Modulation Recognition Based on Denoising Bidirectional Recurrent Neural Network

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Abstract
Modulation recognition is an important research area in wireless communication. It is commonly used in both military and civilian domains, such as spectrum detection and interference identification. Most existing modulation recognition algorithms have a better recognition performance at high signal noise ratio (SNR). However, when SNR decreases to −10 dB or even lower, such as the battlefield and disaster areas and other harsh environment, the recognition rate may decrease dramatically. In order to solve this problem, a modulation recognition algorithm based on denoising bidirectional recurrent neural network is proposed. Firstly, the state memory ability of the signal reconstruction layer in the network is utilized to learn the temporal correlation of the modulated signal, the reconstruction of the received signal is completed and the noise in the modulated signal is suppressed. Then, the reconstructed signal is encoded and decoded by the feature reconstruction layer, in which the feature of reconstructed signal is compressed and reconstructed, thereby the influence of noise can be further reduced. Finally, the reconstructed features are identified and classified by the fully connected layer. Simulation results demonstrate that the proposed network can effectively suppress the noise in the signal. Compared with other existing algorithms, the proposed method has higher recognition accuracy in the low SNR environment.

Keywords Modulation recognition · Denoising bidirectional recurrent neural network · Deep learning · Dilated convolution

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1 Introduction

Modulation recognition, as an important technology of wireless communication, is commonly used in military and civilian domains. In military applications, it can be employed for signal confirmation, spectrum detection, emitter interception and so on. In the civilian domains, its applications include signal verification, cognitive radio, interference identification, etc. Since different modulation types of signals have unique features, the problem of modulation recognition can be solved by recognizing signal features.

In the past few years, many methods have been proposed based on feature classification for modulation recognition. For example, an automatic modulation classification algorithm using instantaneous features (including instantaneous amplitude, phase, and frequency parameters) is proposed [1]. It is clear that the computational complexity of the algorithm is very low, but the recognition rate is greatly affected by noise. This will result in severe performance degradation in the low SNR environment. Therefore, for the purpose of mitigating the noise, a blind filtering myriad-based approach is introduced [2]. A tree-shaped multi-layer smooth support vector machine classifier based on feature selection algorithm is designed for eleven kinds of digital modulation signals [3]. The simulation results show that the recognition rate of the classifier exceeds 97% when the SNR is not less than −1 dB. Ali and Erelebi [4] proposes a unique modulation classification method by using a decision tree classifier to determine the attractive relation between high-order cumulants, thereby improving the extraction of features in the recognition modulation. It has been shown that these algorithms have excellent anti-noise performance and the computational complexity is relatively low. However, these methods require manually extracted features and the performance is still unsatisfied in the low SNR environment.

Deep learning is an effective technique to extract various complex features from the original data automatically. It has been widely used in modulation recognition because of its excellent self-learning ability and nonlinear mapping ability. It can be combined with the simple features to discover more complex features automatically by multiple nonlinear transformations. Because the neural network has the ability of nonlinear mapping, it can solve the difficult classification problem, such as modulation recognition in the low SNR environment. In [5], O’Shea applies deep learning to modulation recognition for the first time and discusses the critical importance of good datasets for model learning, testing, and evaluation. In [6], a modulation recognition algorithm based on deep neural network is proposed. The algorithm uses particle swarm optimization algorithm to optimize the number of neural network nodes, and adaptively selects the optimal number of hidden nodes in the network, which improves the recognition accuracy of modulation recognition in multipath interference environment. A modulation recognition algorithm based on convolutional neural network is proposed in [7]. The algorithm uses the constellation diagram of modulation signal and convolutional neural network to get better recognition performance. An automatic modulation recognition method based on convolutional neural network (CNN) is proposed [8], which can eliminate carrier phase offset to achieve higher classification accuracy. In order to improve the successful recognition probability of the recognition system in the pulse overlapping environment, a new modulation recognition algorithm based on CNN and deep Q-learning network is given [9]. The algorithm can obtain a superior recognition rate when SNR = −6dB.

