Multi-Task Learning with Dynamic Splitting for Open-Set Wireless Signal Recognition

Abstract: Open-set recognition (OSR) is a realistic problem in wireless signal recognition, which means that during the inference phase there may appear unknown classes not seen in the training phase. The method of intra-class splitting (ICS) that splits samples of known classes to imitate unknown classes has achieved great performance. However, this approach relies too much on the predefined splitting ratio and may face huge performance degradation in new environment. In this paper, we train a multi-task learning (MTL) network based on the characteristics of wireless signals to improve the performance in new scenes. Besides, we provide a dynamic method to decide the splitting ratio per class to get more precise outer samples. To be specific, we make perturbations to the sample from the center of one class toward its adversarial direction and the change point of confidence scores during this process is used as the splitting threshold. We conduct several experiments on one wireless signal dataset collected at 2.4 GHz ISM band by LimeSDR and one open modulation recognition dataset, and the analytical results demonstrate the effectiveness of the proposed method.

Keywords: open-set recognition; dynamic method; adversarial direction; multi-task learning; wireless signal

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1 Introduction

With the rapid development of wireless communication technology, the wireless spectrum is getting crowded, especially in the Industrial, Scientific and Medical (ISM) band which is open to the public and takes no authorization. A large number of wireless communication signals share the ISM band, such as Wi-Fi, Bluetooth and ZigBee. These coexisting signals interfere with each other and may cause performance reduction to the communication system[1]. The technology of wireless signal recognition (WSR) is a foundational work to deal with this problem. The WSR technology can be used to identify the wireless signal and hence help to improve the communication system by choosing a better channel or other strategies.

Traditional algorithms of WSR could mainly be separated into two groups: likelihood-based and feature-based methods[2]. Likelihood-based methods obtain the optimal decision based on hypothesis testing theory but suffer high computation complexity[3–4]. Feature-based methods usually extract several features and employed classifiers to realize signal recognition. These features are normally chosen using expert's knowledge. Although feature-based methods may not be optimal, they are usually simple to implement, with near-optimal performance, when designed properly. Feature-based methods heavily rely on expert's knowledge, which may perform well on specialized solutions but poor in generality[5–6]. With the increasing number of wireless signals in the ISM band, communication systems tend to be complex and diverse. As a result, traditional feature-based methods used to detect and recognize the complex signals are confronted with a new dilemma.

In recent years, the method of deep learning has emerged and achieved great success in the fields of image, speech, text and so on. Deep learning is an end-to-end approach that can automatically learn signal representation directly from the original wireless data without the need for designing expert

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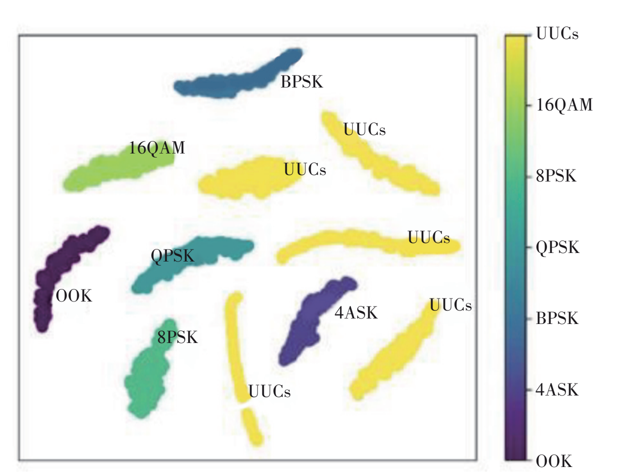
features such as high-order cyclic moments. Inspired by the advantages of deep learning compared to conventional feature-based approaches, more and more researchers use deep learning methods to solve the problem of WSR. Generally, these deep learning methods utilize raw data obtained from devices such as channel state information (CSI) [7–8] and In-phase/Quadrature (I/Q) data[9–10] as the input of a deep neural network. However, most of these methods are under a close-set assumption that the classes in the inference phase all appear in the training phase, which is unpractical. When facing a real scene, we have to deal with classes not seen in the training phase (also known as unknown unknown classes (UUCs) while KKCs means known known classes[11]). As shown in Fig. 1, six classes from the modulation recognition dataset[12] are selected as KKCs during the training phase and all eleven classes are served as testing samples during the inference phase. It challenges the traditional classifiers that they have to predict the unknown classes as one of the known class. In fact, the UUCs will be labeled as one of the KKCs with high probability, generally. Therefore, the purpose of open-set recognition (OSR) is to identify unknown classes while correctly classify known classes[13].

The difficulty of OSR is that there is no knowledge of UUCs during the training stage. Current OSR methods mainly fall into two main categories: discriminative methods and generative methods. The discriminative methods choose an empirical threshold based on samples of KKCs to determine whether testing samples belong to KKCs or UUCs[14]. To take full advantage of the knowledge of KKCs, a few studies use Extreme Value Theory (EVT) to model the tail of evaluation scores so as to determine a better threshold[15–17]. The discriminative methods are sensitive to thresholds but there is no principle of how to choose thresholds. Furthermore, the generative methods utilize a generative model to generate fake data as UUCs[18–20]. The fake data is used in the training phase together with the known data, thus the OSR problem is turned into an N+1 classification problem. In addition, the intra-class splitting (ICS) method selects a certain percentage of samples from known data as atypical samples to imitate UUCs. This method is simple and efficient but also has some drawbacks. For instance, it is very sensitive to the predefined splitting ratio and the method of directly using splitting samples as UUCs is coarse. Besides, the performance of the ICS method degrades significantly in a new environment. We intend to address these drawbacks in this article.



16QAM: 16 quadrature amplitude modulation
4ASK: 4 amplitude shift keying
8PSK: 8 phase shift keying
BPSK: binary phase shift keying
OOK: on-off keying
QPSK: quadrature phase shift keying
UUC: unknown unknown class

▲Figure 1. An example of known known classes (KKCs) and UUCs using t-SNE (t-distributed stochastic neighbor embedding)

Multi-task learning trains multiple tasks at the same time and uses shared representations to learn the common ideas between a collection of related tasks[21]. There are few literatures studying multi-task learning (MTL) in OSR[22–24]. Most of these studies use discriminative methods applied in the image field and thresholds are calculated based on KKCs. Specifically, some researchers train two tasks simultaneously, one for the traditional close-set classification task and the other for evaluating testing samples. The evaluation score of the second task is compared with the threshold to determine whether it belongs to KKCs or UUCs. Besides, the auxiliary task is used to force the network to learn more informative features to improve separation of classes from each other and from KKCs. Different from the above works, we propose an MTL network based on the characteristics of communication signals on a generative method to improve the performance of open-set classifier.

