Artificial-Neural-Network-Based Automatic Modulation Recognition in Satellite Communication

Yumeng Zhang[1,2](✉), Mingchuan Yang[1], and Xiaofeng Liu[1]

[1] Communication Research Center, Harbin Institute of Technology, Harbin, People's Republic of China
616670674@qq.com, {mcyang, liuxiaofeng}@hit.edu.cn
[2] CETC Key Laboratory of Aerospace Information Applications, Shijiazhuang, China

Abstract. In order to improve the correct recognition rate of signals transmitted in satellite communication system, three different structures of artificial neural network (ANN), including feed forward network (FFN), cascade forward network (CFN) and competitive neural network (CNN) are investigated in this paper. Then their performance of correct recognition rate and performance of convergence rate are compared. Results of simulation indicate that typical FFN's performance dramatically deteriorates in the case of Rician fading, CFN's performance is similar to the former one while it has higher convergence rate. CNN's performance of correct recognition rate is the best among these three nets, but in the training process, its performance of convergence rate is not good.

Keywords: Modulation recognition · Artificial neural network
Satellite communication

1 Introduction

With the development of technology in satellite communication, the complexity of modulation type is growing, which makes it more complicated for receivers to recognize these modulation types correctly and effectively. Especially when considering the satellite communication scenario where the received signals are affected by noise, multipath fading and shadowing, the performance of modulation recognition will deteriorate. This paper focuses on improving the performance of modulation recognition of signals transmitted in satellite communication system.

Generally, modulation recognition is used to identify interference or choose the appropriate demodulator, and without correctly recognizing the modulation type of the received signal, further procedures such as demodulation and parameter estimation cannot be accomplished [1]. As modulation recognition plays a significant role in satellite communication applications such as spectrum management, surveillance and electronic warfare [2], it is of great importance to correctly and effectively recognize signals in satellite communication system.

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In recent years, many works have been done on automatically recognizing the modulation type of received signals using artificial neural network [3]. However, most of these signals are assumed to be received in Gaussian channel, which cannot be applied in satellite communication system. This paper investigates the situation where the ANN is used to recognize signals transmitted in the Rician fading channel, and then different structures of ANN which can improve the correct recognition rate in this situation are discussed and compared.

2 The Procedure of Automatic Modulation Recognition

In order to automatically recognize the modulation type of the received signals, the feature-based approach is usually considered as an effective method [4]. The procedure of feature-based modulation recognition is illustrated in Fig. 1.

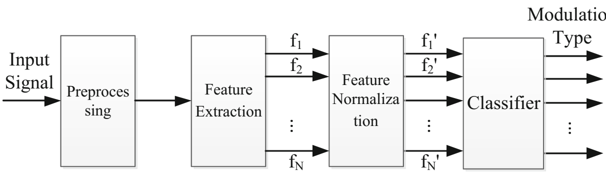

Fig. 1. Procedure of feature-based modulation recognition

The preprocessing module is used to purify the input signal because signal transmitted in satellite communication system can be affected by kinds of noise. It's worth noting that in satellite communication system, the received signal not only has line-of-sight component but also has reflecting component, which contains signal waves reflected by adjacent objects such as buildings and trees. Therefore input signals have to be denoised before feature extraction.

Then the feature of denoised signal can be extracted in the feature extraction module. The procedure of feature extraction is necessary because on the one hand, it can provide similar features of signals of one certain modulation type and that makes the recognition easier; on the other hand, this procedure can reduce the number of elements sent to the classifier, which decreases the computing amount of the classification. There are many kinds of methods with different bases to extract features from modulated signal, such as approaches based on instantaneous parameters [5], high order cumulants [6], spectral correlation [7], and wavelet transformation [8].

The feature normalization module is indispensable because features usually vary considerably in magnitude, which will decrease the convergence rate of the network in classifier. After normalization the average value of each feature will be zero and its variance will be unified, this will improve the performance of classifier [9].

