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RESEARCH ARTICLE

Radar Signal Recognition Based on Multi-Task Learning

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ABSTRACT Radar signal recognition is an important topic in electronic countermeasures. However, with the growing complexity of the electromagnetic environment, accurately identifying radar signals faces great challenges, and insufficient feature extraction is a core factor leading to this issue. In this paper, we proposed a novel method for radar signal recognition based on multi-task learning (MTL) to tackle with the feature extraction problem. The method combines feature enhancement and signal recognition tasks for joint learning, improving model performance by comprehensive utilization of their correlation and feature sharing. Specifically, we adopt a feature enhancement network based on an autoencoder framework to enhance time-frequency features of radar signals. Then the learned representations are used to achieve signal classification with a deep residual network. Finally, this model, as a collaborative optimization algorithm, is end-to-end trained with interactive constrains using our designed loss function. Extensive experiments, including performance comparison, ablation experiments, recognition performance of multi-component radar signals, and hardware-in-the-loop simulation experiment are conducted to validate the effectiveness of the proposed method in different scenarios.

INDEX TERMS Deep learning, multi-task learning (MTL), radar signal recognition, feature enhancement, loss function.

I. INTRODUCTION

Radar signal recognition is an essential component of electronic reconnaissance, with the primary objective of identifying and characterizing the electromagnetic emissions transmitted by radar systems [1], [2]. Radar signal recognition plays a pivotal role in modern electronic countermeasures, encompassing tasks such as target detection, classification, and threat assessment [3]. With the proliferation of radar-equipped platforms and the increasing sophistication of electronic warfare tactics, identifying different radar signals accurately has become paramount. However, this task is inherently challenging due to the diverse and evolving nature of radar signals, coupled with the increasing complex electromagnetic environment [4]. Traditional methods mainly depended on signal characteristic parameters such as pulse description words (PWD) to identify radar signals [5], often struggle to cope with the intricacies of modern radar waveforms [6], especially in low signal-to-noise ratio (SNR) environments. In this context, deep learning techniques have emerged to tackle the complexities of radar signal recognition due to its success in other research fields [7].

Recently, a large number of works based on deep neural networks (DNNs) have been proposed, which leverage the power of data-driven models to enhance the performance and adaptability of radar signal recognition methods, thereby bolstering the effectiveness of electronic warfare operations [8], [9], [10]. On one hand, many methods adopt DNNs to extract time-domain features for signal modulation

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recognition [11], [12], [13], [14], [15]. For example, Wei et al. [12] proposed a method for extracting time-domain features using a combination of a convolutional neural network (CNN) and a long short-term memory (LSTM) network. These features were then utilized by a DNN for signal classification. Subsequently, various DNN models, such as CGDNet [14], CSRDNN [15], have been proposed to perform feature extraction from time-domain signal waveform for modulation recognition. Through an end-to-end approach, these methods directly extract effective features from the original signal for modulation recognition. However, time-domain signals cannot directly reflect changes in frequency components, making it difficult to analyze the spectral characteristics and frequency changes in the signal. On the other hand, time-frequency analysis (TFA) methods [16], [17], [18], [19] are widely used to extract time-frequency characteristics of signals for modularity recognition. Huynh-The et al. [20] utilized the Choi-Williams distribution (CWD) to extract radar signal characteristics. Walenczykowska et al. [21] extracted time-domain features from continue wavelet transform time-frequency images (CWT-TFIs). Then, a number of multi-channel fusion neural networks have been proposed, which are used to integrate different time-frequency features to achieve better recognition performance [22], [23], [24]. Time-frequency features can capture signal variations in both the time and frequency domains, offering a more comprehensive depiction of frequency fluctuations and energy distribution within the signal. This time-frequency representation proves advantageous for the signal recognition task. However, the feature information provided by time-frequency representation is still limited, as in complex electronic warfare environments, radar signals often comprise multiple frequency components and exhibit time-varying frequency characteristics. Traditional TFA-based methods often utilize fixed basis functions, which may not adequately capture all the time-frequency characteristics of radar signals. Therefore, some works have been proposed to enhance TFIs [25], [26], [27]. For example, literatures [25] and [26] presented a TFI enhancement method based on neural networks for high-resolution TFIs. Pan et al. [27] proposed a TFA-Net to learn basis functions via neural networks and convert time-domain signals into TFIs.

Nevertheless, most of the current work on signal modulation recognition and time-frequency enhancement only focuses on a single task, without considering the correlation and dependency among multiple tasks. More recently, multi-task learning (MTL) has shown great potential in knowledge acquisition and modeling from serval related tasks [28], [29], [30]. And it has been gradually introduced for the signal analysis [31], [32], [33], [34], [35].

In this paper, we propose an alternative MTL-based method for radar signal recognition, which considers radar signal recognition and feature enhancement as a MTL problem. Compared to the TFA-based methods that uses TFIs as the input of network, the entire network takes the time-domain representation of the radar signal as input and is trained in an end-to-end manner to avoid the feature loss. First, different from the time-domain feature-based methods that directly perform a time-frequency transformation on the signal, we introduced a feature enhancement network based on a convolutional autoencoder framework to obtain more distinguishable features of radar signals and generate high-quality TFIs. Subsequently, the learned features are employed for the signal recognition task with a deep residual network. Finally, the two tasks are jointly optimized with a compound objective function. By exploiting the correlation between the two tasks, we obtain more abundant time-frequency features, which can also provide more discriminative features for the recognition task and improve recognition accuracy. Different from existing MTL work [31], [32] that directly extract features from time-domain signals, we map time-domain signals into time-frequency space through neural networks, which not only obtains higher-level discriminative features, but also minimizes feature loss. The main contributions of this paper can be summarized as follows:

1) We present a new MTL method for radar signal recognition and time-frequency feature enhancement to address the issue of low recognition accuracy in radar signal recognition. It utilizes the correlation between the feature enhancement task and the signal recognition task to enhance both the signal features and the performance of radar signal recognition.
2) We design a new loss function for joint learning, which consists of mean square error (MSE) loss, perceptual loss and cross-entropy loss. The synergy between the different losses achieves mutual supervision and performance complementarity between the two tasks, significantly enhancing the overall effectiveness and generalization capability of the MTL framework.
3) Experimental results show that the proposed method not only effectively enhances the signal features, but also improves the recognition accuracy of radar signals. When the SNR is 0 dB, the recognition accuracy is above 97%.
4) We conduct a hardware-in-the-loop simulation experiment of radar signals. The experimental result verifies the feasibility of the proposed method in real environments. The recognition rate reaches 89% at 0 dB SNR.

