Preceding Vehicle Detection Method Based on Information Fusion of Millimetre Wave Radar and Deep Learning Vision

Lifu LI¹, Wenying ZHANG¹*, Yi LIANG¹, and Hui ZHOU²

¹ School of Mechanical and Automotive Engineering, South China University of Technology, Guangzhou, Guangdong, 510642, China
² Guangzhou FLYAUDIO Co. Ltd, Guangzhou, Guangdong, 510000, China

* E-mail : 1255112645@qq.com

Abstract. In the preceding vehicle detection based on the fusion of millimetre wave radar and camera, in order to obtain more accurate front vehicle status, a preceding vehicle detection method based on the information fusion of millimetre wave radar and deep learning vision is proposed in this paper. In this method, millimetre wave radar and camera are used to collect the information of preceding vehicle target. Firstly, the space-time coordinates of millimetre wave radar and camera are unified by imaging principle, coordinate conversion and same frame data selection. Then millimetre wave radar senses the state of preceding vehicle and divides the region of interest (ROI) by using the aspect ratio of vehicle. The camera uses YOLOv3-tiny to the ROI, and the deep learning algorithm of neural network model achieves high precision target detection and classification. Finally, the information fusion under different conditions is carried out according to the vehicle detection results of the two sensors and their Intersection-over-Union (IoU). The experimental results show that the recognition rate of the fusion method for typical vehicles is over 90%, and more accurate vehicle information can be obtained.

1. Introduction

Accurate environmental perception is the key to the realization of ADAS and unmanned driving. In environmental perception, preceding vehicle detection is the most important. Only by accurately knowing the existence of preceding vehicle and its speed, acceleration, longitudinal distance, lateral distance and heading angle, etc., can the FCW (Forward Collision Warning), AEB (Autonomous Emergency Braking), ACC (Adaptive Cruise Control) and even unmanned driving system play its best role.

Because millimetre wave radar is little affected by weather and environment factors, and camera has low cost but abundant information, vehicle detection based on information fusion of millimetre wave radar and camera is an effective method in ADAS or unmanned driving system. The fusion methods of millimetre wave radar and camera are generally divided into two types: the first is serial method, for example, using millimetre wave radar to generate hypothetical targets, using camera to verify hypothetical targets [1-3]; the other is parallel method: according to the respective dominant perception range of millimetre wave radar and camera, short-range and lateral movement vehicle target will be detected by camera while millimetre wave radar is responsible for long-range, longitudinal relative dynamic target detection [4]. But the existing research mostly fixes the detection area by the way of edge lane line when generating hypothetical target, failing to select the ROI adaptively to realize the optimal division of preceding vehicle detection, and the detection result of
millimetre wave radar and camera is independent when the vehicle status information is output, failing to fuse the two sensors to complement each other in order to obtain more accurate vehicle information. Therefore, in order to solve the above problems, this paper studies a preceding vehicle detection method based on millimetre wave radar and deep learning visual information fusion.

2. Principle

In this paper, a preceding vehicle detection method based on the information fusion of millimetre wave radar and deep learning vision is studied. In this method, millimetre wave radar and camera are used to collect the information of preceding vehicle targets. The ROI of vehicle targets is generated by millimetre wave radar. The vehicle targets are verified by camera and deep learning algorithm. Finally, the fusion results are calculated according to the fusion rules. The specific principles and steps are as follows:

1) Data acquisition and input: millimetre wave radar and camera simultaneously collect the information of preceding vehicle, and input it into the subsequent unified space-time coordinates.

2) Unification of space-time coordinates: In order to better integrate the information obtained by millimetre wave radar and camera, it is necessary to unify the space-time coordinates of the two sensors. In this paper, firstly, the principle of camera imaging and the transformation relationship of space coordinate system are used to unify the space coordinates, and then the time synchronization under different sampling frequencies is realized by minimum common sampling period.

3) Millimetre wave radar detects targets and determines ROI: In a unified coordinate system, millimetre wave radar detects preceding vehicle targets, generates ROI based on detection information, and determines the potential effective areas of preceding vehicles. Here, in order to make all the interested objects appear in the ROI, the paper adaptively divides the ROI with the help of the aspect ratio of the vehicle.