Finally the normalized features will be sent to classifier, which recognizes the modulation type of the input signal. There are many methods of classifier such as decision tree [10].

3 Feature Extraction

In order to recognize different kinds of modulation types, a combination of features is used more than a single one. And the extracted features are required to be sensitive to different modulation types, while they must be insensitive to parameters of individual transmissions such as signal-to-noise ratio (SNR) and frequency.

Eight kinds of digital signals modulated by 2ASK, 4ASK, BPSK, QPSK, 8QAM, 16QAM, OQPSK and $\pi/4$-DQPSK respectively will be recognized in this article. The features extracted from the instantaneous parameters are listed as follows:

The maximum value of the spectral power density of the normalized centered instantaneous amplitude $\gamma_{\max}$ is defined as:

$$\gamma_{\max} = \frac{\max\{\mathrm{FFT}[a_{cn}(i)]^2\}}{N} \tag{1}$$

where N is number of samples, $a_{cn}(i)$ represents for the normalized centered instantaneous amplitude, and can be given as:

$$a_{cn}(i) = a_n(i) - 1 \tag{2}$$

where $a_n(i) = a(i)/m_a$ and $a(i)$ is the instantaneous amplitude of received signal, m_a represents for the mean value of $a(i)$, i.e. $m_a = \frac{1}{N}\sum_{i=1}^{N} a(i)$.

The standard deviation of the absolute value of the normalized centered instantaneous amplitude σ_{aa} is defined as:

$$\sigma_{aa} = \sqrt{\frac{1}{N}[\sum_{i=1}^{N} a_{cn}^2(i)] - [\frac{1}{N}\sum_{i=1}^{N} |a_{cn}(i)|]^2} \tag{3}$$

The standard deviation of the absolute value of the non-linear component of the normalized centered instantaneous phase of non-weak signal σ_{ap} is defined as:

$$\sigma_{ap} = \sqrt{\frac{1}{c}[\sum_{a_n(i) > a_t} \phi_{NL}^2(i)] - [\frac{1}{c}\sum_{a_n(i) > a_t} |\phi_{NL}(i)|]^2} \tag{4}$$

where a_t is the threshold for $a(i)$ and below which the received signal can be considered too weak and can be ignored, and c is the number of non-weak samples, $\phi_{NL}(i)$ is the value of the central non-linear component of the instantaneous phase, and when the carrier is synchronized it can be given as follows:

$$\phi_{NL}(i) = \phi(i) - \phi_0 \tag{5}$$

where $\phi_0 = \frac{1}{N}\sum_{i=1}^{N} \phi(i)$,and $\phi(i)$ is the instantaneous phase.

The standard deviation of the non-linear component of the normalized centered instantaneous phase of non-weak signal σ_{dp} is defined as:

$$\sigma_{dp} = \sqrt{\frac{1}{c}[\sum_{a_n(i) > a_t} \phi_{NL}^2(i)] - [\frac{1}{c}\sum_{a_n(i) > a_t} \phi_{NL}(i)]^2} \quad (6)$$

The standard deviation of the absolute value of the normalized centered instantaneous frequency of non-weak signal σ_{af} is defined as:

$$\sigma_{af} = \sqrt{\frac{1}{c}[\sum_{a_n(i) > a_t} f_N^2(i)] - [\frac{1}{c}\sum_{a_n(i) > a_t} f_N(i)]^2} \quad (7)$$

where $f_N(i) = \frac{f_m(i)}{R_s}$, $f_m(i) = f(i) - m_f$, $m_f = \frac{1}{N}\sum_{i=1}^{N} f(i)$, and R_s is the symbol rate of the received digital signal.

