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Attention-Enhanced Domain Adversarial Training for Robust Automatic Modulation Classification of Radar Signals

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Abstract

Automatic modulation recognition has a wide range of applications in the field of signal processing. Real-world signal environments are complex and variable, and multiple datasets with domain differences are formed due to different sampling frequencies. However, existing methods usually rely on a single data domain for training, which makes it difficult to adapt to domains with inconsistent distributions. To address this, this paper proposes an attention-enhanced domain adversarial training (AM-DAT) method. Initially, radar signals are transformed into two-dimensional time-frequency images via the Smoothed Pseudo Wigner-Ville Distribution (SPWVD). Subsequently, discriminative and robust features are effectively extracted by the attention-enhanced neural network; while domain adversarial learning strategy is combined to achieve the consistency of feature distributions in the source and target domains, thus improving the generalization ability of the model to data domains with different distributions. Experimental results show that AM-DAT achieves superior classification accuracy across signals-to-noise ratio (SNRs), and its performance is much higher than the methods lacking adversarial training mechanism under low SNR (-2 dB). Our approach demonstrates strong potential for practical radar signal classification applications.

Keywords: automatic modulation classification, radar signal, attention mechanism, domain adversarial learning.

1 Introduction

In the key fields of modern wireless communications, electronic countermeasures and cognitive radios, Automatic Modulation Classification (AMC) is a fundamental technology to realize the sensing, demodulation and identification of communication signals. With the rapid development of 6G communication, intelligent transportation and industry 5.0 and other emerging technologies[1, 2, 3, 4], the modulation mode presents a diversified trend. Identifying the modulation mode of the signal accurately under the conditions of uncertainty and serious noise interference has become a key topic to improve the level of intelligence of the wireless system. In recent years, deep learning technology has been widely introduced into the field of modulation recognition, and due to its powerful automatic feature extraction and end-to-end modeling capabilities, deep models can effectively improve the recognition accuracy compared to traditional statistical methods based on feature engineering , such as maximum likelihood estimation [5], the maximum likelihood estimator in non-Gaussian channels [6]. In particular, convolutional neural networks (CNNs) and their variants show good performance in processing time domain or time-frequency image signals[7, 8] . However, most of the existing studies assume that the training set and the test set obey the independent identically distribution(IID), which lacks the ability to adapt to distributional shifts (e.g., channel variations, SNR fluctuations) in complex real-world environments. Once the channel noise or SNR in the test environment differs from that in the training phase, the model recognition performance is often severely degraded.

To address the above problem, a common solution is to add a large amount of data with different SNRs to retrain the model. Peleka, G et al [9] proposed High Dynamic Range Imaging (HDRIs) for dataset generation and utilized a synthetic dataset to train the model for improved performance. However, this retraining usually requires labeling of numerous new samples, which is costly. Some other studies have attempted to alleviate the model's dependence on specific scenes by introducing migration learning with domain adaptive strategies [10, 11]; however, these methods still suffer from weak feature extraction and insufficient discriminative performance under low SNR conditions. Especially in the case of the lack of labeled data in the target domain, the model migration ability and generalization performance are still limited.

In this study, we propose a domain adversarial training method (AM-DAT) that incorporates an attention mechanism, aiming to enhance the model's modulation classification ability in a cross-SNR environment. Specifically, we first use the smooth pseudo Wigner-Ville distribution (SPWVD) to transform radar signals into time-frequency images with good energy aggregation to enhance the distinguishability of modulation patterns; subsequently, we construct a deep convolutional network and introduce a CBAM attention module to strengthen the model's attention to key features and suppress noise interference; finally, we incorporate a domain adversarial learning mechanism, unsupervised migration from source domain (high SNR) to target domain (low SNR) is realized, so that the model has robust discriminative performance under different and complex channel conditions.

The contributions of this letter are summarized as follows:

- We propose a domain adversarial training framework AM-DAT that incorporates the attention mechanism to solve the problem of decreasing modulation classification accuracy in different SNR environments and improve the cross-scene generalization ability of the model;
- We design a feature extraction network incorporating the CBAM module to enhance the model's robustness in recognizing modulation features under low SNR conditions;
- Conducting experiments under multiple SNR conditions, we verify that the proposed method outperforms traditional DL methods and existing adversarial training methods in low SNR scenarios.

