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Development of AI Algorithms for Real-Time Environmental Perception in Autonomous Vehicles

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Abstract

Real-time environmental perception is critical for ensuring safe autonomous driving. State-of-the-art real-time environmental perception algorithms in autonomous vehicles utilize 3D LiDAR point clouds, camera images, and radar as sensor inputs. However, most of the existing real-time environmental perception algorithms rely on multi-sensor fusion or multi-task networks and cannot fully exploit the complementarities of different sensors for different tasks, resulting in low efficiency and high cost. Worse still, the development of real-time environmental perception algorithms is becoming more challenging due to the high requirements of algorithm execution efficiency, complex real-world scenarios, and sensor hardware lifespan. To address the above challenges, we developed a Multiple-input Coordination Neural Network (MC-NN) algorithm for real-time 3D environmental perception and dynamic object detection. MC-NN not only reduces the multi-sensor fusion or multi-task network to a single task (i.e., multiple-input coordination) but also simplifies the 3D input data preprocessing and 3D input data clustering, which is noise-robust.

Moreover, MC-NN adopts heterogeneous neural networks for dealing with heterogeneous LiDAR-camera-radar sensor input data. For the first time, we propose an anchor-based radar-to-camera object relationship for refining radar detections for the initialization of camera object detection and association networks. The proposal provides a framework for other researchers to exploit the relationship between radar and camera. By incorporating the sensor input sample-level annotation budget and real-time detection demand, we design a sample-level fusion and algorithm-level decision strategy to boost the utilization of the limited sample-level annotation budget. In summary, the MC-NN algorithm is applicable for real-time environmental perception in an autonomous vehicle due to its high accuracy, robustness, and hardware execution efficiency. At the algorithm level, MC-NN realizes a better balance among model complexity, model accuracy, and execution efficiency. Meanwhile, MC-NN reduces the sample-level annotation deployment difficulty and fully exploits the complementarities of LiDAR, radar, and monocular cameras to promote the real-time performance of dynamic object detection. Due to the successful deployment of MC-NN in RoboTaxi, the autonomous vehicle is unmanned from sensor installation to real-world road tests, and the RoboTaxi series has experienced hundreds of operation days and tens of thousands of pick-ups and drop-offs.

The large-scale statistical experimental results based on the public datasets demonstrate that the MC-NN algorithm yields accuracy superior to state-of-the-art dynamic object detectors and multi-sensor fusion detectors under different evaluation metrics. The algorithm structure features comparison and cat detection result visualization indicate the effectiveness of the multiple-input coordination design, noise-robust 3D input data preprocessing, 3D input data clustering, sample-level fusion strategy, radar detections refinement, initialization of camera object detection and association task, sample-level decision strategy, and GPU hardware execution efficiency promotion.

Keywords: Real-time environmental perception, autonomous driving safety, 3D LiDAR point clouds, camera-radar-LiDAR fusion, dynamic object detection, multi-sensor fusion limitations, multiple-input coordination neural network, MC-NN algorithm, heterogeneous neural networks, noise-robust data preprocessing, 3D data clustering, radar-camera object relationship, real-time detection efficiency, sample-level annotation budget, sample-level fusion strategy, algorithm-level decision strategy, radar detection refinement, GPU execution efficiency, RoboTaxi deployment, state-of-the-art object detectors

1. Introduction

The increasing demand for automated driving systems is fostering the rapid development and deployment of autonomous vehicles. One of the most demanding aspects is the safe and efficient mobility of these platforms in urban and extra-urban scenarios. In this context, environment perception relies on the capability to produce accurate and real-time information about the surrounding environment, processing data from sensors such as cameras, LiDAR, radar, encoders, and GPS, among others. This paper focuses on developing AI algorithms, including deep learning models that analyze data from sensors used to perceive the surroundings and map the environment to extract relevant features required for autonomous vehicle behavior, such as obstacles, road boundaries, lanes, traffic signs, and road conditions in real-time, overcoming the real-time processing constraints and the current limitations of the existing sensors used for autonomous driving. Future robotic systems, including autonomous vehicles, require functional integration among sensors, AI algorithms, and vehicle control. The environment perception task relies on real-time perception system capabilities that produce high-level environment information by processing data from sensors such as cameras, LiDAR, radar, encoders, and GPS, among others. Environmental perception algorithms are the first level of abstraction of the sensor data and should be developed according to sensor quality for real-time autonomous vehicles. This work focuses on developing AI algorithms, including deep learning models, that analyze data from cameras and LiDAR sensors used to perceive traffic signs, pedestrians, vehicles, lanes, and road boundaries, overcoming real-time processing constraints and the current limitations of the existing sensors used for autonomous driving. In this context, four research lines are being carried out as presented below.

