Multi-Sensor Fusion and Obstacle Avoidance Algorithms Applied to Autonomous Driving

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Abstract. This paper mainly discusses about automation. Autonomous driving has been studied and developed for decades, and the technology has got better and better. More and more people in different fields start to employ autonomous driving, such as logistics and take-out. Moreover, most car companies have been investing heavily in and developing their own autonomous driving systems, and many of them have brought something surprising to the market, such as Tesla and Waymo. It is essential for an autonomous vehicle to employ multi-sensor fusion and improve the obstacle avoidance algorithms because autonomous vehicles must detect the surrounding environment very precisely and immediately, while single kind of sensor cannot guarantee perfect recognition under extreme weather conditions. Therefore, an autonomous vehicle has a large demand of the integration of different sensors, including camera, LiDAR, and millimeter-wave radar. Besides, researchers have also been improving A* algorithm, RVO, YOLO, and so on. This paper focuses on basic information of multi-sensor fusion and obstacle avoidance algorithms, including the background, the achievements of research, thee influence, and the practical applications.

1 Introduction

Autonomous driving has been developing since the 19th century. Unmanned driving originated from the DARPA (Defense Advanced Research Projects Agency) competition in the United States, and the practical development program was started in 2009 by Sebastian Thrun [1]. It has gone through three periods, namely the germination of technology period (1895—1975), low-speed development period (1976—2016), and high-speed development period (2017—2023) [2]. The two core technologies are environment detection and obstacle avoidance. The former one is for awareness; the latter one is for decision. Firstly, there is a problem the perceptual limitations and uncertainties of a single sensor [3]. For instance, cameras cannot work very well in heavy rain or foggy days, while LiDAR cannot recognize the road signs. Therefore, autonomous vehicles have to use multiple sensors and multi-sensor fusion in order to guarantee precise detection. In addition, it is also very important for autonomous vehicles to make the appropriate response after detecting the obstacles, which depends on obstacle avoidance algorithms. These algorithms can be roughly divided into these categories, which are Artificial Potential Field (APF) algorithm, Probabilistic Road Map (PRM) algorithm, Elastic-Band (EB) algorithm, and Deep Deterministic Policy

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Gradient (DDPG) algorithm. The classifications of autonomous driving per the internationally adopted SAE J3016 standard (published by SAE International and recognized by the U.S. Department of Transportation's National Highway Traffic Safety Administration - NHTSA) are defined as follows:

Level 0: Driver only. The human driver independently controls all aspects of vehicle operation, including steering, throttle, and braking.

Level 1: Assisted driving. Driver assistance systems provide limited support during operation (e.g., Cruise Control or Adaptive Cruise Control – ACC). The driver remains fully responsible for monitoring and control (Year 2000).

Level 2: The vehicle automates at least one driving function (e.g., cruise control and lane centering simultaneously), but the driver must continuously monitor the system and environment (Year 2013).

Level 3: Conditional automation. The vehicle performs all safety-critical driving tasks within specific conditions (Operational Design Domain). The driver may disengage supervision but must be ready to intervene when requested. (Year 2018)

Level 4: High automation. The vehicle handles all driving tasks and monitors road conditions for the entire trip without requiring driver monitoring. However, functionality is limited to predefined conditions (e.g., geofenced areas or specific weather) (Year 2024).

Level 5: Full automation. The vehicle operates autonomously under all driving conditions without any human intervention. No driver is required (Year 2030) [4].

In the second section, this paper will firstly introduce multi-sensor fusion, including the history, basic information, recent research, and applications. In the third section, this paper will discuss obstacle avoidance algorithms, including the history, classification, and recent research.

2 Multi sensor fusion

2.1 The history

Multi-sensor fusion originated from the requirements of military applications in the 1970s, which was called multi-source information fusion. Since in modern warfare, commanders have to use a powerful technology to achieve real-time control of the battlefield situation through the collection, dissemination, synthesis, filtering, and correlation of multi-source information. Therefore, U.S. Department of Defense JDL (Joint Directors of Laboratories) conducted relevant military studies as the first one. Later, under the research of Llinas and Waltz, a general consensus was reached, and multi-source information fusion was defined as multi-sensor data fusion. Its specific definition is that it is an accurate and complete assessment of the detected environment by uniformly evaluating and estimating the data collected by various types of sensors and has adopted data processing processes covering all levels and aspects [5].

