A Novel Self-Learning Filters for Automatic Modulation Classification Based on Deep Residual Shrinking Networks

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Abstract

Automatic modulation classification is a critical algorithm for non-cooperative communication systems. This paper addresses the challenging problem of closed-set and open-set signal modulation classification in complex channels. We propose a novel approach that incorporates a self-learning filter and center-loss in Deep Residual Shrinking Networks (DRSN) for closed-set modulation classification, and the Opendistance method for open-set modulation classification. Our approach achieves better performance than existing methods in both closed-set and open-set recognition. In closed-set recognition, the self-learning filter and center-loss combination improves recognition performance, with a maximum accuracy of over 92.18%. In open-set recognition, the use of a self-learning filter and center-loss provide an effective feature vector for open-set recognition, and the Opendistance method outperforms SoftMax and OpenMax in F1 scores and mean average accuracy under high openness. Overall, our proposed approach demonstrates promising results for automatic modulation classification, providing better performance in non-cooperative communication systems.

Keywords: automatic modulation classification , self-learning filter, center loss, DRSN, open-set recognition

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1. Introduction

Automatic Modulation Classification (AMC) is an essential part of cognitive radio in non-cooperative communication systems. It is also necessary for the estimation of the modulated signal parameters , the correct demodulation and reception[1-5]. Therefore, it has been a hot topic of research to make the technology have a better recognition result.

Two general categories of algorithms can be used to solve AMC problems: likelihood-based (LB)[6-12] and feature-based (FB)[13-22]. LB algorithms are derived from three the likelihood ratio tests: average likelihood, generalized likelihood, and hybrid ratio test likelihood. Due to the high computational complexity of the LB-based algorithm and the requirement for relatively complete prior information, it is difficult to achieve in non-cooperative communication.

The FB algorithm was often chosen in the past. The FB-based algorithms which usually base on the following features: moments, cyclostationary , high-order cumulants , and time-frequency distribution. There are also many interesting studies on classifiers, such as decision trees[18], support vector machine (SVM)[19][20], k-nearest neighbor (KNN)[23], and hidden Markov models [24]. For feature selection, many papers have also described a lot of methods in this field, such as particle swarm optimization and genetic algorithm[25].

In recent research, neural networks have been widely used in AMC technology and obtained better recognition results[26]-[31]. Despite the wide use of neural networks in AMC to achieve better recognition results, it has been found that simply using deep learning without proper data preprocessing cannot lead to further improvements in the recognition rate. To address this issue, a data preprocessing method is proposed in the letter[32] to enhance the receptive field of the CNN network and improve recognition accuracy. Additionally, a learnable distortion correction module is introduced in the letter[33] to eliminate carrier frequency and phase offsets, while the paper[34] converts the signal into an image and uses a neural network for recognition.

But in actual noncooperative communication, noncooperative parties often add new modulation methods to the existing communication protocol. This brings new challenges to AMC technology, so this article will classify unknown signals through open-set recognition. In general, the set of signals in closed-set identification is all known, while the open-set signals are partly unknown. There are also some studies in the field of computer vision to solve the problem of unknown target identification. But so far, little research on this problem has been carried out in the field of modulation recognition. In paper[35] the probability of the unknown class is estimated using the deep learning and OpenMAX method for open-set data. For automatic modulation classification, the transmitter usually increases or decreases the modulation method as the communication protocol changes. However, for the receiver using existing networks or other methods only signals with known modulation types can be identified, while nothing can be done for data sets with unknown signals added.

In this paper, a self-learning filter method is proposed for closed-set modulation recognition, which can be added to the front end of the network. The composite loss function of center loss and traditional loss function is utilized in this method, which can also provide effective candidate features for subsequent open-set recognition. In addition, the Opendistance method is proposed for open-set recognition, which utilizes similar probabilities of multi-dimensional features to classify unknown classes. Our main contributions in this paper are as follows.

- This paper proposes a new self-learning filter structure. Through the self-supervised learning of the structure, the filter structure is generated to improve the channel environment of the signal and obtain more easily identifiable signals.

- In this paper, we also use the DRSN network structure, which can effectively improve the accuracy of CNN network for AMC recognition. In addition, for the loss function, we use the combination of the traditional loss function of cross-entropy loss and center-loss to obtain a combined loss function that is more suitable for AMC.
- In this paper, we also discuss the problem of AMC in the field of open-set and propose an OpenMax method (Opendistance). This method is added based on OpenMax to analyze the effective path of the features from center-loss and proposes the optimal open set recognition scheme by combining the two method.