4) Visual deep learning accurately detects and classifies targets: the ROI determined by millimetre wave radar is input into visual vehicle detection based on deep learning algorithm to achieve high-precision target detection and classification. In order to improve the detection speed on the basis of ensuring the accuracy, this paper uses YOLOv3 deep learning algorithm to realize the deep learning vehicle detection based on YOLOv3-tiny neural network model.

5) Information fusion rules: In order to obtain the final vehicle detection results, the vehicle information detected by deep learning visual method is fused with the vehicle information detected by millimetre wave radar, and the final detection results are calculated and output. In this paper, the information fusion under different conditions is carried out according to the vehicle detection results of the two sensors and their Intersection-over-Union (IoU).

6) Output of fusion results: Output of final fusion detection results for subsequent system decision-making and control.

3. Preceding Vehicle Detection Method Based on Information Fusion of Millimetre Wave Radar and Deep Learning Vision

3.1. Unified Space-Time Coordinates

1) Unification of Spatial Coordinates

Here, there are millimetre wave radar coordinate system (RCS), world coordinate system (WCS), camera coordinate system (CCS), image coordinate system (ICS) and pixel coordinate system (PCS).
in space coordinate system. Firstly, according to the principle of camera imaging, the transformation relationship between WCS and PCS is obtained by camera internal, external and camera calibration; secondly, according to the principle of space coordinate transformation, the transformation relationship between WCS and RCS are obtained. Finally, the RCS and the PCS can be connected through these two steps.

Conversion Between WCS and PCS: Firstly, according to the pinhole imaging model of the camera, the relationship between the coordinate systems is obtained as shown in Figure 3.

\[
\begin{bmatrix}
Z_i \\
u \\
v \\
1
\end{bmatrix} = M \begin{bmatrix}
X_w \\
Y_w \\
Z_w \\
1
\end{bmatrix} = M_2 M_1 \begin{bmatrix}
X_w \\
Y_w \\
Z_w \\
1
\end{bmatrix}
\]

Where \(M_2\) is the camera's external reference matrix, \(M_1\) is the camera's internal reference matrix, \(R\) is the rotation matrix, \(T\) is the translation matrix, which can be measured by installation; \(f_x, f_y\) are the camera focal length, \(u_0, v_0\) are the main point coordinates, which can be calibrated by the camera.

Conversion Between WCS and RCS: When using millimetre wave radar for vehicle detection in front, millimetre wave radar is usually installed in the front bumper of the vehicle. Therefore, the relative position relationship among RCS, WCS and CCS is usually shown in Fig. 4:
Figure 4. Positions of Vehicle Coordinate Systems

As shown in the figure above, \( O_r - X_r Y_r Z_r \) is RCS, \( O_w - X_w Y_w Z_w \) is WCS and \( O_c - X_c Y_c Z_c \) is CCS. \( Z \) is the distance between RCS and CCS in Z axis direction, here is 1884 mm, \( H \) is the distance between RCS and CCS in Y axis direction, here is 1150 mm, \( h \) is the distance between RCS and ground, here is 365 mm. For millimetre wave radar, the detection surface can be approximated to a two-dimensional horizontal plane, as shown in Fig. 5:

Figure 5. Conversion Between RCS and WCS

Because the installation position of the millimetre wave radar and the camera is relatively fixed, the conversion relationship between the RCS and the CCS in the WCS is as follows:

\[
\begin{align*}
X_c &= r \times \sin \alpha \\
Y_c &= -H \\
Z_c &= Z_0 + r \cos \alpha
\end{align*}
\]  \hspace{1cm} (2)

The matrix is expressed as:
Therefore, according to the above two steps, the unification of millimetre wave radar and camera in spatial coordinates can be achieved.

2) Same Frame Data Selection

After the unification of the millimetre wave radar coordinate system and the camera coordinate system in space, even if the time starting point of the two sensors is the same, but because of the difference of their data acquisition frequencies, if the information time is not the same, the fusion results will also have a large deviation. Therefore, in the process of data acquisition, it is necessary to select the data collected by the two methods. Because the data acquisition frequency of the selected sensor is 20 Hz for millimetre wave radar and 30 Hz for camera. In order to acquire the target data at the same time, the minimum common multiple of 100 ms for the two sampling periods is selected as the benchmark to collect and fuse the data, and then the data of the two sensors can be seated through space. The scalar conversion completes the synchronization of time and space. The selection process of time is shown in Figure 6:

![Figure 6. Temporal Data Selection Process](image)

3.2. Region of Interest (ROI) Generation

After unifying the space-time coordinates of millimetre wave radar and camera, millimetre wave radar vehicle detection and ROI generation are needed. The millimetre wave radar detection data are output to the visual screen using ViCanDo - an on-board bus and multimedia data analysis tools. See Figure 7:

![Figure 7. Millimetre Wave Radar Detection Field Map (left) and Detection Display Interface (right)](image)
image plane, a rectangular area centered on the position of vehicle target detected by millimetre wave radar is formed, as shown in Figure 8.