The paper is organized as follows: In Section II, we discuss the related work. Section III introduces the proposed radar signal recognition framework. In Section IV, we conduct extensive experiments to verify the effectiveness of the proposed method. Finally, the conclusions are given in Section V.

II. RELATED WORK

A. RADAR SIGNAL RECOGNITION BASED ON DNNS

Radar signal recognition methods based on DNNs can be divided into categories: time-domain feature-based methods and TFA-based methods. For the former, O'Shea et al. [11] first applied CNNs to automatic modulation recognition, achieving higher recognition accuracy compared to traditional methods. Subsequently, a large number of methods utilizing DNNs to extract time-domain features and perform signal modulation recognition have been proposed. Wei et al. [12] proposed to extract time-domain features by a CNN and a LSTM network and utilize a DNN to classify the signals. On this basis, Xu et al. [13] presented a multi-stream deep learning framework to extract features from individual and combined in-phase symbols of time-domain signals. To take advantage of the complementary relationship between CNN, GRU, and DNN, Njoku et al. [14] proposed the hybrid neural network (CGDNet) to effectively improve the recognition accuracy. Zhang et al. [15] used a CNN to expand the feature space of time-domain signals. These features are then fed into the combined SRNN module, which effectively manages the relationships between signal features. Finally, the recognition results are obtained through the fully connected layer. Through an end-to-end approach, these methods directly extract effective features from the original signal for modulation recognition. However, the distinguishable features contained in time-domain signals are limited, which poses a challenge to radar signal recognition based on time domain features.

TFA-based methods [16], [17], [18], [19] are extensively used in the modularity recognition field due to the strong ability of time-frequency characteristics extraction. Huynh-The et al. [20] utilized CWD to extract the characteristics of radar signals, and designed the LPI-Net to achieve identification of thirteen types of signals. Walenczykowska et al. [21] obtained signal pulse repetition frequency, amplitude and other characteristics from CWT-TFIs, and then fed these TFIs into a CNN for radar signal recognition. Quan et al. [36] fused the time-frequency features from CWD-TFIs and histograms of oriented gradient (HOG) features by a multi-layer perceptron (MLP) and achieved signal recognition with an SVM classifier. Liu et al. [37] designed a triple convolutional neural network (TCNN) to extract high-dimensional features from SPWVD-TFIs. Then a triple loss function is employed as an optimization strategy to enhance the discriminability between different types of radar signals. Time-frequency features can capture the changes in signals in both time and frequency dimensions at the same time, providing more comprehensive information and accomplishing accurate recognition.

B. MULTI-TASK LEARNING (MTL)

MTL is a neural network framework that achieves knowledge transfer by simultaneously training multiple related tasks, thereby improving the generalization ability of the model [38]. Studies have shown that jointly learning multiple tasks shows better performance than learning them independently when tasks are related. The reason is that, when these tasks are related, the knowledge gained from one task can be transferred and utilized in another task, enhancing the overall performance. Due to superiority of MTL, it has been applied in various fields, such as language translation [39], disease [40], and signal recognition [31], [32], [33], [34], [35].

Jagannath et al. [31] proposed a MTL approach for modulation classification and protocol recognition task. It benefits from the mutual relation between the two tasks in improving the recognition accuracy and the learning efficiency with a lightweight neural network model. Huang et al. [32] provided a MTL framework by considering radar signal classification and signal characterization as a joint problem to solve the issue of insufficient signal representation. It introduces the IQ Signal Transformer (IQST) architecture based on the attention mechanism is introduced to directly extract features from the original signal. Wang et al. [33] proposed a radar signal recognition method based on MTL, using signals with different SNRs to complete the training of multiple CNN models and enhance the recognition ability of the network in different SNR environments. Mossad et al. [34] designed a network based on MTL. In addition to the main classification task, they also created 3 different tasks for easily confused signals to reduce confusion between similar categories. Jing et al. [35] minimized multiple losses through multi-task learning, enabling the network to learn and extract feature representations that are both compact and highly discriminative, thereby enhancing the separability between clutter and targets.

III. THE PROPOSED METHOD

In this section, we provided an overview of the basic characteristics of the 12 radar signals employed, introduced the overall framework of the proposed method, along with the joint learning mechanism within the MTL framework. Next, we present a detailed description of the various components of the model.

A. RADAR SIGNALS AND THE PROPOSED METHOD

The signal intercepted by the radar receiver can be expressed as:

$$y(t) = x(t) + w(t) = A(t)e^{j\theta(t)} + w(t) \tag{1}$$

where $x(t)$ is the radar signal, w(t) represents the additive white Gaussian noise (AWGN), and A is the amplitude of signal. $\theta(t)$ is the instantaneous phase of the signal, which can be expressed in detail as $\theta(t) = 2\pi f(t)t + \varphi(t)$, where $f(t)$ and $\varphi(t)$ are respectively the frequency modulation and phase modulation. Therefore, formula (1) can be expressed as:

$$y(t) = A(t)\exp(j(2\pi f(t)t + \varphi(t))) + w(t) \tag{2}$$

In this paper, we consider 12 typical radar signals, including linear frequency modulation (LFM), frequency shift keying (4FSK), binary phase shift keying (BPSK), polyphase coded signal (FRANK, P1-P4), and multi-temporal code signal (T1-T4). The linear frequency modulation is a type of modulation where the instantaneous frequency of the pulse is directly or inversely proportional to time, offering superior range resolution and effective range. The frequency shift keying is characterized by a "thumbtack-shaped" ambiguity function, which effectively minimizes crosstalk between different sub-pulse segments. The binary phase shift keying demonstrates strong anti-jamming capabilities, enhances the Doppler resolution of the radar system, improves signal stealth performance, and reduces loss per unit distance. The polyphase coded signal combines the advantages of both polyphase coded signal and linear frequency modulation, providing excellent radar detection and range resolution capabilities. In addition, multi-temporal code signal represents a new form of polyphase coded signal, where the time occupied by each phase in the waveform continuously changes, distinguishing it from other polyphase coded signals. These signals encompass a wide range of modulation and coding techniques, each with unique characteristics that contribute to radar signal processing.

