Mixing Signals: Data Augmentation Approach for Deep Learning Based Modulation Recognition

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Abstract—With the rapid development of deep learning, automatic modulation recognition (AMR), as an important task in cognitive radio, has gradually transformed from traditional feature extraction and classification to automatic classification by deep learning technology. However, deep learning models are data-driven methods, which often require a large amount of data as the training support. Data augmentation, as the strategy of expanding dataset, can improve the generalization of the deep learning models and thus improve the accuracy of the models to a certain extent. In this paper, for AMR of radio signals, we propose a data augmentation strategy based on mixing signals and consider four specific methods (Random Mixing, Maximum-Similarity-Mixing, $θ$–Similarity Mixing and n-times Random Mixing) to achieve data augmentation. Experiments show that our proposed method can improve the classification accuracy of deep learning based AMR models in the full public dataset RML2016.10a. In particular, for the case of a single signal-to-noise ratio signal set, the classification accuracy can significantly improved, which verifies the effectiveness of the methods.

Index Terms—Deep learning, Automatic modulation recognition, Data augmentation, Mixing Signal

1. INTRODUCTION

AUTOMATIC modulation recognition (AMR) are widely used in wireless communication system [1]. In modern communication environment, radio signals are showing trends such as heavy load, wide spectrum range, and high recognition accuracy requirements, which makes traditional feature extraction based AMR difficult [2]. Especially, in the modern communication environment, radio signals are showing trends such as heavy load, wide spectrum range, and high recognition accuracy requirements, which makes that feature extraction and recognition based on prior knowledge face many difficulties. In recent years, deep learning has also reached new high, exerting its advantages in various fields [3]. Deep learning model can automatically extract features by processing and integrating big data, which coincides with the problem of AMR. Therefore, more and more scholars are beginning to use deep learning algorithms to distinguish the modulation types of radio signals [4]–[8], so signal recognition tend to be automated and avoided manual feature extraction based on experience, improving the ability to recognize complex radio signals finally.

Deep learning based methods often relies on a large amount of data for model training, however, the collection and labeling of real data usually consume a lot of costs, thus data augmentation, as a software-based method, becomes a convenient and effective strategy for creating large-scale dataset [9]. Traditional data augmentation generates new data through simple transformations such as rotation, cropping, slicing and warping [10]–[13] of the real data, this kind of methods are simple and convenient, but have little effect in improving the generalization of the model because they only changes little on the existing data. The deep learning based data augmentation usually use adversarial generative network (GAN) [14]–[16] or transfer learning [17]–[19] to synthesize new data, however, these generative models themselves also require a lot of data to train, so when the amount of real data is small, this kind of methods are also not very effective. Between these two kinds of methods, for image recognition, there is one kind of methods that based on the multi-sample mixing, such as Mixup [20], these methods create new samples by mixing multiple existing samples, increasing the diversity of samples compare with simple sample transformation and are simpler and more convenient compared with the deep learning methods.

In this paper, we focus on the data augmentation of radio signals for the task of AMR. At present, there are few researches on data augmentation of radio signals, mainly through rotation, flip [21] and GAN [22], [23] to expand the dataset, but the signals generated by these methods will face the problem mentioned above, especially when the amount of real data is small. Therefore, inspired by the multi-sample mixing strategy used in image data augmentation, for AMR of radio signals, we propose data augmentation framework based on signals mixing according to the characteristics of signals, which can improve the performance of deep learning based AMR models, especially when the amount of real data is small. The main contributions of this paper can be summarized as follows:

1) We propose Mixing Signals, a simple but effective data augmentation strategy for signals, which generate a large number of samples of known samples by pairwise mixing the samples of the same modulation type.
2) Under Mixing Signals strategy, four specific methods are proposed to achieve the pairwise signals mixing. We found that these methods can effectively improve the classification accuracy of the deep learning model, especially when the amount of real dataset is less than full dataset (at the scenarios of single SNR).
3) The effectiveness of these methods are explored on dif-

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different scenarios and models, and the modulation recognition accuracy of the deep learning model is increased by more than 10% with the samples of single SNR. What’s more, comparing with the traditional methods (flip, rotation, gaussian noise) to comprehensively, we evaluate the practicability of various signal-oriented data augmentation methods and analyze the difference in timing and distribution of samples before and after data augmentation.