The compactness of normalized centered instantaneous amplitude is described by fourth-order moment and can be given as follows:

$$\mu_{42}^{a} = \frac{\mathrm{E}[a_{cn}^4(i)]}{\{\mathrm{E}[a_{cn}^2(i)]\}^2} \quad (8)$$

The compactness of normalized centered instantaneous frequency is also described by fourth-order moment and can be given as:

$$\mu_{42}^{f} = \frac{\mathrm{E}[f_N^4(i)]}{\{\mathrm{E}[f_N^2(i)]\}^2} \quad (9)$$

These seven features are extracted from the received signal and they provide the classifier with necessary information for modulation recognition. In this article, ANN is utilized in classifier to recognize different modulation types. It's worth mentioning that these features should be normalized before sent to ANN, otherwise some of these feature will fall into the saturation region of ANN's transfer function where the gradient of that function is almost zero, which will decrease the convergence rate of the network in training procedure.

4 Structure of Artificial Neural Network

There exist many kinds of structures of ANN such as FFN, CFN, and CNN. Their performances are different when applied in modulation recognition. Moreover, all of these ANNs must be trained before they are used as classifiers, and the error back propagation algorithm is usually used in training step.

4.1 Theory of Error Back Propagation Algorithm

ANN is composed of weights, biases and neuron nodes, which include input nodes, hidden nodes and output nodes. A typical ANN with one hidden layer can be illustrated in Fig. 2, where w_{ji}^{JI} $(j = 1, 2, \ldots, J; i = 1, 2, \ldots, I)$ is the weight between input layer and hidden layer, w_{kj}^{KJ} $(k = 1, 2, \ldots, K; j = 1, 2, \ldots, J)$ is the weight between hidden layer and output layer, b_i^J $(j = 1, 2, \ldots, J)$ is the j_{th} bias of hidden nodes, and b_k^K $(k = 1, 2, \ldots, K)$ is the k_{th} bias of output nodes.

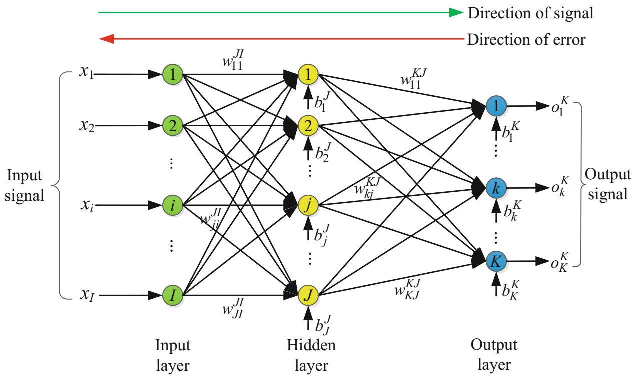

Fig. 2. Model of typical ANN with one hidden layer

Input nodes allot the input signal to hidden nodes, and each input node is connected to every hidden node. In the hidden layer, the j_{th} node sums its input data and adds a bias b_i^J to them before putting them to a certain transfer function. Then the data from hidden layer are sent to output layer where they are processed in a similar way. Usually the output signal is not the desire one, so error back propagation algorithm is used to solve this problem by correcting the weights and biases of network layer by layer.

In ANN the information of input signal is sent forward the network until the output signal is calculated. Then the error between this output signal and desire signal can be known, in order to decrease that error the weights and biases of output layer will be corrected, and after that the weights and biases of hidden layer will be corrected. This indicates that the error information propagates back from output layer to input layer. The procedure of training an ANN using error back propagation algorithm is illustrated in Fig. 3.

The essence of error back propagation algorithm is to find the proper weights and biases of network, which makes output signal to be the best estimate of desire output in minimal mean-square error sense. Moreover, the procedure of training the ANN can be regarded as a step of machine learning. We can use the features of modulated signal as the input signal and set its corresponding modulation type as desire output, after the procedure of training ANN can recognize the modulation type of a received signal according to the extracted features. However, structure of ANN can affect both the convergence rate in the procedure of training the network and the performance of modulation recognition, three different structures of ANN network are discussed and compared in this article.