In radar signal recognition, the recognition performance is closely related to the extracted signal features. Traditional methods often rely on signal statistics, such as correlation function and power spectrum density, which reflect some intrinsic characteristics of the signal. TFA methods, such as short-time Fourier transform (STFT) and multisynchrosqueezing transform (MSST), are widely used to map signals from the time domain to the time-frequency domain, thereby revealing the time and frequency information of the signal. However, while these methods can extract certain signal features effectively, they may suffer from insufficient feature extraction when dealing with complex signals, resulting in low recognition accuracy. To address this issue, the proposed method jointly trains signal feature enhancement and radar signal recognition as related tasks. The overall framework is shown in Figure 1. For feature enhancement task, several modules are designed to capture richer radar signal features. In contrast to TFA methods, which rely on fixed basis functions, the feature mapping module leverages multiple groups of convolution kernels, allowing the network to learn diverse sets of basis functions that enhance radar feature extraction. Additionally, a convolutional autoencoder-based feature enhancement module further extracts the signal features. We take the latent representations learned by the convolutional autoencoder as input, employ a deep residual network for deep feature extraction, and complete the signal modulation recognition task. the proposed model is trained end-to-end with a unified loss function constraint, facilitating collaborative learning across multiple tasks. By sharing parts of the network, this approach encourages the model to learn more generalized feature representations.

B. FEATURE ENHANCEMENT TASK

The feature enhancement task aims to enhance the quality and discriminative power of the extracted features from raw time-domain radar signals, thereby improving the performance of subsequent modulation recognition. Inspired by [27], we develop a time-frequency feature enhancement network based on the convolutional autoencoder framework for the feature enhancement task. It consists of a feature mapping module and a feature enhancement module. First, original time-domain radar signals are mapped into the time-frequency space by the feature mapping module, so as to obtain multiple sets of feature maps containing rich features. Subsequently, multiple time-frequency features are enhanced through the feature enhancement module. The details of the feature mapping module and feature enhancement module are described as follows.

1) FEATURE MAPPING MODULE

In order to obtain more discriminative features of radar signals, we utilized the feature mapping module containing a 1D convolutional layer to map the original time-domain radar signals into the time-frequency space. It realized adaptive learning of STFT matrix weights through CNNs.

First, as neural networks have a powerful ability of feature extraction, we use convolution kernels to adaptively learn the Fourier basis functions. The number and size of the convolution kernels are f_i and $1 \times L_s$, respectively. It can be expressed as:

$$S(k) = \sum_{n=0}^{L_s-1} s(n)W_k(n), k = 0, 1, \ldots, f_i - 1 \tag{3}$$

where W_k denotes the k-th convolution kernel. The convolution process is shown in Figure 2.

Then, in order to reflect the time-varying characteristics of the signal, we performed a windowing processing in the feature mapping module. The window size is set to L_w and the stride is 1. After padding zero, the signal is divided into N segments, denoted as $s_l(n), l = 1, 2, \ldots, N, n = 1, 2, \ldots, L_w$. Taking the l-th segment as an example, the convolution result is defined as:

$$S_l(k) = \sum_{n=0}^{L_w-1} s_l(n)W_k(n), k = 0, 1, \ldots, f_i - 1 \tag{4}$$

where L_w is the window length, s_l represents the l-th signal intercepted by the window.

The specific process of the feature mapping module is further illustrated in Figure 3. Each segment of the signal truncated by the window is sequentially convolved to obtain features with length f_i in frequency domain. Then all the frequency features are concentrated to form a time-frequency feature map with the size of $N \times f_i$. Furthermore, to explore other more useful basis functions, the number of convolution kernels is increased to $C \times f_i$, and C groups of time-frequency feature maps, which obtain richer identification features are finally obtained.

2) FEATURE ENHANCEMENT MODULE

By the feature mapping module, we obtained multiple feature maps based on different types of basis functions, which carry different feature information. Next, we design the feature enhancement module to further enhance the time-frequency features, and finally obtain a concentrated TFI. The feature enhancement module mainly consists of 20 2D convolutional

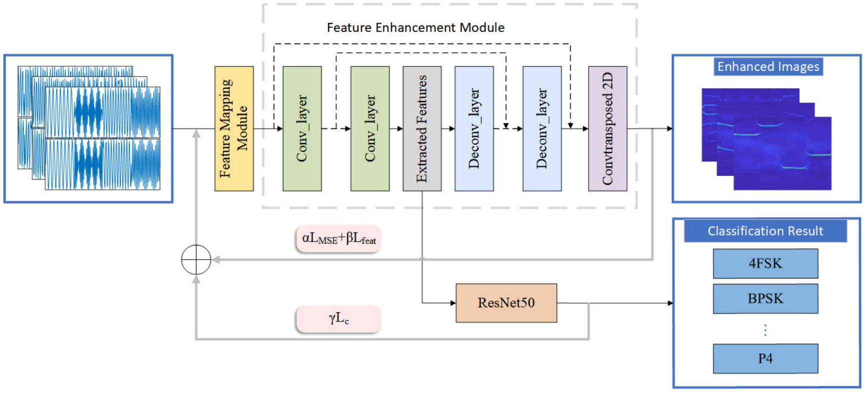

FIGURE 1. The overall structure of the proposed method.

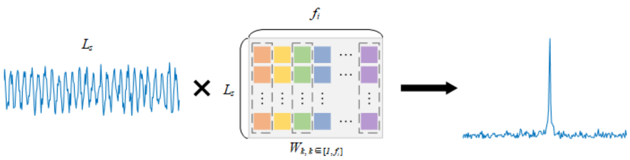

FIGURE 2. Feature mapping process for a signal of length L_S.