The rest of paper is structured as follows. Sec. II introduces the automatic modulation recognition and data augmentation techniques in recent years. In Sec. III, we present the details of our methods and principle. Sec. IV shows the simulation setting and results with analysis. Finally, we conclude the paper and introduce future work in Sec. V.

II. RELATED WORKS

A. Automatic Modulation Recognition

To overcome the problems existing in the long-distance data transmission, the radio signals must be modulated to load the signal spectrum into the high-frequency channel for transmission. Then the receiver analyzes the modulation type of the high-frequency signal through the AMR algorithm, so as to demodulate the signal to realize long-distance transmission. Traditional AMR are typically categorized into likelihood-based methods [24], [25] and feature-based methods [26], [27]. The former is based on hypothesis theory, which analyzes the signal cumulant and compares it with a given threshold for classification. Although it has a complete theoretical foundation, in practical applications, it is limited to a large amount of calculation and the challenge of handling diverse real samples. The latter can identify the received signal in the absence of prior information by extracting the instantaneous amplitude, phase and frequency, Fourier [28] and wavelet transform [29] of the signal, and then choose a suitable classifier for identification. But this method requires high measurement accuracy of feature parameters and is sensitive to noise, so it has low efficiency in engineering.

With the rise of deep learning, deep neural networks (DNNs) have been widely used in many fields such as computer vision [30], machine translation [31] and speech recognition [32]. Many researchers are also combining modulation recognition with deep learning to offer new ideas for solving the difficulty of modulation recognition [4]. O’shea et al., has applied deep learning to signal classification earlier, and proposed an end-to-end Convolutional Neural Networks (CNN) in the literature [3]. They put the modulated signal into the model and get its modulation type by residual block. Huynh-The et al. [6] proposed the MCNet. The network architecture is designed several specific convolution blocks to learn the correlation of spatiotemporal signals through different asymmetric convolution kernels. Xu et al. [7], proposed a novel three-stream deep learning framework to extract the features from individual and combined in-phase/quadrature(I/Q) symbols of the modulated signals. In addition to using the original signal directly, recent studies have included methods for converting the signal to another modality. For example, the SigNet proposed by Chen et al. [33], which adopts a signal-to-matrix operator to convert the original signal into a square matrix, and then combines it with CNN to achieve the task of modulation recognition. Xuan et al. [34] introduced signals into the field of graph machine learning, and achieved the goals by Adaptive Visibility Graph (AVG) algorithm, which aims to adaptively map signals into graphs. Different from popular CNNs, the bidirectional long short-term memory network (DCN-BiLSTM) [8] can extract the contextual information of signals well and address the long-term dependence problems.

B. Data augmentation

Data augmentation is a method that can reduce over-fitting and improve the generalization ability of the model. It is widely used in the training process of neural network models [35]. This method only needs to process the training data to expand the dataset to alleviate many problems such as small amount of data and unbalanced samples, thereby improving the robustness of the model.

For image classification tasks, general data augmentation includes rotation, scaling, cropping, and translation [21]. At present, data augmentation based on multiple samples have gradually attracted attention. Mixup proposed by Zhang et al. [20] and CutMix proposed by Yun et al. [36] are all based on combining multiple samples with prior knowledge to construct neighbors of real samples for effectively expanding new training samples. In addition to these methods by mixing samples, data augmentation based on machine learning have also received attention, such as GAN [14], style transfer [17] to generate new samples, and AutoAugment [37] algorithm to learn the best augmentation strategy by reinforcement learning (RL).

