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Integration of Millimeter-Wave Radar and ResNet A Review and Future Directions

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Abstract

The integration of millimeter-wave (mmWave) radar technology with ResNet, a deep convolutional neural network, has emerged as a promising solution for applications such as autonomous driving, healthcare, and industrial automation. This paper reviews recent advancements in integrating millimeter-wave radar technology with Residual Neural Networks (ResNet) and their significance for future innovations. Millimeter-wave radar offers high resolution and robustness in adverse conditions, making it essential for autonomous vehicles, drone operations, and smart cities. ResNet, a major development in deep learning, tackles gradient issues in neural network training through its residual learning framework. The paper also suggests future research directions to enhance the practical applications of millimeter-wave radar and ResNet in areas like autonomous driving, environmental monitoring, and weather forecasting, highlighting their potential and prospected applications.

Keywords: Millimeter-wave radar, residual neural networks, product innovation.

1.Introduction

Millimeter-wave radar is a radar system that uses millimeter-frequency waves to send, transmit and receive radio signals. Millimeter-wave radar has higher resolution and stronger penetration . Residual Neural Network (ResNet) is an architecture in deep learning to solve the gradient vanishing and gradient exploding problems generated during neural network training in deep learning (Borawar, L et al.,2023). The detection system combining millimeter-wave radar and residual neural network has shown great potential in multiple dimensions such as target recognition, autonomous driving, and depth estimation, and can significantly improve the accuracy, robustness, real-time and reliability of the detection system. The residual neural network significantly improves the robustness of millimeter-wave radar (Abdu, F et al., 2021). The combination of the two enables the system to improve robustness under different usage conditions. When millimeter wave radar assists machine vision, if combined with a residual neural network, the detection accuracy of 3D targets can be improved. The combination of millimeter-wave radar and visual sensors is also another important research area for autonomous driving (Wei, Z et al., 2022). Residual neural networks can be used to fuse data from multiple different visual sensors to improve the classification performance of detected targets This review comprehensively reviews the latest progress in the combination of millimeter-wave radar and ResNet, critically analyzes the limitations of existing research, and proposes future research directions to promote the further development of this technology in practical applications.

2. Research status of millimeter wave radar

With the rapid development of semiconductor technology, the improvement of silicon-based transistor technology, and the significant improvement in the performance of silicon-based CMOS chips, silicon-based millimeter-wave radar has become a new research hotspot (Du Preez et al., 2023). A large number of engineers have redesigned the system structure and related circuit design for millimeter-wave radar, thereby improving the performance of millimeter-wave radar, while improving integration and reducing costs. Millimeter wave radar modules are developing towards 79GHz MIMO based on multi-chip cascade. If millimeter-wave radar wants to develop more deeply in conjunction with intelligent interconnection, it needs to solve some of its own pain points, such as signal sparsity, noise interference (LIN fengtai et al., 2023), etc. Residual neural networks can improve the accuracy of target identification and classification by learning deep features extracted from sparse and noise-affected radar data (SHAO zhengtu et al., 2023).

3.Research progress of residual neural network (ResNet)

Since the residual neural network (ResNet) proposed by Microsoft Research in 2015, it has become an important milestone in the field of deep learning (Khan, A et al., 2023). This section details the basic structure, key contributions and application extensions of ResNet in multiple fields such as image classification, target detection and video analysis. This section also discusses improved versions of ResNet, such as ResNeXt, Wide ResNet, and SENet, and their advancements in lightweight and efficiency (Narayanan, M, 2023).

(1)Basic structure of residual network

The residual neural network is mainly composed of residual blocks, residual links, identity mapping, and gradient flow.

Residual block is the basic building unit of residual neural network. Each residual block contains more than two convolutional layers and at least one jump link. After the input information of the residual block is processed by the convolutional layer, it is superimposed with the input information. The corrected signal is finally output in Figue 1.