However, the recognition rate of the existing deep learning methods such as [5–9] in the low SNR environment is lower. When SNR is less than −10 dB, the recognition rate is less than 30% and some even less than 10%. With the increasing complexity of modern
communication environment, the signal is subject to more and more interference during transmission [10]. In the actual channel, the signal power will gradually fade with the transmission distance, resulting in SNR reduce to − 10 dB or even lower [11]. Therefore, it is necessary to provide a more effective modulation recognition method that is suitable for the low SNR environment.

In this paper, a denoising bidirectional recurrent neural network (DBRNN) is proposed, which can improve the recognition rate of modulation recognition technology in the low SNR environment. The rest of the paper is organized as follows. The data set is described in Sect. 2. Section 3 introduces the proposed method. Section 4 gives some simulation results. Finally, the conclusion is summarized in Sect. 5.

2 Data Model

Assuming that the received signal is given by

\[ x(n) = s(n) + g(n) \]

where \( x(n) \) represents the received signal, \( g(n) \) denotes additive white Gaussian noise having zero mean and variance \( \sigma_g^2 \), and \( s(n) \) is given by:

\[ s(n) = ae^{i(\omega_0 n T + \theta_0)} \sum_{j=-\infty}^{j=\infty} s(l) \rho(nT + j\tau + \epsilon_T) \]

where \( s(l) \) represents the input sequence, \( a \) denotes the signal amplitude, \( \omega_0 \) stands for angular frequency offset constant, \( \rho(.) \) is channel effect, \( \tau \) represents symbol spacing, \( \epsilon_T \) stands for timing jitter and \( \theta_0 \) denotes phase jitter.

3 Algorithm Formulation

In this section, a new network structure called DBRNN is proposed. Figure 1 shows DBRNN network structure. The network consists of signal reconstruction layer, feature reconstruction layer and fully connected layer. Firstly, the signal reconstruction layer receives the input signal, which is processed by the signal reconstruction layer to obtain the reconstructed signal. The signal reconstruction layer can suppress the noise in the signal, thus reducing the influence of noise features on feature extraction, facilitating the feature reconstruction layer to extract the signal features accurately. Then, the feature reconstruction layer processes the reconstructed signal and generates the feature reconstruction signal. It can compress and reconstruct the features of the reconstructed signal to make the signal purer. Finally, the feature reconstruction signal is identified and classified by the fully connected layer. The specific functions of each layer will be described as follows.

3.1 Signal Reconstruction Layer

Firstly, the signal reconstruction layer is used to preprocess the received signal so as to reduce the interference of noise. The signal reconstruction layer is composed of a series of bidirectional cyclic neurons. Bidirectional cyclic neurons can not only receive information from other circulating neurons, but also receive their own information, thereby forming a circular network.
structure, which has the short-term memory function and is suitable for processing time series. The modulated signal can be regarded as a time series, and there is a strong temporal correlation between the signals. The temporal correlation of the received signal can be learned in the signal reconstruction layer. Furthermore, the effective information of the time series is captured and the invalid information is removed. Therefore, the denoising of the received signal is completed. The neurons of the signal reconstruction layer are shown in Fig. 2.

It can be seen from Fig. 2 that the structure of the neurons in the signal reconstruction layer is different from the traditional neuron structure. On the basis of the traditional neuron structure, a delay memory unit is added, which records the state of the next neuron.

The amplitude of the received signal is used as the input of the network. Since the amplitude of the received signal varies widely in a low SNR environment, and it has a relatively discrete characteristic, the input of the network is transformed by one hot encoding, and the encoded vector $\mathbf{x}$ is used as the input to the network. The process of the input layer to the hidden layer can be expressed as

$$A_j = f(Ux + WA_{j-1})$$

(3)
where $U$ represents the weight matrix from the input layer to the hidden layer, $x$ denotes the encoded vector. $W$ stands for the weight matrix between the previous state $A_{i-1}$ and the current state $A_i$, which is a weight matrix of recursion. $f(\cdot)$ is sigmoid activation function.