For time series data augmentation, time domain transformation is the most direct data augmentation method for time series data, mainly including Window slicing, Window warping, Magnitude warping, Jittering, etc. Window slicing [13] randomly crops the time series and interpolates the time series back to the original length. Window warping [38] is a unique time series augmentation method, which selects a random time range, then compresses (down samples) or extends (up samples), while other time ranges remain unchanged. Similar to window warping, Magnitude Warping [13] is to multiply the magnitudes at the beginning of any position by a certain magnitude. Noise injection is a method by injecting small amount of noise into time series without changing the corresponding labels. This includes injecting Gaussian noise, spike, step-like trend, and slope-like trend, etc [39].

Different from image and basic time series, thanks to radio signal classification requires more prior knowledge, the current research of signal augmentation is limited, mainly including rotation, flipping, adding Gaussian noise [21] and the using ACGAN, mentioned by TANG et al. [22], to generate new constellation diagram for the improvement of model’s robustness. Haradal et al. [15] proposed a method for generating time series data based on GAN, and enhanced the classification of biological signals. However, when the data set is short, GAN cannot learn the data distributions of samples, which
leads to a lack of realism in the generated samples. There are also many problems existing such as unstable training, disappearance of gradients and mode collapse, so GAN is not suitable for insufficient radio signal dataset.

III. METHOD

In this section, we introduce the details of Mixing Signals (MS). Firstly, we introduce the AMR task and the overall framework of using MS for AMR data augmentation, then, three specific methods are introduced to achieve MS for new signal generation, and finally, we point out the principle of MS to analyze the reason for its effect.

A. Automatic Modulation Recognition

Usually a communication system includes a transmitter, a channel and a receiver. The input symbol $s(t)$ is converted into a transmission signal by the modulation function $F$, and then the signal is transmitted to the receiver through the signal $h(t)$. The obtained signal can be shown as

$$x(t) = F(s(t))h(t) + v(t)$$

where $v(t)$ is Additive White Gaussian Noise (AWGN). AMR seeks to obtain the modulation function $F$, which serves as the basis for demodulation, which can be seen as a multi-class classification problem of radio signals.

Radio signals are modulated by I/Q modulators and thus can be represented by two channels of I/Q, where I is in-phase, Q is quadrature. I/Q signal is defined as:

$$x(t) = I(t) + jQ(t) = e^{j\varphi(t)}$$

from which a $L$-length signal can be sampled as:

$$\begin{bmatrix}
I = [i_1, i_2, \ldots, i_L] \\
Q = [q_1, q_2, \ldots, q_L]
\end{bmatrix} \text{ and } x = \begin{bmatrix} I \\ Q \end{bmatrix}$$

Therefore, in AMR task, a signal sample is represented by $(x, y)$ with $x \in \mathbb{R}^{2 \times L}$ and its modulation category label $y$. Then, we feed the sample $x$ into the deep learning model $f$ to get the predicted label $\hat{y}$, based on which we can infer the modulation function $F$.

B. Data Augmentation by Mixing Signals

The overall framework of data augmentation by mixing signals is shown in Fig. 1. Specifically, we use MS to largely increase the size of training set, so as to better fit the data distribution and further improve the generalization ability of the DNN model in the test process. In particular, we propose the following three MS methods.

1) Random Mixing (RM): This method mixes two training samples of the same class to generate two new samples by randomly slicing, as shown in Fig. 2. We define the mixing operation as

$$\begin{align*}
\hat{x}_A &= M_A \odot x_A + (1 - M_B) \odot x_B \\
\hat{x}_B &= (1 - M_A) \odot x_A + M_B \odot x_B \\
\hat{y}_A &= \hat{y}_B = y_A = y_B
\end{align*}$$

where $(\hat{x}_A, \hat{y}_A)$ and $(\hat{x}_B, \hat{y}_B)$ are two newly generated samples, while $(x_A, y_A)$ and $(x_B, y_B)$ are two original ones. $\odot$ is element-wise multiplication to multiply the elements at the corresponding positions. $M_A, M_B \in \{0, 1\}^L$ are the binary mask for $x_A$ and $x_B$, where the elements $M_A(p_A + i) = M_B(p_B + i) = 1$ for $i = 0, 1, 2, \ldots, l$ and the others are set to 0. Note that $l$ could be any integer in $(0, L)$, but in practice, it is better to be close to $L/2$ in order to make the original signals mixing as much as possible, so as to generate distinguishing descendants. Once $l$ is settled down, the parameters $p_A$ and $p_B$ are then chosen in $[0, L-l]$. Typically, modulation changes the amplitude and frequency of the carrier signal, exchanging segments will affect these two properties little. Therefore, RM can preserve the original modulation type of the signal by mixing the samples of the same category and allows the model to learn features more effectively.