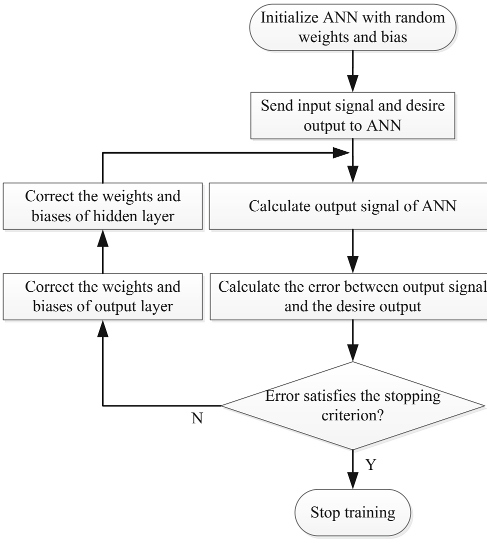

Fig. 3. Procedure of training an ANN with error back propagation algorithm

4.2 Feed Forward Network (FFN)

FFN is a typical structure of ANN, it consists of a series of layers and the first layer has a connection from the input signal. Each subsequent layer has a connection from the previous layer, and final layer produces the output signal. A FFN can be produced using the model described in Fig. 2, and its structure can be simplified in Fig. 4 for convenience's sake.

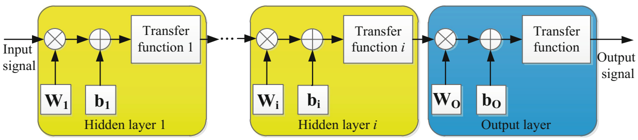

Fig. 4. Structure of feed forward network (FFN)

In Fig. 4, $\mathbf{W_i}$ and $\mathbf{b_i}$ respectively represents for the weight matrix and bias matrix of the i_{th} hidden layer, while $\mathbf{W_O}$ and $\mathbf{b_O}$ respectively represents for the weight matrix and bias matrix of the output layer. Non-linear functions such as sigmoid function, log-sigmoid function, hyperbolic tangent sigmoid transfer function etc. are usually set as transfer functions of hidden layers, while output layer usually uses linear function as transfer function. It is worth noting that every hidden layer can use different transfer function. Furthermore, the number of hidden layers, the transfer function of each hidden layer, and the number of nodes of each layer can be changed according to the complexity of problem.

4.3 Cascade Forward Network (CFN)

CFN is a variation of FFN, and they are quite similar except that CFN has a connection from the input signal to every following layer, its structure is illustrated in Fig. 5. In this network every hidden layer except the first one and output layer has two weight matrixes, one is used to weight the output data from the previous layer, and the other one is used to directly weight the input signal.

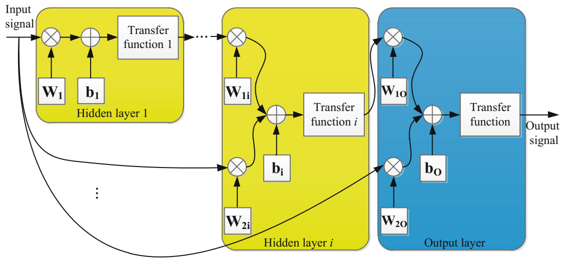

Fig. 5. Structure of cascade forward network (CFN)

This structure can provide the procedure of training with more degrees of freedom, and that will make it easier to solve some complicated problems. On the other hand, this structure can also increase the complexity of training procedure, because in error back propagation algorithm more weights and biases should be corrected. Moreover, if too many data are supplied to train this network it may lead to over fitting, which will affect the performance of modulation recognition.

4.4 Competitive Neural Network (CNN)

CNNs are proposed according to the lateral inhibition in biological neural networks, i.e. when a biological neuron is activated it will inhibit its adjacent neurons, which leads to the competition among neural networks. When the training procedure begins, every neuron has equal opportunity to respond to input signal till one neuron is activated and wins in the competition, at the same time the winner will inhibit other neurons and prevent them from being activated.

CNNs are similar to FFNs, i.e. they have similar structure shown in Fig. 3. However, the transfer functions of CNN's hidden layers are non-liner functions, but the soft max competitive function is usually used in output layer. It is worth noting that these neural networks can be trained by error back propagation algorithm and their convergence rates are different, which will be compared in the next subsection.