After the current state $A_i$ is obtained, the output of the network is calculated as

$$y = g(VA_i)$$  \tag{4}

where $V$ denotes the weight matrix from the hidden layer to the output layer. $g(\cdot)$ stands for ‘tanh’ activation function, which can be expressed as

$$g(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$  \tag{5}

In the signal reconstruction layer, because of the temporal correlation of signal, signal is propagated not only from the input layer to the hidden layer, but also from the hidden layer to the input layer. The reverse process of network from the input layer to the hidden layer can be expressed as

$$A_i' = f(U'x + W'A_{i+1})$$  \tag{6}

where $U'$ represents the weight matrix from the hidden layer to the input layer, and $W'$ stands for the weight matrix between the next state $A_{i+1}$ and the current state $A_i'$.

According to (2) and (5), the output vector of the signal reconstruction layer can be given by

$$y_i = g(VA_i + V'A_i') = g(Vf(Ux_i + WA_{i-1}) + V'(U'x_i + W'A_{i+1}))$$

$$= g\left(Vf(Ux_i + W(f(Ux_{i-1} + WA_{i-2}))) + \ldots + V'f(U'x_i + W'(f(U'x_{i+1} + W'A_{i+2})))\right)$$  \tag{7}

where $x_i$ represents the network input at $i$th time and $y_i$ stands for the network output at $i$th time.

In the back propagation process of signal reconstruction layer, the partial derivative of parameter $(U, V, W)$ is calculated respectively.

Assume that the derivative of hidden state is $\delta^{(i)}$ at time $t$, the partial derivative of the function $L$ regard as the parameter $V$ can be expressed as

$$\frac{\partial L}{\partial V} = \sum_{t=1}^{T} (\hat{y}^{(i)} - y^{(i)}) (A^{(i)})^T$$  \tag{8}

where $L$ represents the mean square error loss function, $\hat{y}^{(i)}$ indicates the expected output of the network, and $y^{(i)}$ stands for the real output of the network.

The partial derivative of the function $L$ regard as the parameter $U$ can be written as

$$\frac{\partial L}{\partial U} = \sum_{t=1}^{T} \text{diag} \left(1 - (A^{(i)})^2\right) \delta^{(i)} (x^{(i)})^T$$  \tag{9}

where $x^{(i)}$ represents the input data of the network at $t$ time and $A^{(i)}$ represents the state $A_i$ at $t$ time.

The partial derivative of the function $L$ regard as the parameter $W$ can be given by
\[
\frac{\partial L}{\partial W} = \sum_{i=1}^{T} \text{diag}(1 - (A^{(t)})^2) \delta^{(t)}(A^{(t-1)})^T
\]

where \(A^{(t-1)}\) represents the state \(A_{i-1}\) at \(t\) time.

The noise of the received signal is reduced by the signal reconstruction layer, this process provides the basis for the subsequent network layer processing.

### 3.2 Feature Reconstruction Layer

After the signal reconstruction layer, the received signal has been reconstructed. And the amplitude, frequency, phase and other effective information of the signal have emerged from the noise. However, the noise in the received signal has not been completely removed. The residual noise affects the internal feature representation of the signal, resulting in poor representativeness of the signal feature and low recognition accuracy. In order to obtain the more effective features from the reconstructed signal, the feature reconstruction layer is used to reconstruct the signal feature in this section. The structure of the feature reconstruction layer is shown in Fig. 3.

First, the reconstructed signal \(r(t)\) is mapped to the corrupted signal \(\tilde{r}(t)\) by the random damage process \(q_D\), which can be expressed as

\[
\tilde{r}(t) = q_D(r(t))
\]

The random damage process \(q_D\) randomly sets the sampling points of \(r(t)\) to zero, and this process randomly removes some sampling points that may have large noise, thereby the signal \(\tilde{r}(t)\) whose a part of amplitude value is 0. Then, \(\tilde{r}(t)\) and \(r(t)\) are combined to form the training sample pair \((r(t), \tilde{r}(t))\) as an input to the feature reconstruction layer.