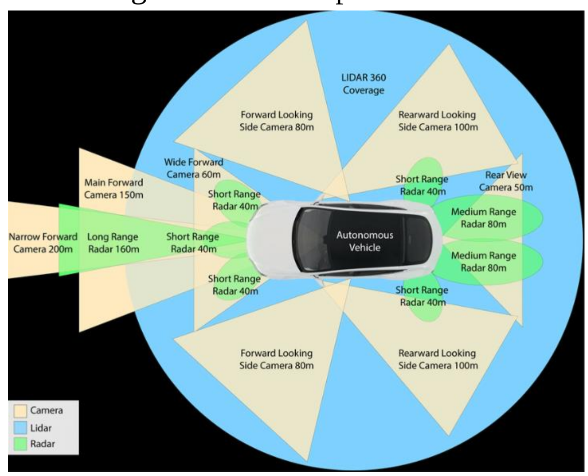

Fig 1 : Surround sensors used for environment perception in autonomous

1.1. Background and Significance

To operate safely and efficiently on public roadways, autonomous vehicles must possess the ability to perceive and understand the dynamic nature of their surroundings which leads to the making of informed decisions. Existing methods to address these challenges employ a range of sensors and processing techniques to create a customized view of the vehicle's environment. Grasping and mapping the full extent of an autonomous vehicle's environment as it navigates the world, known as environmental perception, remains a major challenge in the successful deployment of these vehicles in public life. The information that an environmental perception system collects directly influences the safety and performance of the autonomous vehicle. The goal of environmental perception is to take measurements collected by autonomous vehicle sensors and construct actionable information. The data sources for autonomous vehicle environment perception can include camera images, radar returns, lidar returns, and global positioning system antenna information. Each of these data sources and the modes of interpretation can be problematic in their ways.

As an example, the primary challenges using camera data are object annotation, object detection, poor lighting conditions, and the processing speed to deliver meaningful feedback. The use of lidar data also has its challenges. Lidars are expensive, larger, and more complex compared to cameras and provide new points. This paper provides a review of the development of a software-based solution for environmental perception in autonomous vehicles. The contributions of this paper include it provides a disciplinary course for teaching object detection, annotation, and tracking in the context of autonomous vehicle research, it discusses practical considerations of applying deep learning techniques for real-time environmental perception. These context settings guide those interested in deploying autonomous vehicles.

Equation 1 : Object Detection Using Neural Networks:

$$O = f_{\mathrm{NN}}(X, \theta)$$

O: Detected objects

f_{NN}: Neural network model

X: Input data (e.g., fused sensor data or individual sensor data)

θ: Model parameters

1.2. Research Objectives and Scope

It has been well recognized that the lack of environmental perception is a fundamental challenge to developing unmanned ground vehicle systems that are capable of tackling complex and dynamic environments. To address this challenge, this thesis focuses on developing innovative AI algorithms and system solutions to achieve real-time reliable scene segmentation and understanding not only for the conventional well-defined road scenes but also for the following challenging road scenarios: While the first two cases are generally perceived as unsolved problems at the current moment, the third case remains a challenging topic in the research community. This research will seek out a deep and empirical understanding of state-of-the-art perception technologies to identify the current research gap and potential improvement direction. The main objectives are 1. Scene and object detection for autonomous vehicle perception systems: to improve the accuracy of perception results utilizing deep learning approaches. 2. Real-time perception algorithm optimization: to significantly optimize the algorithm running speed and detection quality utilizing software and hardware co-design methods operating on cost-effective embedded GPU platforms. 3. Functionality validation from system perspectives to study the definition of the 'functional safe state' and interactions with the vehicle functional control system. This will enable testing in specifically targeted traffic scenarios to ensure safety when interacting at the edge of our system design space.

