Joint Signal Adaptive Modulation Recognition and Radio Frequency Fingerprinting Based on Multi-task Learning

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Abstract. Radio Frequency Fingerprinting Identification (RFFI) leverages inherent discrepancies in radiation source hardware, which are challenging to mimic and counterfeit. This attribute enhances the security of wireless networks and ensures the protection of data privacy, vital for secure communications. Inherent challenges such as channel fading and frequency drift affect radio signals. This paper explores the synergy between Automatic Modulation Recognition (AMR) and RFFI by employing a multi-label dataset to strategically influence the relationship between signal labels and individual radiation sources. We propose an advanced multi-gate mixture-of-experts convolutional neural network model, the MMOE-CNN-Transformer, which operates within a multi-task soft sharing framework. Our empirical results reveal that this model significantly enhances RFFI classification accuracy, particularly at a 0dB signal-to-noise ratio, outperforming traditional single-task learning (STL) approaches and surpassing the efficacy of hard sharing architectures, exemplified by the Shared-Bottom model. This study underscores the potential of integrating sophisticated neural network architectures in enhancing the robustness and precision of radio frequency identification systems.

Keywords: Radio frequency fingerprint · deep learning · automatic modulation recognition · multi-task learning

This work is supported by the National Natural Science Foundation of China (No: 62201172), the National Key Research and Development Program of China (2022YFE0136800). This work is also supported by Science and Technology on Electronic Information Control Laboratory.

H.-H. Chen and W. Meng (Eds.): WiSATS 2024, LNICST 605, pp. 324–337, 2025.
https://doi.org/10.1007/978-3-031-86196-3_28

1 Introduction

With the advancement of networking, informatization and intelligence, the number of radio equipment has surged, and electromagnetic spectrum resources have become more and more scarce. The ability of modulation methods and other parameters [1], especially in the field full of confrontation and games, has pushed the competition for the electromagnetic spectrum to a new height, and these factors have led to a more complex electromagnetic environment for radio equipment to work, more difficult to use and control the electromagnetic spectrum, and more severe challenges in maintaining the security of electromagnetic space. Radio frequency fingerprinting (RFF) is derived from the difference in the hardware of the radiation source, which is difficult to imitate and clone, which can enhance the security of wireless networks, protect data privacy [2] , improve the anti-spoofing capabilities in key civilian fields such as the Global Positioning System (GPS) and Automatic Dependent Dependent Broadcast (ADS-B) systems [3], and improve the capabilities of electronic intelligence detection and reconnaissance and situational awareness of the electromagnetic spectrum [4] It is one of the key technologies for maintaining national electromagnetic space security, and has broad application prospects in both civil and military fields. [5]Automatic Modulation Classification (AMR) is also an important means to monitor and manage spectrum resources [6].

Automatic Modulation Classification (AMR) [7–11] and Radio Frequency Fingerprinting (RFFI) [12–14] are two important technologies for wireless signal classification. AMR refers to the automatic identification of the modulation pattern of the signal after the signal reaches the receiver but before demodulation, which provides a basis for subsequent signal extraction and processing [15]. AMR is a novel technology in which the modulation class of a signal can be successfully identified by the signal receiver using AMR technology. In a non-cooperative communication scenario. Proper identification of the modulation type can help reduce communication overhead and help better identify unknown signals [16] .RFFI is based on Radio frequency fingerprinting (RFF) characteristics,these characteristics are caused by random hardware defects in the manufacturing process of wireless devices. These defects typically manifest as direct current (DC) bias, harmonic distortion, filter error, phase noise, I/Q gain imbalance, local oscillator leakage, nonlinearity, and quadrature offset [17,18] , and carrier frequency offset. These features can be extracted from component defects during the manufacturing process [19] to identify different emitter entities . Two technologies, Automatic Modulation Classification (AMR) and Radio Frequency Fingerprinting (RFFI), are of great interest in both the military and civilian sectors.