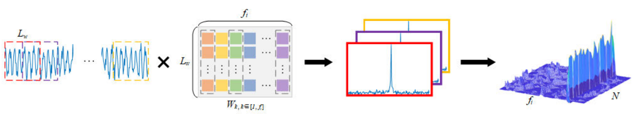

FIGURE 3. Feature mapping process using sliding windows.

layers and 20 symmetric 2D deconvolutional layers. Each layer is followed by a rectified linear unit (ReLU) layer. The convolutional layers play the role of feature extraction, capturing the important features of image while removing noise. And the deconvolutional layers recover the image based on the extracted features. In addition, the gradual deepening of the network may lead to the loss of features, which is not conducive for deconvolutional layers to recover the image. Therefore, we add skip connections between every two convolutional layers and the mirrored deconvolutional layers, so that some features extracted in the convolutional layers can be directly passed to the deconvolutional layers without being processed by the intermediate layers. Thus, more details of images are retained, which helps deconvolutional layers recover the image better. A transposed convolutional layer is added at the end of the module to integrate the complementary information of all images and finally obtain a concentrated TFI. The TFIs generated by the module are shown in Figure 4. For clarity, the network parameters of the feature enhancement module are provided in Table 1.

C. RADAR SIGNAL RECOGNITION TASK

The proposed method obtains time-frequency features of radar signal through the feature enhancement process based on CNNs. Subsequently, we utilize these features to achieve the radar signal recognition task. In order to illustrate the superiority of the feature maps, we compare them with the MSST-TFIs. Figure 5 and Figure 6 illustrate MSST-TFIs and the feature maps of Frank and P3 at an SNR of 20 dB, respectively. For Frank and P3, the corresponding MSST-TFIs are similar, which gives rise to signal confusion. However, as can be seen from Figure 6, the difference between them is more significant after the feature enhancement module.

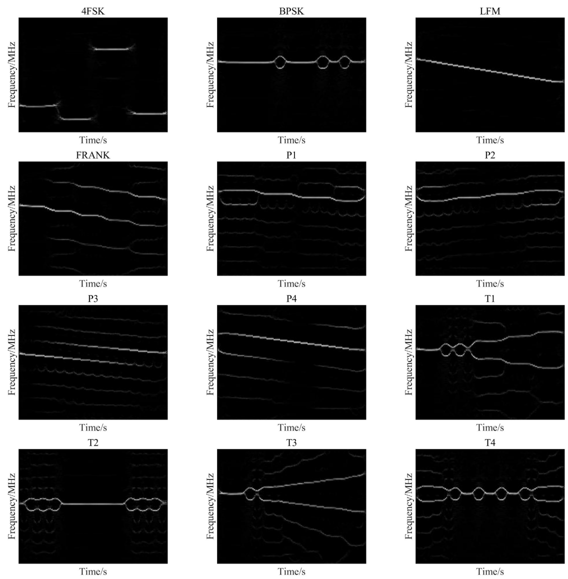

FIGURE 4. Images generated by the decoders.

TABLE 1. Parameters of network in the feature enhancement module.

Layer	Layer parameters
Conv2d #1	$C_{in} = 16, C_{out} = 32, K = (3,3), stride(2,2)$
Conv2d #2-20	$C_{in} = 32, C_{out} = 32, K = (3,3), stride(1,1)$
Deconv2d #1-19	$C_{in} = 32, C_{out} = 32, K = (3,3), stride(1,1)$
Deconv2d #20	$C_{in} = 32, C_{out} = 16, K = (3,3), stride(2,2)$
ConvTranspose2d	$C_{in} = 16, C_{out} = 1, K = (3,1), stride(3,1)$

As shown in Figure 6 (a), the feature map of the FRANK code is "staircase" shaped, while the feature map of P3 in Figure 6 (b) is very smooth, which helps the network to correctly distinguish them.

In our MTL model, the time-frequency features are extracted from the convolutional layers of feature enhancement module, which still belongs to shallow feature representation and cannot be directly used for signal recognition. Therefore, we employ a deep residual network for deep feature learning and signal modulation classification. Specifically, ResNet50 is chosen to extract deep time-frequency features and a softmax classifier is used to implement the recognition task.

D. MULTI-TASK LEARNING AND JOINT OPTIMIZATION

To jointly optimize two distinct target tasks by sharing parameters between the aforementioned tasks, we devised a MTL framework based on the hard parameter sharing strategy. As shown in Figure 1, the two tasks share the feature mapping module and the convolutional layers in the proposed MTL model, which is used to learn common feature representations from raw signals. The proposed MTL model is trained in an end-to-end manner by optimizing a multi-task objective function. To ensure the model effectively optimizes for different objectives, we introduce a novel loss function designed to achieve a more balanced and interactive optimization between the two tasks.

Specifically, to enhance the performance of the feature enhancement task, we employ the MSE loss [41] and the perceptual loss [42] as the objective function for the task. This approach ensures both pixel-level accuracy and visual fidelity in generating TFIs. MSE is a loss function based on pixels,

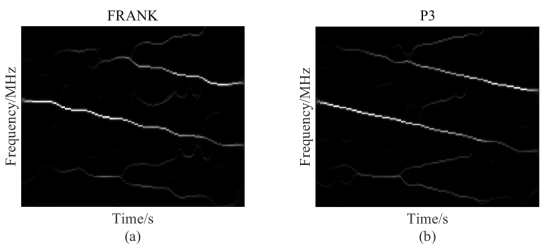

FIGURE 5. TFIs of FRANK and P3 obtained by MSST method.

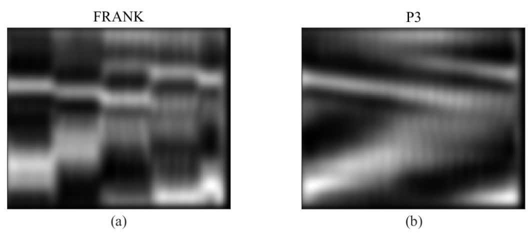

FIGURE 6. Feature maps of FRANK and P3 obtained by the proposed method.

which is formulated as:

$$L_{MSE}\left(y, y'\right) = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_i'\right)^2 \tag{5}$$

where n represents the total number of pixel points in an image, y_i is the i-th pixel in the target image, $y_i{}'$ is the i-th pixel in the generated image.