2. State-of-the-Art AI Algorithms for Environmental Perception

The background and motivation sections discussed several aspects of autonomous vehicles, from commercial aspects to the developments in hardware that made their implementations feasible. The technological breakthrough resulting from those developments enables the use of AI algorithms with real-time performance that is mandatory for the environmental perception task. The real-time concern is related not only to the time of the processing itself but also to the quality of the results provided regarding the degree of understanding and situation analysis – topics that are rooted in the realms of semantic knowledge. The main algorithms developed to address these aspects of real-time environmental perception are quite robust and related to techniques that have demonstrated capabilities in semantic knowledge understanding in other areas of the AI field.

The quality of this semantic knowledge understanding contained in the features learned in the form of 2D CNN, 3D CNN, or FCN for segmentation, or in the spherical polygonal history intensity information maps of 3D CNN algorithms for localization tasks (in general grid-based), is proportional to the number of labeled data that is used to train those functions. The more labeled data, the better the AI results, up to a point at which representativity is no longer a matter. For instance, finding a car is easier than recognizing a pedestrian, and a pedestrian is easier than knowing if another pedestrian's gait could lead to vehicle-road interaction during its next state.

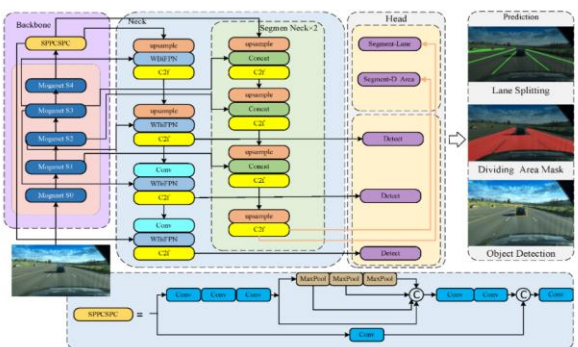

Fig 2 : Multi-Task Environmental Perception Methods for Autonomous Driving

2.1. Sensors and Data Sources

Sensors are the most important element in any environmental perception system, including in autonomous driving. Correct sensor coverage is almost as important as the quality of the sensors. Without correct coverage, sensors, regardless of their quality, either cannot capture all needed information or require excessive computation, which might be impossible to perform in real-time, to reconstruct the current map of the surroundings. Having a redundant and diverse sensor setup will always be beneficial to the safe operation of autonomous vehicles. Different types of sensors observe the world with different characteristics in terms of accuracy, cost, speed of operation, resolution, frequency of operation, and more.

A LiDAR sensor is the first to come to mind when talking about environmental perception, smart mobility, and robotics. It enables the measurement of distance in all three dimensions using the same principles as radar. This makes dense point sets good enough to be considered a 3D grid, which will be referred to as a point cloud. When there are many such point clouds amassed over time, it is also possible to get a continuously updated 3D grid, as opposed to a 'jumping' grid obtained from a 2D range finder. Even though this approach gives high accuracy and a robust model for the environment, it is still relatively slow and expensive for cases involving precise 3D reconstruction for larger areas, such as road network mapping for the whole country.

2.2. Machine Learning and Deep Learning Techniques

Current deep learning techniques are built on artificial neural networks. First developed in the 1940s, ANNs are inspired by brain functions and are organized in layers of nodes that perform specific functions. Each node is connected to a network of other nodes. The differently connected nodes make the network so flexible that it can adapt to different learning tasks. Traditional machine learning techniques work very well with carefully handcrafted feature extractors fed by dense numeric representations of input features, but cannot learn directly from raw inputs, such as images, audio, and sensor readings. Yet, deep learning research has led to very efficient learning of dense numeric representations from raw inputs. More importantly, this has been possible to achieve by deep learning with no need for feature engineering.