In this paper, we propose an MTL network with a dynamic method to determine the splitting ratio for the OSR problem. The splitting ratio will be used to split known data into two subsets: inner samples and outer samples, which are applied to imitate UUCs[25]. The contributions of the proposed method are described as follow: Firstly, we propose an MTL network based on the characteristic of wireless signal to improve the OSR performance in new environment. Secondly, we provide a dynamic method to automatically select the splitting ratio. Specifically, we perturb a sample from the center of one class toward its adversarial direction and the change point of confidence scores during this process is used as the splitting threshold. Thirdly, we perform numerical experiments to demonstrate the effectiveness of the proposed method.

2 Related Work

This paper studies the OSR problem of wireless signals by using an MTL network with the dynamic splitting method. Some studies are related to this work. We will review these studies in three subsections that present the research of WSR, OSR, MTL, respectively.

2.1 Wireless Signal Recognition

WSR is a fundamental task to enable any form of cross-technology ISM band signals' coexistence mechanism. Traditional feature based algorithms extract features for preprocessing and then employ them to realize classification. PALICOT et al. used channel bandwidth and its shape as reference features, which was found to be the most discriminating parameter among others[5]. KIM et al. used cyclostationary features that was caused by the periodicity in the signal or in its statistics like mean and autocorrelation or they can be intentionally induced to assist spectrum sensing[6]. However, these algorithms rely heavily on expert's knowledge to extract features and are poor in generality.

On the other hand, deep learning based approaches have shown great advantages in terms of performance and no need for expert's knowledge. These approaches utilize different information to train deep neural networks. YI et al. used Received Signal Strength Indication (RSSI) values as input data to train a Convolutional Neural Network (CNN) classifier[26]. The proposed model can achieve an accuracy of over 93% for detecting the different classes of interference with minimal computational resources. KIM et al. used k-nearest neighbor (kNN) and neural networks to train models with CSI values as the input[7]. The proposed model can classify tens of signal sources with over 90% accuracy. CROCE et al. adopted the artificial neural network, with which a Wi-Fi device could detect the presence of an LTE-U signal by examining the error pattern of a received Wi-Fi signal[27]. The proposed method reached an average accuracy of over 95% in recognizing ZigBee, microwave, and LTE (in unlicensed spectrum) interference. In Ref. [9], a CNN classifier trained on In-phase/Quadrature (IQ) vectors and amplitude/phase vectors can recognize ZigBee, Wi-Fi, and Bluetooth signals and achieve an average accuracy of more than 98% in a high signal-to-noise ratio (SNR) scenario. Thus we choose IQ data as the input of deep neural network considering its rich information. However, open-set recognition of WSR is rarely studied, which is very common in real world.

2.2 Open-Set Recognition

The discriminative methods usually identify unknown samples based on an empirical threshold. MENDES et al.[14] introduced an open set version of Nearest Neighbor classifier (OSNN) to deal with the OSR problem based on the traditional Nearest Neighbor classifier. Some studies used the extreme value theory (EVT) to model the tail of data so as to determine a better threshold. BENDALE and BOULT[15] proposed the OpenMax model by replacing the SoftMax layer with an OpenMax layer. Specifically, the training samples' distances from their corresponding class mean activation vectors (MAV) are calculated and used to fit the separate Weibull distribution for each class. SCHEIRER et al.[16] proposed a Weibull-Calibrated SVM (W-SVM) model, which combined the statistical eEVT for score calibration with two separated SVMs. YOSHIHASHI et al. [17] presented the classification-reconstruction learning algorithm for open set recognition (CROSR), which utilized latent representations for reconstruction and enabled robust UUCs' detection without harming the KKCs' classification accuracy. However, these EVT-based methods provide no principled means of selecting the size of tail for fitting.

The generative methods usually use generative neural networks to generate fake data imitating UUCs. Although such methods suffer from the difference between the fake data generated by generative models and the real data of UUCs, they are still highly promising to turn an OSR problem into an N+1 classification problem. Counterfactual image generation (OSRCI)[18] adopts an encoder-decoder GAN architecture to generate the synthetic open set examples that are close to KKCs, yet do not belong to any KKCs. JO et al.[19] adopted the GAN technique to generate fake data as the UUCs' data to further enhance the robustness of the classifiers for UUCs. The ICS method[28] used a pretrained close-set network to score known samples and select atypical samples as samples of UUCs. In the meantime, a closed regular term was proposed in order to ensure the accuracy of close-set classification. Although the ICS method is simple and effective, the selection of atypical samples is very sensitive to the predefined splitting ratio and pretrained network. SCHLACHTER et al.[29] proposed a one-stage method based on alternating between ICS and the training of a deep neural network, which removed the need for the pretrained network but still relied on the predefined splitting ratio. MIYATO et al.[30] provided a fast way to calculate the adversarial direction of the current network. Here, the adversarial direction for a given datum is the direction to which the probabilities of each class change most and it is toward the decision boundary[31]. Inspired by the DICS method and adversarial direction, we propose a novel dynamic method to automatically select the splitting ratio.

2.3 Multi-Task Learning

In recent years, some researchers have tried to use multitasking learning to solve the open-set recognition problem. PERERA et al.[22] proposed a multi-task network to learn more descriptive features where an auxiliary classifier performed self-supervision. The self-supervision task had to determine which transformation was applied and thus the network needed to learn structural properties of image content such as shape and orientation. OZA et al.[23] combined a classifier network and a decoder network with a shared feature extractor network within a multi-task learning framework. Reconstruction errors from the decoder network were utilized for open-set rejection and the tail of the reconstruction error distribution from KKCs was modeled by the EVT to improve the overall performance. YU et al. [24] proposed a multi-task curriculum learning framework to perform the task of detecting out-of-distribution samples and semi-supervised learning. The in-distribution samples in unlabeled data having small out-of-distribution scores were selected and used with labeled data for training the deep neural networks in a semi-supervised manner. SONG et al.[32] proposed a framework incorporating GAN with a multi-task discriminator, which simultaneously discriminated category, reality, and client identity of input samples. In this paper, based on the characteristics of communication signals, we propose an MTL network on a dynamic generative method.