Moreover, the basic idea of perceptual loss is to compare the differences of the high-level features between the generated image and the target image, which are extracted by a pre-trained VGG16. For the j-th layer of the VGG16 network, the loss of the image is given by:

$$Loss_{feat}^{\varphi,j}\left(y, y'\right) = \frac{1}{C_j H_j W_j}\left\|\varphi_j(y) - \varphi_j\left(y'\right)\right\|_2^2 \tag{6}$$

where φ represents VGG16 network, j is the layer index, $\varphi_j\left(y'\right)$, $\varphi_j(y)$ are the features of the generated image and the target image through the j-th layer of VGG16 network, respectively, and C_j, H_j, W_j is the channel, height, width of the feature of the j-th layer.The loss functions of each layer are added to obtain the whole perceptual loss, which is expressed as:

$$L_{feat} = \sum_{j=0}^{N} Loss_{feat}^{\varphi,j}\left(y, y'\right) \tag{7}$$

where N is the total layer number of the VGG16 network.

In addition, we employ the cross-entropy loss to optimize the recognition task, which calculates the loss between the predicted label and the given label. The cross-entropy loss is formulated as:

$$L_c = \frac{1}{n}\sum_{i=1}^{n} L_i = -\frac{1}{n}\sum_{i=1}^{n}\sum_{c=1}^{M} y_{ic}\log\left(p_{ic}\right) \tag{8}$$

where M is the total number of signal categories, y_{ic} is the symbolic function (takes 1 if the true class of i-th signal is equal to c, otherwise takes 0), p_{ic} is the predicted probability that the i-th signal belongs to the c-th category. Finally, we jointly optimize the proposed MTL model with a compound objection function. The total loss of the model is summarized as:

$$L_s = \alpha L_{MSE} + \beta L_{feat} + \gamma L_c \tag{9}$$

where α, β, γ are balance weights used to control the ratio of the three loss functions. The proposed MTL method minimizes L_s by adjusting model parameters so that the two relative tasks can be improved mutually. On the one hand, the features learned by the feature enhancement task facilitate the judgment of the recognition network, thereby improving the recognition performance. On the other hand, the feedback from the recognition network also enables the feature enhancement network to learn more representative features. The mutual reinforcement between the two tasks contributes to the improvement of radar signal recognition performance.

IV. EXPERIMENTS

A. DATASET PREPARATION

In our experiments, we use 12 categories of classical radar signals to validate the effectiveness of the proposed model. We generated this dataset through simulation with different parameter settings, which includes 4FSK, BPSK, LFM, FRANK, P1, P2, P3, P4, T1, T2, T3 and T4. The uniform distribution based on the sampling frequency f_s is represented by $U(\cdot)$. For example, $U(1/3, 1/2)$ is a random number in the range of $(f_s/3, f_s/2)$. The sampling frequency f_s is set to 200MHz. The detailed settings of radar signal parameters are shown in Table 2. 200 training samples and 80 test samples were generated for each signal type under each SNR. All the samples are added with Gaussian white noise, and the SNRs vary from 0 dB to 20 dB. The dataset consists of a training set of 26,400 samples and a test set of 10,560 samples. All methods were conducted in Pytorch with a 16-core CPU and a single GeForce RTX 3090 GPU. For further research, the code for dataset and MTL model is available at https://github.com/stu-cjlu-sp/rsrc-for-pub/tree/main/MTL.

TABLE 2. The settings of radar signal parameters.

Signal types	Types of parameters	Range of parameters
ALL	Sampling frequency f_s	1(f_s=200MHz)
4FSK	Fundamental frequency f_m	$U(1/80, 1/2)$
BPSK	Carrier frequency f_c	$U(1/8, 1/4)$
	Barker codes N_c	{7,11,13}
LFM	Carrier frequency f_c	$U(1/8, 1/4)$
	Bandwidth B	$U(1/16, 1/8)$
FRANK	Carrier frequency f_c	$U(1/8, 1/4)$
	Samples of frequency stem M	[4,8]
P1-P4	Carrier frequency f_c	$U(1/8, 1/4)$
	Samples of frequency stem M	[4,8]
T1-T2	Carrier frequency f_c	$U(1/8, 1/4)$
	Number of segments k	[4,5]
T3-T4	Carrier frequency f_c	$U(1/8, 1/4)$

B. PERFORMANCE COMPARISON

To evaluate the performance of the proposed MTL method, we compare it with several existing algorithms that take time-domain signals as input. Four representative approaches are selected as baselines, named CLDNN [12], MCLDNN [13], DPM-SCNN [43], CSRDNN [15], respectively. The experimental results are shown in Figure 7. It can be observed that the proposed MTL method achieves higher recognition accuracy than the baselines. For CLDNN and MCLDNN, the recognition precision is relatively low. The reason is that both of them stack CNN, LSTM, and DNN, and primarily focus on time-domain features, which cannot fully capture frequency-domain information. However, the proposed method maps time-domain signals to the time-frequency domain, which can capture both temporal dependencies and detailed frequency-domain information, providing more discriminative features for recognition. The recognition performance of CSRDNN is relatively better than that of CLDNN and MCLDNN, as each recurrent unit in CSRDNN extracts different temporal features. However, its feature fusion capabilities are limited. Our model enhances the fusion of features from multiple tasks by sharing feature extraction layers, thereby enhancing the multi-task collaborative processing capability of the model and ultimately improving the recognition accuracy. DPM-SCNN significantly improved recognition accuracy via extracting the real part, imaginary part, amplitude and phase of the original signal. However, the preprocessing leads to the feature loss, which is not conducive to recognition. In contrast, the proposed MTL framework can identify all signals with an accuracy of over 97% at an SNR of 0 dB, far exceeding other baselines. In the feature enhancement task, we map the time domain signal to the time-frequency space to obtain richer signal features. In addition, we use end-to-end training to reduce the feature loss caused by pre-training. More importantly, we balance the two tasks through the designed joint loss function to achieve overall performance improvement.