2 Review of related literature

2.1 Automatic modulation classification using deep learning

Among deep learning models, Convolutional Neural Networks (CNNs) are widely used in modulated signal classification tasks due to their great feature extraction capability. O'Shea et al. [12]

were the first to introduce CNNs into AMC scenarios, realizing automatic feature extraction of signals and significantly improving recognition accuracy. Since then, Zeng Y et al [13] utilized the Short Time Fourier Transform (STFT) to convert a 1D radio signal into a 2D time-frequency image and classified it by CNNs, thus making full use of the time-frequency feature distribution of the signal. To further enhance the expressive ability of the model, some research works try to fuse multimodal feature information. For example, Zhang Z. et al [14] proposed a multimodal modulation grouping technique on CNN. This technique utilizes a multimodal fusion method, amalgamating image features with artificial features to formulate the associated features, thereby enhancing the model's ability to recognize complex modulations.

Most of the above methods assume that the training data and the test data follow the same distribution (IID). However, in real communication environments, the sampling frequencies or receiving terminals are often different, and there are channel interference, SNR fluctuations and other variables, which lead to significant distributional offsets between the training data and the actual application data. This domain shift between the source and target domains will seriously affect the generalization ability of the model in the actual deployment process.

2.2 Automatic modulation classification based on transfer learning

To alleviate the above distributional differences, some studies in recent years have attempted to introduce transfer learning and domain adaptation methods to migrate the model from the source domain to the target domain to improve the recognition ability in unknown scenarios. Wang Q et al. [15] achieved initial migration under cross-channel conditions based on a two-channel CNN model, fusing multi-scale features and initializing the target domain classifier with source domain parameters. However, this method relies on a large number of target-domain label samples which is difficult to generalize in real-world scenarios. To reduce label dependency, K.Bu et al. [10] proposed an adversarial training framework based transfer learning ALTA, which introduces a domain discriminator and achieves feature alignment under different sampling rates. Although ALTA can improve the model performance under limited target data, its feature extractor structure is relatively simple and fails to fully model the time-frequency characteristics of the signal. Li et al [16] designed a few-shot classification framework based on capsule network for the task of small-sample recognition. This method can realize classification with very few labeled samples, but its performance is unstable when dealing with cross SNR and strong noise scenarios, and the structure of the network is complicated and the training cost is high. In addition, Domain-Adversarial Neural Network (DANN) [11] proposed by Ganin et al. as a generalized domain-adversarial learning method. The method achieves domain invariance by jointly training the feature extractor and domain discriminator, making the extracted features indistinguishable between the source and target domains. Although DANN is effective in the image domain, there are still limitations in its migration performance with complex time-frequency structure and drastic SNR variations.

2.3 Attention mechanism

The Attention mechanism, an approach that simulates the human visual and cognitive system, enables neural networks to focus on crucial areas within input data. This is achieved by introducing an attention mechanism that permits CNN to learn independently and selectively focus on important input data. Such a process augments the model's performance and generalization. Zaafouri.A et al. [17] extracted features using the local power spectrum (LPS) features map and then utilize CNN model for downstream tasks such as detection and recognition. Pisal, P.S et al. [18] utilized the AAqOA algorithm optimize CNN classifier to update the weight parameters. The Squeeze-and-Excitation Networks [19] employed the Channel Attention for adaptive calibration of the channel-level feature responses. This was to attain better generalizability across different datasets by visually portraying the interdependencies among channels. The Gather-Excite [20] used spatial dimensions to further extract feature context information. Building upon these earlier works, certain researchers have introduced the dual attention network (DAN) [21] and the CBAM [22], which combine both spatial attention and channel attention. CBAM asserts that SENT can only reach the Gap's secondary characteristic attributes. To counteract this, CBAM uses global max pooling and average pooling to enhance performance.

3 Problem

3.1 Time-frequency transformation

The signal accepted by the Receiver is showed as:

$$r(t) = G(s(t)) + n(t) \tag{1}$$

where G indicates dynamic wireless channels, $s(t)$ indicates the modulation signal Transmitter, $n(t)$ indicates Additive White Gaussion Noise. The modulation task mainly identity G according to $r(t)$. In order to better utilize the feature extraction capability of the deep learning network, the received signal is converted into an image by smooth pseudo-wigner-ville distribution (SPWVD). SPWVD can better attenuates the effect of the coherence term, makes the energy and time-frequency aggregation stronger, so that the time-frequency relationship of the signal is more easily seen.There have been many works proving the effectiveness of SPWVD in AMC [23, 24, 25]. The specific formula is as follows:

$$\mathrm{SPWVD}_x(t,f) = \iint x\left(t - v + \frac{\tau}{2}\right) x^*\left(t - v - \frac{\tau}{2}\right) h(\tau) g(v) e^{-j2\pi f\tau}\, dv\, d\tau \tag{2}$$

Where $g(v)$ indicates time domain smooth window. $h(\tau)$ indicates frequency domain smooth window. x^* indicates Conjugate Function. $x(t)$ is the analytic form of $r(t)$ constructed from the Hilbert transformation. Carrying out SPWVD transformation, eight types of single-component radar signal are obtained. The result is shown as Figure 1.