2) Maximum Similarity Mixing (MSM): Here, we further consider the similarity between the exchanging signals. We argue that the newly generated signals could be more consistent with the original ones, if the more similar parts are exchanged, and thus may benefit the subsequent classification task. Denoting $T_A$ and $T_B$ as the exchanging parts of $x_A$ and $x_B$, respectively, which have the same length $l$, we seek to maximize their similarity, or minimize their distance, as following:

$$\arg \min_{D(T_A, T_B)} D(T_A, T_B)$$

We then obtain the following MSM method, by considering definition of distances between vectors. Here, we use DTW as metrics. Note that DTW changes the alignment between time series data points from "one-to-one" to "one-to-many"
of Euclidean distances to accommodate phase shifts and amplitude changes between time series.

DTW-MSM: This algorithm \cite{40} uses dynamic programming to calculate the degree of alignment of two time series data.

\[ D(T_A, T_B) = DTW(T^i_A, T^i_B) \]  \hspace{1cm} (6)

Then, according to the recursive formula (9), we can calculate the solution from \( DTW(T^i_A, T^i_B) \) to \( DTW(T^i_A, T^j_B) \), one by one.

\[ D(T_A, T_B) = DTW(T^i_A, T^j_B) + \begin{cases} DTW(T^{i-1}_A, T^j_B) \\ DTW(T^i_A, T^{j-1}_B) \\ DTW(T^{i-1}_A, T^{j-1}_B) \end{cases} \]  \hspace{1cm} (7)

And the distance corresponding position of two signals is defined as

\[ dis(T^i_A, T^j_B) = \sqrt{|T^i_A - T^j_B|^2} \]  \hspace{1cm} (8)

Through the two-steps grid searching, we can get a more accurate global optimal solution, so that any two signals can be mixed to expand dataset and achieve the purpose of improving the comprehensive performance for the classification model.

3) \( \theta \)-Similarity Mixing (\( \theta \)-SM): To compensate for the pros and cons of random mixing and Maximum Similarity Mixing, we introduce a hyperparameter \( \theta \) to evaluate the similarity of swapped region, called \( \theta \)-Similarity Mixing. This method aims to find a balance between disordered signals and optimal signals, so that the augmented dataset contains both the regularization of random signals and the authenticity of the original data.

For any two samples to be mixed, we randomly select two signal segments \( T_A \) and \( T_B \), and then calculate their similarity \( D(T_A, T_B) \) by DTW. If its similarity \( D \) is less than a given parameter \( \theta \), the signal segment is mixed. Obviously, with the gradual increase of \( \theta \), the exchanged segments are no longer constrained by the similarity, making it tend to RM. Meanwhile, with the gradual decrease of \( \theta \), the exchanged segments tend to be consistent, and the method will evolve into MSM.

4) \( n \)-times Random Mixing (nRM): MSM and \( \theta \)-Similarity Mixing describe the similarity from the amplitude, frequency and other features of the signal itself, which means that two samples mix once. Therefore, we further explore the feature diversity of data and extend the RM method. On the basis of random mixing, we use multiple mixing to make the samples contain more modulation information, so it’s called \( n \)-times Random Mixing (nRM). Method As shown in Fig.3, we perform multiple iterations over the initial signal by MS.

Just like RM, we further break up the original signal. We find that the performance of the model is mainly restricted by the amplitude and frequency of the carrier signal, and its timing characteristics have little effect on modulation recognition. Therefore, this method is still valid for AMR tasks.