As shown in Fig. 3, the feature reconstruction layer encodes the reconstructed signal, so as to the features of the reconstructed signal is learned and compressed to a set of smaller feature vectors. Then through the decoding process, the feature vector is reconstructed into more representative signal features. The encoding and decoding process of the feature reconstruction layer will be described as follow.

In the process of encoding, one hot encoding is applied to \((r(t), \tilde{r}(t))\), so that it can be transformed into \(x = (x_1, x_2, x_3, \ldots, x_n)\) that the value of one position is 1 and the value of the other positions value is 0. \(x\) is processed by the first nonlinear layer, which can be expressed as

![Fig. 3 The structure of the feature reconstruction layer](image)
\[ h_k^{(1)} = f(W_1x + b_1) \] (12)

where \( k \) represents the length of the feature vector. \( W_1 \) stands for the weight matrix, and \( b_1 \) denotes the bias vector. \( f(\cdot) \) represents ‘sigmoid’ activation function. The next layer feature is a compressed representation of the previous layer feature.

After the input signal encoding, the signal feature coding \( h_k^{(1)} \) is further compressed. The process can be expressed as

\[ h_l^{(2)} = f(Wh_k^{(1)} + b) \] (13)

where \( l \) represents the length of the feature vector, in order to compress the signal feature to a smaller length, let \( l < k \).

According to (12) and (13), the input signal \((r(t), \tilde{r}(t))\) is compressed into the feature vector \( y \). The vector \( y \) retains the original features of the input signal as much as possible, and randomly removes the noise in the signal.

Then the feature vector \( y \) is decoded, and the decoding process of \( y \) is the reconstruction process of signal feature. By reconstructing the feature vector \( y \) multiple times, a more representative signal feature is obtained. The first reconstruction process in the decoding phase can be expressed as

\[ \hat{h}_k^{(1)} = f(W'y + b') \] (14)

where \( W' \) represents the weight matrix corresponding to the first decoding, \( b' \) is the bias to the first decoding. \( \hat{h}_k^{(1)} \) is the first reconstructed feature vector. The process of decoding and reconstructing features after the second layer can be expressed as

\[ \hat{h}_l^{(1)} = f(W'\hat{h}_k^{(1)} + b') \] (15)

In the process of feature reconstruction, a few original features are used to recover the noiseless features, feature vector maps from the lower dimensional space to the higher dimensional space.

Finally, the vector \( \hat{x} \) is obtained by the reconstruction process multiple times, which can be expressed as

\[ \hat{x} = f(W'\hat{h}_l^{(1)} + b') \] (16)

where \( \hat{x} \) represents the reconstructed feature vector obtained by the reconstructed signal encoding and decoding process.

The error function of backpropagation can be expressed as

\[ L_H(x, \hat{x}) = \sum_{n=1}^{N} ||x - \hat{x}||^2 + \eta \rho(h^{(n)}) \] (17)

where the error function adopts the mean square error loss function, \( \eta \) represents the penalty factor. \( \rho(\cdot) \) denotes the sparse metric function, which can be specifically expressed as
where $\rho^*$ represents a constant, $\hat{\rho}_j$ is the average activity value of the $j$th neuron in the middle layer, and $KL(\rho^*|\hat{\rho}_j)$ denotes the KL distance between $\rho^*$ and $\hat{\rho}_j$, which is used to measure the difference between $\rho^*$ and $\hat{\rho}_j$.

### 3.3 Fully Connected Layer

After reconstructing the signal feature, each input signal has a new feature representation, and the reconstructed feature are identified and classified by the classifier. In this section, the 14-layer neural network will be used to identify and classify the reconstructed signal feature. The network structure is shown in Fig. 4.