Deep learning methods have shown great advantages in the fields of image processing and text translation, unlike data such as images, radio signals do not have a visual form that can be intuitively understood, and a receiver is required to convert the RF signal into a complex baseband signal, which is often saved as in-phase/quadrature (I/Q) data. The size of I/Q data is generally $2\times N$, the first dimension is 2, representing the isotropic component I and the orthogonal component Q, and the second dimension is N, representing the length of the sequence along the temporal direction. [20]At present, most emitter identification datasets contain only one modulation scheme [21–24]. Theoretically, even if the same device uses different modulation methods to send signals, it can extract fingerprint features, that is, it has a certain degree of robustness, and the performance will not be greatly reduced due to the change of modulation mode. Moreover, the individual radiation source is inadvertently modulated due to confounding factors, and the modulation recognition task extracts the modulation features, and the extracted intentional modulation feature theory can help the RFF filter the redundant features of non-confounding factors, thereby helping to extract the fingerprint features. Multi-task learning (MTL) [25] aims to improve model generalization by utilizing domain-specific information contained in the training signals of related tasks. In the era of deep learning, MTL translates into designing networks capable of learning shared representations from multitask-supervised signals. Compared to single-task situations, related tasks have the potential to improve performance if they share complementary information or act as regularizers for each other. For example, many radios can operate in transmitter signal modes with different modulation schemes and parameters.The two tasks, AMR and RFFI, can complement each other to improve their performance. The main contribution made by this article:

1. In this paper, a soft-shared multi-task network (MMOE-CNN-Transformer) is designed, which uses a multi-gate mixture-of-experts network (MMOE) to solve two tasks (AMR and RFFI) at the same time using a multi-label dataset, which is much better than the single-task learning baseline method, and when the performance of AMR task is not much different, it is better than the hard-sharing model.

2. The Transfomer encoder module is introduced, which combines the technologies of self-attention mechanism, global attention mechanism and residual connection, which can effectively encode the input sequence, transmit information between different positions, and capture the long-distance dependencies in the sequence at the head of each task, so as to help each task extract better features unique to each task outside the shared network.

2 Problem Formulation

From the receiver's point of view, the wireless signal can be represented in the presence of additive white Gaussian noise (AWGN):

$$s[h] = x[h] + n[h], 0 <= h <= H \tag{1}$$

where x[h] represents a wireless signal without any noise, n[h] represents additive Gaussian white noise, H is the number of sampling points, and h is the sampling index point.

In this paper, the dataset used includes eight modulated waveforms: BPSK, QPSK, 8PSK, 16PSK, 16QAM, 64QAM, 256QAM, and 1024QAM, which are modulated signals from six emitter transmitting devices. The datasets used are described in detail in Sect. 4.

For n learning tasks $\{T\}_{i=1}^{n}$,MTL is a learning paradigm in which n tasks share a part of the network for joint learning, so as to achieve the effect of knowledge transfer and sharing between tasks [26]. In this paper, an MTL scheme is adopted that is the soft parameter sharingcite [27] , and unlike the hard parameter sharing as shown in Fig. 1, networks with hard-parameter sharing completely share a backbone network to extract features, and each passes through the shared backbone network for single-head output. The soft shared network used in this paper is a multi-task learning network based on the Multi-Gate Hybrid Expert [28] (MMOE) structure, as shown in Fig. 2. The formulation of the joint AMR and RFFI tasks as MTL tasks can be expressed as:$\mathcal{T} = \{\mathcal{O}_A, \mathcal{O}_R\}$,where $\mathcal{O}_A$ and $\mathcal{O}_R$ represent AMR and RFFI tasks, respectively. Let $X = \{x_j|1 \leq j \leq K\}$ represent the training data, and $Y = \{(\mathbf{y}_j^A, \mathbf{y}_j^R)|1 \leq j \leq K\}$ corresponding to the training target, where K is the number of samples. The AMR task and the RFFI task share the same training data $X \in \mathcal{X}$,$Y \in \mathcal{Y}$, in which each training data has two labels $\mathcal{Y}^A$ and $\mathcal{Y}^R$, representing the modulation type label and the RFF label, respectively. The multitasking definition is shown in Fig 1. The corresponding modulation type is obtained by the AMR task, which is denoted as $y_j^A = \{c_j \mid 1 \leq j \leq K\}$. RFFI task is denoted as $y_j^R = \{d_j \mid 1 \leq j \leq K\}$. Thus, the function $\mathcal{H}_{MTL} : \mathcal{X} \rightarrow \mathcal{Y}$ is formulated using a training dataset that maps the data space $\mathcal{X}$ to the corresponding target space $\mathcal{Y}$. The learning function $\mathcal{H}_{MTL}$ achieves both AMR and RFFI tasks to get the output of each task.