In this section, we evaluate MS for its performance to improve the classification models on radio signal datasets.

\[ \square \]

IV. SIMULATIONS

In the field of computer vision, there are currently Mixup \cite{20}, Cutout \cite{41}, CutMix \cite{36} and other methods. Among them, although Mixup makes full use of the pixels in the images, it will introduce unnatural artifacts. And Cutout makes the model to focus on the parts with poor discrimination in the object, but does not make full use of all the pixels, which reduces the training efficiency. CutMix ensures that two objects can be identified from the partial attempts of a single image by sharing activation, so as to improve training efficiency.

Since there are no obvious multiple objects in the signal sample, and usually its information of frequency and phase is contained in the waveform. So some of its features also exist in the whole waveform, rather than in the parts. If we still adopt the mode of sharing the active object, the data may be introduced noise information. More seriously, this will lead to a fundamental change in the type of modulation, especially in FM signals. Therefore, we are inspired by the two aspects and adopt the same object fusion for electromagnetic signals to prevent serious distortion of the waveform.

In order to observe the differences between the various methods, we made a visual analysis of the 18db signal in the RML2016 dataset. The constellation diagram is shown in the Fig.4 from top to bottom, the order is original, RM-based, MSM-based, \( \theta \)-SM-based and nRM-based signals. From the Figure, we find that although mixing signals changes the sequence of the signal, it doesn’t affect the modulation type of the signal to a certain extent. Compared with rotating and flipping, mixing signals maintains the original channel characteristics based on the combination of real samples, because of which all mixing signals maintain high similarity with the original signals. So, generated samples is effective to enhance the generalization ability of DNN.
A. Dataset, scenarios and methods

1) Dataset: We evaluate the proposed data augmentation strategy with the public dataset RML2016.10a [42]. The dataset is simulated by GNU Radio, contains 11 modulation types and 20 Signal to Noise Ratio (SNR) levels ranging from -20dB to 18dB. Each sample has 128 sampling points and IQ channels. We divide the dataset into training set and test set according to the ratio of 4:1, the training set and test set contain 176,000 and 44,000 signal samples.

2) Scenarios: Specifically, we set up two scenarios to verify our methods:

- **Scenarios I:** Simulation with partial training samples based on a single signal-to-noise ratio. Since most models cannot be effectively trained on low signal-to-noise ratio signals and data with low signal-to-noise ratios are of little value in practical applications, in this simulation, we ignore the low SNR (less than -6 dB) samples, and choose three different levels of SNR, -6dB, 0dB, 10dB and 18dB respectively, as the research target. In order to set up partial training samples scenario, we select the -6dB, 0dB, 10dB and 18dB samples in the training set respectively as three new training sets, and all test samples of -6dB, 0dB, 10dB and 18dB are set to the corresponding test set respectively.Each training set size is 8800 (800 samples for per modulation type) and each test set is 2200 (200 samples for per modulation type).

- **Scenarios II:** Simulation with full training set, which means the training set size is 176000 and test set size is 44000.

For the former, we verify the effect of our methods in the case that only a part of real data can be obtained, such case is more in line with the application scenario of our proposed methods, and for the latter, we verify the effect of our methods in the case of relatively sufficient real data.

B. Influence of some hyperparameters on mixing signals results

In order to maximize the benefits of the MS strategy, we firstly conduct a simple analysis of the hyperparameters to
determine more appropriate values, which are used as the basis for the experiments. We mainly analyze the hyperparameter length of fragment \( l \), enhancement factor \( N \), similarity threshold \( \theta \) for \( \theta \) – Similarity Mixing and the times of mixing \( n \) for nRM. Especially for parameter \( N \), it’s obvious that deep learning model get preciser and robuster performance with the increasing of the enhancement factor. However, these hyperparameters necessarily have reasonable values to balance the performance and training efficiency, which is the goal of the next experiments.