The 14-layer neural network is a fully connected BP neural network. The input vector of the fully connected layer is the output vector of the feature reconstruction layer. After the feature is input to the fully connected network, the process of the fully connected network can be expressed as

$$ n_j = \sum_{i=1}^{n} w_{ji} x_i + \theta_j $$

where $i$ is input neuron serial number, $j$ is output neuron serial number, $x_i$ represents the reconstructed feature, $w_{ji}$ denotes the weight of the hidden layer, $\theta_j$ is the bias of the the
hidden layer, \( b_j \) represents the output feature of the hidden layer, and \( f(\cdot) \) stands for the relu activation function.

In the last layer of the network, the output of the network needs to be identified, so the last layer of the network uses the softmax function. The error between the actual output and the expected output is calculated. The process can be expressed as

\[
E = \frac{1}{2} \sum_{k=1}^{q} (O_k - y_k)^2 + \Omega(\omega)
\]

where \( O_k \) represents the expected output of the \( k \)th neuron, \( y_k \) represents the actual output of the \( k \)th neuron, and \( \Omega(\omega) \) denotes the regularization term.

According to the back propagation of the network, continuously optimize the network weights until the network training is completed. The received signals through the signal preprocessing, feature reconstruction and signal recognition, the classification results are obtained.

3.4 Summary of the Proposed Method

The procedure of the proposed DBRNN can be summarized as follows.

**Step. 1** According to (2)–(9), the signal reconstruction layer is used to mine the temporal correlation information of the signal, the received signal is reconstructed and the noise in the signal is suppressed;

**Step. 2** According to (10)–(12), the reconstructed signal feature is encoded, and the feature is mapped into a set of extremely small feature vector \( y \), which retain the noiseless feature;

**Step. 3** According to (13)–(17), the reconstructed feature vector \( y \) is decoded, \( y \) maps from the low dimensional space to the high dimensional space, and the signal feature \( \hat{x} \) is obtained, thereby the signal reconstruction process is completed;

**Step. 4** According to (18)–(19), the back propagation algorithm is used to train the neural network, the reconstructed signal feature \( \hat{x} \) is reconstructed and modulation recognition of the received signal is completed.

4 Simulation Results

In this section, the proposed algorithm is verified by simulation. This section shows the processing effect of the signal reconstruction layer, compares the performances of BRNN-DAE with the performances of DAE and BPNN respectively in the different SNR environments, shows the confusion matrix of DBRNN algorithm in the different SNR environments, and shows the recognition rate curve between the proposed method and the existing modulation recognition algorithms in the different SNR environments. The modulated signal data set used in this paper is generated by matlab software. The data set contains 11 modulation types: 2ASK, 2PSK, 2FSK, 4PSK, AM, SSB, DSB, VSB, FM, 16QAM, 64QAM. The signal symbol is generated randomly by matlab, and the noise of signal is Gaussian White Noise. The range of signal to noise ratio(SNR) is -20 dB to 6 dB, and the interval is 1 dB. Each modulated signal generates 40 sampling points at different SNR, a total of 15,400 samples. Among them, 12,320 samples are used to train the network model and 3080 samples are used to test the model. Each sample carries a label, which
is a vector that length is 11, the value of one position is 1 and the value of the other positions value is 0. For example, if the modulation type of a sample is 2ASK, the sample label is \((1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0)\). The Euclidean distance of the same sample label is 0. The Euclidean distance of the different sample label is 1. This makes it more convenient to calculate the loss function or the accuracy. The software environment used in the training model is Python 3.6 and Tensorflow-gpu 1.3.0. The hardware environment is CPU Intel® Xeon® E5-2560, GPU NVIDIA Tesla K80, RAM 64GB.

Figure 5 shows the relationship between the received signal and the reconstructed signal. The solid line indicates the original signal with SNR= −10 dB. The dotted line represents the modulated signal is processed by the signal reconstruction layer. It is obvious from the Fig. 5 that the received signal has no obvious signal feature in the low SNR environment. The amplitude, frequency, phase and other features of the modulated signal have been submerged in the noise and cannot be directly observed. If the original received signal is used as an input to the neural network, the recognition accuracy of the modulation recognition will be greatly reduced. Compared with the original received signal, the signal is processed by the signal reconstruction layer has relatively obvious signal feature. Because the noise in the reconstructed signal is reduced, thereby the amplitude, frequency and phase information of the signal are clearly displayed.

