Dean&Francis
ISSN 2959-6157

Integration of Radar Technology in Autonomous Driving: A Comprehensive Review of Applications, Methods, and Future Directions

Bairui Zhang

School of Ulink Collge, Shanghai, China

*Corresponding author: bairui.zhang@ulink.cn

Abstract:

Autonomous driving refers to the capability of a vehicle to operate independently, without human intervention through the integration of both hardware and software systems. Radar technology is crucial in hardware detection. This essay seeks to thoroughly examine radar integration technology in self-driving cars and offers comprehensive reviews of technology and future directions. It will encompass an overview of radar components, various detection methodology, and their practical application in autonomous vehicles. Additionally, the type of radar and its approach of measurement are also mentioned briefly in the text. In the last section, two models are applied to test the performance of radar object detection. Based on the calculation of accuracy, precision and recall from the nuScenes dataset, The RCS-based model and machine learning based are designed for virtual testing. The results evaluate the performance of two radar models, indicating the great performance and accuracy of identification of the machine learning model yet over-optimization of RCS model.

Keywords: radar, autonomous vehicles, autonomous driving

1. Introduction

Over the last ten years, autonomous driving has grown to be one of the most widely used transportation solutions in terms of lowering accidents and traffic, drawing hundreds of businesses that are solely focused on this field. The size of the global autonomous vehicle market was estimated to be worth USD 1,500.3 billion in 2022. Over the course of the projection year, it is expected to increase at a compound annual growth rate of 32.3%, from USD 1,921.1 billion in 2023 to USD 13,632.4 billion by 2030.

However, some challenges are still required to improve the performance of intelligent cars, including the detection of scenarios for complex road conditions using three-dimensional object detection and resistance to adverse weather conditions. Here, radar is

ISSN 2959-6157

an excellent component that can be applied in autonomous vehicles for its simplicity, cheapness and high resolution. Applying sensor fusion technology, the advantages of various sensors is compensated to each other to upgrade the overall performance. Typically, the radar, Lidar, ultrasonic sensor, camera, GPU and IMU are combined together to map the virtual graph for object detection and further analysis[1].

In this essay, the principle of autonomous driving is presented in section 2. Precise demonstrations of radar , involving the type, working principle and application are shown in the rear sections.

2. Literature Review

2.1 Overview of Autonomous Driving Technology

A wide range of technologies, which can be divided into many main categories, are integrated into self-driving technology, including motion control, path planning, pedestrian detection, and environment perception. LiDAR, cameras, and radars are commonly used to monitor the surroundings, allowing for the collection of copious amounts of data on object shape, velocity, and distance[1]. Various imaging models are used for object detection. For example, there are two types of point-voxel-based 3D object detection: single-stage and second-stage detection. While single-stage detectors combine these procedures, second-stage detectors incorporate region proposal and classification stages. Second-stage detection techniques like R-CNN, Fast R-CNN, and Faster R-CNN give up accuracy for time economy. On the other hand, single-stage approaches such as SSD and YOLO provide faster detection at the expense of reduced resolution, accuracy, and capacity to detect smaller objects[2].

Using GPS data, path generation can be optimized with the spline interpolation method, which offers advantages such as smooth curves and consistent vehicle movement[3]. Motion planning, on the other hand, can be facilitated through artificial intelligence, sampling-based approaches like fuzzy sliding mode control, or discrete optimization control. Thus, environmental monitoring forms the foundation of autonomous vehicle technology.

2.2 Brief History and Development of Radar

The initial automotive radars were introduced in the 1980s for automated cruise control (ACC) and parking assistance. Radars were utilized in collision warning systems operating at 24 GHz. Soon, the introduction of 77 GHz radars provided advantages such as wider bandwidth and reduced environmental attenuation. Early radar systems relied on the Gunn diode, which was expensive and cumbersome. However, the development of Monolithic Microwave Integrated Circuits (MMICs) enabled a broad range of radar functionalities within a compact space, supporting a variety of frequencies. This innovation facilitated the broader adoption of automotive applications. With advancements in high-frequency silicon technology, radars can now be manufactured using SiGe and RF CMOS technologies, which are more cost-effective and portable[4]. Currently, sensor fusion technology is employed to enhance the capabilities of self-driving cars by integrating various sensors, including LiDAR, cameras, and radars, to improve overall detection performance and efficacy.