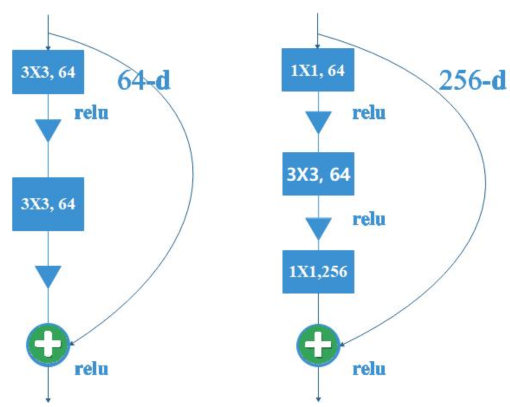

Figure 1. Schematic diagram of the residual block model

The residual link is the core of the residual neural network. This link can directly transfer information bypassing one or more convolutional layers, so that the network can learn the difference between the input signal and the output signal, that is, the residual. Instead of direct learning output.

Identity mapping means that if the convolutional layer does not learn any features, the input signal and output signal should be the same. In this way, the network can obtain the identity function through transfer, which will not cause the gradient to disappear.

Mathematically, the identity map can be expressed as:

$$\mathrm{H}(\mathrm{x}) = \mathrm{F}(\mathrm{x}) + \mathrm{X} \quad (1)$$

Among them, $\mathrm{H}(\mathrm{x})$ is the output of the residual block, $\mathrm{F}(\mathrm{x})$ is the signal after the convolution layer, and X is the input signal. $\mathrm{F}(\mathrm{x})$ does not learn any useful features, then $\mathrm{H}(\mathrm{x})$ should be equal to X, that is, this part of the network will not change the input signal.

Gradient flow means that the residual link can be directly passed from the output of the residual block to the input of the next or a certain residual block, bypassing the internal convolution layer, allowing the gradient to flow deep in the network, reducing the disappearance of the gradient. .

ResNet's main contribution in the field of deep learning is the discovery of "Degradation" and the invention of "Shortcut connection" for the degradation phenomenon, which greatly eliminates the difficulty of training neural networks with excessive depth. The proposal and successful application of ResNet have promoted the development of the field of deep learning and become one of the important milestones in the field of deep learning. ResNet has made significant progress in the field of image classification, and has also shown wide application potential in many fields such as natural language processing, speech recognition, and target detection.

(2) Improved version and development trend of residual neural network

Since the birth of ResNet, a variety of improved models have been derived, which have been recognized by all parties in terms of lightweight and high efficiency. ResNeXt introduces grouped convolution and stacked residual unit structure based on ResNet. This model enhances model performance by increasing the number of channels of the overall model rather than simply deepening the network width. This design draws on the stacking idea of the VGG network and the split-transform-merge strategy of the Inception network, and proposes the concept of "cardinality" (Huang, G. et al., 2017).

The main innovation of Wide ResNet is to improve the performance of large models by increasing the width of the network. This structure has been experimentally verified that compared with the thin and deep network structure, the wide residual network (WRN) performs better in reducing feature reuse and has a faster training speed (Debgupta, R et al., 2020).

SENet introduces the Squeeze-and-Excitation module based on the ResNet architecture, which allows the model to significantly improve the expression ability and accuracy while maintaining lightweight (Hu, J et al., 2018)

ResNet-D improves the sampling module, which uses a more optimized feature extraction method to improve the accuracy of feature representation (He, T et al., 2019).

The core concept of ResNeSt is the Split-Attention module. This structure enables ResNet to effectively allocate attention between different feature areas, thereby achieving more efficient information capture (Zhang, H et al., 2022).

MobileModels is a benchmark for lightweight AI models. MobileModels can achieve model compression, structural optimization, hardware optimization and cross-platform support. MobileModels also provides network structures suitable for the computing characteristics of mobile devices, such as MobileNetV2, ShuffleNet, etc., which can maintain good accuracy with smaller scale and less calculations (Xiaoyu Chuet al., 2021).