Figure 6 shows the modulated signal processed by the signal reconstruction layer. The reconstructed signal has obvious signal feature. It has two different carrier frequencies and the signal amplitude is basically constant within 0.05 s, so the modulation type of the signal shown in Fig. 6 is FSK.

Figure 7 shows the relationship between iteration times and test accuracy in −14 dB, −6 dB, and 2 dB SNR environments. It can be seen from the Fig. 7 that with the increase of the iterations, the test accuracy of the algorithm gradually increases, and when the iterations reaches a certain number, the accuracy of the algorithm always fluctuates within a small range. Figure also shows the curve of test accuracy in three...
different SNR environments. When the iterations is the same, the test accuracy increases as the SNR increases. When the SNR = −14 dB, the test accuracy of the proposed algorithm is close to 70%. When the SNR = -6dB, the test accuracy of the proposed
algorithm exceeds 80%. This proves that compared with other algorithms, the proposed algorithm has better recognition accuracy in the low SNR environment.

Figure 8 shows the relationship between iteration times and network loss in $-14$ dB, $-6$ dB, and $2$ dB SNR environments. It can be seen from the figure that with the increase of the iterations, the loss of the network gradually decreases and tends to be stable. When the SNR = $2$ dB and $-6$ dB, the loss of the network is stable when the iteration exceed 300. When the SNR = $-14$ dB, the loss of the network is stable when the iteration exceed 600. With the increase of SNR, the loss of network decreases gradually. When the iterations of the network is constant, the higher the SNR, the smaller the network loss. When the SNR = $-14$ dB and the network loss is stable, the network loss value is about 0.25. It can be seen that the proposed algorithm has low network loss in the low SNR environment.

Figures 9, 10 and 11 show the confusion matrix of DBRNN algorithm in different SNR environments. It can be seen from the figure that when SNR is $-14$ dB, according to the data distribution of the confusion matrix, the data located in the diagonal is more than the data outside the diagonal, and the sum of the numbers off the diagonal is smaller, and the recognition error of each modulation signal is about 1/2. From the data distribution, the recognition accuracy is more than 65%. Compared with the obfuscation matrix with the SNR = $-14$ dB, when the SNR = $-6$ dB, as the amount of data on the diagonal of the obfuscation matrix increases, the amount of data off the diagonal decreases, and the amount of recognition errors of each modulation type also decreases, which proves that with the increase of SNR, the recognition accuracy of the proposed algorithm increases, and the recognition accuracy is above 80%. When the SNR = $2$ dB, except for a few data distributed outside the diagonal, the rest of the data are all correctly distributed on the diagonal. It can be concluded that the recognition accuracy of the proposed algorithm is close to 95%, which further proves that the proposed algorithm has a high recognition rate in the low SNR environment.

![Fig. 8 The test error of network versus iterations](image-url)
Figure 12 shows the recognition rate curve between the proposed method and the existing modulation recognition algorithms in the different SNR environments. In addition to the curves of DBRNN algorithm, the figure also includes the curves of generalized likelihood ratio test (GLRT) [12], high-order cumulants (HOC) [13], k-nearest neighbors (KNN) [14],
linear support vector machine (LSVM) and backpropagation neural network (BPNN) classifiers [15]. In GLRT, assume that the prior probabilities of the eleven modulated signals are the same, the threshold of the classified classification is set to zero, and the probability of correct classification is the average of 1000 independent experiments. In HOC, the mean and variance