2.3 Radar Application and its Functionality

Environment perception involves the cooperation of several sensors.

Firstly, Millimeter wave radar, applying several approaches like frequency modulation continuous and frequency shift keying(FSK), can measure the velocity and distance simultaneously and perform well in all kinds of weather with high resolution and fast speed[5]. With the aid of multi-range radar technology, versatility in range detection can be achieved which covers various ranges and is effective in complex environments[6].

Next, Laser radar, also called lidar, can detect the environment using various methods, including pulse, amplitude modulation and frequency modulation, to measure the distance. This provides superior range resolution and accuracy for detailed environment mapping. However, it is heavily limited by weather conditions and daylight intensity[7].

Consequently, sensor fusion is a crucial technology that enables several sensors to cooperate to increase the precision of radar, Lidar, cameras, and other sensors. Furthermore, sensor fusion enhances the stability of perception and creates a fundamental base for advanced modeling. For example, the camera has high-resolution images yet works poorly in dark conditions; the Lidar has great range resolution and long range detection but may struggle with severe weather; the radar provides comprehensive enhancement in all kinds of categories though being afraid of long-range detection. A combination of different sensors may improve reliability and gain immunity to harsh weather, like fog, rain and snow[8].

2.4 Future Challenge and Outlook

Now, autonomous driving is still facing significant challenges and is waiting to be overcome, including the accuracy of environment perception, real-time and capacity to resist disturbance. Improvement of hardware systems of detection, V2X (Vehicle-to-everything) and application of predictive modelling is the future objectives to solve the drawbacks of the current situation.

3. Overview of Radar System

3.1 Introduction to Modern Radar Technology

3.1.1 Millimeter wave FMCW radar

Millimeter wave FMCW radar is a kind of radar that works in the range of 30 to 300GHz, typically 76 to 77GHz, with the approach of frequency modulation for continuous waves to estimate the distance and velocity. Specifically, the velocity of the target can be measured using Doppler effect and distance can be calculated depending on the chirp of the radar.

The radial velocity v_r (the relative velocity between the object and the host vehicles) can be determined using Doppler frequencies:

$$f_d = 2\frac{v_r}{\lambda} \tag{1}$$

λ refers to the wavelength of the transmitted signal and f_d refers to doppler frequency.

The distance can be estimated using triangular waveform. The intermediate frequency f_{beat} which is the difference of frequency of between transmitted and received signal can be used combining with the chirp rate which is the gradient of the modulated frequency, frequency modulation bandwidth ΔF /time period of transmitted signal T_m for the calculation of distance.

The equation is given by:

$$R = \frac{T_m}{\Delta F} \bullet \frac{c \bullet f_{beat}}{2} \tag{2}$$

Range resolution ΔR can be calculated using the formula:

$$\Delta R = \frac{c}{2?F} \tag{3}$$

For the bandwidth of 150MHz, the range resolution will reach 1m which is not enough for precise and accurate detection of self-driving. But it has a continuous operation which has real-time detection and adaption in all kinds of weather with a few degrade in working ability[9].

3.1.2 Lidar

Environmental perception of autonomous cars requires high accuracy leading to the introduction of Lidar compensated with cameras and radar. Using different approaches, Lidar can be further operated in two methods:

1) Time-of-Flight(ToF) Lidar

It is a kind of radar system that demands the output of a short pulse with amplitude modulated to measure the distance, azimuth and verticle angle based on the strength of received signal.

2) FMCW Lidar

The wavelength is the main distinction between FMCW LiDAR's and millimeter-wave FMCW radar's operating principles. LiDAR operates in the infrared spectrum, whereas millimeter-wave radar operates in the millimeter-wave range. Distance and velocity can be calculated by examining the reflected signals' beat frequency.