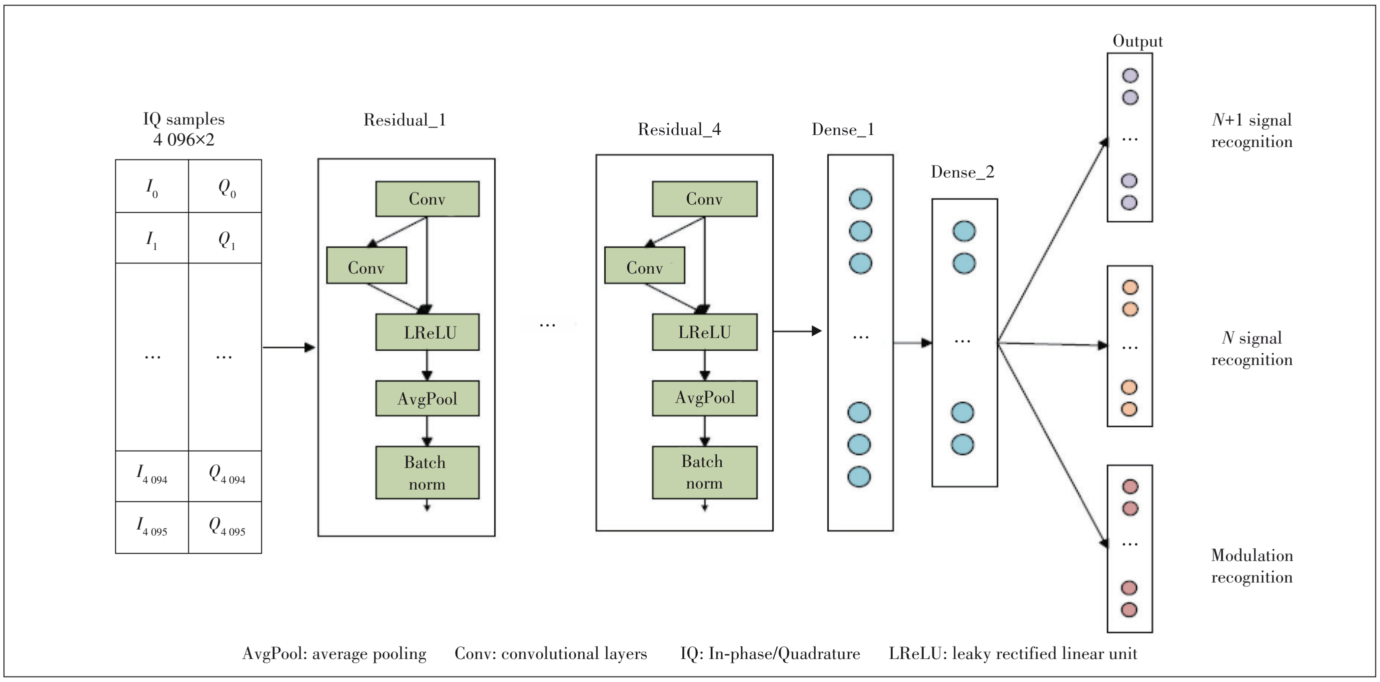
3 Proposed Method

In this section, we first describe the MTL network architecture of our method, and then we present the dynamic method to automatically select the splitting ratio. Finally, we demonstrate the procedure of the proposed scheme.

3.1 MTL Network

To deal with the OSR problem of WSR, we propose an MTL network architecture (Fig. 2). Inspired by the idea of ICS, we use dynamically split samples to imitate unknown classes, and thus turn the OSR problem into an (N+1)-class signal recognition task. However, the split samples are actually from known classes and their new labels differ from the ground truth. Hence, a naive neural network with (N+1)-class output will result in low closed-set accuracy, because the split samples are incorrectly predicted. To prevent this situation, we take the same strategy as that proposed in Ref. [28] of training a closed-set regularization subnetwork simultaneously which forces the split samples to be correctly classified. Meanwhile, in order to mitigate the decline of identification accuracy of a trained network applied in new scenes, we introduce an auxiliary task of modulation recognition to learning more generalized expression. The MTL network consists of one shared deep neural network and three individual task-specific layers. The purpose of the (N+1)-class signal recognition task is to classify all testing samples, including KKCs and UUCs, where the (N+1)-th class represents UUCs and is trained with dynamically split samples with data augmentation. The modulation recognition task is designed as an auxiliary task to help learn more generalized expression. Besides, we keep the N-class signal recognition task of classifying known classes to guarantee a high closed-set classification performance. The shared deep neural network is composed of four residual blocks and two dense layers. Each residual block includes two convolutional layers (Conv), an activation layer with a leaky rectified linear unit (LReLU), an average pooling (AvgPool) and a batch normalization layer. Each of three individual task-specific layers contains one output layer. The MTL network takes IQ data samples as the input and maps them to a specific category. The dimensions of one sample are 4 096×2. In the inference phase, only the (N+1)-class signal recognition task is used as an end-to-end classifier for open-set recognition.

Formally, given a training set of samples x_i, where i indicates one of the known N classes, we divide x_i into two subsets: inner samples $x_{i,inner}$ and outer samples $x_{i,outer}$ using the dynamic splitting method. The number of outer samples is too small to learn knowledge about UUCs at the beginning of training. To keep the network training in a good direction, we employ data augmentation on the outer samples. The augmented outer samples $x_{i,aug}$ are served as samples of unknown classes



▲**Figure 2. Multi-task learning (MTL) network architecture of the proposed method** with a new label y_{N+1} while the inner samples $x_{i,inner}$ are also used to train the $(N+1)$-class signal recognition task. In the meantime, all x_i are used as the input of the N-class signal recognition task and modulation recognition task with the original label y_i. The cross entropy loss functions of three tasks are denoted as:

$$L_{OS} = -\frac{1}{B}\sum_{b=1}^{B}\sum_{j=1}^{N+1} y_{OS}^{(b)}(j)\log\left(\hat{y}_{OS}^{(b)}(j)\right), \tag{1}$$

$$L_{CS} = -\frac{1}{B}\sum_{b=1}^{B}\sum_{j=1}^{N} y_{CS}^{(b)}(j)\log\left(\hat{y}_{CS}^{(b)}(j)\right), \tag{2}$$

$$L_{MR} = -\frac{1}{B}\sum_{b=1}^{B}\sum_{j=1}^{N'} y_{MR}^{(b)}(j)\log\left(\hat{y}_{MR}^{(b)}(j)\right), \tag{3}$$

where B indicates the batch size of one epoch. $y_{OS}^{(b)}(j)$ and $\hat{y}_{OS}^{(b)}(j)$ present the j-th element of a true one-hot type OSR label and the predicted one of the b-th sample, by which the augmented outer samples are assigned with UUCs label. Meanwhile, y_{CS} and y_{MR} are the true signal category label and modulation category label of known classes. Therefore, the loss function of the shared deep neural network is given as:

$$L_{\text{total}} = \alpha L_{OS} + \beta L_{CS} + \lambda L_{MR} + \eta L_2, \tag{4}$$

where L_2 represents the L_2-norm regularization term. The total loss L_{total} is a linear combination of the loss of each task and regularization term. α, β, λ and η indicate the weight of each item. By training with shared weights, the deep neural network can learn generalized expression between multiple related tasks. Consequently, minimizing the first term forces the network to classify between the inner and outer samples, i. e., completing the task of open-set recognition. On the other hand, minimizing the second and third terms corresponds to reducing the empirical risk on the known classes. Hence, the classifier learns to identify unknown classes while correctly classifying known classes.