2. Signal Model and Open-set Data Selection

In this section, the overall recognition process framework is presented in **Fig. 1**. The public RadioML2016.10a(RML2016.10a) dataset is utilized to make this letter more convincing.

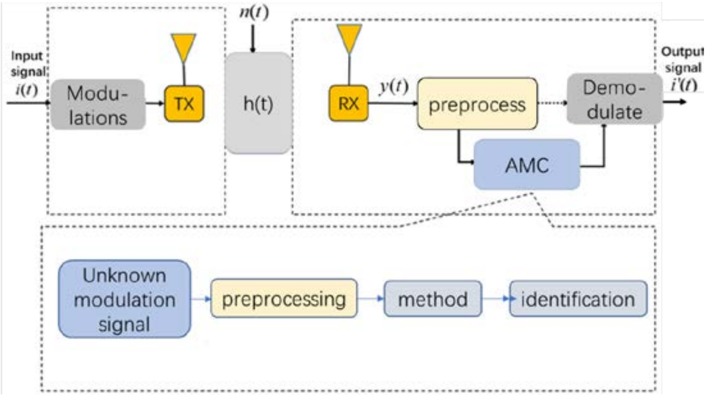


Fig. 1. Modulation identification process framework

2.1 Signal Model in RadioML.2016.10A

Digital signals and analog signals are the conventional modulation methods of communication. Digital and analog signals are modulated differently by controlling the carrier different characteristics, such as: frequency, amplitude and phase. However, the digital and analogue signals change the original signal characteristics through the channel and adding noise, which makes modulation identification more difficult. The modulation types in this paper mainly use the mathematical model of RML2016 signal, as a typical signal model in a complex electromagnetic environment. The received signal can be represented as：

$$s(t) = h(t) * x\left(t - \tau\right) + n(t), \tag{1}$$

Where $n(t)$ is the additive noise received by the signal, $h(t)$ represents the channel impulse response, and $*$ denotes the convolution operation. $s(t)$ is the modulated signal. Furthermore, $x(t)$ is the received signal. τ is the delay of the signal passing through the signal channel.

The dataset RadioML.2016.10A, which is simulated based on GNU Radio. It has the complex channel environment and adding Additive White Gaussian Noise (AWGN) at the end further degrades the signal quality, which brings the data closer to reality. The specific parameters of the signal are shown in **Table 1**. It gives some parameters for the public dataset when creating the signal. These include the number of signal sampling points, multipath, and fading, the channel model and other relevant data. It also contains 11 modulation signals, which includes eight digital modulation schemes and three analog modulation schemes. Each modulated signal contains 20 signal-to-noise ratios SNR ranging from -20dB to 18dB, Each SNR has 1000 samples, and every sample data is a 2 × 128 vector. Therefore, overall set size is: 220000×2×128.

Table 1. RML2016.10a channel parameters

Parameter	Value
Sampling frequency	200kHz
Sampling rate offset standard deviation	0.01Hz
Maximum sampling rate offset	50Hz
Carrier frequency offset standard deviation	0.01Hz
Maximum carrier frequency offset	500Hz
Number of sinusoids used in frequency selective fading	8
Maximum doppler frequency selective	1
Fading model	Rician
Rician K-factor	4
Fractional sample delays for the power delay profile	[0, 0.9, 1.7]
Magnitudes corresponding to each delay time	[1, 0.8, 0.3]
Filter length to interpolate the power delay profile	8
Standard deviation of the AWGN process	$10^{-\frac{SNR}{10}}$

Therefore, the article was selected from dataset RadioML.2016.10A for two reasons:
1. For channel simulation, the dynamic channel model hierarchical block is used, which is defined by frequency offset, sample rate offset, AWGN, multipath, and fading. This makes the signal even more relevant
2.The dataset RadioML.2016.10A is a publicly available dataset and it is more convincing to work on this dataset.

