Deep Neural Network-based Automatic Modulation Classification Technique

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***Abstract*—Deep neural network (DNN) has recently received much attention due to its superior performance in classifying data with complex structure. In this paper, we investigate application of DNN technique to automatic classification of modulation classes for digitally modulated signals. First, we select twenty one statistical features which exhibit good separation in empirical distributions for all modulation formats considered (i.e., BPSK, QPSK, 8PSK, 16QAM, and 64QAM). These features are extracted from the received signal samples and used as the input to the fully connected DNN with three hidden layer. The training data containing 25,000 feature vectors is generated by the computer simulation under both additive Gaussian white noise (AWGN) and Rician fading channels. Our test results show that the proposed method brings dramatic performance improvement over the existing classifier especially for high Doppler fading channels.**

***Keywords*— Deep neural network; automatic modulation classification, digital modulations, fading channels**

I. INTRODUCTION

In wireless communications, automatic modulation classification (AMC) is performed to identify the modulation format used by the sender from the received signal without the knowledge of system parameters. While the modulation information is commonly shared between the transmitter and the receiver in standard communication scenarios, we consider the scenarios where the receiver does not know the modulation format the sender used so it should be blindly detected via the AMC scheme. The well-known application for such scenarios is signal intelligence for military purpose.

Basically, there are two different approaches to the AMC task [1]. First approach is to build the statistical model describing communication systems and employ the modulation class detection scheme based on maximum likelihood (ML) criteria. However, such approach suffers from the model mismatch when there is discrepancy between the system model and true system. For example, in order to account for the frequency offset and timing drift, the substantial computational complexity is needed to handle them in ML-based detector. The alternative approach is feature-based learning which extracts the features from the data and classifies the modulation class using the classifier. Since training data is used to find the good classifier for this approach, they are more robust to variations of system and channel parameters. In order to achieve good classification accuracy, it is required to find effective features and provide the sufficient number of the training data which experiences various system/channel conditions.

So far, various feature-based AMC schemes have been proposed. In [2,3], the decision tree method has been proposed, which uses the cumulants and cyclic moments of the time-domain signal waveforms. In [4,5], support vector machine (SVM) is employed as a classifier and in [6,7,8], artificial neural network with shallow structure is used with SCG and CONJGRAD algorithms. While these methods were developed and optimized for additive white Gaussian noise (AWGN) environments, these methods suffer from performance degradation in real field environments such as fading channels. Recently, performance of feature-based AMC has been investigated for fading channels [9].

In this paper, we first present the deep neural network (DNN)-based AMC technique, which leverages great classification performance of DNN [10,11]. As a classifier, we use fully connected DNN structure with three hidden layers. As an input to the classifier, we extract twenty one features from the received data samples. Using the softmax layer at the output layer, our classifier produces the probability of each modulation class at each node. Even though the dimension of the feature space has increased over that (6~8) used for the conventional AMC methods, we see that the DNN offers good classification performance even with such high dimensional features. All twenty one features we use are carefully selected based on the analysis of the empirical distribution for each modulation class. For successful training of the deep learning architecture, we generate large number of 21-dimensional feature vectors under various channel conditions via computer simulations. We test the proposed AMC for both additive white Gaussian noise (AWGN) and Rican channels environments with several Doppler frequencies and signal to noise ratios (SNRs). We observe that the performance of the existing AMC method degrades much for high Doppler cases while the proposed DNN-based method achieves the classification accuracy over 90% for the same condition.

The rest of this paper is organized as follows. In Section 2, we describe the model for overall communication systems. In Section 3, we introduce the features, the network structure, and training configurations used for the proposed scheme. We provide the simulation results in Section 4 and conclude the paper in Section 5.