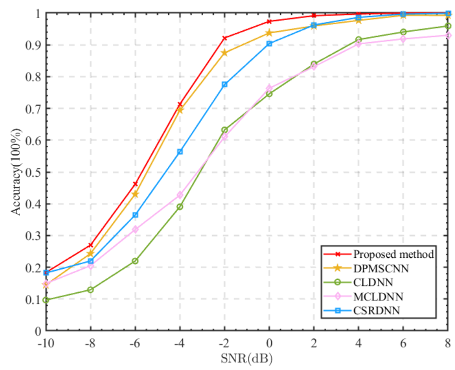

FIGURE 7. Performance comparison with methods based on time-domain features.

Simultaneously, we compare the proposed method with other TFA-based methods, including LPI-Net [20], and CWT-CNN [21], which are based on CWD and CWT respectively. Besides, a method based on dual-channel CNN [36] was selected for comparison. As the MSST TFIs are regarded as the target images, we also designed a MSST-based approach for comparison. Specifically, the time-frequency features of radar signals are extracted by MSST, which are fed into the ResNet50 for signal recognition. As shown in Figure 8, the proposed MTL method shows a stronger ability in identifying radar signals than TFA-based methods. It is due to the fact that TFA-based methods often rely on fixed basis functions for time-frequency transformations. While these methods can effectively extract time-frequency information, the inflexibility of the basis functions limits their ability to handle complex and varied signals. In contrast, the proposed MTL method introduces multiple sets of convolutional kernels to learn a variety of basis functions, enabling it to flexibly adapt to complex signal variations and extract more

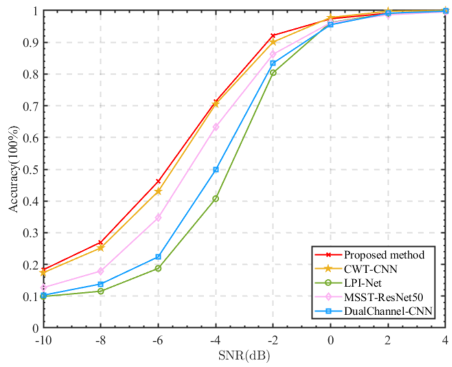

FIGURE 8. Performance comparison with TFA-based methods.

comprehensive and diverse time-frequency features, which improves the ability to distinguish signals and finally achieve high recognition accuracy.

In order to further verify the ability of the proposed method in distinguishing confusing signals, we presented confusion matrices at the SNR of -2 dB. Figure 9 (a) shows the confusion matrix of 12 types of radar signals based on MSST-based method. Obviously, some of the signals are prone to confuse with each other, leading to poor accuracy recognition. As mentioned before, FRANK and P3 are signals easily confused. In Figure 9 (a), 24% of P3 is misidentified as FRANK. In addition, 19% of P4 are confused with P1. The reason is that, when the SNR is low, the signal is easily interfered by noise, making it difficult for the network to extract useful features and ultimately leading to low recognition accuracy. The proposed MTL method uses noiseless TFIs obtained by MSST as the target TFIs for updating the matrix weights. This approach acts as a form of denoising and has the potential in generating more distinctive features and improving the recognition performance. As shown in Figure 9 (b), the recognition accuracy of both P3 and P4 increased by 21%, demonstrating that the proposed method can effectively reduce the confusion between different types of signals.

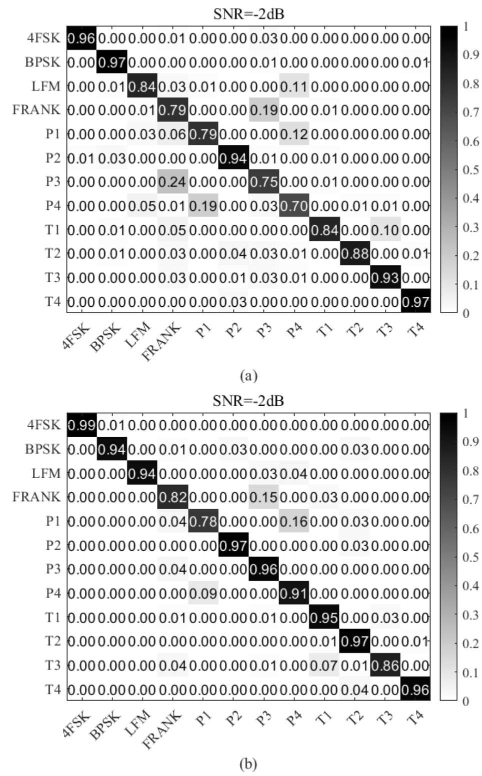

FIGURE 9. The confusion matrix for different methods: (a) MSST-based method, (b) The proposed MTL method.

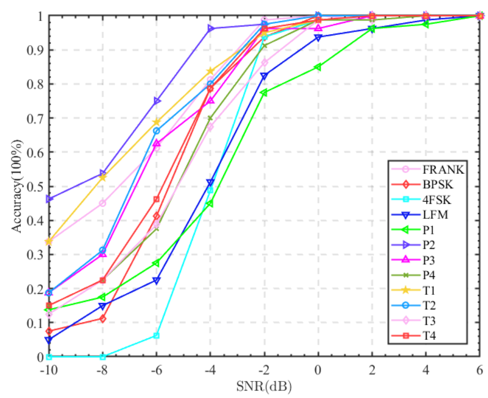

FIGURE 10. Recognition results of 12 types of radar signals.

Figure 10 shows the recognition accuracy of 12 modulation types of radar signals across various SNRs. It can be observed from Figure 10 that the recognition accuracy improves as SNR increases. Under low SNR conditions, the proposed MTL method shows excellent recognition performance, especially for T1, P2 and FRANK. The recognition accuracies of them all maintain above 80% at the SNR of -4 dB. When the SNR exceeds -2 dB, the proposed MTL method can identify them with nearly 100% accuracy. This is mainly due to their more discriminating characteristics than other types of signals, resulting in correct judgments of the classification network.