2.2 Open-set Data selection

As the open-set is identified, we should select the known signal class and the position signal class. To ensure a relatively large difference between the known signal set and the unknown signal set, so we select the digital signals as the known signal set and the analogue signals as the unknown signal set. The signal modulation types are mainly shown in **Table 2**:

Table 2. Signal type in RML2016.10a

Signal type	type
digital modulation(known)	8PSK BPSK CPFSK GFSK QAM16 QAM64 QPSK PAM4
analog modulation(unknown)	AM-DSB AM-SSB WBFM

3. Proposed Network and Opendistance Method

3.1 Deep Residual Shrinking Networks

The CNN model employed in this letter mainly uses three network forms: CNN, Resnet(RSN), and DRSN. Resnet(RSN) and DRSN are variants of CNN. Resnet adds a residual module to the CNN network. DRSN adds an attention mechanism and soft thresholding based on the residual module. Soft thresholding is a significant step in many signal denoising methods. Its purpose is to set the features whose absolute value is lower than a certain threshold to zero and adjust other features towards zero, called shrinkage. Soft thresholding formulas and derivatives can be represented as

$$f(x)=\begin{cases} x-\tau, x>\tau \\ 0, -\tau \le x \le \tau \\ x+\tau, x<-\tau \end{cases} \tag{2}$$

$$\frac{\partial f(x)}{\partial x}=\begin{cases} 1, x>\tau \\ 0, -\tau \le x \le \tau \\ 1, x<-\tau \end{cases} \tag{3}$$

The attention mechanism allows the network to ignore other surrounding environmental factors and thus capture more details of the target object. Therefore, using attention mechanisms in the model can enhance useful information and suppress redundant information in data filtering. The basic structure of DRSN is shown in **Fig. 2**.

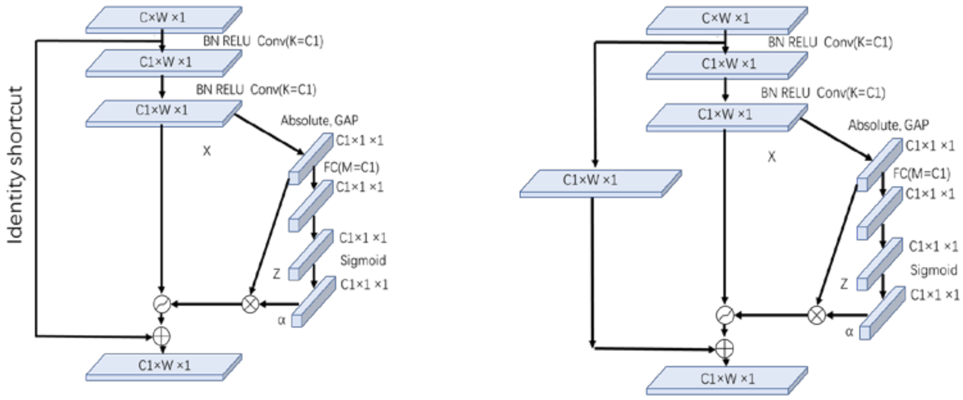


Fig. 2. The basic structure of DRSN

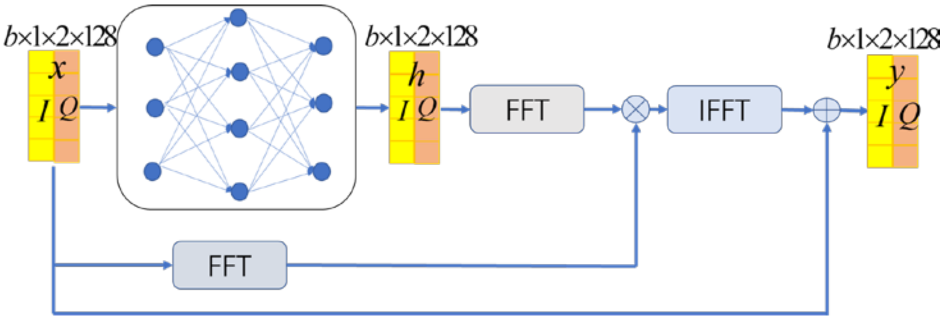
3.2 Self-learning Filter

From **Fig. 5(a)** we can see that increasing the number of layers of the network does not effectively increase signal recognition. Therefore, a more effective method is needed to improve the recognition rate. In this paper, a self-learning filter module is designed based on the concept of filters in communication. It is placed in the front end of the identification network. In communication, filters allow specific parts of the frequency signal to pass smoothly while significantly suppressing other parts of the frequency signal. It can be regarded as a frequency selection circuit, or as a transformation between a response function and a signal spectrum in the frequency domain.