2.2 Basic Information

2.2.1 Sensor fusion generations and the roles of sensors

Since 2007, the autonomous driving system can be divided into four generations. The first generation mainly uses Velodyne64-line lidar and camera separate processing scheme. The second generation adopted multiple 16- or 32-line radar fusion cameras and other sensors for positioning and target recognition. The third generation upgrades the second-generation lidar to solid-state lidar, and moves it to the front of the vehicle. The fourth generation will remove

the steering wheel, which is the final goal of all of the car companies [1]. At this stage, car companies usually combine different types of sensors. For instance, Apollo Go combines four lidars, twelve cameras, five millimeter-wave radars, and twelve ultrasonic radars. Lidars are used to realize 360° environmental modeling and high-precision obstacle detection. Cameras are used to detect lane lines, identify traffic signs and traffic lights. Millimeter-wave radars are used for long-range target detection, such as high-speed vehicles, and resistance to bad weathers conditions, including rain, snow, and fog conditions. Ultrasonic radars are used to detect close-range obstacles in parking and other low-speed scenarios.

2.2.2 Classification

There are three classifications of data fusion, which are pixel-level image fusion, feature-level fusion, and decision-level fusion.

Pixel-level fusion is to fuse the raw data of each sensor or the minimally processed data. It is generally used in the central-level fusion structure. If the data to be fused comes from different sensors, it will need to face the problem of data registration when processing.

Feature-level fusion is to firstly extract the features of each sensor's observation data to obtain one feature vector. And then, fuse these feature vectors and determine the identity according to the fused feature vectors. Feature-level fusion can be used for both central-level and sensor-level data fusion structures.

Decision-level fusion is to process the data obtained by each sensor independently, detect and classify the targets, and then fuse the results from each sensor through fusion decision. If the signals received by each sensor are not independent, then the classification performance of feature-level fusion is better than the classification performance of decision-level fusion.

2.3 Recent research

2.3.1 The main algorithms of data fusion

There are seven main algorithms of data fusion, as Table 1 shown.

Table 1. Seven main algorithms and the explanation of data fusion [6].

Name	Explanation
Weight-based fusion method	This method is also known as the weighted average method, which is the simplest and most intuitive fusion method for processing information in real time.
Parameter estimation-based information fusion method	The method includes maximum likelihood estimation, Bayesian estimation, etc.
Dempster-Shafer evidence theory-based fusion method	This method is an extension of Bayesian estimation. It can separate the strict conditions of premise from the possible establishment, so that any lack of information involving a priori probability can be displayed.
Kalman-filter-based fusion method	Kalman filter is used for real-time fusion of redundant information in dynamic environments.
Fuzzy neural network-based fusion method	The environmental information provided by multiple sensors is uncertain, and its information fusion is essentially an uncertainty

	reasoning process. Fuzzy inference is performed on the fuzzy set based on the fuzzy rule. Fuzzy inference can obtain the fusion results of environmental information.
Rough set theory-based fusion method	To use the rough set theory-based fusion method, the data collected by each sensor is regarded as an equivalent class, and the simplification and compatibility of the rough set theory can be used to analyze the sensor data, eliminate the compatible information, find the least invariant kernel, find out the decision information useful for decision-making, and obtain the fastest fusion algorithm.
Cluster Analysis	It can be divided into hard clustering, fuzzy clustering, and probability clustering.

2.4 Application in reality

Multi-sensor fusion has been used in autonomous driving, humanoid robots, intelligent surveillance, medical imaging, medical imaging, and environmental monitoring, as Table 2 shown.