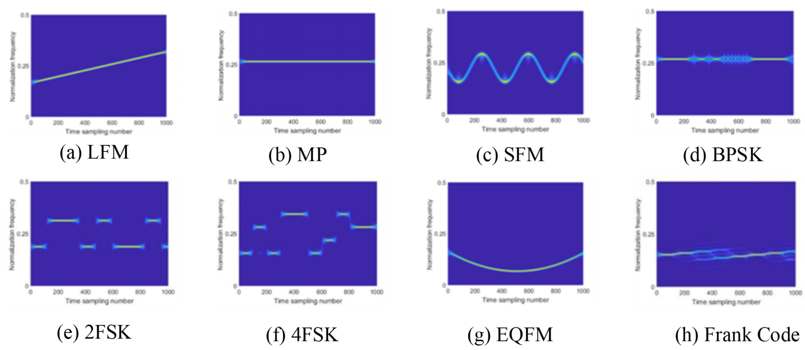

Figure 1: Smooth pseudo-wigner-ville distribution transformation results of eight types of radar signals

3.2 Domain adaptation

This study focuses on the problem of model performance being influenced by inconsistency in channel noise during modulation classification. Specifically, datasets collected in high SNR scenarios can train accurate classification models. However, these models exhibit poor detection performance when identifying low SNR data. The aim of this paper is to effectively address this issue through domain adaptation methods.

During the modulation classification process, when the channel noise of the source domain and the target domain are inconsistent, the detection effect of the model is reduced, which limits the application of the model in real-world environments. Domain adaptation may solve the above-mentioned issues. Domain adaptation is a kind of transfer learning that enables knowledge transfer from the source domain to the target domain when the task is the same but the data distributions are inconsistent. Assume that D_s is the signal source domain with label information, which can be represented as

$D_s = \{x_i, y_i\}$, $i \in (1, n)$. D_t is the signal target domain without label information, which can be represented as $D_t = \{y_j\}$,$j \in (1, m)$. It is assumed that D_s and D_t share the same signal features and signal classes, but have different marginal distributions. Domain adaptive learning is grouped into two steps: first, using the labeled data from D_s to train a classifier $f : x_s \to y_s$; second, applying a domain adaptation method to the above-obtained classifier to achieve effective classification of target samples. The designed transfer model can transfer classifiers trained under specific SNR scenarios to recognize unlabeled samples in other SNR scenarios.

4 The proposed methodology

Aiming at the problem of degradation of trained classification models under different SNR scenarios, this paper proposes a transfer learning method based on domain adversarial learning fused with attention mechanism (AM-DAT). This framework integrates attention-guided feature extraction and domain-adversarial learning to improve the robustness and transferability of modulation classification across different SNR conditions.

4.1 Network architecture

The proposed AM-DAT shown as Figure 2 consists of four components: a source encoder Encoder_S, a target encoder Encoder_T, a Classifier and a Discriminator. The one-dimensional modulation signal is first converted into a two-dimensional time-frequency image with good time-frequency aggregation via the SPWVD to enhance the distinguishability of the features. Subsequently, the model receives this time-frequency image as input through the embedding layer and passes it to the encoder module for feature extraction. Where Encoder_S is used to extract discriminative features from labeled source domain data, Encoder_T is responsible for extracting structurally consistent feature representations from unlabeled target domain data. Both are structurally consistent, but the parameters are trained independently to accommodate data features from different domains. The features extracted by the encoder will be fed into the Classifier for modulation type discrimination. At the same time, the model uses a Discriminator to determine whether the features come from the source or target domain. Through the adversarial training mechanism, the features generated by the encoder in the target domain can deceive the discriminator, so as to realize the consistency of the distribution of features between the source and target domains.The network structure parameters are shown in Table 1.