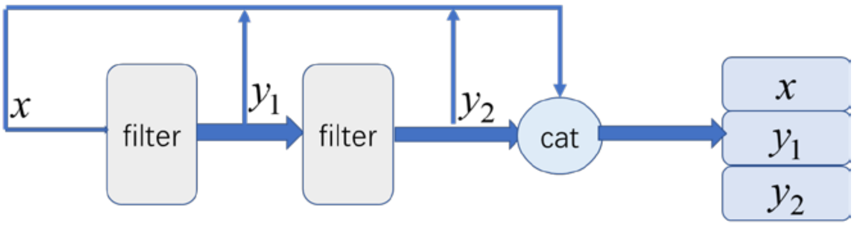
If the input signal is $s(t)$ whose spectrum is $S(\omega)$. For a filter, its input function is $h^{'}(t)$, its spectrum can be represented as $H'(\omega)$.

$$y(t) = s(t) \otimes h^{'}(t) \tag{4}$$

$$Y(\omega) = S(\omega) \bullet H^{'}(\omega) \tag{5}$$



(a) Self-learning filter module



(b) Multi-order filter

Fig. 3. The overall structure of the self-learning filter module

In the paper, a DNN network is used to generate a filter. Since the signal form of RML is $1 \times 2 \times 128$, $s(t)$ and $h^{'}(t)$ are plural forms, their plural forms are $s(t) = s_I(t) + js_Q(t)$ and $h^{'}(t) = h_I^{'}(t) + jh_Q^{'}(t)$, respectively. After fourier transform, multiplying they can get the output $Y(\omega) = S(\omega) \bullet H^{'}(\omega) = Y_{Real}(\omega) + jY_{Imag}(\omega)$. It can be easily obtained via inverse fourier transform the time domain output : $y(t) = y_I(t) + jy_Q(t)$. The overall structure of the self-learning filter module network is shown in **Fig. 3**. Among them, **Fig. 3(a)** is a self-learning filter module, and **Fig. 3(b)** is a multi-order filter(F).

In **Fig. 3(a)**, we choose fully connected layer for the self-learning filter module. the parameters are in **Table 3**.

Table 3. The structure parameters of the Fully connected layer

Layer	Output size
input	Batch_size*2*128
reshape	Batch_size *256
Linear(256,512)	Batch_size *512
Linear(512,512)	Batch_size *512
Linear(256,512)	Batch_size *256
reshape	Batch_size*2*128

In **Fig. 3(b)**, the filter is composed of a Self-learning filter module, and the output of multiple Self-learning filter modules is stitched together to obtain the final input data to the DRSN network.

3.3 Loss Use in the Paper

In this paper, the network uses a double loss function(L) for back-propagation, and the overall loss function can be expressed as:

$$loss = loss_C + loss_{CE} \tag{6}$$

$loss_C$ is center-loss, which provides a class center for each class, and its expression can be expressed as:

$$loss_C = \frac{1}{2N}\sum_{i=1}^{N} | x_i - c_{y_i} |_2^2 \tag{7}$$

$loss_{CE}$ is the cross-loss entropy. If the classification result of the i–th neuron of the network is $\{O_1,\ O_2, ...,\ O_n\}$,and its expression can be expressed as:

$$y_i = \text{Softmax}\left(O_i\right) = \frac{e^{O_i}}{\sum_{c=1}^{i} e^{O_i}} \tag{8}$$

$$loss_{CE} = -\frac{1}{N}\sum_{i=1}^{N} \text{y}_i \log\left(\hat{y}_{\text{i}}\right) \tag{9}$$

The overall recognition network is illustrated in **Fig. 4**. The data is first filtered through a Multi-order filter and then fed into the DRSN network module. The center-loss is applied before entering the fully connected layer, followed by the output from the fully connected layer. **Fig. 4** shows the overall structure of the network.

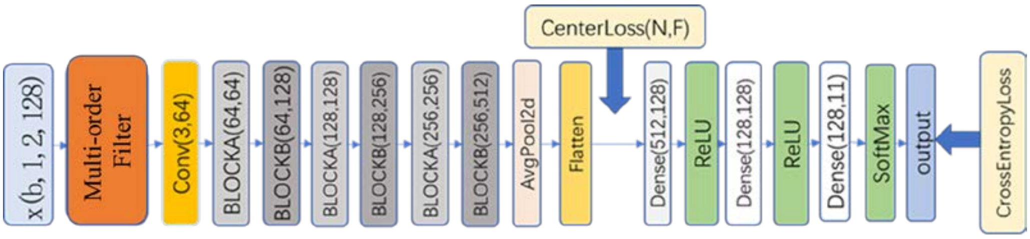


Fig. 4. overall recognition network

3.4 Opendistance Method

For the OpenMAX algorithm, the selected feature map is the first layer of the output. But this layer does not fully represent the signal features, especially when there are few known species. Therefore, a new algorithm is proposed in the paper(Opendistance). However, since the fully connected layers often lead to the loss of some feature information. So the paper selects the data after the flatten layer in **Fig. 4**. Using the feature data can increase the feature sample size. Furthermore, the features are more aggregated due to the center loss is utilized in the network. Assume that the output feature for correct classification in the training sample is known as x.

