flow in urban areas; thus, the generalization and perception capabilities of the system are limited by all kinds and various sizes of vehicles. In addition, due to the changes in traffic conditions and high speeds of vehicles, keeping up with and constantly tracking them both in space and time has technical difficulties.

In light of the problems above, the next step in technological progress will be to make perception models and multi-dimensional scene understanding more adaptable. In the future, more studies will be conducted on the development of adaptive multiscale geometric modeling techniques. Free from the constraints of a fixed size, the system can now flexibly match and reassemble the geometric features of all kinds of objects to meet the full-scene perception requirements of complex mixed traffic, and one of the necessary developments to improve the foresight prediction ability of the perception system is automatic identification of object categories at long distances and construction of stable spatio-temporal correlations among multiple objects. Finally, by continuous adjustment of algorithms and improvements in the mechanisms for self-motion compensation and autonomous driving perception technology, the problems of occlusion and tracking in complex environments will be fully solved, and safe application in all scenarios and various weather conditions will be realized.

5. Conclusion

With the start of autonomous driving on the road, vehicle occlusion has been an obstacle to traditional perception technology for a long time. To solve the problem of a perception bottleneck, a four-rectangle measurement model based on likelihood fields was constructed, and then it was employed in conjunction with an annealing search strategy. Through the combination of spatio-temporal differentiation and self-motion compensation, a stable dynamic tracking system has been established, and in cooperation with the previous beam-based perception model, it has been found that our new system can effectively solve the problem of detection omission and tracking failure caused by direct line-of-sight obstruction in heavy traffic and vehicle occlusion. It can significantly improve both the success rate and stability of dynamic target detection, provide strong technical support for dynamic targets in complex and rapidly changing road conditions, but current models still have some issues in actual application; that is to say, most current models have fixed-dimension geometric models and limitations in generalization and reconstruction when faced with all kinds of mixed traffic flow in urban areas.

Research has also been carried out on new ways of likelihood field theory and probabilistic soft assignment for vehicle measurement. The research carried out by the above scholars has provided some references for engineers in the design of high-level perception systems and researchers in the field of urban traffic safety; currently, these methods can be applied to solve the problem of continuous target tracking under severe occlusion and offer a reliable and practical technical path. Looking ahead, it will be necessary to add the functionality of multi-scale adaptive geometric model construction and precise identification of distant targets on the horizon to the perception system to address problems in complex environments and truly advance the commercial application of all-weather, all-scenario safety.

Disclosure statement

The author declares no conflict of interest.

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