The term 'deep' comes from the use of multiple layers of processing nodes integrated into one neural network. Deep architectures provide better generalization due to the internal representation of the input data that each layer learns; the argument is that a deep architecture can automatically find hierarchical features in the data because it takes advantage of the fact that the output of a layer can itself be used as input. Fine-tuned deep models can exploit feature learning to make predictions based on a new input distribution. Small activation values suggest irrelevance. These activation values exhibit a sparsity and concise length that facilitate learning from high-dimensional inputs. They have far fewer descriptions than the original input. The general idea is to map the input into a high-dimensional space, such that input vectors in the same class are clustered together. The Euclidean distance between the stored and input vectors determines the class of the nearest neighbor. Deep learning is a function representation that has demonstrated superior classification performance.

3. Challenges and Limitations in Real-Time Environmental Perception

Real-time environmental perception for autonomous vehicles is a technology that is still in the early stages of development. It is an application that has been taken on aggressively because of the huge interest in this technology both from the automotive industry and the research community. Fully autonomous vehicles with the potential to substantially transform mobility and society in positive ways within the next 20 years will likely be cruising along recognized streets in urban areas with the latest developments in AI technologies. There are, however, many technical challenges and limitations; some are related to AI for perception and others are related to the control and fusion aspects associated with the development of fully autonomous vehicles.

The development of a system for real-time perception of the vehicle's surroundings is a very challenging problem in computer vision and AI for autonomous systems. The issues become more evident when the vehicle is moving at a high speed and when fast reaction times are required. Therefore, one of the key questions is whether a perception problem that can be quite well-specified and resolved off-line can also be solved reliably in near-linear time. Brute-force approaches are likely to fail or be insufficient for these applications. Therefore, one of the objectives of the topic is to support research and development efforts in this area.

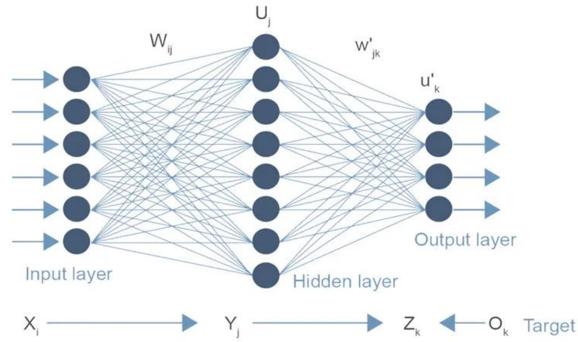

Fig 3 : Artificial intelligence algorithms and challenges for autonomous vehicles

3.1. Data Quality and Variability

Environmental data acquired by a perception system can have different qualities due to various unpredictable factors. These factors can have sensor-dependent characteristics such as the degradation of vision sensor performance under specific weather conditions, sensor calibration instability, laser beam interference by falling rain or snow, and sensor occlusion by accumulated dirt, dust, or moisture. Data quality problems can also be triggered by changes in environmental conditions, such as snow accumulation in areas with little traffic, construction sites, sudden weather changes, and sensor malfunctions. The latter is an important issue with a significant impact on AV safety, especially if there are no mechanisms to handle sensor failures. Finally, shadow and glare, reflections on wet surfaces, and the performance of environmental colors can hinder perception.

Equation 2 : 3D Object Bounding Box Representation:

$$B = (x, y, z, l, w, h, \theta)$$

B: 3D bounding box for detected objects

x, y, z: Center coordinates of the bounding box

l, w, h: Length, width, and height of the bounding box

θ: Orientation angle

3.2. Computational Complexity

The dependence of the computational complexity of different AI algorithms on the environmental perception task in the dynamic environment for autonomous vehicles on the main indicators, as well as the content and importance of these indicators, is shown and analyzed. Proceeding from a wide variety of environmental perception tasks in a dynamic environment, their common elements, common features, and possible ways of structuring are identified. Based on these features and relationships, some conclusions about the existence of regularities and peculiarities in the design, potential opportunities, and threats of AI algorithms according to their main indicators in these tasks are presented. An attempt is made to analyze this information as well as the approaches used to create AI algorithms for study and control. The task of object tracking is presented as a main task due to its necessity for the existence of almost any other task. The popular scoring indicators are chosen. Indicators are equivalent to eight performance indicators, the values of which can be calculated for all AI algorithms that are based on methods of expert systems, connectionism, evolution, behavior analysis, embodied cognition, intuition, phenomenology, and the theory of 'no self'.