For MS, hyperparameters \( l \) and \( N \) affect all MS strategies, so we experiment with controlled variables at first. To evaluate the effect of \( l \) on this method, we fix the enhancement factor \( N \) and simulate in scenario I. In order to fully reflect the MS methods, we increase the amount of enhanced samples to 4 times of the initial dataset, which means the enhancement factor \( N = 5 \). Then, We traverse the ratio of the length of the mixing region for the total signal length \( L \) with a step length of 5%, and use the partial dataset(RML2016.10a) to conduct multiple experiments. Ultimately, we compare the average classification accuracy with different experiments to select a appropriate value. As shown in Fig[5] with the gradual increasing of \( l \), the recognition capability of the model presents a trend of firstly rising and then falling. Especially, when the proportion is 0.5, the new signal sample at this time preserves more features of the two original signals before and after Mixing Signals, such as the key information of frequency and amplitude, so the generalization ability of the model reaches the extreme value. Therefore, in order to obtain a more superior classification model, we set the proportion of \( l/L \) to 0.5 in the next MS experiments.

Secondly, we continue to analyze the enhancement factor \( N \) on the basis of \( l/L = 0.5 \) on the first scenarios. Among them, rotation gradually expands the dataset at fixed angles, and MS randomly selects two samples of the same category for mixing. In this section, We evaluate the influence of \( N \) on different methods in the dataset, and the average classification accuracy is shown in Fig[6]. Since the CNN cannot learn operations with the rotation of large angles, rotation takes advantage when the enhancement factor is low. However, with the increase of the enhancement factor, the nonlinear activation in the model has a regular effect on the rotation of smaller angles, so that the rotation with denser angles can no longer compensate for the defects of the model, resulting rotation has little effect on the model. And MS can still make the model obtain more detailed recognition patterns by expanding the amount of data, especially while the enhancement factor \( N = 13 \), the enhancement effect is more outstanding and we take this way as the basis of the following experiment.

For the hyperparameter \( n \) in nRM, we adopt the same way, take scenario I as an example, set \( N = 13 \) as baseline. When the length of the mixing region is small, the method may have the situation that the mixing region fail to overlap, which is inconsistent with the situation that the mixing region overlaps. Therefore, we consider the influence of the length \( l \) of the mixing region and the number of mixing \( n \) on the method, the result is shown in the Fig[7]. In the Figure, the x-axis is the mixing length ratio \( l/L \), and the y-axis is the number of mixing \( n \). It can be found from the heatmap that with the increase or decrease of \( l \), the unfused region gradually shrinks, and the method tends to RM, so the performance reach its best when \( l/L=0.5 \), which is consistent with the experimental results of the influence of the parameter \( l/L \). However, the number of mixing \( n \) has a weak influence on this method, so we take the parameters \( l/L = 0.5 \) and \( n = 4 \) when the model performance reaches the best (91.82%).

C. The performance of MS on the first scenarios

1) Comparison with other data augmentation methods: In this section, we compare flip, rotation and MS on the first scenarios with different models, such as CNN, ResNet and MCLDNN. Note that flip only includes horizontal flip and vertical flip, thus, its enhancement factor \( N = 3 \). Table[4] shows that the comparison results of the augmented models and the original models with proposed method and others. It can be found that the MS method achieves similar classification accuracy comparing with flip and rotation, and can achieve an accuracy improvement of 1.82%~13.19% on partial samples,
which verifies the MS can improve the classification performance of the Convolutional Neural Network. By pairwise combining signal samples, more features are merged into one sample, so that the timing features can be better captured by the model. Especially in Fig. 6, we found that with the increasing of enhancement factor, rotation fail to get better results.

Comparing CNN and ResNet, for models with simpler structures, the effect of mixing signals is not as good as rotation, such as CNN, which is easier to capture features with obvious changes, but cannot easily capture changes in signal time-domain exchange. Furthermore, compared with complex models, such as ResNet and MCLDNN, these models are good at mining the information in the data itself without requiring more complex samples, which makes the MS better than Flip and Rotation. From the perspective of model depth, we compare CNN, MCLDNN and resnet, and we can find that this method(MS) is more suitable for deep networks. Under the action of convolution operation, the receptive field obtained by the high-dimensional features of the shallow network is smaller, which makes the model pay more attention to local features, while the deep network pays more attention to the overall features. Then MS can be understood as a regular term that introduces local features, so that the deep network (ResNet) takes into account both the whole and the local, while the shallow network pays more attention to the local. So it is obvious that ResNet can obtain more knowledge, which also supports the experimental results of more accuracy improvement.