3.2 Dynamic Splitting Method

The original ICS method[28] is restricted to the predefined splitting ratio and pretrained network. The improved version[29] removes the restriction on the pretrained network but still relies on the predefined splitting ratio. In this subsection, we propose a dynamic method to automatically select the splitting ratio by continuously perturbing samples toward the adversarial direction of current network. An approximate curve of confidence score and deviation during this process is constructed and the change point of this curve is acquired and used to determine the splitting ratio.

First, we select some candidate samples of the class center by ranking the evaluation confidence score of known samples. Formally, let $f(x)$ represent the predicted probability of a trained classifier on sample x, which is one-dimensional vector after softmax. The confidence score represents the degree to which the sample belongs to the category. The higher the score, the more centralized the sample is. It is denoted as:

$$\text{score} = \max\left(f(x)\right)\cdot I\left(f_{oh}(x) = y\right), \tag{5}$$

where y is the label, $f_{oh}(x)$ is the predicted result in one-hot and $I(\cdot)$ is an indicator function that returns 1 if the predicted class is the same as the true label and otherwise returns 0. We choose several samples per class with the highest score as candidate samples of the class center. Then we continuously disturb these samples toward adversarial direction to generate adversarial samples. Here, the adversarial direction for a given datum is the direction to which the probabilities of each class change most and it is toward the decision boundary[31]. The adversarial direction $r_{advr}(x,\varepsilon)$ for given ε is calculated by

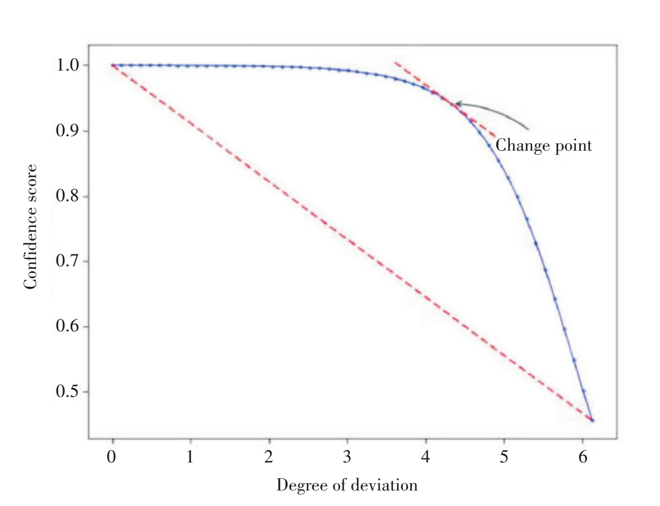
$$r_{advr}(x,\varepsilon) = \underset{r;\|r\|\le\varepsilon}{\arg\max}\, D_{KL}\left(f(x)\,\|\,f(x+r)\right), \tag{6}$$

where D_{KL} indicates Kullback-Leibler divergence and r indicates slight perturbation constrained by parameter ε; $f(x)$ and $f(x+r)$ represent the predicted probabilities of the samples before and after perturbation. Generally, it is hard to obtain a closed form for the exact adversarial direction r_{advr}, so we use a fast approximation method to compute it the same as in Ref. [30]. Thereby, the adversarial samples are formulated as

$$x_{adv}(\delta) = x + \delta r_{advr}(x,\varepsilon)/\left\|r_{advr}(x,\varepsilon)\right\|, \tag{7}$$

where δ is a parameter that denotes the degree of disturbance toward the adversarial direction. We continuously vary this parameter to generate adversarial samples from the center of a class to the decision boundary. The scores of adversarial samples will be calculated and used to approximate a curve.

As shown in Fig. 3, the horizontal axis shows the degree to which the sample deviates from the center of one class, and the vertical axis shows the corresponding confidence score. When the sample of class is moved away from the center, the confidence score begins to plummet at some points. Similar to Ref. [33], the point with the furthest distance from the straight line connected by two points of the maximum and minimum confidence scores, is selected as the change point. Thereby, the sample whose confidence score is lower than the change point is selected as the outer sample. The change point is improper and the candidate sample should be discarded if the confidence score is almost constant within a certain range of disturbance or the confidence score of change point is less than 0.9. The former means this sample is hard to achieve the decision boundary toward current approximate adversarial direction. For convenience, we abandon this kind of candidate



▲**Figure 3. An example of confidence score approximate curve**

samples. The latter usually indicates this sample is not in the center of class while the confidence scores of the most known samples are normally higher than 0.9, which will lead to too many outer samples. To prevent this situation, we also abandon this kind of candidate samples. When the candidate samples of one class drop more than a certain number, which means that the current network may not be trained well, the samples of this class will not be spilt and all used as inner samples to retrain the network. After a certain period of training, the splitting ratio of the neural network is adjusted by the method above until the stable performance is achieved.

It may happen that the outer samples are too many or too few so that the neural network becomes worse and worse or remains unchanged during the training process. To avoid such a situation, we choose to set a maximum splitting ratio and perform data augmentation for the segmented samples. In our experiment, the maximum splitting ratio was set to 0.2 and the automatically calculated splitting ratio exceeding the threshold will be limited to 0.2. In Ref. [34], three augmentation methods based on the characteristics of modulated signals are considered, i.e., rotation, flip, and Gaussian noise, and remarkable results are achieved. We choose to use a combination of these methods to enhance the outer samples. The enhanced outer samples are randomly chosen at an appropriate amount.