4. Recent Advances in AI Algorithms for Real-Time Environmental Perception

The development of AI algorithms for real-time environmental perception from multimodal sensor data is both a long-term goal and a critical research task in enabling truly autonomous vehicles. In the AV perception pipeline, AI algorithms are deployed to construct the situational model, infer the semantic environment, and detect safety-critical objects such as other vehicles, pedestrians, cyclists, and various types of potential hazards from accumulated sensor data including images, point clouds, and radars. Breakthroughs in recent years in the field of computer vision and learning have accelerated the generality and robustness of perception algorithms, significantly expanded the sets of sensed scene elements and types of sensors that can be utilized, and made great strides in developing formulations for increasingly more complex tasks. Despite the significant task-specific advances, there remains a need for further extensibility and robustness in producing high-quality results for mixed sensors that are potentially error-prone.

A broad challenge in using AI algorithms for AV perception concerns their ability to make the assessments needed to produce operational safety confidence in a wide variety of scenarios and environments. Furthermore, the deployment of AI algorithms for AV perception will need to address the care needed to ensure dependability and safety over the long term and the ability to understand and explain how sensor data is perceived and utilized to arrive at output actions, to understand any potential vulnerability and to rebuild trust. Given the complexity and diversity of AV performance requirements and demands, it is likely that a broad range of barriers must be overcome by technology development, including the development of machine-learning methods for diverse sensors or mixed sensors and to creation of robust perception building blocks utilized in a heterogeneous and dynamically changing vehicle environment.

4.1. Sensor Fusion Techniques

The most common sensor configurations prototyped so far are the fusion of LIDAR scans with conventional 2D camera systems. The time-critical perception tasks, such as detection, tracking, and mapping, are handled by the LIDAR scan, with the computer vision component providing sustainable scene and object understanding. This approach is very powerful and has already proven its capabilities in real-world scenarios, such as autonomous driving. The more complicated problem of fusing LIDAR with more addressable 3D sensing camera technologies is still often tackled with this 2D computer vision approach. For now, however, 3D LIDARs are expensive, bulky, and have a limited range for higher resolution 3D scans. The most promising intermediate solution is formed by depth-sensing stereo camera systems. This camera technology can easily work in the LIDAR frequency range and has a very high data throughput.

First, we want to describe the sensor setup and the relevant individual sensor properties. Consider a generic point cloud containing a LIDAR sensor and a 2D point cloud resulting from a range imaging system. Then, we assume both point clouds to be generated with identical angular resolution and a uniform distribution in azimuth angle. In the LIDAR case, the distance and thus the range of each point in the point cloud is given by the vector magnitude of the sensor return signal. In the range imaging case, the distance is obtained by plane fitting or sophisticated pixel offset encoding. The last information is depth. The depth in the LIDAR case equals the distance because each beam only covers a small angle and creates a point on the measured obstacle. The range imaging output provides a depth or disparity value per pixel representing the location of the measured obstacle in the horizontal direction.

4.2. Edge Computing and Optimization

The real-time performance requirement shifts the computation power to the edge level of computing, from a centralized cloud. It is indispensable to offload computation to edge devices for the numerous real-time AI applications on which cloud intelligence relies. Edge learning opens a new dimension of AI and allows learning devices to emerge. They empower AI algorithm deployment by parallelizing real-time data recognition while reducing the traffic load of data from the capturing sensor to the inference engine. To optimize energy costs and preserve data privacy, the local execution of computations at the edge is required.