Laser is generated through the laser diode when electric current passes through it leading to oscillation of photons due to electron-hole recombination. There are two kinds of laser sources, which is Edge-emitting laser(EEL) and surface-emitting semiconductor laser (VCSEL) where the first one emits a cyclical waveform and the latter one transmits an elliptical waveform requiring further waveform transformation. A wavelength of 850-950nm (near infrared) or 1550nm (short wave infrared) is produced because of the concern of cost, safety and environment attenuation.

Photodiode is used for the detection of echo signal, like PIN diode, avalanche photodiode, silicon photon multiplier and so forth. The primary principle is the conversion of received photons to electricity through PN junction.

Lidar provides good performance in range resolution and availability in different light conditions, unlike the cameras that work poorly in dark conditions. However, the cost is the main obstacle in the development of Lidar which is commonly thousands of dollars. Further, it works poorly in adverse weather conditions due to the impedance of particles including snow, droplets and dust. Interference with other laser radars is also a concern[10].

3.1.3 Ultrasonic sensor

Ultrasonic sensor uses ultrasonic sound for the measurement of short-range distance with working wavelength of about 40 to 50kHz which is beyond the limit of human hearing. This sensor is ideal for the driving application for short range detection like parking assistance and blind spot detection. The distance can be calculated using ToF which is cost-effective and simple. However, limitation on small range detection is serious for the severe attenuation of environment, like humidity and temperature. Interference of noise may also a challenge in measuring the distance[11].

3.2 Transceiver for Radar

A Voltage Controlled Oscillator (VCO) generates an operating frequency that can be adjusted by varying the input voltage. This can be achieved using a varactor diode. The VCO output is then processed through a frequency synthesizer, which includes components such as a phase-

ISSN 2959-6157

locked loop (PLL), frequency mixer, low-pass filter, and dielectric resonator oscillator. This process allows for the generation of a specific frequency waveform with stable and accurate values, minimizing sensitivity to temperature changes[10].

The signal received by the antenna typically undergoes noise cancellation before being sent to a mixer. The mixer produces an intermediate frequency (IF) by comparing the signal with the frequency from the VCO, using a ring modulator. The IF allows for the estimation of range and velocity in FMCW radar systems. Final processing steps, including low-pass filtering and analog-to-digital conversion (ADC), enable the calculation of these parameters.

Utilizing a Multiple Input Multiple Output (MIMO) system with a modified four-port balanced antipodal Vivaldi antenna enhances detection capabilities. This configuration provides 90-degree field-of-view for each antenna, enabling 360-degree detection and pattern diversity. This design improves sensitivity to the angle of the received signal, leading to enhanced angular resolution[12].

3.3 Noise Filter and Cancellation

Noise cancellation is significant in the calculation of radar for the correct identification of object detection and avoidance in erroneous readings leading to concern for safety. Here are some methods of noise cancellation technology.

In order to reduce the impact on the measurement, clutter suppression uses an approach to identify the clutter and compress it. By comparing the received signal with the signal from a high-clutter environment, clutter can be recognized. Constant false alarm rate (CFAR) algorithms can be used to further filter the output, making it easier to detect clutter and keeping the false alarm rate low[13].

Adaptive filtering utilizes the technology where filter parameter is adjusted automatically according to the property of input signal. This enables the adaptation of filter in changing environment to achieve the optimistic approach from the received signal to the ideal processing signal continuously by updating the parameters[14].

4. Application of Radar

4.1 Three-dimensional Object Detection

3D object detection has 3 types of method, separately point-based, grid-based and point-voxel-based.

4.1.1 Point-based 3D object detection

For point-based 3D object detection, localized object can be illustrated in three-dimentional space using point cloud data with the application of Lidar. Raw data can be directly processed into 3D cartesian coordinates (x,y,z) to represent the location of the object in the point cloud. Additional data may also be represented like the color, materials and shapes.