Table 4. Opendistance-based open set identification algorithm

Algorithm 1	Opendistance based open-set identification algorithm.
Input	Initial data x, y, discriminant threshold μ ,data length N, Known signal class C_i.
Output	signal class C.
1:	$AV = \text{soft}\max(x)$

$\mathrm{MAV}_{i,j}^{\mathrm{train}} = \mathrm{mean}\left(AV_{i,j}^{\mathrm{train}}\right)$

$\mathrm{dist}(i, j,:) = |\ AV_{i,j}^{\mathrm{tain}} - MAV_{i,j}|$.

$\text{dist-max}_i = \max(\mathrm{dist}(i, j,:))$.

$\mathrm{num}_i = \mathrm{sum}((\mathrm{dist}_i^{test} - \mathrm{dist\_max}_i) <= 0)$

$\mathrm{P}_i = \mathrm{num}_i/\mathrm{N}$

$\mathrm{P}_{dist} = \mathrm{Softmax}(\mathrm{P_i})$

$\mathrm{P}_{unkonwn} = \mathrm{OpenMax(y)}$

$\mathrm{P} = [\mathrm{P}_{dist} \bullet (1\text{-}\mathrm{P}_{unkown}), \mathrm{P}_{unkown}]$

if $\mathrm{P}_{dist} \bullet (1\text{-}\mathrm{P}_{unkown}) < \mu_1$ or $\mathrm{P}_{unkown} > \mu_2$

$\quad C = unkwon$

else

$\quad C = kwon$

$\quad$ if $C = kwon$

$\qquad C = C_i$

$\quad$ end if

end if

Step 1: Deflate the features and perform Softmax on them. The equation can be expressed as :

$$AV = \mathrm{soft\,max}(x) \tag{10}$$

Step 2: Based on the classification results, the known data that are correctly classified are obtained.

And the feature centers of different classes can also be obtained according to different classes. The mean value is used as the center point in this letter. The equation can be expressed as :

$$\mathrm{MAV}_{i,j}^{\mathrm{train}} = \mathrm{mean}\left(AV_{i,j}^{\mathrm{train}}\right) \tag{11}$$

Step 3: The distance between each class's center vector and that signal's vector can be found. The equation can be expressed as :

$$\mathrm{dist}(i, j,:) = |\ AV_{i,j}^{\mathrm{tain}} - MAV_{i,j}| \tag{12}$$

In this equation, i represents the number of correctly classified signals.

Step 4: The maximum value of each element of each class from the dist can be obtained. The equation can be expressed as:

$$\text{dist-max}_i = \max(\mathrm{dist}(i, j,:)) \tag{13}$$

Step 5: Let the test set perform to get its dist. The number of elements in the dist less than the max-dist is recorded. The equation can be expressed as:

$$\mathrm{num}_i = \mathrm{sum}((\mathrm{dist}_i^{test} - \mathrm{dist\_max}_i) <= 0) \tag{14}$$

Step 6: The similarity is obtained from the num value, the length N of the data, and the probability of obtaining the degree of similarity.

$$\mathrm{P}_i = \mathrm{num}_i/\mathrm{N} \tag{15}$$

Step 7: Perform Softmax operation on the obtained similarity probability to obtain the recognition probability.

$$\mathrm{P}_{dist} = \mathrm{Softmax}(\mathrm{P_i}) \tag{16}$$

Step 8: Do OpenMax operation in the final result y in the network to obtain the corresponding unknown possibility

$$P_{unkonwn} = \text{OpenMax}(y) \tag{17}$$

Step 9: The final recognition probability is obtained by combining the possibility of the two algorithms with the following formula.

$$P = [P_{dist} \bullet (1\text{-}P_{unkown}),\ P_{unkown}] \tag{18}$$

Step 10: Determine whether it belongs to unknown type by threshold. If not, it will be classified according to the result y .