C. ABLATION EXPERIMENT

In this section, we conduct the ablation experiment to analyze the mutual influence of the feature enhancement task and the signal recognition task. First, to verify that the feature enhancement task contributes to signal recognition, we constructed a variant, called single task-signal recognition(ST-SR) model, to perform the single task of signal recognition, where the deconvolutional layers are removed from the feature enhancement module and the features extracted by the convolution layers are directly sent to the ResNet50 for signal recognition. Figure 11 shows the overall recognition performance of the proposed MTL method and ST-SR method. The recognition accuracy of the proposed MTL method is obviously higher than that of the ST-SR method, especially when the SNR is lower than

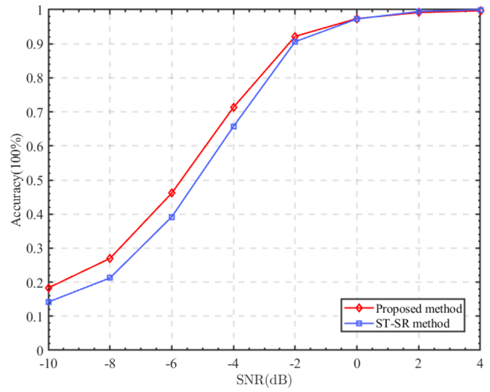

FIGURE 11. Comparison with ST-SR method.

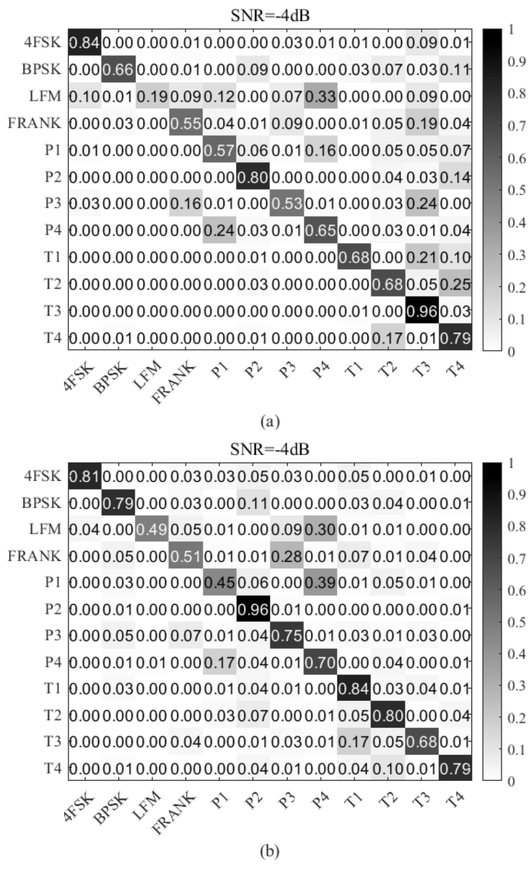

FIGURE 12. The confusion matrix for different methods: (a) ST-SR method, (b) The proposed method.

−4 dB. It can be concluded that the feature enhancement task has a positive impact on signal recognition. This is mainly due to the scheme of joint training, where the enhanced images provide more abundant features for the recognition task.

Furthermore, we employ confusion matrices to further analyze the recognition accuracy of the two methods, as shown in Figure 12. When the SNR is −4 dB, the ST-SR method can easily cause signal confusion, which is presented in Figure 12 (a). 33% of LFM were misidentified as P4, and 24% of P3 were misidentified as T3. The main reason is that the information that can be utilized for recognition in the ST-SR method is limited. Thus, signals with similar characteristics are easily confused. However, the proposed MTL method effectively solves this problem. As shown in Figure 12 (b), compared with the ST-SR method, the proposed MTL method reduces the possibility of signal confusion when the SNR is −4 dB. The accuracy rate of LFM rises from 19% to 49%, and the accuracy rate of P3 increases to 75%.

Besides, we define another variant, named single task-feature enhancement (ST-FE), where the ResNet50 is removed, to assess the impact of signal recognition task on the feature enhancement task. We employ the structure similarity index measure (SSIM) [44] to measure the similarity between the images generated by the proposed method and the target images, as well as the similarity between the images generated by the ST-FE method and the target images. As revealed in Figure 13, the similarity of both methods increases as the SNR rises. When the SNR is 0 dB, the similarity of the proposed method reaches 84%. And the images generated by the proposed MTL method are more similar to the target images than that of the ST-FE model, proving the recognition task is beneficial to feature extraction. The superior recognition performance can guide the model to obtain images with high quality.

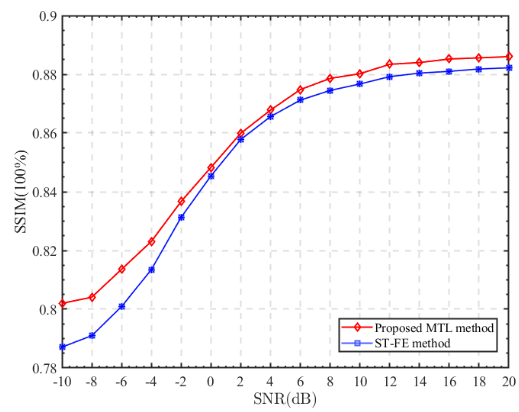

FIGURE 13. SSIM of images generated by the proposed MTL method and ST-FE method.

D. RECOGNITION PERFORMANCE OF MULTI-COMPONENT RADAR SIGNALS

To verify the applicability of the proposed method in solving other signal processing tasks, the proposed method is extended to the field of multi-component radar signals. We selected 4FSK, BPSK, LFM, and FRANK (signal parameters consistent with Table 2) and combined them in pairs to obtain six types of multi-component signals. The SNR of the training set is set to 0 dB to 20 dB, and 200 training samples are generated for each signal at each SNR. The dataset consists of a training set of 13,200 samples and a test set of 5,280 samples. The recognition accuracy obtained by

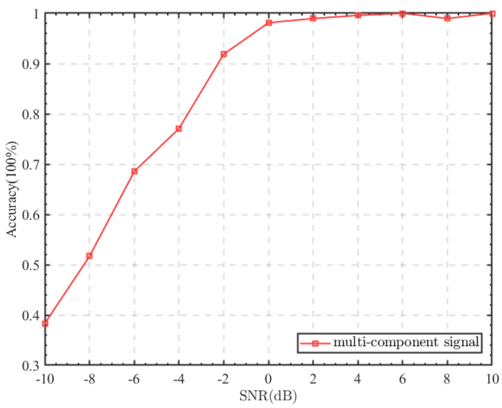

FIGURE 14. Recognition performance for multi-component signal.