Then applying point cloud sampling techniques, like farthest Point sampling(FPS), efficiency of processing improves which provides a uniform density of points while remaining important features. After that, the feature learning can be used which is a machine learning algorithms allowing automatic extraction of relevant features from raw data. This avoid the human intervention and makes the classification and identification process intelligent and efficient, like PointNet that automatically learn hierarchical features including edges, textures and shapes at different layers of the network.

Finally, the bounding boxes will be generated containing objects of interest with the label of measuring value that includes the location, size and class.

4.1.2 Grid-based 3D object detection

Grid-based 3D detection localize the object in three-dimensional space by dividing the area into a grid format such as voxels(3D grid cells), Pillars and Bird's-Eye View. Neural networks like Convolutional Neural Networks(CNNs) can be applied for feature learning and finally output the object prediction.

4.1.3 Point-voxel based 3D object detection

Point-voxel based 3D object detection is a hybrid technology that combines the point-based and voxel-based methods for the detection of object, compensating for the shortcomings of each and achieving both high efficiency and detailed accuracy. There are two primary approaches: single-stage and two-stage detection.

In the single-stage method, voxel features and point clouds are processed in a single step, using point-to-voxel and voxel-to-point transformations to extract features. For two-stage detection, the process begins by generating 3D object proposals through a voxel-based detector, followed by a refinement step using point cloud data. The refined data is then used for the final object prediction.

This combination of methods improves detection accuracy while maintaining efficient processing[15].

4.2 Advanced Driver Assistance Systems

Advanced Driver Assistance Systems(ADAS) are a collection of technologies to enhance driving safety and experience by applying various sensors. Utilizing the sensor integration, reliability and accuracy of detection may improve because sensor fusion technology can gather excessive and comprehensive information while compensating for their weakness. Here are some driving assistance features: adaptive cruise control(ACC), lane keeping assist(LKA), blind spot detection(BSD), automatic emergency braking(AEB) and traffic sign recognition(TSR).

4.2.1 Sensor fusion

The first step is to identify the measurement target for each sensor. Millimeter-wave radar can estimate both distance and velocity simultaneously and performs well in adverse weather, though it is prone to frequency interference and has a high false alarm rate from metallic objects like road signs. Cameras provide detailed information on colour, texture, and shape, making them valuable for deep learning applications, but they are limited in range resolution and struggle in poor weather. LiDAR is useful for 3D object detection and creating detailed 3D maps to recognize both dynamic and static elements, such as lanes and vehicles. However, it is expensive and can be hindered by severe weather conditions. Ultrasonic sensors excel in short-range estimation but are also affected by weather and limited in detection range. GPS provides precise real-time positioning by receiving signals from multiple satellites, while the Inertial Measurement Unit (IMU) measures acceleration and angular velocity, supplying motion data.

Once these sensors collect data, sensor fusion technology combines and processes it, sending it to various systems for further operation.

4.2.2 ACC

ACC can automatically adjust the car's speed in the safety zone according to the distance from the vehicle ahead. By monitoring the distance in front of the car from the fused data utilizing ultrasonic sensors or cameras, speed regulation can be achieved for safety in the following distance.

4.2.3 LKA

LKA is a system that helps the driver maintain within its lane on the road. Based on the host vehicles current driving speed and direction, trajectory can be estimated to create the situation model that whether the car follows the maneuver of the centre of the lane or shift to one sides. If the system detects that unintentional movement occurs without the turn of signals, a feedback will be provided, commonly in the form of visual alerts or vibration of wheel.

4.2.4 AEB

The AEB systems combine the cameras, sensors and algorithms to avoid potential collisions and automatically apply the brakes to prevent accidents. Using the real-time fusion data and the construction of 3D mapping, the measurement of the velocity of the vehicles relative to the other vehicles or obstacles is created. Then the algorithm can predict the potential collisions according to the motion of the object and the host vehicles. If the collision is anticipated and the driver does not take the corresponding action, the AEB will start. Before the initiation of AEB, the auditory alert may be provided to warn the driver. Then the automatic braking may be applied to avoid accidents if drivers do not respond correctly. Integrated with other systems like ACC and LKA, the working performance of the vehicle will be improved[16].