4. Simulation Results

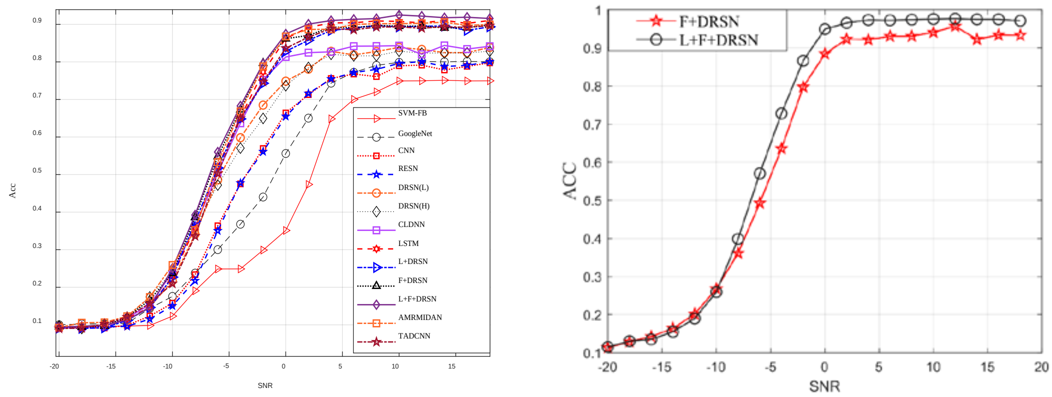
Table 5. The experimental environment for this paper

No	Parameter	Value
	Number of batch size	128
CPU	CPU model	i7-11800
GPU	GPU model and Memory	RTX3070 8GB
Data Scale	Number of samples in RML2016	$11\times 20\times 1000$
Data set	training set ,validation set and test set	6:1:3

In the following experiments, we partition the dataset in 6:1;3, where 60% is the training set, 10% is the validation set and 30% is the test set. Openness is defined as the ratio of unknown signal types to known ones. In **Table 5** presents the data sizes, data division methods and hardware types used in our experiments.

4.1 Average Recognition Rate Comparisons for Close-set

In this section, our proposed identification method is compared with other commonly used methods in closed-set data. In the comparison of network models, we guarantee that the CNN module has the same number of layers.



(a) Accuracy curves of closed-set eleven signals

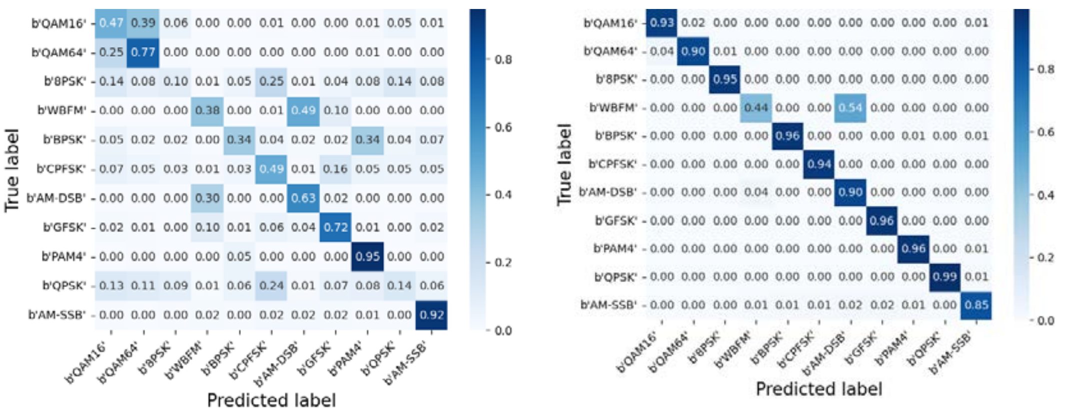
(b) Accuracy curves for the eight digitally modulated signals of the closed-set

Fig. 5. Accuracy curves for closed-set signals

From **Fig. 5(a)**, it can be seen that increasing the number of layers of the network DRSN does not further improve the performance after reaching a certain number of layers (where H and L denote different layers and H denotes a higher number of layers). It can also be seen that the LSTM algorithm has better results than the usual convolutional network, which is because LSTM takes fully into account the continuous relationship of the signal in time. From **Fig. 5(a)**, it can be observed that the proposed self-learning filter method can improve the accuracy of signal recognition. Because it changes the time domain characteristics of the signal through the frequency domain and preserves the original characteristics of the signal through splicing operation, which can further improve the recognition rate through the central loss method. We also compared our method with the two latest approaches [26][27], and our method showed a significant improvement in recognition performance. The comparison shows that using the method of this letter can make the DRSN network exceed the effect of LSTM. Effectively improves the characteristics of DRSN in the time dimension. In open-set identification, since the known signal set only consists of digitally modulated signals, the overall recognition accuracy of the eight digital modulations is shown in **Fig. 5(b)**.