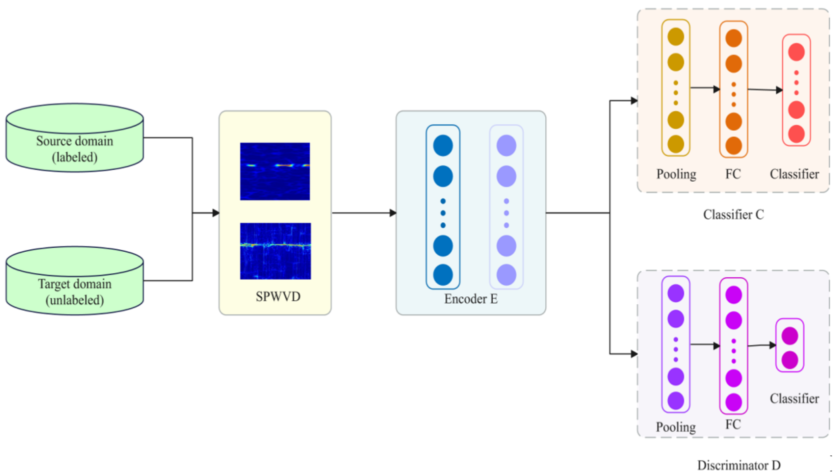

Figure 2: The architecture of AM-DAT

In order to enhance the model's ability to focus on key features, this paper embeds Convolutional Block Attention Module(CBAM) in the encoder network, which are placed in the first and last layers of the encoder respectively. The structure of CBAM is shown in Figure 3. CBAM consists of two sub-

Table 1: Details for AM-DAT

Module	Layer	Output
Encoder	Conv2D+BN+ReLU+CBAM+Maxpool2D	64*32
	RestNetBasicBlock*2	64*16
	RestNetDownBlock+RestNetBasicBlock	128*8
	RestNetDownBlock+RestNetBasicBlock	256*4
	CBAM+Maxpool2D	256*1
Classifier	FC	256*128
	ReLU+Dropout+FC	128*8
Discriminator	FC	256*128
	FC+LogSoftmax	2

modules in series: channel attention module (CAM) and spatial attention module(SAM). The CAM learns the importance of each channel and gives higher weights to channels rich in feature information; the SAM identifies the key areas in the input feature map, highlights the areas with obvious modulation pattern signals, and suppresses noise interference. And CBAM has a small number of parameters and is a lightweight attention mechanism module that does not increase the computational overhead, but can significantly enhance the network's discrimination performance.