5. Test and Evaluation Model

Radar detection plays a key role in autonomous driving. Driving datasets, like the nuScenes dataset, including numerous and diverse annotated data with over 1000 labelled scenes and 23 object classes, improve the driving perception which plays an important role in sensor model. Additionally, it provides environmental conditions, like daytime and weather conditions.

5.1 the NuScenes Dataset

Two Renault Zoe supermini electric vehicles equipped with the same sensor configuration are used to drive in Boston and Singapore in order to gather the data set. The table displays the type of sensor that was used. Additionally, the figure shows how the sensor is configured. The field of view (FOV) of the front, side, and rear cameras is 70 degrees, while the rear camera has 110 degrees and a lidar on top of 360 degrees of FOV.

5.2 Hardware of Models

On the long range radar sensor, the model evaluations are generally dependable (Continental ARS 408-21). The ego automobile has five different radars: front, front right, front left, back right, and back left. The measurement approach of FMCW yields an operating frequency range of 77GHz to 78GHz. The capture frequency of 13 Hz results in a maximum detection range that is less than 250 meters. The reflected signals are analyzed in various steps to determine the most representative location when the received signals are collected in cluster mode. Radar is tested in conjunction with other sensors to ensure its functionality. These include six RGB cameras (Balser acA1600-60gc) with a 12Hz capture frequency and a 1/1.8” CMOs sensor with 1600 x 900 resolution, as well as one full view LIDAR (Velodyne HDL32E, 20Hz capture frequency, 32 beams, range<70m up to 2cm accuracy, points per second up to 1.4 million). As shown in the Fig 1[17].

ISSN 2959-6157

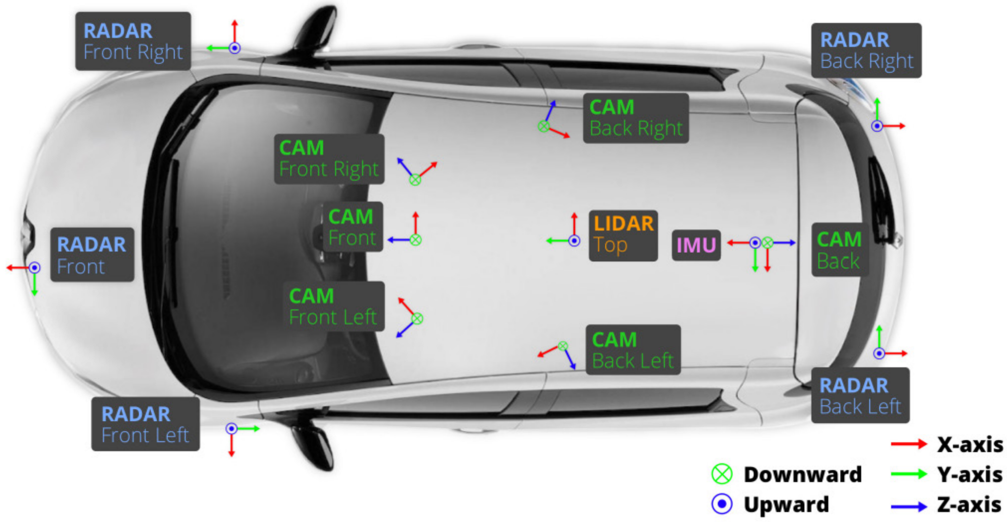

Fig 1. Sensor setup for nuScenes data collection

5.3 Important Parameters

5.2.1 Precision of radar clusters

It is defined as the ratio of true positive radar cluster detections to the total number of radar cluster detections. Here is the step of taking the measurement

1. Transforming the coordinates of the radar cluster of all object bounding boxes into the coordinate system of individual radar
2. Then check whether the coordinates fall within the volume of extended object bounding box(commonly 20% increase)
3. select and count the number of true positives(TP) which refers to the cluster assigned in the labelled object bounding box and false positives(FP) that are not defined to any object.