![Figure 8. Projection Area of Millimetre Wave Radar](image)

According to the results of millimetre wave radar detection, all potential vehicles in this area are rectangular with their edge points. In order to avoid missing detection, the rectangular area is extended by 20% as the potential area of the vehicle in front of them. See Figure 9 specifically:

![Figure 9. Formation of Region of Interest for Millimetre Wave Radar](image)

3.3. Deep Learning Vehicle Detection Based on YOLOv3-tiny

In order to validate and classify vehicle targets in potential areas, a deep learning detection algorithm based on YOLOv3-tiny is used to validate and classify the ROI captured in Figure 9. YOLOv3[7] is the fastest target detection network in deep learning algorithm. The convolutional neural network can locate and classify targets simultaneously, and achieve end-to-end target location and classification. The simplified and compressed YOLOv3-tiny neural network model achieves the real-time requirement on the basis of little reduction in detection accuracy. It is an ideal deep learning target detection algorithm at present. The verification results are shown in Figure 10:

![Figure 10. YOLOv3-tiny Test Results](image)
3.4. Information Fusion Rules for Millimeter Wave Radar and Camera

In order to obtain the final vehicle detection fusion results, the vehicle information detected by YOLOv3-tiny is fused with the vehicle information detected by millimetre wave radar, and the final detection results are calculated according to the fusion rules. When fusing the detection results, the YOLOv3-tiny algorithm detects the potential area of the vehicle as the coordinate plane, establishes the image pixel coordinate system, projects the detection results of millimetre wave radar into the coordinate, calculates the Intersection-over-Union (IoU) of the two detection recognition frames, see formula (4):

\[
\text{IoU} = \frac{S_A \cap S_B}{S_A \cup S_B}
\]

(4)

Among them, \( S_A \) is the rectangular frame area of YOLOv3-tiny algorithm detection and \( S_B \) is the rectangular frame area of the millimetre wave radar projection.

When \( \text{IoU} \in [0.5, 1] \), the results of the two methods are consistent. Because the millimetre wave radar has higher detection accuracy for vehicle status information, the vehicle type and position detected by YOLOv3-tiny algorithm and the vehicle status output detected by millimetre wave radar are used. The fusion rules are shown in Fig. 11:

![Figure 11. Fusion Rule for IoU ∈ [0.5, 1]](image)

When \( \text{IoU} \in (0, 0.5) \), the detection results of the two methods are quite different, but the target still exists. Considering the respective advantages of millimetre wave radar and visual camera, the vehicle type detected by YOLOv3-tiny algorithm and the vehicle position and state detected by millimetre wave radar are output until \( \text{IoU} \in (0.5, 1) \). The fusion rules are shown in Figure 12:

![Figure 12. Fusion Rules for IoU ∈ (0, 0.5)](image)

When \( \text{IoU} = 0 \), if \( S_A \neq 0, S_B = 0 \), then YOLOv3-tiny algorithm fails to detect the vehicle in front of it. It considers that the camera misses the detection of the preceding vehicle, defaults the target type as a sedan, and output the position and state detected by millimetre wave radar until it is \( \text{IoU} \neq 0 \). If \( S_A \neq 0, S_B = 0 \), only YOLOv3-tiny algorithm detects the preceding vehicle, and because millimetre wave radar has better robustness to the environment than camera. Therefore, it is considered that YOLOv3-tiny arithmetic has the phenomenon of false detection and does not output the detection result until \( \text{IoU} \neq 0 \). If \( S_A \neq 0, S_B \neq 0 \), it is considered that there is a big error in the detection of
millimetre wave radar and YOLOv3-tiny arithmetic, it does not output the detection result until IoU ≠ 0. The fusion rule is shown in Figure 13:

![Fusion Rule for IoU = 0](image)

According to the above fusion rules, the position of the preceding vehicle can be fused under different conditions, and more accurate output of the front vehicle position can be obtained.