These improved models and related developments of the models demonstrate the important applications of the ResNet series in terms of lightweight and high efficiency, and also provide more usage possibilities for the application of deep learning on resource-constrained devices.

4.Current status and problems of combining millimeter-wave radar with ResNet

This section provides an in-depth discussion of the latest progress in combining millimeter wave radar with ResNet in the fields of target detection, image segmentation and depth estimation (XU shengjun et al., 2022). This article not only summarizes the advantages of RadarResNet in the RAD YOLO Head task, but also discusses the application of multi-modal fusion, feature extraction and deep learning technology. At the same time, this article also points out the challenges facing this field, including cost loss, signal processing, environmental interference, privacy and data protection issues, as well as system integration and optimization issues of deep learning algorithm integration.

(1) Progress of ResNet&Rader in the direction of target detection

The ResNet&Rader system can systematically compare different backbone networks in 3D and 2D detection tasks. The results show that RadarResNet is better than other backbone networks in the RAD YOLO Head task (Zhang, A et al., 2021). During the processing, the original input signal is transmitted and superimposed by the residual block, which helps to transmit and maintain data features.

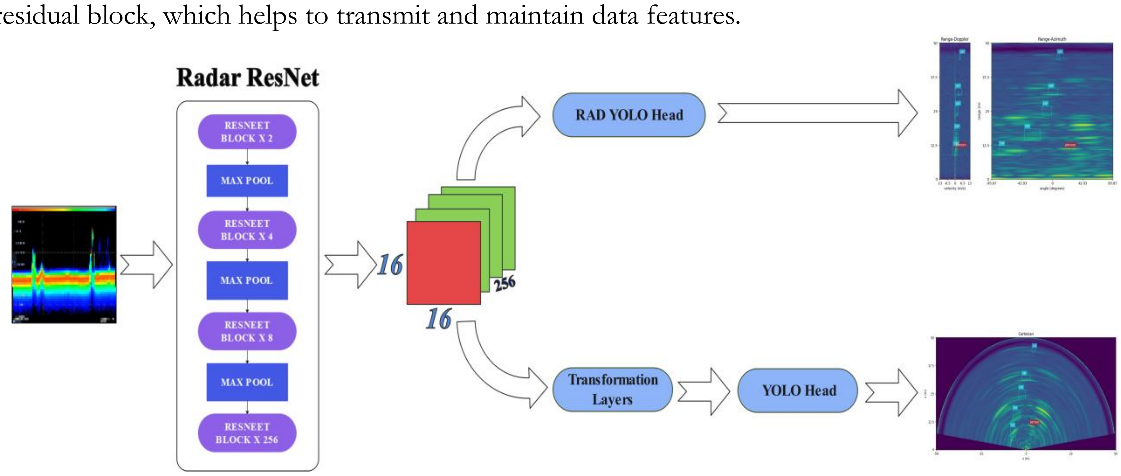

Figure 2. RAD YOLO Head Principle structure diagram

Some researchers have developed a decision-level, feature-level and data set fusion model for the ResNet&Rader system (Zhao, P et al., 2021), and proposed a decision-level target detection method for millimeter wave radar and image fusion. The application of this method in complex scenes shows stronger robustness and ensures a balance of speed and accuracy. Other research proposed an attention-based millimeter wave radar and vision fusion target detection algorithm, which uses a fusion network of ResNet-18 and long short-term memory network (LSTM) (Atila, Ü ed at., 2022), Time-frequency features and sequence features were extracted, and the improved average accuracy was announced. ResNet&Rader is constantly developing and innovating in the field of target detection, especially in applications such as multi-modal fusion, feature extraction and deep learning technology. Significant progress has been made.