3.3 Training Procedure

The proposed scheme enhances the generalization ability of the network by using multi-task learning and dynamically selects the splitting ratio. The training procedure of the proposed scheme is summarized in Algorithm 1. The input of this scheme are samples of known classes including data and multiple labels. At first, we pretrain the (N+1)-class classifier $f_{OS}(\cdot)$ with N-class data x since there is no samples of unknown classes in the training data. Then we utilize the pretained classifier $f_{OS}(\cdot)$ to evaluate all samples as Eq. (5) and a few samples with the highest score of each class are selected as candidate samples. We continuously disturb the candidate sample toward its adversarial direction of the current network and record the confidence score to approximate a curve. The change point of this curve is modified as splitting ratio ρ if it is appropriate. The samples with confidence scores less than ρ are selected as x_{outer} and the rest are x_{inner}. The data x_{outer} are enhanced to $x_{outer,aug}$ using the method of rotation, flip, and Gaussian noise. The $f_{OS}(\cdot)$ is retrained with x_{inner} served as KKCs and $x_{outer,aug}$ served as UUCs. At the same time, the $f_{CS}(\cdot)$ and $f_{MR}(\cdot)$ with x, y_{CS} and y_{MR} are trained to learn a generalized expression. The loss functions are shown as Eqs. (2), (3) and (4). The $f_{OS}(\cdot)$ is then used to calculate the splitting ratio ρ again until the performance of the open-set classifier is stable. Finally, only the (N+1)-class network is used as the open-set classifier.

Algorithm 1. Proposed scheme

Inputs:
x: Data of KKCs
y_{CS}: Signal type label of KKCs
y_{MR}: Modulation type label of KKCs
Output:
$f_{OS}(\cdot)$: Open-Set Classifier
1: Pretrain the (N+1)-class classifier $f_{OS}(\cdot)$ with x and y_{CS}, where all KKCs are used as inner samples
2: Calculate the splitting ratio ρ of each class using the proposed dynamic method based on $f_{OS}(\cdot)$
3: Modify the splitting ratio and spilt x into two subsets: x_{inner} and x_{outer}. Enhance the data x_{outer} to x_{aug}
4: Train $f_{OS}(\cdot)$ with x_{inner} and x_{aug} that assigned with new labels. Meanwhile, train $f_{CS}(\cdot)$ and $f_{MR}(\cdot)$ with x, y_{CS} and y_{MR} to learn a generalized expression.
5: Return to 2 until the stable performance is achieved.

4 Experiment

In the section, we will firstly introduce the two wireless signal datasets used in our experiment. The evaluation criteria of the proposed method are shown next. Then we describe six baseline methods including four state-of-the-art methods from the literature and two variations with different configurations for comparison. Finally, a number of experimental results and analysis are presented.

4.1 Datasets

A wireless signal dataset collected at 2.4 GHz ISM band by LimeSDR and a publicly available modulation dataset, which are used for evaluating the performance of the proposed model, are detailed in this section. For convenience, we use WS to represent the wireless signal dataset and RML to represent the radio modulation dataset.

The dataset of WS contains 10 kinds of signals that mainly work on the 2.4 GHz unlicensed frequency band, namely Wi-

Fi, ZigBee, Bluetooth, microwave oven, analog video monitor, narrowband digital signal, wideband OFDM signal, game control signal, cordless phone signal and wideband FM signals. We collect the IQ orthogonal data of all classes except for narrowband digital signals and wideband OFDM signals by using a LimeSDR receiver to receive wireless signals from different transmitters. The seven main transmitters are shown in Fig. 4. From top to bottom and left to right, they are microwave oven, ZigBee, smartphone, game controller, analog video monitor, cordless phone and camera. The smartphone is used for transmitting Bluetooth and Wi-Fi signals. The analog video monitor together with the camera is used for creating wideband FM signals. Besides, the narrowband digital and wideband OFDM signal are both generated by MATLAB R2019a, where non-ideal power amplifiers are considered therein. The nonlinearity of the power amplifier is modeled in a memoryless polynomial form. Each class is collected at six scenes including line-of-sight (LOS) and non-line-of-sight (NOS) conditions with different communication distances between the transmitter and the LimeSDR receiver. The synthetic signal is added noise with corresponding degree to simulate six collecting scenes. Table 1 shows the specific dataset collection settings of different signals including the center frequency, bandwidth and communication distance between the transmitter and receiver. Furthermore, each class has 7 500 samples of which there are 1 250 samples for each scenes and the dimensions of each sample are 4 096×2.

▲Figure 4. Pictures of main transmitters used in WS dataset collection

To further verify the performance of the proposed method, we also test it on one public modulation signal dataset. O'SHEA et al.[12] provide two different types of the datasets, both of which are synthetically generated datasets using GNU Radio with commercially used modulation parameters. Some realistic channel imperfections are included in the datasets, including channel frequency offset, sample rate offset, and additive white Gaussian noise along with multipath fading. The "Normal" dataset consists of 11 classes that are all with relatively low information density and are commonly seen in impaired environments. These 11 signals can be used for classification tasks at a high SNR. The "Difficult" dataset contains 24 modulations. These include a number of high order modulations (QAM256 and APSK256), which are used in the real world in very high SNR and low-fading channel environments. Detailed specifications and generation details of the datasets can be found in Ref. [12]. The specific modulations along with the parameter list can be found in Table 2. The dimensions of one sample are 1 024×2. In this paper, we use 4 096 samples each class of one high SNR scene in the Normal dataset to train the proposed network and use samples of different SNR scenes to test the performance of the trained network. We design a related task of distinguishing the modulation type of phase modulation, frequency modulation and amplitude modulation to help the task of modulation recognition learn richer knowledge.

▼Table 1. WS dataset parameters

Signal Types	Scenes	Frequency	Bandwidth	Samples per Classes
Wi-Fi, Bluetooth, cordless phone, wide-band FM, ZigBee, microwave oven, analog video monitor, narrow-band digital signal, wide-band OFDM signal, game control signal	Line-of-sight (1, 3, 5, 7 m); Non-line-of-sight (1, 3 m)	2.442 GHz	20 MHz	7 500

OFDM: orthogonal frequency-division multiplexing WS: the wireless signal dataset

▼Table 2. RML dataset parameters

Normal Classes	Difficult Classes	Sample Length	SNR Range	Samples per Classes
OOK, 4ASK, BPSK, QPSK, 8PSK, 16QAM,AM-SSB-SC, AM-DSB-SC, FM, GMSK, OQPSK	OOK, 4ASK, 8ASK, BPSK, QPSK, 8PSK, 16PSK, 32PSK, 16APSK, 32APSK, 64APSK, 128APSK, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM, AM-SSB-WC, AM-SSB-SC,AM-DSB-WC, AM-DSB-SC, FM, GMSK, OQPSK	1 024	−20 dB to 30 dB	106 496

AM: amplitude modulation
APSK: amplitude phase shift keying
ASK: amplitude shift keying
BPSK: binary phase shift keying
DSB: double sideband
FM: frequency modulation
GMSK: Gaussian filtered minimum shift keying
OOK: on-off keying
OQPSK: offset- quadrature phase shift keying
PSK: phase shift keying
QAM: quadrature amplitude modulation
QPSK: quadrature phase shift keying
RML: the radio modulation dataset
SC: suppressed carrier
SSB: single side band
WC: with carrier