Furthermore, in order to reflect the influence of the data augmentation method on low SNRs, we retrain the full-sample pre-trained model to enhance the generalization ability of low SNR signal classification. The results are shown in Table II. We still test CNN, ResNet, and MCLDNN. In the case of low signal-to-noise ratio, data augmentation has little benefit, and the impact of noise cannot be offset by expanding the dataset.

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TABLE I
Comparison result of proposed method and others on partial dataset

| Model    | SNR  | w/o data augmentation | Flip | Rotation | Gaussian noise | RM    | Mixing Signals(MS) | θ-SM | nRM    |
|----------|------|-----------------------|------|----------|----------------|-------|-------------------|-------|--------|
|          | -6dB | 51.14%                | 47.91%|          | 50.41%         | 54.59%| 54.18%            | 53.27%| 59.64% |
|          | 0dB  | 66.68%                | 70.14%| 72.77%   | 69.09%         | 71.18%| 69.82%            | 71.77%| 74.55% |
|          | 10dB | 72.23%                | 75.19%| 80.14%   | 73.32%         | 76.09%| 74.05%            | 77.36%| 78.00% |
|          | 18dB | 71.45%                | 74.86%| 81.45%   | 73.18%         | 76.14%| 76.05%            | 77.46%| 82.23% |
| CNN      | -6dB | 61.86%                | 60.41%|          | 65.46%         | 60.41%| 63.96%            | 61.32%| 62.68% |
|          | 0dB  | 77.27%                | 80.86%| 88.59%   | 74.27%         | 88.68%| 85.18%            | 82.91%| 86.50% |
|          | 10dB | 80.64%                | 84.91%| 84.86%   | 73.09%         | 89.55%| 92.86%            | 83.36%| 88.36% |
|          | 18dB | 78.64%                | 85.05%| 85.18%   | 67.05%         | 88.59%| 87.18%            | 88.23%| 91.82% |
| ResNet   | -6dB | 62.68%                | 65.14%|          | 63.00%         | 64.09%| 64.91%            | 64.09%| 64.32% |
|          | 0dB  | 81.43%                | 77.86%| 81.77%   | 80.18%         | 84.50%| 83.73%            | 83.14%| 84.55% |
|          | 10dB | 83.86%                | 84.41%| 91.36%   | 85.68%         | 91.68%| 88.91%            | 90.05%| 90.36% |
|          | 18dB | 83.09%                | 84.95%| 90.91%   | 86.18%         | 90.09%| 91.82%            | 90.90%| 90.86% |
| MCLDNN   | -6dB | 62.68%                | 65.14%|          | 63.00%         | 64.09%| 64.91%            | 64.09%| 64.32% |
|          | 0dB  | 81.43%                | 77.86%| 81.77%   | 80.18%         | 84.50%| 83.73%            | 83.14%| 84.55% |
|          | 10dB | 83.86%                | 84.41%| 91.36%   | 85.68%         | 91.68%| 88.91%            | 90.05%| 90.36% |
|          | 18dB | 83.09%                | 84.95%| 90.91%   | 86.18%         | 90.09%| 91.82%            | 90.90%| 90.86% |

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TABLE II
Comparison result of proposed method and others on low SNRs

| Model    | SNR  | w/o data augmentation | Flip | Rotation | Gaussian noise | RM    | Mixing Signals(MS) | θ-SM | nRM    |
|----------|------|-----------------------|------|----------|----------------|-------|-------------------|-------|--------|
|          | -10dB| 30.05%                | 32.73%| 32.00%   | 30.68%         | 33.05%| 32.86%            | 31.23%| 35.32% |
|          | -18dB| 10.27%                | 11.05%| 10.64%   | 10.59%         | 10.96%| 10.73%            | 10.36%| 11.55% |
| CNN      | -10dB| 38.86%                | 38.73%| 37.73%   | 38.77%         | 39.64%| 39.09%            | 39.27%| 39.73% |
|          | -18dB| 13.14%                | 13.05%| 12.23%   | 12.32%         | 13.46%| 12.64%            | 12.64%| 13.00% |
| ResNet   | -10dB| 40.32%                | 39.73%| 38.00%   | 38.77%         | 40.14%| 39.14%            | 40.46%| 38.55% |
|          | -18dB| 12.09%                | 11.86%| 11.50%   | 11.46%         | 12.36%| 11.96%            | 11.14%| 11.86% |