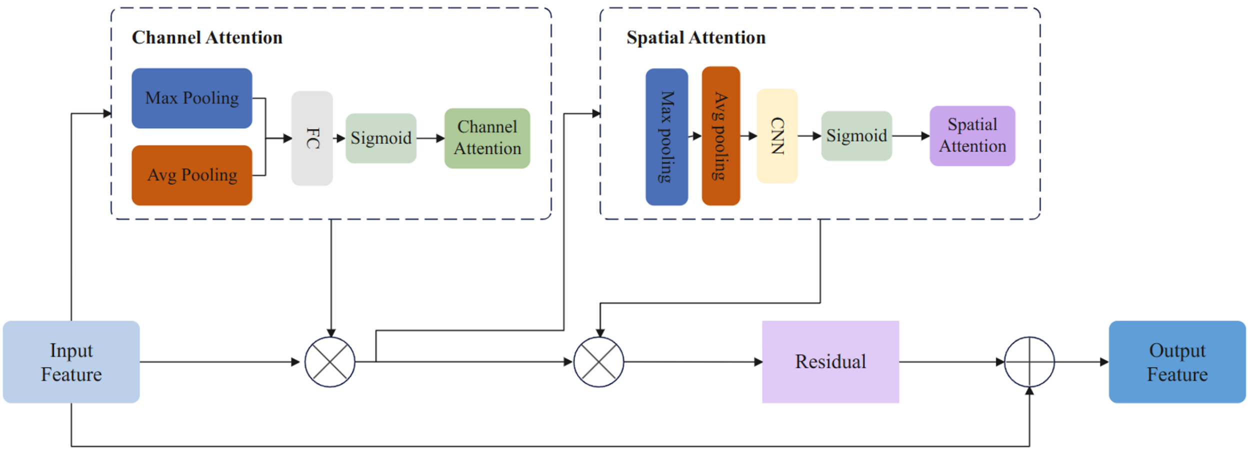

Figure 3: The architecture of CBAM

4.2 Domain adaptation and adversarial training strategy

In practical applications, the SNR differences caused by different communication channels and sampling frequencies will cause significant distribution shifts between the source and target domains. If the source domain training model is directly applied to the target domain, the performance will be greatly degraded. Therefore, this paper introduces a domain adversarial training strategy to achieve the transfer generalization of the model under different SNR conditions. Specifically, we add a domain discriminator to the model, whose responsibility is to distinguish whether the input features come from the source domain or the target domain; at the same time, the Encoder_T continuously adjusts its parameters through adversarial training to deceive the discriminator, making it difficult to distinguish features from different domains. This structure is similar to the Generative Adversarial Network (GAN), but the purpose is align the source domain and target domain samples in the feature space. During the training process, the model first jointly optimizes the Encoder_S and the Classifier on the source domain data to ensure the ability to distinguish the modulation classification. We use the Cross-Entropy Loss as the classification loss function. Then, the parameters of Encoder_S are shared with Encoder_T. At the same time, the source domain and target domain samples are input into Encoder_T and the Discriminator. By maximizing the adversarial loss of the Discriminator in distinguishing the output features from different domains, the parameters of Encoder_T are updated to promote feature alignment.The global domain adversarial loss function L_D is as follows:

$$L_D = -E_x \log[1 - D_w(E_S(x_s))] - E_x[D_w(E_T(x_t))] \tag{3}$$

where x_s and x_t denote the data from the source and target domain.

5 Experiment

5.1 Dataset and settings

To assess the classification performance of the suggested method, we employed experiments on various modulation signals as the dataset. For the selection of modulation categories, we sampled 8 categories including ASK2, ASK4, ASK8, FSK2, FSK4, FSK8, QAM16, and QAM32, with SNR $\in \{-2\,\text{dB}, 8\,\text{dB}\}$ in steps of 2 dB. The sampling frequency is 40 kHz. There are 1000 signal data for each category at each SNR. Each sample is converted into a 64×64 image by SPWVD transform and processing. In this way, the domain adaptation experiment is conducted by using data from a specific SNR as the source domain, while data from different SNR are utilized as separate target domains. The experiment uses RTX 3090 as the GPU and implements the corresponding algorithm with PyTorch. Adam is chosen as the optimizer

5.2 Experiments and discussions

To evaluate a efficiency of a attention mechanism in signal categorization, we conducted comparative studies on VGG [26], ResNet [27], AlexNet [28], and our network, respectively. The comparative results of the experimental performance is shown in Figure 4 and Figure 5.

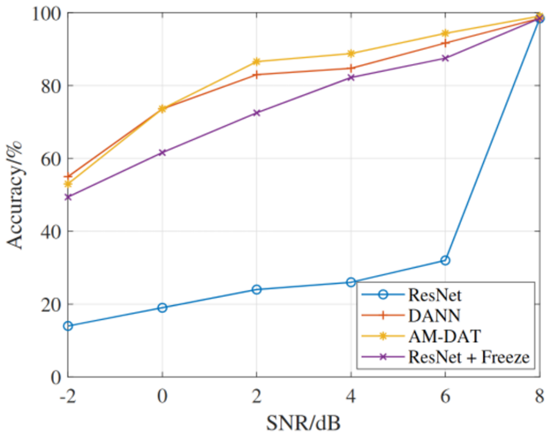

Figure 4: The classification abilities of models with different SNRs

Figure 4 shows the trend of model classification accuracy under different SNR conditions. It can be seen that as the SNR gradually increases from –2dB to 8dB, the recognition accuracy of all models has improved, but the AM-DAT curve is always at the top. Whether under extremely low SNR (–2dB) or high SNR (8dB) conditions, its classification performance is significantly better than other baseline. This phenomenon shows that AM-DAT maintains excellent robustness in the entire SNR range, especially in low SNR, where its performance decreases the least, indicating that the proposed method can still effectively extract discriminant features when noise interference is severe. In detail, Figure 5 shows the average classification accuracy of the four networks under –2dB conditions. Among them, the average recognition rate of AM-DAT is about 70%, which is 26% higher than that of Alexnet. This is because in extremely low SNR scenarios, the traditional CNN structure is sensitive to noise, and its input features are often submerged by noise; while AM-DAT benefits from the high-energy