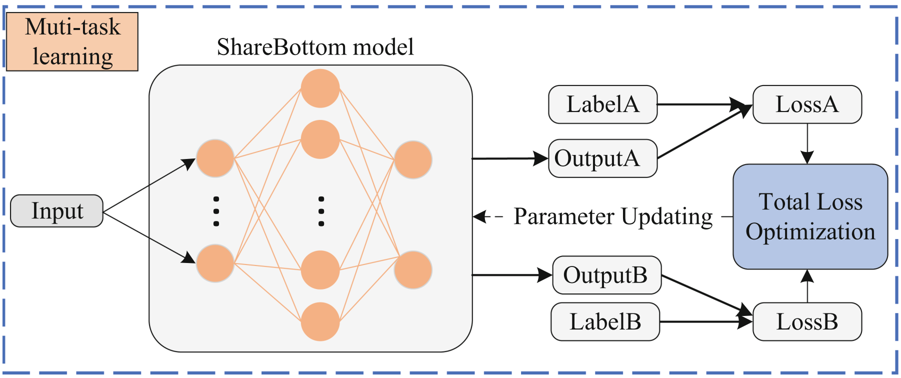


Fig. 1. Shared-Bottom model.

3 Method

This section introduces the MMOE-CNN-Transformer model, and the overall processing framework is shown in Fig 2. First, the overall framework is introduced, and then the two major modules in the framework, namely the shared

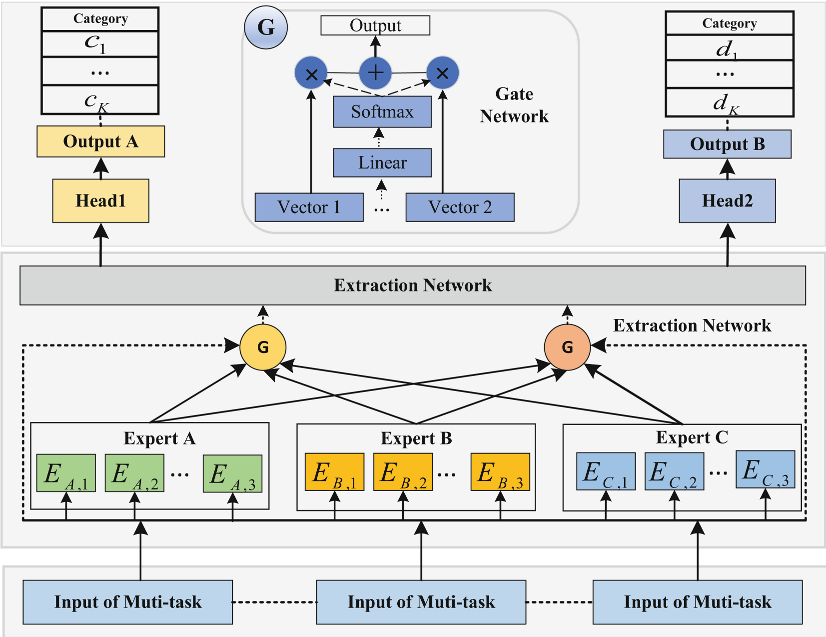


Fig. 2. Schematic diagram of an MMOE-CNN-Transformer for joint AMR and RFFI identification tasks. Three layers of shared experts extract shared features from the inputs, passing to the AMR and RFFI to implement the prediction classes.

layer module and the task-specific output module (i.e., AMRHead and RFFI-Head), are elaborated in detail.

3.1 A Framework of MMOE-CNN-Transformer

Let's say there are M tasks, the ShareBottom(SB) model ,the hard-shared model in multi-task , It can be expressed as a function f and a M tower network h_m, where m = 1, 2,...,M represents tasks. Each task in the SB network fully shares a special extraction network, and the multi-head output is performed at the end. Output of each task is $\mathcal{Y}_m$. For task m, SB net model can be represented as Eq. 2.

$$y_m = h^m(f(x)) \tag{2}$$

MMOE-CNN-Transformer network is based on the Multi-task Learning with Multi-gate Mixture-of-Exper (MMOE) model in soft sharing, which can better capture the differences between tasks without the need for more model parameters layer), each expert network is represented as. Add a separate gated network $g^m(x)$ for each task m. The weights of each expert network in task m are controlled by the training gated network, and then the characteristics extracted by each task in the shared expert network are obtained by weighting, and the whole process of extraction network can be expressed as Eq. 3 and Eq. 4.