4.2 Confusion Map with Different SNR for Close-set

The confusion diagram depicted in **Fig. 6**, which clearly represents the classification effect of different kinds of signals. The data on the diagonal corresponds to the probability of being correctly classified as observed data. All other data are the probability of being incorrectly classified into other categories of observations. For negative SNRs in **Fig. 6(a)**, PAM4 and AM-SSB are easier to identify when the input signal sequence is at a negative SNRs. The SNRs have a significant impact on the classification results of the 8PSK and QPSK modulation methods. 8PSK and QPSK are very difficult to classify truly at negative SNRs. For non-negative SNRs in **Fig. 6(b)**, significant confusion between QAM16 and QAM64, WBFM, and AM-DSB can be observed. When the SNRs are non-negative, signals using WBFM still cannot be accurately classified. As depicted in the confusion map of confusion map in non-negative SNRs, QPSK is best for recognition at non-negative SNRs, it has a 99% precision rate.



(a) Confusion map for closed-set identification with negative SNRs

(b) Confusion map for closed-set identification with non-negative SNRs

Fig. 6. Confusion map with different SNRs for close-set

For low SNRs, the performance may be affected because the network may not capture the distinguishing characteristics of signals with these modulations through only 128 points, leading to confusion and misclassification.

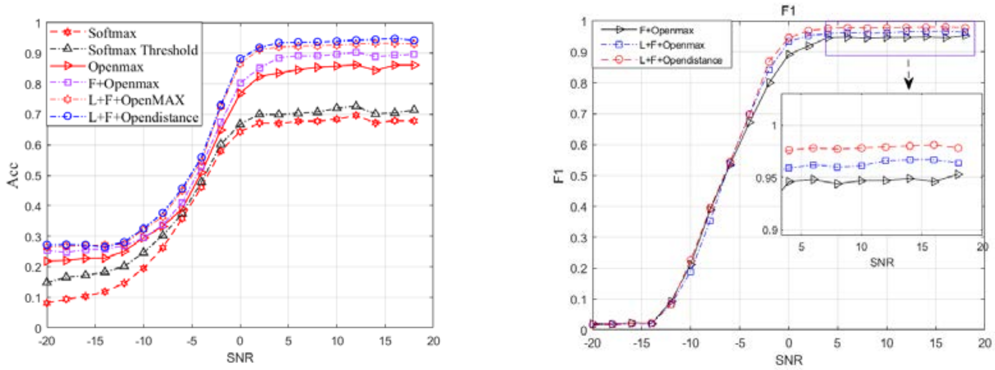
4.3 Average Recognition Rate Comparisons in Open-set

In this paper, digitally modulated signals are treated as a known signal class and analog signals as an unknown signal class. **Fig. 7(a)** shows the recognition rate for open-set recognition, and **Fig. 7 (b)** shows its F1 score. F1 score is a statistical measure of the accuracy of a classification model. It incorporates both the accuracy and recall of a classification model. Its expression can be expressed as:

$$\text{Recall}_i = \frac{TP_i}{TP_i + FN_i} \tag{19}$$

$$\text{Precision}_i = \frac{TP_i}{TP_i + FP_i} \tag{20}$$

$$F1 = 2\times\frac{\text{Precision}_i \times \text{Recall}_i}{\text{Precision}_i + \text{Recall}_i} \tag{21}$$



(a) Accuracy curves for the open-set (b) F1 scores for open-set signals

Fig. 7. Accuracy curves for closed-set signals

It can be seen from **Fig. 7** that the filtering structure and loss function proposed in this letter are better differentiated from the unknown signal by improving the convergence of the known signal. The Opendistance method has a small improvement on the OpenMax method in terms of recognition effect and F1 scores. It is well known that the reduction of data volume is often performed in the DNN network layer so that the final output results in the corresponding number of classifications, which tends to make part of the data information lost. And using Flatten layer in this part of the following two benefits: 1. more data volume, which is a more complete preservation of the characteristics of the data. 2. In this letter here using center-loss, the method makes the data features here more aggregated at the center point.

Table 6 discusses F1 scores of the two methods at different openings. It can be seen that Opendistance is better than OpenMax at large openings. This is because our proposed method has more characteristic parameters to obtain more subtle variability. The main reason is that when OpenMax is used, it is not effective to establish Weibull models for a small number of categories, while Opendistance not only uses Weibull models, but also uses corresponding distances to correct.

