Effective Feature-Based Automatic Modulation Classification Method Using DNN Algorithm

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***Abstract*— In this paper, we propose an effective feature-based automatic modulation classification (AMC) method using a deep neural network (DNN). In order to classify the modulation type, we consider effective features according to the modulation signals. The proposed method removes the meaningless features that have little influence on the classification and only uses the effective features that have high influence by analyzing the correlation coefficients. From the simulation results, we observe that the proposed method can make the AMC system low complexity.**

***Keywords*—automatic modulation classification, deep neural network, cumulant, correlation, effective features**

I. Introduction

An automatic modulation classification (AMC) technique is used to identify the modulation type from received signals without prior knowledge of wireless systems. The conventional AMC technique is classified into maximum likelihood method and machine learning method. In this paper, since the machine learning method can operate well in various environments and have a low amount of calculation compared to the maximum likelihood method, we consider the machine learning method. Generally, in order to classify the modulation type, various high order statistic features such as second and fourth cumulants ($C_{20}, C_{21}, C_{40}, C_{41}, C_{42}$) are used [1,2]. However, since the influence of each feature is different according to the modulation type, we try to find some effective features on classification by analyzing the correlation coefficients. Then, we use the effective features as the input of a deep neural network (DNN).

II. Analysis of Features Using Correlation

Since the correlation means the degree of similarity between two data, the feature that has a high correlation coefficient is relatively less important in the AMC. Thus, in order to reduce the calculation complexity of the DNN and to increase the classification efficiency, we calculate the correlation coefficients between the features to find some effective features. The correlation coefficient between two random variables X and Y is expressed as [3]

$$cor(X,Y) = \frac{C(X,Y)}{\sigma_X \sigma_Y} = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sigma_X \sigma_Y} \quad (1)$$

where $C(X,Y)$ represents the covariance between X and Y [3], σ_x and σ_y are the standard deviation of X and Y, respectively. Moreover, $\bar{x}, \bar{y}, x_i$, and y_i denote mean values of x, mean values of y, i-th data of x, and i-th data of y, respectively. Then, the effective correlation value for each modulation type is obtained by the following procedures.

Step 1: The correlation coefficients between each feature of the modulation type x_i ($i = \{1, \cdots, N\}$) are obtained.

Step 2: The number of modulation types N are calculated by (1) and the obtained values are summed.

Step 3: Then, the feature which has the lowest value in Step 2 is set as the highest effective feature and other features are given the ranking according to the result in Step 2.

The effective correlation value ECV_i for the i-th modulation type can be expressed as

$$ECV_i = \sum_{j=1}^{M} \sum_{\substack{k=1 \\ k \neq j}}^{M} \left| cor(x_{ik}, x_{ij}) \right| \quad (2)$$

where M denotes the number of features, x_{ij} denotes the j-th feature of the i-th modulation type. Therefore, the sum of the correlation coefficients between the j-th feature and k ($k = \{1, \cdots, M\}, k \neq j$) -th feature can be obtained. In order to evaluate the performance, we consider the wireless channel signal-to-noise ratio (SNR) ranges from -5dB to 10dB with 5dB interval. Moreover, in order to evaluate the classification performance, we consider BPSK (Binary Phase Shift Keying), QPSK (Quadrature PSK), 8-PSK, 16-QAM (Quadrature Amplitude Modulation), and 64-QAM.

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In [4,5], the optimal feature values can be obtained by

$$I(x_q;c) = \iint P(x_q,c)\, log \frac{P(x_q,c)}{P(x_q)P(c)} dx_q dc \qquad (3)$$

$$max_{x_p \in X-S_{r-1}} \left[I(x_p;c) - \frac{1}{r-1} \sum_{x_q \in S_{r-1}} I(x_p;x_q) \right] \qquad (4)$$

where $P(x_q, c)$ denotes the probability distribution of x_i and c, $I(x_j, c)$ denotes the mutual information value between the feature and the signal, and S_r denotes a set of feature selected up to r times. Table 1 shows the optimal feature values obtained from (3) and (4).