$$g^m(x) = \text{softmax}(W_{gm}x) \tag{3}$$

$$f^m(x) = \sum_{i=1}^{n} g^m(x)_j f_j(x) \tag{4}$$

where $g^m(x)_j$ represents the probability that the m-th task corresponds to the j-th expert, and n represents the total number of tasks and $W_{gm} \in \mathbb{R}^{n \times c}$. n is the number of experts, and c is the feature dimension. Finally, each task passes through a specific head network to obtain its own output, as shown in Eq. 5.

$$y_m = h^m(f^m(x)) \tag{5}$$

3.2 Shared Experts and Head

As shown in Fig. 3, the share layers of the MMOE-CNN-Transformer model all use three identical nine-layer CNN expert networks as the shared feature pools, and adopt adaptive pooling and a Flatten layer in the last layer to perform weighted fusion with the gate network. Gate uses a full connectivity layer to connect to a network of three experts.

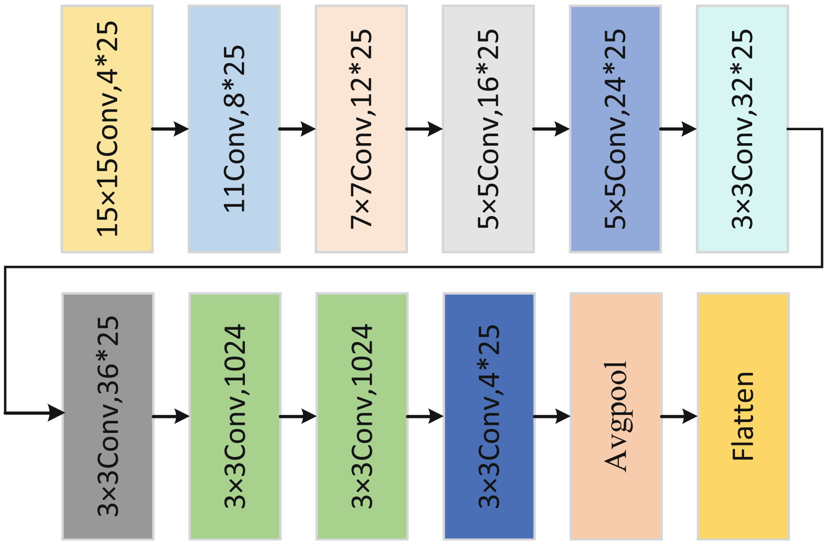


Fig. 3. Shared Expert layers

The two task Headers are classified and output by a Transformer module and a fully connected layer respectively. The Transformer module uses the attention mechanism to better extract the characteristics of AMR tasks and RFFI tasks. The self-attention mechanism allows the output of each position to take into account the information of all other positions in the input sequence, thus capturing global dependencies. In signal processing, this means that the model can take into account the characteristics of the entire signal at the same time, without being limited by the size of the local window. The Transformer Decoder module used is shown in Fig. 4.

In the training phase, during the training phase, the total loss is the linear sum of the two tasks. The overall loss function L_{mtl} is shown in Eq. 6.

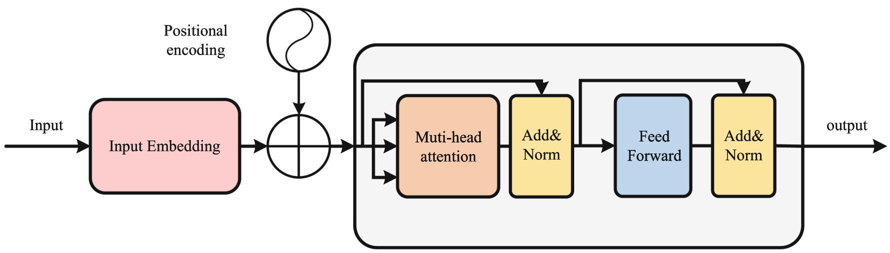


Fig. 4. Transformer Encoder.

$$L_{mtl} = w_R L_R + w_A L_A \tag{6}$$

L_A represents the AMR task loss function, L_R represents the RFFI task loss function, $w_R L_R$ and $w_A L_A$ represent the weights of the two tasks, respectively. An important research direction of MTL is task optimization methods. For MTL particularly, we optimize the training process between balanced tasks to avoid being dominated by a single task and negative migration. Fixed-weight MTL is considered a baseline method for task balancing.