II. Overall System Description

We first describe the digital communication systems used for the AMC. We generate the binary information bits which are modulated into one of the five modulation formats; BPSK, QPSK, 8PSK, 16QAM and 64QAM. The modulated symbols are filtered by the root-raised cosine shaping filter with roll-off factor 0.5 and the filtered signal is transmitted over the RF frequency band. The receiver receives the RF signals and converts it to the complex base-band signals. The same root-raised cosine filter is applied and AMC is applied to these baseband samples. We assume that the baseband signal is sampled at $1/T_s$ rate and the symbol rate is given by $1/T_{sym}$ (The oversampling rate for our system is given by OVR = $\frac{T_{sym}}{T_s}$). We assume that the symbol rate $1/T_{sym}$ is known to the receiver.

III. DNN-Based Automatic Modulation Classifier

In this section, we introduce the details of the proposed DNN-based AMC (DNN-AMC).

A. Features for DNN-AMC

First, we introduce the twenty one features used for our proposed DNN-AMC. Among many features available, we choose good ones such that they exhibit sufficiently nice separation between the empirical distributions of each modulation class (see the example shown in Fig. 1).

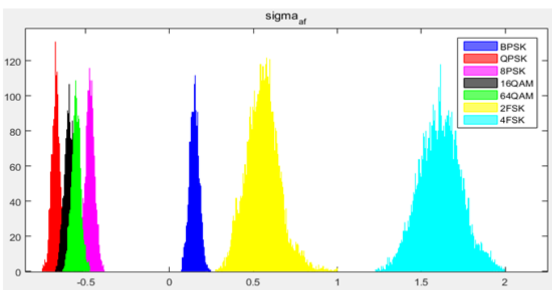

Fig 1. Histogram of $\boldsymbol{\sigma_{af}}$ feature for each modulation class for AWGN channels

The first feature used is the ratio of in-phase component and quadrature component signal power [12,13]

$$\beta = \frac{\sum_n a_Q^2[n]}{\sum_n a_I^2[n]} \qquad (1)$$

where $a_I[n]$ and $a_Q[n]$ are the in-phase and quadrature samples for the complex baseband signal. The second feature is the standard deviation σ_{dp} of the direct instantaneous phase

$$\sigma_{dp} = \sqrt{\frac{1}{C}\left(\sum_{a_n[i]>a_t} \varphi_{NL}^2[i]\right) - \left(\frac{1}{C}\sum_{a_n[i]>a_t} \varphi_{NL}[i]\right)^2} \qquad (2)$$

where a$[i]$ =$a_I[n]$ +j$a_Q[n]$, $a_n[i] = \frac{a[i]}{mean(a[i])}$, $\varphi_{NL}[i]$ is the instantaneous phase at time instant t = $T_s i$, c is the total number of samples used, and a_t is the threshold. The third feature is the standard deviation σ_{ap} of the absolute value of the non-linear component of the instantaneous phase

$$\sigma_{ap} = \sqrt{\frac{1}{C}\left(\sum_{a_n[i]>a_t} \varphi_{NL}^2[i]\right) - \left(\frac{1}{C}\sum_{a_n[i]>a_t} |\varphi_{NL}[i]|\right)^2} \qquad (3)$$

The fourth feature is the standard deviation σ_{aa} of the absolute value of the normalized instantaneous amplitude of the simulated signal

$$\sigma_{aa} = \sqrt{\frac{1}{N}\left(\sum_{i=1}^{N} a_{cn}^2[i]\right) - \left(\frac{1}{N}\sum_{i=1}^{N} |a_{cn}[i]|\right)^2} \qquad (4)$$

where $a_{cn}[i]$ is $\frac{a[i]}{mean(a[i])} - 1$ and N is the number of the samples for $a_{cn}[i]$. The fifth feature is σ_{af} which is the standard deviation of the absolute normalized centered instantaneous frequency for the signal segment

$$\sigma_{af} = \sqrt{\frac{1}{N_s}\left[\sum_{i=1}^{N_s} f_N^2(i)\right] + \left[\frac{1}{N_s}\sum_{i=1}^{N_s} |f_N(i)|\right]^2} \qquad (5)$$