Table 2. Application in reality and brief introduction

Application	Brief Introduction
Autonomous driving	By fusing data from cameras, lidar, and millimeter-wave radar, it achieves comprehensive perception of the surrounding environment and improves the accuracy of target identification and tracking.
Humanoid robots	In complex scenarios, multi-sensor fusion technology is used to improve the visual perception ability of robots and help them replace the environment for recognition and understanding.
Intelligent surveillance	Multi-sensor fusion enhances the reliability and accuracy of the monitoring system, capable of maintaining good performance in different lighting weather conditions.
Medical imaging	Combine data from different sensors to improve the clarity of impact and diagnostic accuracy.
Environmental monitoring	Various sensors are used to detect changes in the environment and provide more comprehensive data support.

3 Obstacle avoidance algorithms

3.1 The history

In early 1950, the first self-guided vehicle was produced in the United States. It started the development of intelligent vehicles (IV). From 1980s to 1990s, with the breakthrough of computer, robot control and sensing technologies, the development of autonomous driving has started to develop rapidly. This period was marked by extensive collaboration among the military, universities, and car companies, leading to the successful development of several autonomous vehicle prototypes. These vehicles mainly used vision-based systems to sense their surroundings, with computers analyzing images to control the cars. Carnegie Mellon University 's NavLab series, the VaMoRs (P) series from University of the Bundeswehr Munich, and the ARGO project by University of Parma VisLab [7]. Today, companies like Google, Huawei, and Tesla have all made breakthroughs in the field of intelligent vehicles. Researchers have been developed different types of algorithms, including A* algorithm, D* algorithm, and Dijkstra algorithm [8].

3.2 Classification

Obstacle avoidance algorithms can be divided into three categories, which are artificial potential field (APF), intelligent optimization algorithms, and reinforcement learning algorithms [7].

3.3 Recent Research

3.3.1 Artificial potential field (APF)

It is a virtual force method proposed by Khatib in 1986, which is a traditional algorithm. The target gravity and the repulsion of surrounding obstacles work together to control the motion trajectory of the autonomous vehicles.

The traditional artificial potential field method helps to control the real-time obstacle avoidance of smart vehicles and plan relatively safe paths. However, when encountering a certain point where gravity and repulsion are just equal in magnitude and in the opposite direction, the smart car will fall into the local optimal solution or produce the phenomenon of shock swing. When there are obstacles near the target location, the repulsion force is much greater than the gravitational force, and it will be difficult for the smart car to reach the target position: When the object is relatively far away from the target position, the gravitational force is much greater than the repulsion force, and the relatively small repulsion force may be ignored at this time, and the smart car may encounter obstacles.

Therefore, there are several improvement methods. The first one is local optimal improvement method. The second one is improvement methods for encountering obstacles. The third one is improvement methods that do not reach the target points. The fourth one is the improved method for avoiding dynamic obstacles [7].

3.3.2 Intelligent optimization algorithms

Intelligent optimization algorithms are a category of heuristic optimization methods, encompassing approaches such as fuzzy logic algorithms, genetic algorithms (GA), ant

colony optimization (ACO), particle swarm optimization (PSO), simulated annealing (SA), neural network-based optimization algorithms, and tabu search (TS) [7].

3.3.3 Reinforcement Learning Algorithms

Reinforcement learning is a bio-inspired algorithm where intelligent vehicles continuously interact with the environment via sensors to acquire unknown environmental knowledge. It involves four core components: (1) policy (mapping perceived states to actions); (2) reward (immediate feedback representing short-term objectives); (3) value function (expected cumulative rewards indicating long-term performance criteria); (4) environment model (probabilistic state transition dynamics). Through iterative cycles—where the vehicle observes states, receives rewards, applies learned policies to select actions, and triggers state transitions—algorithms like Sarsa and Q-Learning efficiently solve obstacle avoidance problems within finite timeframes while delivering optimal solutions. This approach features online learning and autonomous adaptation capabilities [7].

4 Conclusion

Based on the history and recent research of multi-sensor fusion and obstacle avoidance algorithms, this paper introduces the basic information and the practical applications of multi-sensor fusion and obstacle avoidance. This paper found out that the history of research on autonomous driving is really long, while the researchers have got many significant research achievements. This paper first discusses the origination of multi-sensor fusion, the classification and several main data fusion algorithms, and the actual applications of multi-sensor fusion for car companies and other fields. After that, this paper discusses the history, classification, and three main algorithms for obstacle avoidance.

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