4 Experimental Setting and Results

In this section, we first describe the multi-label dataset used in this paper and the specific experimental setup. Secondly, this section verifies the network designed in this paper based on multi-task learning: MMOE-CNN-Transformer improves the generalization performance and accuracy of RFFI tasks compared with single-task baseline CNN-Transformer and CNN, and verifies that the network designed in this paper is better than CNN-Transformer and Share Bottom model, then the correlation fusion experiment was designed, and finally the influence for different task's weights on MTL was studied, and compared with other task balancing methods.

4.1 Dateset and Setting

The signal dataset used is from literature , and the acquisition device consists of a signal generator (VSG 60 A), a signal receiver (BB60C), a personal computer (PC), and six target power amplifiers (PA). The stable hardware characteristics of the transmitter, such as the amplitude, phase, and frequency distortion of the signal, can be reflected by the nonlinear distortion of the power amplifier. Therefore, nonlinear distortion of power amplifiers is often cited as the main cause of RFF. The center frequency of the signal sample in the dataset is 2.4 GHz, and the sampling rate is 10 Msample/s [28]. The size of the raw I/Q data is 17.8GB and includes a total of eight modulation schemes, i.e., BPSK, QPSK, 8 PSK, 16 PSK, 16 QAM, 64 QAM, 256 QAM, and 1024 QAM from 6 PAs. Table 1 shows the specific acquisition settings.

Table 1. Signal acquisition settings

numbers of devices	Setting
Data dimension	6
numbers of modulations	8
Center Frequency	2.4 GHz
Symbol rate	1 MHz
Sampling Frequency	2.4 GHz
Signal generator	VSG60A
Spectrum analyzer	BB60C

By adding noise to the original dataset in MATLAB software, the dataset with SNR in the range of 0,5,10,15,20 dB was obtained and normalized. The dimension of data is 6000×2. The experimental environment is based on Python 3.9, and the experimental setup is shown in Table 2.

Table 2. Experiment Setting

Data dimension	Setting
Data dimension	6000×2
Optimizer	Data6
Batch-size	128
Learning rate	0.1
Epoch	100
Sample size	36000
The proportion of the training, validation, and test sets	7:2:1
SNR	{0, 5, 10, 15, 20}dB

4.2 Multi-task Learning and Single-Task Learning

In this section, AMR and RFFI tasks are executed under the CNN baseline network and CNN-Transformer baseline network, respectively, and AMR and RFFI tasks are jointly executed using the hard-shared ShareBottom model in multi-tasking, and the accuracy of the above tasks is compared with that of the joint execution of AMR and RFFI tasks in MMOE-CNN-Transformer, and the superiority of the multi-task network designed in this paper is verified. The simulation results are shown in Table 3, where uniform represents the equal weight of the loss function of the two tasks, because in multi-task learning, each task is considered to be equally important, and the equal weight is taken as the baseline method. SB stands for Hard Sharing Model.

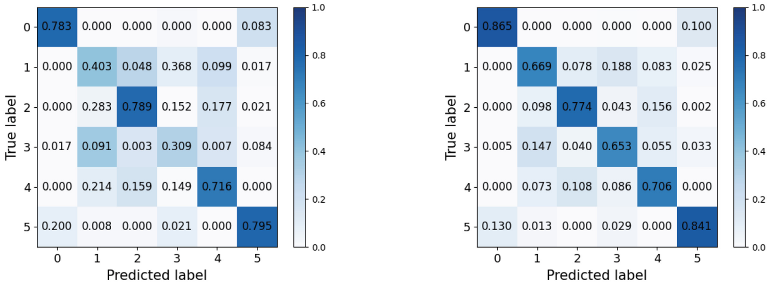
Table 3. MMOE-CNN-Transformer classification precision shared with single-task baseline methods and hard.