where $f_N(i)$ is the centered instantaneous frequency. The next feature is obtained from

$$\sigma_v = \sqrt{\frac{1}{N}\left(\sum_{i=1}^{N} a_v[i]^2\right) - \frac{1}{N}\left(\sum_{i=1}^{N} |a_v[i]|\right)^2} \qquad (6)$$

where a_v is the normalized signal amplitude, i.e. $\sqrt{\frac{a[i]}{var(a[i])}} - 1$. The seventh feature is the mixed order moments v_{20}[14]

$$v_{20} = \frac{M_{4,2}(y)}{M_{2,1}^2(y)} = \frac{E(|a[i]|^4)}{E(|a[i]|^2)} \qquad (7)$$

The eighth feature is the mean value of the signal magnitude [15]

$$X = \frac{1}{N}\sum_{n=1}^{N} |a[i]| \qquad (8)$$

where a[i] is the instantaneous amplitude. The next two features are the normalized square root value of sum of amplitude of signal samples

$$X_2 = \frac{\sqrt{\sum_{i=1}^{N} |a[i]|}}{N} \qquad (9)$$

and the maximum value of power spectral density(PSD) of the normalized signal samples

$$\gamma_{max} = \frac{1}{N} \max \ |DFT(a_{cn}[i])|^2$$
(10)

The next features are cumulants calculated with the equations below;

$$C_{20} = E[a^2[n]] \qquad (11)$$

$$C_{21} = E[|a[n]|^2] \qquad (12)$$

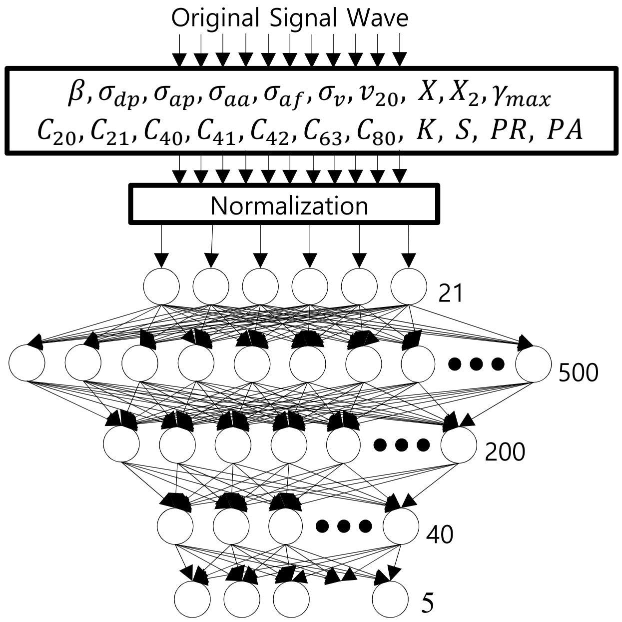

Fig 2. Structure of proposed DNN-AMC

$$C_{40} = M_{41} - 3{M_{20}}^2 \tag{13}$$

$$C_{41} = M_{41} - 3M_{20}M_{21} \tag{14}$$

$$C_{42} = M_{42} - |M_{20}|^2 - 2M_{21}^2 \tag{15}$$

$$C_{63} = M_{63} - 6M_{20}M_{40} - 9M_{42}M_{21} + 18{M_{20}}^2M_{21} + 12{M_{21}}^3 \tag{16}$$

$$C_{80} = M_{80} - 35{M_{40}}^2 - 28M_{60}M_{20} + 420M_{40} - 630{M_{20}}^4 \tag{17}$$

where $M_{p+q,p}$ denotes $E\left[a[n]^p a[n]^{*q}\right]$. The other two features are the kurtosis which measures the tailedness of the distribution written

$$\mathrm{K} = \left|\frac{E\left[(a-E[a])^4\right]}{E[(a-E[a])^2]^2}\right| \tag{18}$$

and the skewness quantifying the asymmetry of the distribution given by

$$\mathrm{S} = \left|\frac{E\left[(a-E[a])^3\right]}{E[(a-E[a])^2]^{3/2}}\right| \tag{19}$$