4.2 Evaluation

In the field of open-set recognition, there are N known classes and K unknown classes. The concept of openness is to define how open the problem is[13]. Larger openness corresponds to more open problems, while the problem is completely closed when the openness equals 0. We changed the number of N and K to get different openness in the following experiments. The openness is denoted by O, and its definition is the same as that in Ref. [13] and can be simplified to:

$$O = 1 - \sqrt{\frac{2N}{2N + K}}. \tag{8}$$

The close-set accuracy P is used to evaluate the performance of an close-set recognizer and denoted as

$$P = \frac{1}{m}\sum_{j=1}^{m} I\left(f\left(x^j\right) = y^j\right), \tag{9}$$

where m is the total number of known samples. x^j and y^j represent the j-th sample of known classes and the corresponding label. The balanced accuracy (T) is used to evaluate the performance of an open-set recognizer. T balances the accuracy of unknown classes and unknown classes with the same weights. Accordingly, it is defined as

$$T = \frac{1}{2}\left(P + \frac{1}{n}\sum_{k=1}^{n} I\left(f\left(x^k\right) = y^k\right)\right), \tag{10}$$

where n is the total number of unknown samples. x^k and y^k represent the k-th sample of unknown classes and the corresponding label. In the end, the area under curve (A) is taken into consideration for keeping consistent with prior studies.

4.3 Baseline Methods

We selected five baseline methods including three state-of-the-art methods from the literature and two variations with different configurations for comparison. In the baseline methods, six categories of both datasets are selected as KKCs during the training phase and all categories are used in the inference phase. The networks are basically the same as that in Fig. 2 but with different tasks. The Adam optimizer is adopted among these methods and the batch size is set to 32. The ratio of training set to testing set is set to 4:1.

1) Intra-class splitting (ICS): The ICS method was implemented in Ref. [28]. The pretrained network is similar to the proposed network but only has the N-class classifier. The network with the best performance was saved during 50 pretraining epochs. The splitting ratio was set to 0.2 for both datasets and the training epochs of open-set network was set to 100.

2) Dynamic intra-class splitting (DICS): The DICS method was implemented in Ref. [29]. The hyper-parameters were set the same as those for ICS.

3) Open-set interference signal recognition using boundary samples (OSISR): The OSISR method was implemented in Ref. [25]. The hyperparameter ε used in adversarial-sample generation was equal to 10^{-6} and the corresponding learning rate η and the number of iteration epochs were set to 0.01 and 100. The splitting ratio μ of adversarial samples was selected as 80 for both datasets.

4) Deep CNN-based multi-task learning for open-set recognition (MLOSR): The MLOSR method was implemented according to Ref. [23]. We modified the network structure to fit the sample shape of WS and RML datasets. The hyperparameters were kept as those in Ref. [23]. The MLOSR method is a discriminative method and does not have an open-set classifier. So we just evaluated T and P of this method.

5) ICS with data augmentation (ICS-aug): In order to explore the difference between the proposed dynamic splitting method and the predefined method, we consider ICS-aug the same as the proposed method to get rid of the impact of data augmentation. The method of data augmentation consists of rotation, flip, and Gaussian noise. The hyperparameters were kept the same as those in Ref. [34].

6) The proposed method without MTL (P-w/o MTL): In order to explore the importance of using MTL, we considered to train a network without MTL as a baseline. The difference between using or not using MTL is whether modulation recognition task is employed. Specifically, the loss function of the proposed method without MTL is given as:

$$L_{\text{total}} = \alpha L_{OS} + \beta L_{CS} + \eta L_2, \tag{11}$$

where the symbol meanings are the same as those in the proposed method. The performance of the trained network with and without MTL was measured in new scenes.

4.4 Basic Experiment

Firstly, the proposed method and the other baselines were compared on both the datasets. In each experiment on one dataset, we selected six classes as the known classes used in the training phase and all classes were used in the testing phase to evaluate the capabilities of network. Each experiment was repeated three times and the means and standard deviations (STD) of evaluation were reported.

The results with performance metrics (STD) on both datasets are shown in Table 3. The proposed method outperforms four baseline methods and achieves comparable performance to the proposed method without MTL. Specifically, the proposed method achieved an improvement of T by more than 4% on the WS dataset and by more than 7% on the RML dataset compared with the state-of-the-art method OSISR. The method of ICS-aug has an increase of T by about 2% than OSISR on the WS dataset, which indicates that the operation of data augmentation effectively expands the simulated samples of unknown classes. Meanwhile, the proposed method has better performance of T by about 2% on the RML dataset compared with ICS-aug, which means that the dynamic method of select-

▼Table 3. Results with performance metrics (STD)

Metrics	Dataset	ICS/%	DICS/%	OSISR/%	MLOSR/%	ICS-aug/%	P-w/o MTL/%	Proposed/%
T	WS	91.2(±1.1)	91.5(±0.7)	93.1(±0.5)	81.6(±0.3)	95.0(±0.6)	97.1(±1.3)	**97.2**(±0.9)
	RML	88.7(±3.0)	88.6(±2.3)	90.3(±2.1)	80.3(±0.5)	96.3(±2.1)	**98.0**(±2.1)	97.9(±2.3)
P	WS	92.3(±0.9)	91.6(±0.6)	93.2(±0.4)	**98.8**(±0.3)	95.3(±0.5)	97.2(±1.4)	97.3(±1.0)
	RML	88.3(±2.9)	87.8(±2.1)	91.4(±2.0)	**98.6**(±0.4)	97.5(±2.1)	98.3(±1.9)	98.2(±2.4)
A	WS	95.6(±1.3)	96.0(±1.0)	97.2(±0.5)	-	98.5(±0.9)	99.3(±1.1)	**99.4**(±0.8)
	RML	94.1(±3.1)	94.0(±2.9)	91.3(±3.4)	-	98.8(±2.3)	**99.8**(±2.2)	**99.8**(±2.4)

DICS: dynamic intra-class splitting
ICS: intra-class splitting
ICS-aug: ICS with data augmentation
MLOSR: deep CNN-based multi-task learning for open-set recognition
OSISR: open-set interference signal recognition using boundary samples
P-w/o MTL: the proposed method without multi-task learning
RML: the radio modulation dataset
STD: standard deviation
STWS: the wireless signal dataset