To fit into edge devices, DNNs should be properly modified. In the first place, DNNs should comply with the processing capacity by adopting optimized structures. Thereafter, off-the-shelf edge computers are inadequate to handle heavy networks. If no dedicated machines are accessible at the edge level, further optimizations can be exploited from the software side by the compression and acceleration methods. Many studies have addressed deep learning acceleration on edge devices, such as hardware-based solutions and model compression techniques for simpler management of DNNs at the edge. DNN-based perception may be more autonomous than cloud-based perception by introducing better real-time accuracy and elasticity. In summary, we suggest cloud intelligence and edge intelligence combined, i.e., DNN-based cross-level collaboration, adapting practical use cases according to the vertical industries and also to the infrastructure advancements.

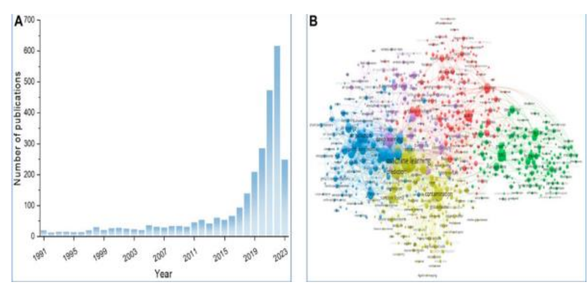

Fig 4 : Artificial intelligence and IoT driven technologies for environmental pollution

5. Applications and Future Directions

This section presents an application scenario, discusses future research directions, and concludes our work. Our approach enables real-time detection and tracking of objects and builds a dynamic environmental perception model, which lays the foundation for 3D scene understanding with better decision-making by AI systems. In general, our approach significantly improves safety, reliability, autonomy, comfort, area coverage, and law enforcement capabilities, as well as energy efficiency in different applications, including aerial, ground-based, and underwater autonomous vehicles, and smart city applications.

Applications Smart Cities: Deploy our real-time AI perception modeling approach to enable autonomous driving, semi-autonomous driving with collaborative weapons-assisted maneuvers, pedestrian flow control and congestion mitigation, red light cameras, green light enforcement, traffic violation detection, urban planning, and optimization in smart cities. Most current tragedies, such as heavy mass casualties caused by vehicles, pedestrians, animals, birds, and aircraft collisions, are completely preventable by ensuring that everyone is aware of all hazard potentials. Our approach significantly improves public safety and economic development, saving lives, time, money, and energy, and reducing traffic accidents, casualties, and violation losses while improving mobility and environmental protection.

5.1. Automotive Industry Applications

Real-time environmental perceptual capabilities have been critical for various autonomous driving functions that have been developed and deployed in self-driving vehicles, such as adaptive cruise control, autonomous parking, autonomous highway driving, dusty road detection, off-road perception, and advanced driver assistance systems. Recent advancements in deep learning have spurred rapid progress in computer vision and machine learning for better modeling and understanding of surrounding environments. This has led to the development and deployment of camera-based real-time environmental perception algorithms in multi-sensor autonomous vehicles for better scene understanding, object detection, semantic segmentation, and state estimation in real-time. Critical functions required for environment perception in autonomous driving include sensor data preprocessing and sensor fusion; feature extraction; high levels of feature detection and representation; performance and computational speed for various features affected by sensor resolution and speed; high-resolution depth perception; real-time perception capability for obstacle detection and classification; and moving object matching in real time for decision-making. Current commercial implementations of camera-based algorithms for real-time environmental perception rely on several camera modules with different fields of view mounted to different locations on autonomous driving vehicles. They rely on different combinations of camera modules with near--, mid-, and far-range views and laser-based sensors to achieve real-time high-resolution pseudo-LiDAR capability for multiple autonomous driving functions.