Fig. 11 Confusion matrix with SNR= 2dB

Fig. 12 Recognition accuracy versus SNR
of the modulating signal statistic are calculated in each Monte Carlo experiment. The fourth-order cumulants and the optimal threshold of the signal are calculated by mean and variance, which are compared and identified. In KNN, the genetic operator crossover has a probability of 90% and the probability of mutation is 10%. 10,000 sampling points are generated for different SNR values. The 10,000 sampling points are tested using the optimal tree and the results are summarized. In LSVM, the amplitude, phase, real part, and imaginary part of the signal are respectively calculated to identify the modulated signal. In BPNN, the two layers neural network is adopted and 50 nodes are used in the hidden layer. Compared with other algorithms, the proposed algorithm has higher recognition accuracy in the low SNR environment. When the SNR exceeds −18dB, the recognition accuracy of the proposed algorithm is more than 60%. Compared with the existing modulation recognition algorithm based on BPNN, the recognition rate is improved by about 20%. Compared with other existing algorithms in the low SNR environment, when the SNR is greater than −10dB, the recognition rate of the proposed algorithm has reached more than 70%, which proves that the proposed algorithm has better recognition performance in the low SNR environment.

For briefly, the recognition accuracy of the proposed algorithm and other modulation recognition algorithms are compared in Table 1.

It can be clearly seen from Table 1 that the recognition accuracy of the proposed algorithm is significantly better than other algorithms, especially in a low SNR environment.

5 Conclusions

Most existing modulation recognition algorithms have low recognition rate in the low SNR environment. In order to solve this problem, a modulation recognition algorithm based on DBRNN is proposed in this paper. Firstly, the state memory ability of the signal reconstruction layer in the network is used to learn the temporal correlation of the modulated signal, the reconstruction of the received signal is completed and the noise in the modulated signal is suppressed. Then, the reconstructed signal is encoded and decoded by the feature reconstruction layer, in which the feature of reconstructed signal is compressed and reconstructed, thereby the influence of noise can be further reduced. Finally, the reconstructed features are identified and classified by the fully connected layer. Simulation results show that the proposed network can effectively suppress the noise in the signal. Compared with other existing algorithms, the proposed method has higher recognition accuracy in the low SNR environment.

6 Future Scope

Our future work will focus on the following aspects:

| Table 1 | Modulation recognition accuracy versus SNR for different algorithms |
|---------|---------------------------------------------------------------|
| SNR (dB) | GLRT | HOC | GP-KNN | LSVM | BPNN | Proposed |
| −10      | 0.000 | 27.572 | 19.456 | 43.079 | 47.282 | 76.123 |
| 0        | 18.043 | 63.551 | 58.333 | 69.347 | 70.072 | 87.608 |
| 10       | 58.804 | 96.775 | 97.065 | 98.079 | 98.369 | 98.515 |

5 Conclusions

Most existing modulation recognition algorithms have low recognition rate in the low SNR environment. In order to solve this problem, a modulation recognition algorithm based on DBRNN is proposed in this paper. Firstly, the state memory ability of the signal reconstruction layer in the network is used to learn the temporal correlation of the modulated signal, the reconstruction of the received signal is completed and the noise in the modulated signal is suppressed. Then, the reconstructed signal is encoded and decoded by the feature reconstruction layer, in which the feature of reconstructed signal is compressed and reconstructed, thereby the influence of noise can be further reduced. Finally, the reconstructed features are identified and classified by the fully connected layer. Simulation results show that the proposed network can effectively suppress the noise in the signal. Compared with other existing algorithms, the proposed method has higher recognition accuracy in the low SNR environment.

6 Future Scope

Our future work will focus on the following aspects:
1. The actual communication environment is complex and changeable, such as multipath fading channels, non-cooperative communication, etc., will have a certain impact on the accuracy of the modulation recognition algorithm. Therefore, how to deal with the complex actual communication environment is one of the future research work.

2. Optimize the neural network structure to reduce the computational complexity while maintaining the recognition accuracy. Real-time recognition of modulated signals is the future work.

Author Contributions RD: Conceptualization, Validation, Resources, Writing—review & editing, Supervision. FL: Methodology, Validation, Resources, Writing—original draft, Supervision. LZ: Software, Validation, Resources, Writing—review & editing. YJ: Writing—review & editing, Supervision. JX: Writing—review & editing. FG: Methodology.

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Data Availability The data and material generated during and analysed during the current study are available from the corresponding author on reasonable request.

Code Availability The code generated during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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