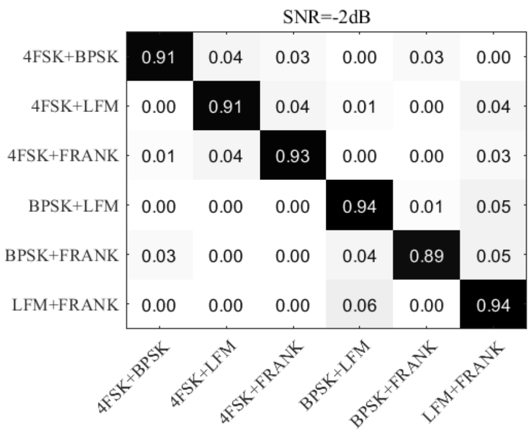

FIGURE 15. The confusion matrix for multi-component signal.

the proposed model is shown in Figure 14. When the SNR is 0 dB, the recognition accuracy of the proposed method for multi-component signals is over 98%. Furthermore, the confusion matrix for multi-component signal is presented in Figure 15. It can be observed that the proposed method can effectively distinguish multi-component radar signals, demonstrating its strong transfer ability to be applied to other signal processing tasks.

E. HARDWARE-IN-THE-LOOP SIMULATION EXPERIMENT

In order to further verify the effectiveness of the proposed method, a hardware-in-the-loop simulation experiment platform, as shown in Figure 16, was constructed to collect radar signals in a real environment for recognition [45]. The system works in the C band, supporting a maximum bandwidth of 200 MHz for transmitting and receiving signals. The bit widths of transmit and receive waveform are 16 bits each, and the sampling rate is 3 GSa/s.

The hardware-in-the-loop simulation experiment platform consists of a simulation host computer, a signal simulator, a transmit antenna, a receive antenna and a signal collector. First, the simulation host computer is responsible for generating 12 types of radar signals with SNR ranging from −10 dB to 10 dB. For each signal at each SNR, 80 samples

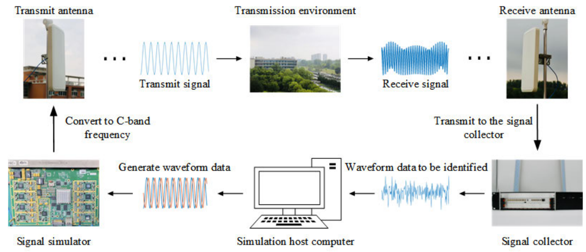

FIGURE 16. Hardware-in-the-loop simulation experiment platform for radar radiation source signal recognition.

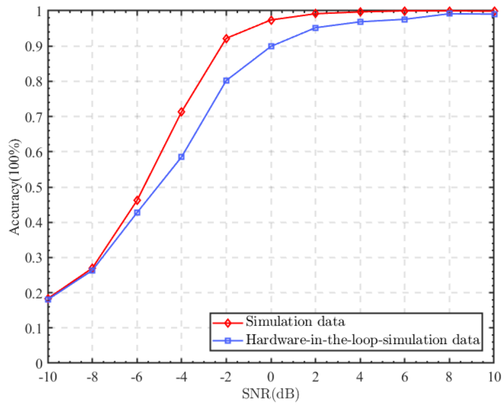

FIGURE 17. Recognition accuracy based on hardware-in-the-loop simulation data.

are generated, and a total of 10,560 samples are obtained. Each signal is labeled and sent to the signal simulator at certain intervals. The signals are converted from digital to analog in the signal simulator and transformed to the C band, and then transmitted to an open area through a transmit antenna. The receive antenna sends the received signal to the signal collector, where signals complete down-conversion, analog-to-digital conversion and pulse extraction, and finally generates a hardware-in-the-loop simulation dataset. We utilized the obtained dataset for identification to verify the feasibility of the proposed method in a real environment. The hardware-in-the-loop simulation data is publicly available and can be found at https://github.com/stu-cjlu-sp/rsrc-for-pub/tree/main/MTL/dataset/hardware-in-the-loop-simulation-data.

Figure 17 shows the recognition result. It can be observed that the overall recognition accuracy of the hardware-in-the-loop simulation experiment is slightly lower than that of the simulation experiment. It is due to the fact that the signals collected by the hardware-in-the-loop simulation experiment platform are affected by the radio wave propagation channel, resulting in fluctuations in the SNR and signal fading, which ultimately affecsts the recognition accuracy. However, the recognition accuracy of the hardware-in-the-loop simulation is still high when the SNR is low, which reaches 89% at an SNR of 0 dB, indicating that the proposed method has a good recognition accuracy in a realistic engineering application environment.

V. CONCLUSION

In this paper, we proposed a novel MTL-based method for radar signal recognition. We consider feature enhancement task and signal recognition task as a MTL problem. By utilizing their correlation and sharing features, the performance of the model is improved. The features learned by the feature enhancement task are utilized for signal modulation recognition task. Additionally, the feedback from the recognition network also enables the feature enhancement network to learn more representative features. Moreover, we design a new loss function to achieve better balance and interaction between different tasks. Experimental results show that compared with several existing typical radar signal recognition methods, the proposed method not only achieves higher recognition accuracy, but also effectively enhances the feature representation of radar signals. The hardware-in-the-loop simulation experiment verifies that the proposed method has high recognition accuracy in real engineering application environments, which is of great significance in the field of artificial intelligence. It is expected to promote the widespread application of artificial intelligence technology in the radar field and lay a solid foundation for the development of future intelligent radar systems.

In future work, we will explore additional applications of the feature enhancement task. For instance, within a MTL framework, we can achieve precise signal parameter measurements using enhanced time-frequency representations, allowing radar parameter estimation without prior knowledge. This will help radar systems better distinguish between target signals and interference signals, thereby mitigating false alarm rates and bolstering overall system stability.

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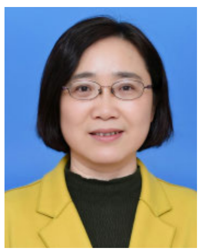

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