We also use peak-to-rms ratio PR and peak-to-average ratio PA defined as

$$\mathrm{PR} = \frac{\max\ |a|^2}{\frac{1}{N}\sum_{i=1}^{N}(a[i])^2} \tag{20}$$

$$\mathrm{PA} = \frac{\max\ |a|}{\frac{1}{N}\sum_{i=1}^{N}a[i]} \tag{21}$$

B. *Structure of DNN-AMC*

Fig. 2 depicts the structure of the proposed DNN-AMC. The proposed DNN has five layers and the number of nodes at each layer is specified in Fig. 2. The all twenty one features are fed into the input layer after l2 normalization for each feature. At the final layer, the soft-max function is used to produce the probability metrics associated with all five modulation classes (BPSK, QPSK, 8PSK, 16 QAM and 64QAM). The class with highest score in soft metric is chosen as a final decision. Note that rectified linear unit function is used as a nonlinear function for each perceptron.

C. *Configurations of DNN-AMC*

Specific configurations of the DNN-AMC are provided in Table I. We use the negative-log-likelihood function as a cost. function and employ the stochastic gradient descent method with learning rate of 0.01. Note that when validation error rate stops to decrease we decrease the learning rate by half to search for the refined DNN weights. In training, we set the batch size to 50, and update the network weights update for every 50 feature inputs.

TABLE I. CONFIGURATIONS OF PROPOSED DNN-AMC

Parameters	Value
Number of input nodes	21
Number of hidden layers	3
Number of nodes of 1st hidden layer	500
Number of nodes of 2nd hidden layer	200
Number of nodes of 3rd hidden layer	40
Number of output nodes	7
Activation function of hidden layer	ReLU
Activation function of output layer	Softmax
Max number of epochs	15000
Cost function	Negative-log-likelihood
Training method	SGD
Learning rate	< 0.01
Number of train data	15,000
Number of validation data	5,000
Number of test data	5,000
Batch size	50

IV. RESULTS AND DISCUSSIONS

A. *Simulation Setup*

The features are computed using the 200,000 baseband data samples containing 20,000 data symbols (OVR=10). The training data is generated under AWGN and Rician fading scenario with two Doppler values (100Hz and 300Hz) as well as with five SNR values (-5dB, 0dB, 5dB, 10dB and 15dB). In Rician fading channels, the parameter κ (i.e., the ratio of the power in the direct path and that in the scatter path) is set to 0.5. Note that a total of 25,000 feature vectors are generated for training. Among them, 20,000 feature vectors are used for training and 25% of them are used for validation. After training, the performance of the DNN-AMC is tested with 5,000 test feature vectors.

In our simulations, we compare the performance of the proposed DNN-AMC with that of the conventional artificial neural network (ANN) with shallow structure [6]. Note that this conventional ANN scheme uses only first six features of what we used. Table II and III provide the classification accuracy measured with the test data for the proposed method and conventional method, respectively. We observe that the proposed method achieves significantly higher classification accuracy than the ANN over all scenarios considered. The proposed method achieves the accuracy above 90% for all cases while the performance of the conventional method degrades for high Doppler scenarios. Note that even for 300 Hz Doppler channels, the proposed DNN-AMC achieves 100% accuracy in the SNR range above 10dB.