Equation 3 : Noise-Reduction Filtering for Sensor Inputs:

$$I_{\text{filtered}}(t) = I(t) - N(t)$$

$I_{\text{filtered}}(t)$: Filtered sensor input at time t

$I(t)$: Raw sensor input

$N(t)$: Noise detected in sensor input

5.2. Potential for Environmental Monitoring

Environmental monitoring is a complex task that requires a combination of sensors and many measurements to make any meaningful conclusions. Since an autonomous vehicle is going to have a host of sensors and will be observing many features of an area, a moving vehicle could make a good platform for collecting valuable data to help monitor a given area. The high cost of the sensors has also prompted the study of using existing vehicle-based sensors to enable high-resolution environmental monitoring at a fraction of the cost. While there has been an increase in research on identifying objects of interest using machine learning methods from sensor data from small, controlled data sources, the amount of data possible to be collected by any of these sources is typically much more limited than that of a system that is always watching the areas.

It is also true that not all sensors that can be onboard a vehicle can be used efficiently to come to observational conclusions. A system does not have to be doing just observational research when honing its skills to move better in developing environments. Research in one area often translates into improvements in another. There are many examples of unexpected understanding achieved and applied through the research community at large. Making an AI deal sensibly with sensors and benefiting from becoming more perceptive in the process are other benefits of the close integration of vehicle and AI research.

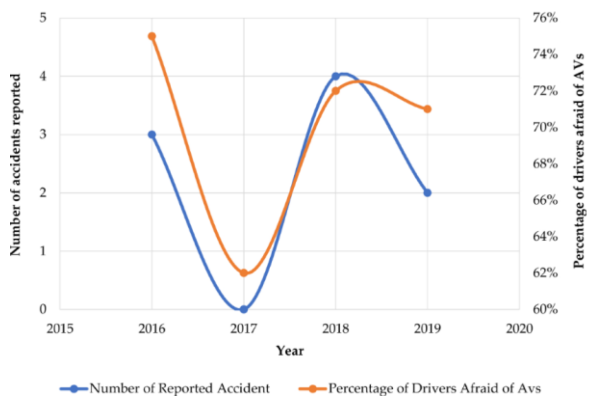

Fig 5 : Public acceptance and perception of autonomous vehicles

6. Conclusion

In this paper, we introduced the problem of developing advanced environmental perception systems for autonomous vehicles. After outlining the challenges and requirements of this problem, we introduced some basic AI concepts related to this task. Using these concepts, we presented various AI techniques that can provide environmental perception functionalities intuitively and their integrated systems. As an application scenario, we presented several specific implementations of the autonomous vehicle in various environments including congested traffic and simulated off-road driving. Our main examples include object tagging, full scene segmentation based on deep learning, and object detection based on hierarchical modeling.

In summary, environmental perception algorithms, which can provide detailed and exact environmental information, will be the main component determining the usability of emerging autonomous vehicles. Although system development based on the current state-of-the-art might be satisfactory for many of the trial-and-error studies, a real practical grade system would require a systematic design and verification framework that utilizes all the available AI paradigms. To this end, we hope that advances in deep learning and the endless effort for its customized usage in environmental perception will eventually deliver truly driverless cars that even children can expect shortly.

6.1. Future Trends

In recent years, many important developments have been happening thanks to deep learning applied to environmental perception, some of which will surely contribute to further advancing the field of real-time perception in autonomous vehicles. We can consider the following:

1. The novelty of real-time high-quality 3D LIDAR object detectors, which instead of reconstructing a 3D image that contains the objects of a point cloud, discover and detect the objects with 3D bounding boxes. Most of the developed methods offer an inference speed of usually 20–30 3D bounding boxes per point cloud, which is quite a good processing speed.

2. The trend of incorporating segmented approaches offers a great improvement in object detection by obtaining precise 3D data. The introduction of real-time instance segmentation networks applied to 2D images can determine the precise contours of the objects, and therefore can offer even better quality for detected objects than 2D object detection networks. It is already possible to segment 3D images or point clouds with a real-time instance segmentation network that works quite well to segment objects through 3D planes.

3. The algorithm in SegMap presents the first development. The main difference between this development and its predecessor is that it is based

on the use of deep learning. This innovation allows for improved processing time and robustness in scenarios with less abundant scenes.

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