Table 6. Mean F1 and Mean Average Accuracy with different degrees of openness

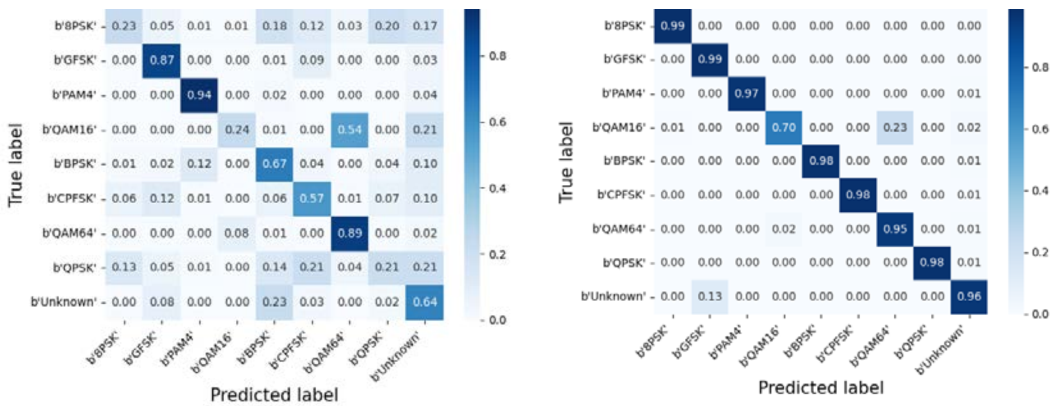
Openness		parameter	**3/8**	**3/6**	**3/4**
Methods	L+F+OpenMax	Mean F1	0.6178	0.5725	0.5408
		MAA	0.6474	0.6178	0.5718
	L+F+Opendistanc	Mean F1	0.6218	0.6088	0.5842
		MAA	0.6562	0.6425	0.6284

Table 7 compares the complexity of the two methods. It can be seen that the complexity of Open-distance test is slightly higher, but the recognition effect is better. There are two reasons for this. Firstly, the method retains more data volume, resulting in a more complete preservation of data characteristics. In addition, in this paper, central loss is used, which makes the data features here more concentrated at the central point. Lastly, this method not only employs OpenMax but also incorporates signal distance classification probability into the center-loss function.

Table 7. complexity comparison for open-set

Method	**Test(s)**	**Parameters(MB)**	**Flops(G)**
L+F+OpenMax	15	9.36	0.096
L+F+Opendistance	19	9.54	0.097

4.4 Confusion Map with Different SNR for Open-set



(a) Confusion map for open-set identification with negative SNRs

(b) Confusion map for open-set identification with non-negative SNRs

Fig. 8. Confusion map with different SNRs for open-set

The confusion diagram depicted in **Fig. 8**, which clearly represents the classification effect of different kinds of signals. The data on the diagonal corresponds to the probability of being correctly classified as observed data. All other data are the probability of being incorrectly classified into other categories of observations.

For the negative SNR in **Fig. 8 (a)**, when the input signal sequence is at the negative SNR, PAM4, GFSK and QAM64 are easier to identify, but QAM16 can easily be divided into QAM64. Modulated 8PSK and QPSK are sensitive to SNR. The classification accuracy of

8PSK and QPSK drops sharply at low SNR. For the non-negative SNR in **Fig. 8 (b)**, obvious confusion between QAM16 and QAM64 can be observed. When SNR is non-negative, the signal with QAM16 is the most difficult to predict. As shown in the confusion diagram of the confusion map in the non-negative SNR, With the exception of QAM16, the accuracy of all signals (including unknown signals) is above 95%. This may be the fact that the deep network cannot differentiate between the subtle differences in signal characteristics between QAM16 and QAM64, or that additional means are needed to distinguish them.

5. Conclusion

This paper proposes an effective AMC method that combines the center loss and the self-learning filter method, which processes the signal in the signal frequency domain and effectively improves the signal recognition rate. In open-sets, center-loss can be effective in removing unknown signals. This is because center-loss allows the ideal baseband modulated signal to be considered as a central vector, and it allows training samples to be clustered towards that central vector. By comparing the accuracy and F1 scores, the proposed method shows a significant improvement in OSC(Open-Set Classification) performance compared to OpenMAX, effectively identifying known signals and unknown ones simultaneously. Although our method requires more complexity than OpenMAX, we believe it is acceptable in OSC. In conclusion, the proposed AMC method with the center loss and the self-learning filter method is an effective approach for signal recognition, especially in open-set scenarios.

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