SNR	0dB	5dB	10dB	15dB	20dB
CNN-RFF	55.58%	80.19%	93.03%	98.17%	99.58%
CNN-AMR	99.94%	100%	100%	100%	100%
CNN-Transformer-RFF	62.97%	83.69%	95.58%	98.58%	99.19%
CNN-Transformer-AMR	99.92%	100%	100%	100%	100%
SB-CNN-Transformer-RFF(uniform)	73.86%	90.56%	97.25%	98.83%	99.14%
SB-CNN-Transformer-AMR(uniform)	99.86%	100%	100%	100	100%
MMOE-CNN-Transformer-RFF**(ours)** (uniform)	75.14%(↑19.56%)	90.89 %(↑10.7%)	97.47%(↑4.44%)	99.17%(↑1%)	99.67%(↑0.09%)
MMOE-CNN-Transformer-AMR**(ours)** (uniform)	100%	100%	100%	100%	100%

As can be seen from Table 3, MMOE-CNN-Transformer ensures that the AMR accuracy is close to 100% in the multi-label dataset used, and effectively reduces the error of RFFI. By combining the characteristics of RFFI and AMR, multi-task enables two identification tasks to share information to discover relationships and improve performance. The RFFI task is greatly improved, because the emitter individual produces unintentional modulation due to confounding factors, and the modulation recognition task extracts the modulation features, and the extracted intentional modulation feature theory can help the RFF filter the redundant features of non-confounding factors, so as to help better extract the fingerprint features. Two confusion matrices are also presented, as shown in Fig. 5, which are the confusion matrix for MMOE-CNN-Transformer pair of RFFI classification at 0dB and the confusion matrix for RFFI classification under CNN-Transformer single-task learning.

4.3 Ablation Experiments

The proposed MMOE-CNN-Transformer network consists of multiple CNN shared expert network layers and task layers, with the task-specific layer containing AMR and RFFI headers, both of which are composed of Transformer modules and fully connected classifiers for extracting individual features for each



(a) Accuary of Confusion matrix is 62.07%

(b) Accuary of Confusion matrix is 75.14%

Fig. 5. (a) Confusion matrix for RFFI classification at 0 dB MMOE-CNN-Transformer (b) Confusion matrix of RFFI classification under CNN-Transformer single-task learning

task. This section validates the contribution of different treatment steps by using different configurations for ablation studies.

1) Verify that the MTL is retained to a single task-specific header, so that the two tasks can share information, effectively improving the performance of the RFFI task, and these configurations are represented as single-head AMR and single-head RFFI; The two single-task structures are represented as MMOE-CNN-Transformer-A and MMOE-CNN-Transformer-R.

2) The header is configured without a Transformer (MMOE-CNN), MMOE-CNN-RFF represents the RFFI recognition accuracy and MMOE-CNN-AMR represents the AMR recognition accuracy in this configuration.

The performance of AMR and RFFI using different structures on the dataset is shown in Fig. 6, and it is particularly noted that in the multi-task architecture, the performance of AMR under the five signal-to-noise ratios is close to 100% under the three configurations, and the RFF performance decreases greatly at 0dB and 5dB under the MMOE-CNN configuration. Moreover, the multi-task method we designed is also much improved under the low signal-to-noise ratio compared with the MMOE-CNNTransformer-R configuration, which proves that multi-task knowledge sharing can help RFFI tasks extract features that are more difficult to extract from a single task to identify the correct individual. It can be seen from Fig. 6 that the RFFI task performance of our network is always the highest under the five signal-to-noise ratios, and the designed network effectively improves the recognition performance of RFFI tasks on the basis of ensuring that the modulation recognition does not decrease.Therefore, this paper chooses the DWA task balancing method to train the MMOE-CNN-Transformer network.