4. Validation
In order to verify the effectiveness of the fusion method, this paper chooses a clear and visible road section for experiment. Static and dynamic tests were carried out on buses, sedans, vans, SUVs, semi-trailer tractors and box trucks respectively. The test results are shown in Table 1, and the main parameters of the millimetre wave radar and camera are listed in Table 2.

| Target Type          | Motion State  | Longitudinal Distance | Detection Number | Recognition Rate |
|----------------------|---------------|------------------------|------------------|------------------|
| Bus                  | Static/Motion | 5,15,35                | 20               | 92%              |
| Sedan                | Static/Motion | 5,10,15,25,35          | 30               | 95%              |
| Van                  | Static/Motion | 5,15,25                | 20               | 90%              |
| SUV                  | Static/Motion | 5,10,15,25,35          | 30               | 95%              |
| Semi-trailer tractor | Static/Motion | 5,15,35                | 20               | 84%              |
| Box truck            | Static/Motion | 5,15,35                | 20               | 90%              |
Table 2. Main Parameters of Millimetre Wave Radar and Camera

| Main parameters of millimetre wave radar |   |
|-----------------------------------------|--|
| Maximum detection distance              | 170 m |
| Detection accuracy-Range                | 0.11 m |
| Detection velocity range                | -110~+55 m/s |
| Detection azimuth                       | 60 °  |
| Detection accuracy-velocity             | 0.05 m/s |
| Detection Accuracy-Angle                | 0.1 °  |

| Main parameters of camera               |   |
|-----------------------------------------|--|
| Principal point coordinates             | (307,199) |
| focal length                            | (1242,1245) |
| Resolving power                         | 640×480 |

From the above 2 tables, the fusion method has a high detection and recognition rate for the preceding vehicles. Except for the semi-trailer tractor, the typical vehicle recognition rate is more than 90%, and more accurate vehicle information can be obtained.

5. Conclusion

This paper presents a preceding vehicle detection method based on information fusion of millimetre wave radar and deep learning vision. In this method, millimetre wave radar and camera are used to collect the information of preceding vehicle target. The space-time coordinates of millimetre wave radar and camera are unified by imaging principle, coordinate conversion and same frame data selection. Then the region of interest (ROI) of vehicle target is generated by millimetre wave radar and vehicle aspect ratio. The accurate vehicle information is obtained by camera and deep learning algorithm based on YOLOv3-tiny neural network model. Finally, information fusion under different conditions is carried out according to the detection results and their Intersection-over-Union (IoU). The experimental results show that the recognition rate of the fusion method for typical vehicles is over 90%, and more accurate vehicle information can be obtained.

Acknowledgement

This work was supported by the Guangzhou Science and Technology Program (Project No. 201604046006), researched as a major project of collaborative innovation of Guangzhou Industry, University and Research - “the Intelligent Driving Assistance System for Automobile Safety and Health Based on Internet”.

Reference

[1] Alessandretti G , Broggi A , Cerri P . (2007) Vehicle and Guard Rail Detection Using Radar and Vision Data Fusion. IEEE Transactions on Intelligent Transportation Systems, 8(1):95-105
[2] Wang X, Xu L, Sun H, et al. (2016) On-Road Vehicle Detection and Tracking Using MMW Radar and Monovision Fusion. IEEE Transactions on Intelligent Transportation Systems, 17(7):2075-2084.
[3] Lu J, Meng-Yin F U, Mei-Ling W, et al. (2014) Vehicle detection based on vision and millimeter wave radar. Journal of Infrared & Millimeter Waves, 33(5): 465-471
[4] Song W, Yang Y, Fu M, et al. (2018) Real-Time Obstacles Detection and Status Classification for Collision Warning in a Vehicle Active Safety System. IEEE Transactions on Intelligent Transportation Systems,19(3):758-773.
[5] Zhang Z. (2000) A Flexible New Technique for Camera Calibration. IEEE Transactions on Pattern Analysis and Machine Intelligence,22(11):1330-1334.
[6] State Bureau of Technical Supervision of China. (2016) GB/T 1589-2016 : Limits of dimensions, axle load and masses for motor vehicles, trailers and combination vehicles. Standards Press of China. Beijing.
[7] Redmon J, Divvala S, Girshick R, et al. (2015) You Only Look Once: Unified, Real-Time Object Detection. https://arxiv.org/abs/1506.02640.