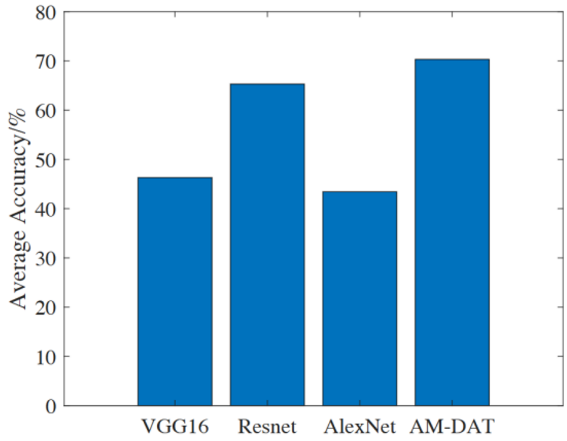

Figure 5: Comparison of average accuracy of different models when SNR = -2dB

time-frequency diagram of SPWVD conversion and the dual weighting of key channels and key spatial areas by the CBAM module embedded in the encoder, which effectively suppresses noise interference and strengthens the time-frequency characteristics of the modulation signal, thereby significantly improving the discrimination ability in a noisy environment.

Signal data has some common features under different SNR environments. These commonalities enable the ResNet network trained only on source domain data to maintain a certain classification accuracy when applied to the target domain, but the accuracy drops significantly as the SNR decreases. From the experimental results, it can be seen that both DANN[11] and AM-DAT significantly surpass the traditional pre-training fine-tuning strategy of the ResNet network. This is because they use the domain adversarial learning method to introduce a discriminator to enable the model to learn the common key features of the source domain and the target domain, thereby enhancing the cross-domain adaptation ability. Although DANN introduces an adversarial training mechanism, it does not consider the focus on key information in the feature extraction process, resulting in its unstable performance in low SNR environments. AM DAT further introduces an attention mechanism on this basis, and improves the model's ability to focus on the time-frequency feature area through the CBAM module, effectively making up for the insufficient performance of DANN in low-noise environments.

During the training process of AM-DAT, the second step is to use the data of the target domain and the source domain as input to train the model. The proportion of the target domain dataset in the training set, λ, will affect the classification performance of the model. To examine the impact of λ on the classification performance of the AM-DAT model, we keep the SNR in the target domain at 6dB and then set λ to 0.1, 0.2, 0.4, 0.6, and 0.8. The experimental results are shown in Figure 6.

The experimental results demonstrate that when λ is greater than or equal to 0.4, the model maintains a relatively high average classification accuracy level. However, as λ decreases further, the classification accuracy declines. Specifically, at $\lambda = 0.1$, the model achieves an average classification rate of only 55.53. This suggests that in the adversarial learning process, the quantity of data in the target domain directly impacts the training quality of both the generative and discriminative models. With a smaller target domain dataset, there is a risk of overfitting for the generator and discriminator models, resulting in insufficient generalization ability of the model and lower quality of generated synthetic data. Conversely, a larger target domain dataset allows the model to more effectively grasp the distribution characteristics of the data, thereby generating more authentic data samples. Therefore, during the training process of AM-DAT, having an ample amount of target domain data is crucial for enhancing the model's categorization proficiency in the target domain.

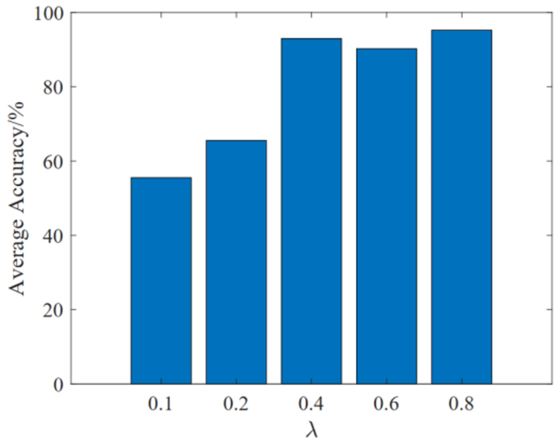

Figure 6: Impact of target domain data proportion "λ" on the classification performance of AM-DAT

6 Conclusion

In this study, we propose an automatic modulation classification method AM-DAT that integrates attention mechanism and domain adversarial learning. It solves the problem of model performance degradation caused by inconsistent distribution of target domain and source domain. In data domains with different distributions, the model fully captures the common discriminant feature information through adversarial training so that improves the classification performance of the model in the target domain. Experimental results show that this method exhibits strong robustness and cross-domain generalization ability, so the model can be applied to automatic modulation classification in complex environments. In future work, we will explore small sample training to reduce training costs and improve the practicality of the model under larger scale and more signal patterns.

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