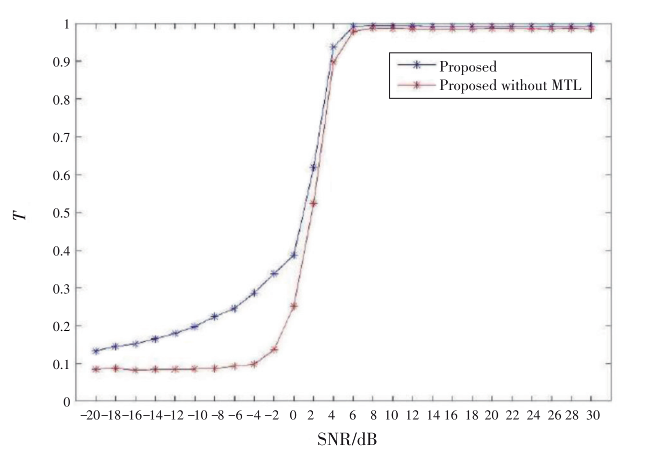
ing the splitting ratio is superior to the predefined method by automatically selecting the suitable splitting ratio of each class. Thereby, we argue that the proposed method can automatically select the appropriate splitting ratio per training period. This means that more precise outer samples are selected for imitating unknown classes, which leads to better performance of the open-set recognizer on more complex datasets.

P is a measurement of the ability of an open-set recognizer to correctly classify a sample from known classes while A is a measurement of the effect of the open-set classifier. As shown in Table 3, P and A show a similar trend as T and the proposed method outperforms the other baseline methods except the method of not using MTL. The values of A are generally larger than those of P and the proposed method seems to be more superior for the RML dataset. Besides, the MLOSR method achieves the best performance of P, due to its use of a close-set classifier to classify known classes.

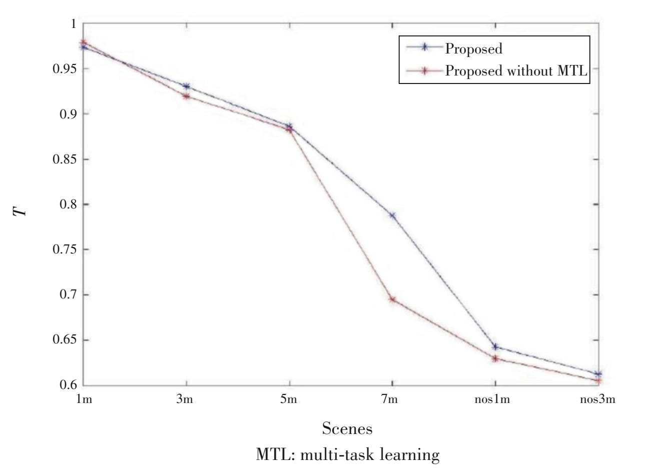
4.5 MTL Experiment

We also compared the performance of the proposed method using MTL and that not using MTL in new scenes. We used part of the WS dataset collected in the scene of LOS condition with 1 m communication distance to train the networks and the samples of the other five scenes were used to test the performance. Different kinds of signals in the training set have different SNRs and the total SNR of the training set ranges from 20 dB to 50 dB. As for the RML dataset, we use the samples with an SNR equal to 8 dB to train the two kinds of networks and test them with other 25 scenes with various SNRs from −20 dB to 30 dB.

The results of the proposed methods with and without MTL trained on one scene and tested on other collecting scenes on two datasets are shown in Figs. 5 and 6. Firstly, on the RML dataset, the networks trained in the 8 dB SNR scene maintained their performance in higher SNR scenes. Secondly, the performance declined rapidly with the decrease of SNR from 4 dB to −4 dB and then tended to be stable on the RML dataset. While on the WS dataset, T also decreased with the increase of communication distance and complexity. Thirdly, the MTL method had a comparable performance with the method not using it in higher SNR scenes but outperforms in low SNR scenes on both datasets. Specifically, the proposed method achieved an improvement of T by about 10% on the scene "7 m" of the WS dataset and by more than 10% on the scene "−2 dB" of the RML dataset. Thereby, we argue that the proposed method can benefit from learning shared ex-



▲Figure 5. T of proposed methods with and without MTL on the radio modulation dataset (RML) dataset



▲Figure 6. T of proposed methods with and without MTL on the wireless signal dataset (WS) dataset pression of a collection of related tasks and improve the performance in new scenes.

4.6 Openness Experiment

Openness is an important parameter in the problem of OSR, which describes how open an OSR problem is. The definition of openness is denoted as in Eq. (8). On the RML dataset, we used six classes from the Normal dataset to train the network and used different numbers of unknown classes from the Difficult dataset to test. Specifically, the number of KKCs were set from 1 to 18. In this case, a larger number of UUCs means larger openness. While on the WS dataset, we used different numbers of classes as KKCs to train the network and the rest were served as UUCs on the WS dataset. The number of KKCs was chosen from 3 to 9 and the corresponding openness was from 0.32 to 0.03.

The results of the proposed method and two baseline methods under different openness on each dataset are shown in Figs. 7 and 8, respectively. It can be seen that the performance of three methods decreases with the increase of openness. This is because that the proportion of KKCs and all classes becomes small so that it is difficult to learn enough knowledge from KKCs. The accuracy of KKCs stays high but the accuracy of recognizing UUCs gets lower and T declines. Besides, the performance of the proposed method outperforms the other two baseline methods regarding T. As discussed before, this improvement is brought by the efficient data augmentation and better robustness of the proposed method that is achieved by dynamic splitting ratio determining.

4.7 Data Augmentation Experiment

In order to solve the problem that there are too few outer samples at the beginning of the training process and to make the experiment in a good direction, we used the method of data augmentation to enhance the split outer samples. The specific methods are basically the same as those in Ref. [34]. In this work, we evaluate the effects of different data augmentation methods on the proposed method under different scenes.