TABLE II. CLASSIFICATION ACCURACY RATES OF THE CONVENTIONAL ANN METHOD

	-5dB	0dB	5dB	10dB	15dB
AWGN	76.74%	93.85%	99.84%	100%	100%
100Hz Doppler	60.01%	65.38%	70.96%	73.41%	73.99%
300Hz Doppler	62.28%	67.26%	66.68%	69.76%	66.93%

TABLE III. CLASSIFICATION ACCURACY OF THE PROPOSED DNN METHOD

	-5dB	0dB	5dB	10dB	15dB
AWGN	99.95%	99.99%	100%	100%	100%
100Hz Doppler	100%	100%	99.80%	100%	100%
300Hz Doppler	100%	97.98%	98.75%	100%	100%

V. CONCLUSION

This paper proposes the new automatic modulation classification method based on deep neural network. The proposed method uses the twenty one features extracted from the base-band signal samples for the DNN and five layer fully connected DNN structure is used to classify the 5 modulation formats (BPSK, QPSK, 8PSK, 16QAM and 64QAM). Our intensive simulations performed over various channels and conditions show that the proposed classifier rate, outperforming ANN-based classifier with shallow structure especially for high Doppler fading channels.

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REFERENCES

[1] Z. Zhu, A. K. Nandi (2015). "Automatic Modultaion Classification: Principles, Algorithms and Applications," London : Wiley

[2] A. Swami, B. Sadler, M. Brian. "Hierarchical digital modulation classification using cumulants," *IEEE Trans. Commun,* vol. 48, no.3, pp. 416-429, Mar. 2000

[3] A. K. Nandi, E. E. Azzouz, "Algorithms for automatic modulation recognition of communication signals," *IEEE Trans. Commun.,* vol. 46 no.4, pp. 431-436, Apr. 1998.

[4] H. Gang, L. Jiandong, L. Donghua. "Study of modulation recognition based on HOCs and SVM." *VTC 2004-Spring. 2004,* pp. 898-902.

[5] M. W. Aslam, Z. Zhu, A. K. Nandi, "Automatic modulation classification using combination of genetic programming and KNN," *IEEE Trans. wireless commun,* vol. 11, no. 8, pp. 2742-2750, Aug. 2012.

[6] J. J. Popoola, R. V. Olst, "Effect of training algorithms on performance of a developed automatic modulation classification using artificial neural network," *AFRICON, 2013. IEEE.* pp. 1-6.

[7] J. J. Popoola, R. V. Olst, "Development and Comparative Study of Effects of Training Algorithms on Performance of Artificial Neural Network Based Analog and Digital Automatic Modulation Recognition," *Journal of Engineering Science & Technology Review,* vol. 8, issue. 4, pp. 135-144, Nov. 2015

[8] M. L. D. Wong, A. K. Nandi, "Automatic digital modulation recognition using artificial neural network and genetic algorithm," *Signal Processing,* vol. 84, no. 2, pp. 351-365, Feb. 2004

[9] J. Bagga, N. Tripathi, "Automatic Modulation Classification using Spectral and Statistical features and Artificial Neural Networks," *The Journal of Applied Sciences Research,* vol. 1, no. 4, pp.250-260, Dec. 2014

[10] A. Krizhevsky, I. Sutskever, G. Hinton, "Imagenet classification with deep convolutional neural networks," *Advances in neural information processing systems*, pp. 1097-1105, 2012.

[11] K. Xu, J. Ba, R. Kiros, A. Courville, R Salakhutdinov, R. S. Zemel, Y. Bengio, "Show, attend and tell: Neural image caption generation with visual attention," *arXiv preprint, arXiv:1502.03044*, 2015.

[12] O. A. Dobre, et al. "The classification of joint analog and digital modulations," *MILCOM 2005.*

[13] E. E. Azzouz, A. K. Nandi, "Automatic identification of digital modulation types," *Signal Processing,* vol. 47, no. 1, 55-69, Nov, 1995.

[14] N. An, B. Li, M. Huang, "Modulation classification of higher order MQAM signals using mixed-order moments and Fisher criterion," *Computer and Automation Engineering (ICCAE),* pp. 150-153.

[15] F. Huang, et al. "Modulation recognition of symbol shaped digital signals" *ICCCAS 2008. ,* pp. 328-332.