5 Simulation Results and Performance Analysis

In this subsection, the learning ability of each structure is compared by its convergence rate. After training these networks are utilized to recognize the modulation type according to the extracted features discussed above, and then their performance of correct recognition rate will be compared.

5.1 Simulation on Training Procedure

In order to compare the learning ability of these three structures of ANNs, they are respectively trained with the same set of rational normalized training samples. In simulation every network has only one hidden layer with 10 neuron nodes, the number of neuron nodes in input layer and output layer is equal to the number of extracted features and the number of modulation types respectively. Moreover, the transfer functions in every hidden layer are set as hyperbolic tangent sigmoid transfer function. Figure 6 illustrates the training result, and the maximum training epoch is set as 1600.

It can be known from Fig. 6 that at the beginning of training process CFN has the highest convergence rate among these three structures, while its best performance of mean squared error (MSE) is 0.0460 and this value remains the same when this net is trained over 40 epochs. On the other hand, the MSE performance of competitive neural net decreases along with the increase of epochs and can reach its minimum value 4.9717×10^{-4} at the maximum epoch. However, the convergence rate performance of competitive neural net is not good. Furthermore, the minimum MSE performance of feed forward net is 0.0541, which is the worst among these networks, but it is less complicated to train that net because of its simple structure. The results of simulation in this part show that the structure of network may affect its learning ability.

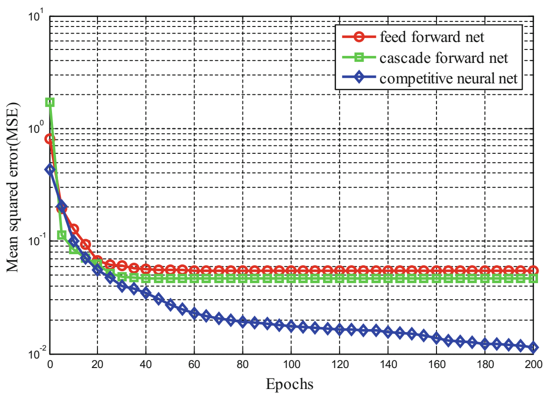

Fig. 6. Training procedure of different ANNs

5.2 Simulation on Modulation Recognition

After the training procedure, these networks can be used to recognize modulation types of received signals. The performance of each net is investigated with eight different modulation types: 2ASK, 4ASK, BPSK, QPSK, 8QAM, 16QAM, OQPSK and $\pi/4$-DQPSK. The received signals are assumed to transmit in the Rician fading channel where the Rician K-factor is set as 5 dB. The training sample contains 200 sampled signals for each modulation type, while the testing sample is composed of 1000 sampled signals for each modulation type. In simulation, every ANN is trained by the same training sample and tested by the same testing sample.

Figure 7 illustrates the correct recognition rate for each modulation type when the SNR of receiver is 6 dB. For comparison, the correct recognition rate in Gaussian channel with the same SNR is 100% for each modulation type, which can be seen in Fig. 8. The reason why the misrecognition occurs is that the difference of features between modulation types is not recognizable because of the impact from Rician fading.

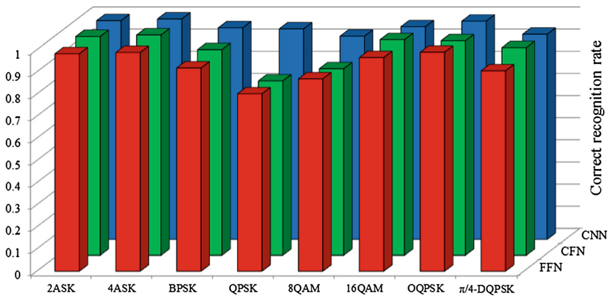

Fig. 7. Correct recognition rate for each modulation type (SNR = 6 dB)

Simulation results show that these three ANNs exhibit a satisfactory performance for the signals affected by Rician fading channel when the SNR is 6 dB. Each network's overall average correct recognition rate vs. SNR is illustrated in Fig. 8, and the corresponding performance in Gaussian channel, which is recognized by FFN, is also simulated for comparison.