FP may be caused by the object that is not contained in the nuScenes classes, like the infrastructure, such as buildings, bridges, railways and so forth.

5.2.2 Radar reflection properties of objects

It alludes to the capacity of reflected waves to reach sensors from varied objects, which is crucial for evaluating how well a radar system can locate and identify an object in a variety of settings. To study the radar reflection qualities, two further factors are needed: the radar cross section (RCS) and the number of clusters (NC).

1. Convert each item bounding box's radar cluster coordinates into the coordinate system of a single radar
2. If one or more clusters are assigned to an item, it is said to have been discovered. The cluster points that lie inside the enlarged bounding box are regarded as the corresponding object.
3. The yaw angle—that is, the angle between the radar line of sight and the object's orientation—is determined.
4. For every object that is detected, the number of clusters NC that remain within the bounding box is computed.
5. For each item, the total RCS value of every cluster point to the object is determined.

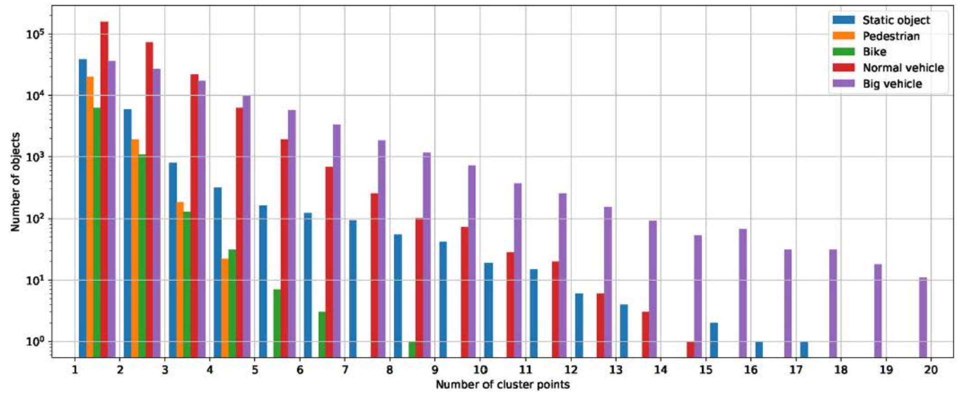

Figure 2. Distribution of number of cluster points NC for each object class

From the Figure (2), 1 cluster point is probable for almost all classes. Typically, small objects have fewer NC and larger objects have larger NC which the big vehicle can range from 15 to 20 NC.

table 1. average RCS value of each object class

Static object	4.81dBsm
pedestrian	1.74dBsm
bike	3.46dBsm
Normal vehicle	8.98dBsm
Big vehicle	19.97dBsm

Hence, according to the table1 , conclusion can be made that larger the objects, higher the RCS.

5.2.3 Visibility and occlusion for radar

Bounding boxes and radar FOV are utilized to calculate visibility. Two crucial characteristics are required whenever an object is located in the field of view (FOV): the relative viewable area (VIS), which indicates the region that is not obscured, and the number of occluders (NOCC). The ratio of objects identified to total objects in the radar's field of view is known as detection probability. In addition to the weather, object classes, and relative velocity that are predicted for detection in the nuScenes dataset, the VIS and NOCC are used in the computation of detection probability.

Table 2. Detection probability in different NOCCs, relative velocity and VIS

NOCC	Detection probability%
0	33.59
1	26.96
2	22.88
3	20.04
4	19.29
5	19.56
6	19.25
7	19.59
8	19.18
9	23.41
V(m/s)	Detection probability%
0-0.5	26.04
0.5-1.5	13.06
1.5-2.5	22.19
2.5-3.5	54.85
3.5-4.5	59.01
4.5-5.5	59.50
5.5-6.5	60.47
6.5-7.5	60.21
7.5-8.5	60.21
8.5-9.5	59.62
9.5-10.5	54.66
10.5-11.5	49.36
11.5-12.5	49.91
12.5-13.5	45.74
13.5-14.5	44.90
14.5-15.5	43.44