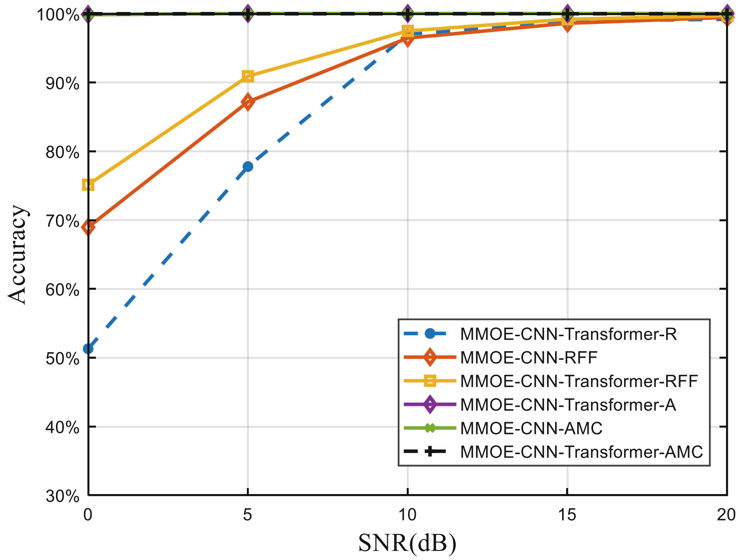


Fig. 6. Ablation experiments

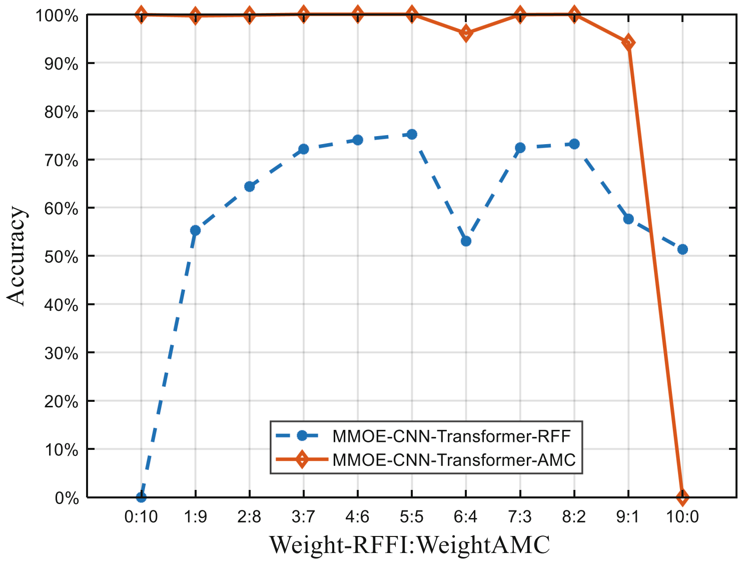


Fig. 7. Identification performance of RFFI and AMR tasks under different weights

4.4 Task Balance

In this section, the task balancing method in multi-task learning is studied, the unform represents the baseline method of task equal weight, the training process of MMOE-CNN-Transformer is optimized by using grid search, Dynamic Weight Average (DWA) [29], and uncertain [30] method, and decrease the weight distribution by using steps of 0.1 to set the weight ration of loss function of two signal recognition tasks, as shown in Fig. 7. It can be seen that when the weight ratio of RFFI and AMR is 1:1, the RFFI performance is improved to 75.14%, and the difference between the AMR recognition accuracy and other weight ratios is very small. Therefore, this weight is chosen as the best weight for grid search.

The specific results of different task balancing methods are shown in Table 4, in which the DWA method dynamically updates the weights to balance the training speed of the two methods. The accuracy of different task balancing methods for AMR tasks is almost the same, while the accuracy of the DWA method for RFFI tasks is the highest at 0, 5, 10, and 20 dB, and it is only 0.28% lower than that of the gridsearch method for RFFI tasks at 15 dB.

Table 4. Different task balancing methods identify effects

SNR	0 dB	5 dB	10 dB	15 dB	20 dB
MMOE-CNN-Transformer-RFF(uniform)	75.14%	90.89%	97.47%	99.17%	99.67%
MMOE-CNN-Transformer-AMR(uniform)	100%	100%	100%	100%	100%
MMOE-CNN-Transformer-RFF(grid)	75.14%	90.89%	97.47%	99.17%	99.67%
MMOE-CNN-Transformer-AMR(grid)	100%	100%	100%	100%	100%
MMOE-CNN-Transformer-RFF(uncertain)	74.28%	90.50%	97.22%	98.75%	99.17%
MMOE-CNN-Transformer–AMR(uncertain)	99.29%	100%	100%	100%	100%
MMOE-CNN-Transformer-RFF(DWA)	75.67%	90.97%	97.44%	98.89%	99.67%
MMOE-CNN-Transformer–AMR(DWA)	99.86%	100%	100%	100%	100%

5 Conclusion

In this paper, we design an MMOE-CNN-Transformer method to achieve two signal recognition tasks, i.e., AMR and RFFI. Experiments show that our method can access successfully better individual emitter recognition performance compared with single-task learning and hard-shared multi-task learning when the performance of AMR task is almost constant, especially in the case of low signal-to-noise ratio.The multi-task based method proposed by ge in this paper makes use of knowledge sharing among radiation source individuals with different modulation modes, so as to help better extract the characteristics of each radiation individual.

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