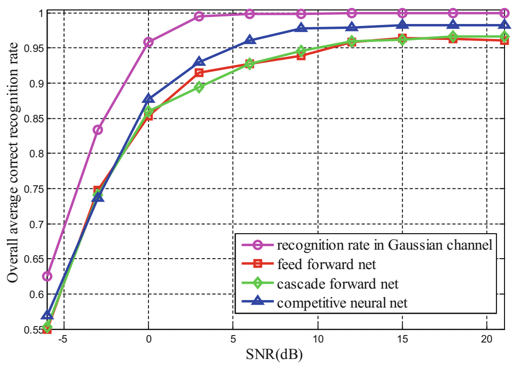

Fig. 8. Overall average correct recognition rate vs. SNR

It can be seen from Fig. 8 that the Rician fading affects the ANNs' performance of correct recognition rate and the performance of FFN deteriorates dramatically in Rician fading channel. And the overall average recognition rate of CFN is similar to that of FFN. Moreover, CNN performs better than the other two nets in the satellite communication system.

6 Conclusion

In this paper, ANNs are utilized to recognize the modulation type of signals transmitted in satellite communication system, the results of simulation show that typical FFN's performance of correct recognition rate will dramatically deteriorate because of Rician fading, but it is easier to train a FFN. In the case of Rician fading, CFN performs similarly to FFN in overall average correct recognition rate, but its convergence rate in training process is the highest among these nets. Moreover, CNN's overall average correct recognition rate is the best and it has the lowest performance of MSE in training procedure, but its convergence rate is not good.

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References

1. Zeng, C.-Z., Jia, X., Zhu, W.-G.: Modulation classification of communication signals. J. Commun. Technol. **48**(3), 252–257 (2015)
2. Chen, M., Zhu, Q.: Cooperative automatic modulation recognition in cognitive radio. J. China Univ. Posts Telecommun. **17**(2), 46–52 (2010)
3. Gao, Y.-L., Zhang, Z.-Z.: Classifier of modulation recognition based on modified self-organizing feature map neural network. J. Sichuan Univ. (Eng. Sci. Edn.) **38**(5), 143–147 (2006)
4. Dobre, O.A., Abdi, A., Bar-Ness, Y., et al.: Survey of automatic modulation classification technoques: classical approches and new trends. J. IET Commun. **1**(2), 137–156 (2007)
5. Dubuc, C., Boudreau, D., Patenaude, F., et al.: An automatic modulation recognition algorithm for spectrum monitoring applications. In: IEEE International Conference on Communications, vol. 1, pp. 570–574. IEEE (1999)
6. Declouet, J.A., Naraghi-Pour, M.: Robust modulation classification techniques using cumulants and hierarchical neural networks. In: Proceedings of SPIE - The International Society for Optical Engineering, pp. 6567171 J–65671 J-11 (2007)
7. Eremenko, Y., Poleshchenko, D., Glushchenko, A.: Study on neural networks usage to analyse correlation between spectrum of vibration acceleration signal from pin of ball mill and its filling level. J. Appl. Mech. Mater. **770**, 540–546 (2015)
8. Yang, F., Zan, L.I., Luo, Z.: A new specific combination method of wireless communication modulation recognition based on clustering and neural network. Acta Scientiarum Naturalium Universitatis Sunyatseni **54**(2), 24–29 (2015)

9. Wang, K., Xie, J., Zhao, L.: Automatic modulation recognition of software radio communication signals based on neural networks. Comput. Autom. Measur. Control **12** (9), 877–878 (2014)
10. Satija, U., Ramkumar, B., Manikandan, M.S.: A novel sparse classifier for automatic modulation classification using cyclostationary features. Wirel. Pers. Commun. **96**, 1–23 (2017)