ISSN 2959-6157

15.5-16.5	37.91
16.5-17.5	38.22
17.5-18.5	34.91
18.5-19.5	40.33
VIS%	Detection probability%
0	7.26
10	26.06
20	34.08
30	37.94
40	38.14
50	36.73
60	35.77
70	33.73
80	30.82
90	28.65
100	34.28

5.3 Real-world Performance

In the table2 , the probability of detection can be observed in various conditions. As there are no occluders which NOCC is 0, the detection probability is 33.59% yet whenever NOCC is 9, detection probability decreases to 23.41% which is still have a relatively good performance. For VIS at 0%, it is impossible to be detected. However, low VIS has a minor influence in the detection probability. Furthermore, the detection probability of higher relative velocity is obviously higher than that in lower speed because of the minor Doppler frequency which is hard to discover by the receiver. The above analyses are fully based on the Continental-ARS-408-21, illustrating the stability of detection in different environmental conditions.

5.4 Related Radar Model

5.4.1 RCS-based radar model

This model compared the value from ground-truth object list in environmental simulation and the minimum value of RCS to justify whether the object is detected, where the minimum parameter is processed and provided by nuScenes data set.

5.4.2 ML-based radar model

Based on the ground-truth object list and environment parametres provided by environment simulation, input parameters are collected by the simulated sensor. Then, the machine learning algorithm is trained using nuScenes dataset so that a balance representation is shown for the test of detected and undetected objects.

The types of machine learning algorithms used are Linear Support Vector Classifier(SVC), random forest model and gradient boosting model.

5.5 Evaluation of the Model

Using the tested dataset, the following parameters can be calculated for the evaluation of radar models:
True positives(TP): amount of correctly detected objects
False positives(FP): amount of wrongly detected objects
True negatives(TN): amount of correct undetected objects
False negatives(FN): amount of wrongly undetected objects
Accuracy:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{4}$$

Precision:

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

Recall:

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

Accuracy means that the the probability of correct detection for overall data. Precision indicates that as an object is detected, it is likely to be correct. Recall inclines how well the model performs to capture the positive instances among the true positives and false negatives.
For RCS-based model, the accuracy is 51.03%, precision is 50.67% and recall is 87.91%.
For linear SVC model, the accuracy is 69.58%, precision is 65.41% and recall is 83.49%.
For random forest model, the accuracy is 83.35%, preci-

sion is 82.46% and recall is 84.86%.

For gradient boosting model, the accuracy is 85.50%, precision is 85.18% and recall is 86.06%.

According to the data, RCS-based model requires less input data but has a significant low accuracy and precision relative to the ML-based model

The ML-based models, especially random forest and gradient boosting algorithm, has a good overall performance of detection by considering environmental factors and multiple objects. Therefore, it is much more suitable for virtual testing of ADAS and AD because of their high reliability to deal with the complex scenarios[18].

6. Conclusion

Radar technology plays a crucial role in various fields, particularly in autonomous driving, where it helps navigate complex environments. It has been used in ADAS for several decades, supporting functions such as ACC, LKA, and AEB. With advancements in integrated circuits and multi-sensor fusion technology, radar performance has significantly improved, providing higher-resolution imaging and more detailed information. Multi-range radar allows self-driving cars to operate in more complex scenarios, enabling precise detection at various distances.

More recently, 4D radar technology has emerged, offering not only distance measurement but also the ability to determine azimuth and elevation angles. This is particularly useful for distinguishing between objects on different planes, such as overpasses with slopes.

Looking ahead, autonomous cars are expected to reach Level 5 autonomy. Integrating radar with artificial intelligence is seen as a key trend, as AI enhances the interpretation of radar signals, improves object classification, strengthens environmental sensing, and anticipates future trajectories. There will also be a continued focus on reducing the cost and size of radar systems and mitigating signal interference to improve overall performance, benefiting both commercial applications and broader societal needs.