Formally, let (I, Q) represent the original IQ orthogonal signal, which has a length of 1 024 in the RML dataset, and $(\hat{I}, \hat{Q})$ represent the augmented signal. According to the rotation formula in two dimensional planes, the rotated signal is defined as:

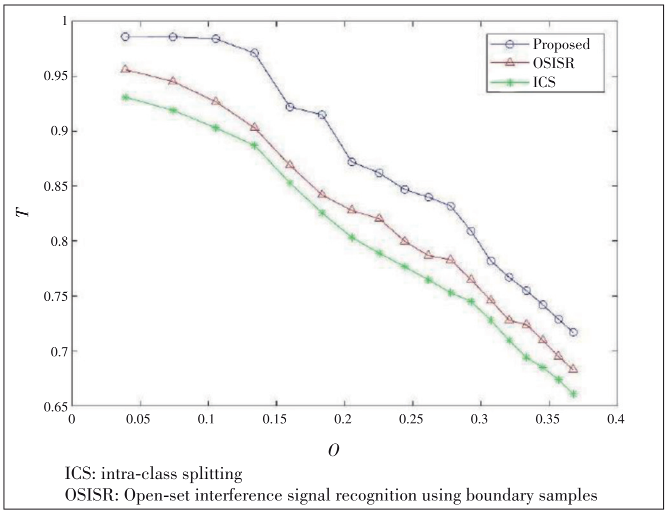
$$\hat{I} = I\cos\theta - Q\sin\theta,\ \hat{Q} = I\sin\theta + Q\cos\theta, \tag{12}$$

where θ is the angle of rotation, which was set to $\pi/2$, π, and $3\pi/2$. The flip of a signal is given as:

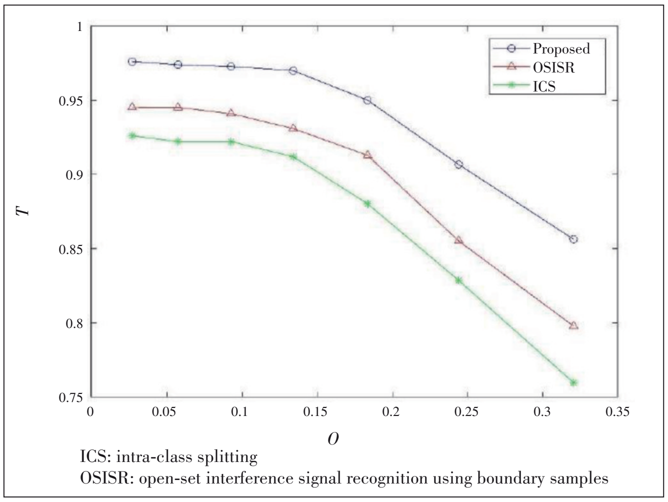
$$\hat{I} = \pm I,\ \hat{Q} = \mp Q. \tag{13}$$

The two types of flips were both used in this study. We also augmented signal samples by adding a Gaussian noise. The standard deviation of the Gaussian noise was set to 0.000 1, 0.000 5 and 0.001. Besides, we also considered a combination of three methods and only part of the augmented samples were randomly selected to keep the data balanced.

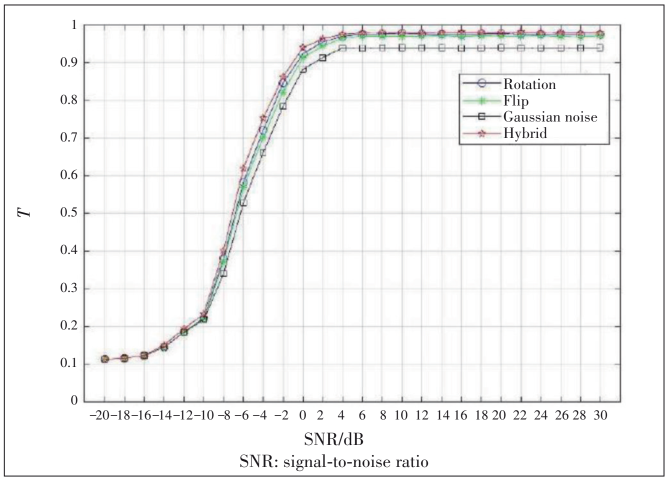
Figs. 9 and 10 show the T of the proposed method using four data augmentation methods trained on different scenes of two datasets. It can be seen that the performance declined under low-SNR or complex scenes. On both datasets, the hybrid method achieves the greatest performance at a higher SNR ($\geqslant -8$ dB). The rotation and flip data augmentation methods achieve secondary performance and the noise data augmentation method performs the worst. Intuitively, adding Gaussian noise reduces the SNR of the original data sample, which in turn generates more signal samples with low SNRs. However, the improvement of the noise method is trivial because the resulting classification accuracy in a low SNR is small. Therefore, the hybrid approach was selected for our experiments.



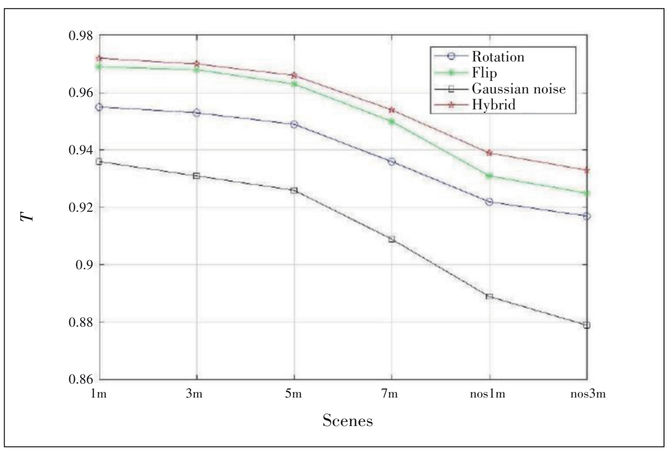
▲**Figure 7. *T* of the proposed, OSISR and ICS methods under different *O* on the radio modulation dataset (RML) dataset**



▲**Figure 8. *T* of the proposed, OSISR and ICS methods under different *O* on the wireless signal dataset (WS) dataset**



▲ **Figure 9. *T* of proposed methods using different data augmentation methods on the radio modulation dataset (RML)**



▲ **Figure 10. *T* of proposed methods using different data augmentation methods on the wireless signal dataset (WS)**

5 Conclusions

In this paper, we propose an MTL network with dynamical splitting ratio determining for wireless signal open-set recognition. Specifically, the dynamic method automatically selects the splitting ratio per class by continuously perturbing class center samples toward the adversarial direction of the current network. The change point of a sample's confidence score during this process is acquired and used to determine the splitting threshold. After adjusting improper splitting thresholds, the original samples of KKCs with higher scores than the threshold are selected as inner samples while the rest are served as outer samples. We use a hybrid data augmentation method to enhance the outer samples, which are used to imitate UUCs later. The network will keep training using the latest splitting data until the performance is stable. Besides, we simultaneously train the original signal classification task and the auxiliary modulation classification task using the MTL method. By learning a shared expression of the related tasks, the network extracts generalized feature and improves the performance loss when applied in a new environment. We conducted our experiments on one wireless signal dataset collected at 2.4 GHz ISM band by LimeSDR and one open modulation recognition dataset. The results of different experiments show the superiority of the proposed method over state-of-the-art methods regarding a compromise of closed set accuracy and rejection capability. The experiments indicate that the proposed method still has poor performance in high openness, although it is better than baseline methods. Therefore, future work could focus on improving the identification accuracy under high openness.

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