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Fig. 7. The influence of $l/L$ and $n$ for nRM on 18dB dataset.
2) Comparison with coupled methods: In the previous section, we explore the performance of individual augmentation methods on the model. In this section, we explore whether there is a coupling phenomenon between different methods, and the interaction between traditional methods and MS to further improve the performance of MS. To this end, we take the 18db signal and ResNet as an example to explore their interaction, and set the parameters $l/L=0.5$, $\theta=0.2$, $N=13$, $n=4$. At first, we use different methods to expand the dataset by 6 times to keep the data size after the pairwise combination, then $N=13$, the experimental results are shown in the Table III.

Comparing the Table I and the Table III, our proposed method can make up for the disadvantages of traditional methods to a certain extent, and obtain better performance. However, the performance of the model is also affected because a part of the mixing samples are replaced by rotated or noised samples. Especially for the noised samples, the performance of the model is significantly degraded compared to the single MS method. For the coupling between MSs, the table shows that there is no strong coupling phenomenon, on the contrary, different combinations of methods will inhibit the model from acquiring features in a certain enhanced mode.

D. The performance of MS on the second scenarios

Since RM and nRM still have a good effect in experiments with partial dataset, in this section, we evaluate the data augmentation between flip, rotation, RM and nRM on different models in the second scenarios. In whole experiments, training set is doubled, so the training set and test set contain 352,000 and 44,000 signal samples. We take $l/L = 0.5$ for MS and $n=4$ for nRM.

As shown in Fig 8, our proposed method can increase the signal classification accuracy by about 5% when SNR is between 4dB and 18dB. However, when SNR is lower than -4db, various augmentation methods cannot work, and even inhibit the classification ability of the model. Although the MS has more side effects on the classification of low SNR signals. As the noise gradually decreases, RM can make full use of the effective features in the samples, especially at 8db, which improves the classification accuracy of the model about 6.14% at most. In Fig 9, we observed that this classification suppression phenomenon is common in the DNN model, and when the SNR is -6db, the model’s distinction between the signal itself and the noise is in the critical. However, more noisy data will only cause the model to fit the noise and fail to capture the modulation characteristics. Only in relatively clean data, MS can play a regular role for the model, filter out more noise, and improve the classification of the model.

According to the above results, we no longer use signals less than -6dB into the data process of MS, and the result (Resnet+Random-Mixing2) is shown in Table IV. Hence, removing part of the noise interference can obtain a better classification accuracy.

In general, MS is more sensitive to noise than rotation. As shown in Figures 6 and 8, while there is a lot of noise, the amplified data will decrease the model’s recognition ability, but it also shows excellent performance in data with high SNR, which improves the overall modulation recognition capability.
TABLE IV
THE RESULT OF REMOVING SIGNALS LESS THAN -60dB

| Method     | Accuracy |
|------------|----------|
| Resnet     | 58.74%   |
| Resnet+RM  | 59.63%   |
| Resnet+RM2 | 60.83%   |

V. CONCLUSION

This paper proposes a data augmentation method for signals. Through mixing multiple samples, a large number of generated samples are expanded to train the deep learning model, so that the generalization ability of the modulation recognition model could be improved. Especially in partial dataset, this method improves the accuracy of the model by more than 10% at most, verifying its good performance in signal augmentation. In addition, we consider some MS strategies, and conduct experiments on partial datasets and full datasets. It was found that the method we proposed is more suitable for samples with less noise and hindered the classification of samples with low SNR. In future work, we will consider more MS strategies or mixing tests, and exchange the more obvious feature regions in the signal for training and testing in a certain way, so as to further improve the accuracy and robustness of the deep learning model.

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