References

[1] Ignatious Henry A, Khan Mohammed. An overview of sensors in Autonomous Vehicles. Procedia Computer Science, 2022, 198: 736-741.

[2] Pan Li, Diao Jian, Wang Zhi, Peng Shuo, Zhao Cheng. *HF-YOLO:* Advanced Pedestrian Detection Model with Feature Fusion and Imbalance Resolution. Neural Processing Letters, 2024, 56(2): 90.

[3] Dai Yan, Lee Seong Gyeong. Perception, planning and control for self-driving system based on on-board sensors. Advances in Mechanical Engineering, 2020, 12(9): 1687814020956494.

[4] Walden Mark. Automotive Radar—From Early Developments to Self-Driving Cars. Proceedings of the ARMMS RF and Microwave Society Conference, Thame, UK, 2015, 20-21.

[5] Abdu Farah J, Zhang Ying, Fu Min, Li Yali, Deng Zhen. Application of deep learning on millimeter-wave radar signals: A review. Sensors, 2021, 21(6): 1951.

[6] Enayati J, Asef P, Wilson P. Resilient Multi-range Radar Detection System for Autonomous Vehicles: A New Statistical Method. Journal of Electrical Engineering & Technology, 2024, 19(1): 695-708.

[7] Royo S, Ballesta-Garcia M. An overview of lidar imaging systems for autonomous vehicles. Applied Sciences, 2019, 9(19): 4093.

[8] Yeong DJ, Velasco-Hernandez G, Barry J, Walsh J. Sensor and sensor fusion technology in autonomous vehicles: A review. Sensors, 2021, 21(6): 2140.

[9] Li Da Dong, Luo Shu Cheng, Knox Robert M. Millimeter-wave FMCW radar transceiver/antenna for automotive applications. Applied Microwave and Wireless, 1999, 11: 58-69.

[10] Li Yang, Ibanez-Guzman Juan. Lidar for autonomous driving: The principles, challenges, and trends for automotive lidar and perception systems. IEEE Signal Processing Magazine, 2020, 37(4): 50-61.

[11] Xu Wei, Yan Cheng, Jia Wei, Ji Xiaoyan, Liu Jun. Analyzing and enhancing the security of ultrasonic sensors for autonomous vehicles. IEEE Internet of Things Journal, 2018, 5(6): 5015-29.

[12] Araghi Ali, Khalily Mohammad, Xiao Ping, Kosari Amir, Zarrabi Hamed, Tafazolli Reza. Millimeter-wave MIMO balanced antipodal Vivaldi antenna design for autonomous cars. In 2018 International Symposium on Networks, Computers and Communications (ISNCC), 2018, June 19: 1-4.

[13] Yoon Jae, Lee Sang, Lim Seong, Kim Seong Cheol. High-density clutter recognition and suppression for automotive radar systems. IEEE Access, 2019, 7: 58368-58380.

[14] Gustafsson F. Adaptive filtering and change detection. New York: Wiley, 2000.

[15] Mao Jun, Shi Sheng, Wang Xia, Li Hong. 3D object detection for autonomous driving: A comprehensive survey. International Journal of Computer Vision, 2023, 131(8): 1909-1963.

[16] Ziebinski A, Cupek R, Grzechca D, Chruszczyk L. Review of advanced driver assistance systems (ADAS). AIP Conference Proceedings, 2017, 1906(1): 1-9.

[17] Caesar H, Bankiti V, Lang AH, Vora S, Liong VE, Xu Q, Krishnan A, Pan Y, Baldan G, Beijbom O. nuscenes: A multimodal dataset for autonomous driving. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020,11621-11631.

[18] Muckenhuber S, Museljic E, Stettinger G. Performance evaluation of a state-of-the-art automotive radar and corresponding modeling approaches based on a large labeled dataset. Journal of Intelligent Transportation Systems, 2021, 26(6): 655-674. doi: 10.1080/15472450.2021.1959328.