(2) Progress in ResNet&Rader image segmentation direction

In recent research, some researchers have performed semantic segmentation of millimeter wave point clouds based on the improved PointNet model(incomplete ResNet based on convolutional neural network)(Li, J et al., 2023). This study optimizes the problem that traditional point clouds easily lose important foreground point information during the downsampling process by integrating a self-attention module in perceptual sampling, and retains more foreground point information that is crucial to achieving high-precision semantic segmentation tasks. . In addition, combining the self-attention module not only further improves the classification performance of the instance-aware downsampling module, but also enriches the model's ability to capture global contextual information, significantly improving the performance of semantic segmentation of millimeter-wave point cloud images. The following is the schematic diagram of ResNet&Rader image segmentation.

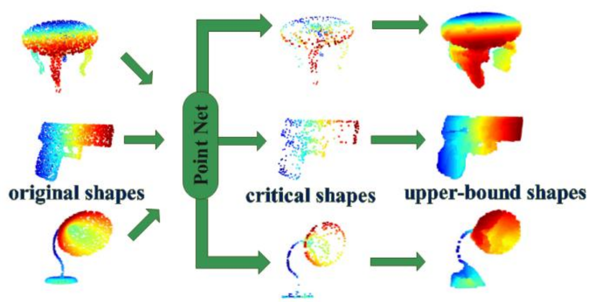

Figure 3. **PointNet model Principle structure diagram**

There are also studies that use BEVFORMER to complete the lift operation (converting image features to BEV space) "without parameters" and fuse radar point cloud feature maps for segmentation tasks. The performance surpasses previous segmentation models. This work shows that millimeter-wave radar information plays an important role in the image segmentation task of multi-modal fusion. By fusing radar feature maps, the segmentation performance can be significantly improved.

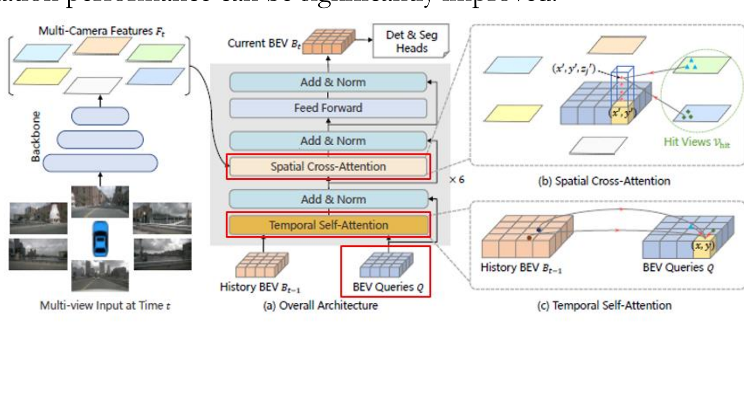

Figure 4. BEVFORMER model Principle structure diagram(Li, Z ed at., 2022)

The above research progress shows the latest development of millimeter-wave radar combined with ResNet in different fields, especially in target detection, multimodal fusion, feature extraction and the application of deep learning technology.

Problems and challenges faced by the ResNet&Rader system

The cost of using the ResNet&Rader system is relatively high, and further research is needed on how to improve its cost performance.

The signal processing algorithm of the ResNet&Rader system is the core technology of the ResNet&Rader system. It is necessary to improve the performance of the radar system and achieve high-precision target detection and tracking.

The application of the ResNet&Rader system will involve issues related to personal privacy and data protection. The government needs to specify and strengthen the formulation of relevant laws and regulations and ensure the implementation of personal privacy protection measures.

ResNet&Rader system integration is the key to achieving its high performance and wide application. Researchers need to improve the performance and reliability of millimeter wave radar systems by continuously optimizing the system structure, designing efficient signal processing algorithms, and establishing reliable data transmission and processing platforms.

Results and Discussion

Although the technology combining millimeter wave radar and ResNet still faces some challenges, this article is optimistic about its wide application in future target detection, environmental monitoring, weather prediction, and autonomous driving. This review not only provides a comprehensive review of the current status of this technology, but also provides guidance for future research directions. This paper hopes that research in this field can provide more technical support and solutions for human daily life.

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