TABLE 1. Optimal feature values of the second and the fourth cumulants in various SNR environments for the conventional method [4,5]

SNR	C_{20}	C_{21}	C_{40}	C_{41}	C_{42}
-5 dB	7.5630	6.7804	7.9753	8.4592	8.5818
0 dB	6.5694	5.6250	6.8910	6.8581	6.7813
5 dB	5.7073	4.6600	5.8626	5.9123	5.3678
10 dB	5.0487	3.9380	5.0765	5.2685	4.6001

The conventional method uses the difference between the mutual information and the correlation coefficient. However, the proposed method finds some effective features by using the sum of the correlation coefficients between the features. In order to verify the proposed method, we consider the second and the fourth cumulants, and show whether any feature value greatly affects the classification. Table 2 shows the results of the effective correlation values. As shown in Table 2, the correlation coefficient of C_{40} shows the lowest value in all SNR environments among the five cumulants.

TABLE 2. Effective correlation values of the second and the fourth cumulants in various SNR environments for the proposed method

SNR	C_{20}	C_{21}	C_{40}	C_{41}	C_{42}
-5 dB	4.3029	1.3234	1.3079	3.6576	0.7045
0 dB	5.5141	3.4890	2.2008	5.3551	2.2613
5 dB	6.7185	6.3845	3.5278	6.6853	4.4993
10 dB	7.3723	8.4791	5.2012	7.3656	7.2603

Table 3 shows the ranking of each feature. Since the conventional method considered the mutual information, the biggest value summed in various SNR environments may be the highest ranking. However, since the proposed method considered the correlation coefficient, the lowest value summed in various SNR environments may be the highest ranking, which means the highest effect on the classification.

TABLE 3. The ranking of each feature

Ranking / Type	1	2	3	4	5
Conventional method	C_{41}	C_{40}	C_{42}	C_{20}	C_{21}
Proposed method	C_{40}	C_{42}	C_{21}	C_{41}	C_{20}

III. DNN STRUCTURE AND RESULTS

In order to classify the modulation type, we consider DNN-based AMC method. Figure 1 shows the DNN structure considered in this paper. The DNN structure consists of an input layer, two hidden layers, and an output layer. We consider five feature values with a fully connected layer for the input layer and the hidden layers consists of 30 nodes and 10 nodes. The output layer consists of 5 nodes. The hidden layers used the rectified linear unit (ReLU) function and the output layers used the softmax. In order to train the DNN structure, we set the epoch to be 200 and the batch size was 64. Then, the training set was obtained by 20,000 data for each modulation type and we used a total of 100,000 data for the classification.

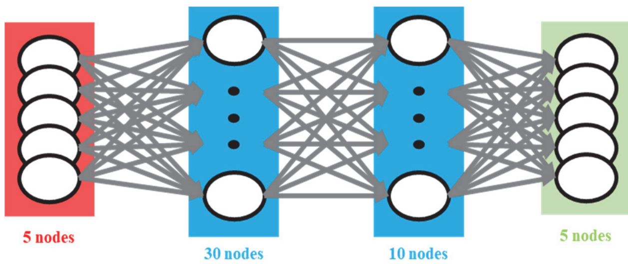

Fig 1. DNN structure

Tables 4 and 5 show the classification performances according to the elimination of each feature. From the results, C_{40} has a low correlation coefficient in the training and the testing process. Thus, we conclude that C_{40} is the effective feature on the classification.

TABLE 4. Classification performance according to elimination of each feature (training accuracy) [%]

SNR	C_{20}	C_{21}	C_{40}	C_{41}	C_{42}	All
-5 dB	92.95	91.6	80.13	87.04	89.89	93.24
0 dB	98.5	99.02	91.09	97.04	98.48	99.03
5 dB	99.97	99.91	92.45	99.96	98.88	99.98
10dB	100	99.99	93.31	99.99	99.85	100

TABLE 5. Classification performance according to elimination of each feature (test accuracy) [%p]

SNR	C_{20}	C_{21}	C_{40}	C_{41}	C_{42}	All
-5 dB	85.61	85.14	80.98	83.97	84.31	86.2
0 dB	95.7	96.79	88.76	94.12	92.56	97
5 dB	99.02	98.43	90.99	96.65	96.65	99.08
10 dB	99.69	99.09	92.38	99.58	97.54	99.71

Tables 6 shows the difference of classification performance between C_{20} and C_{40}. From the results, C_{20} has a little effect on the classification according to SNR about 0.02%p~1.3%p, whereas C_{40} has an effect about 5.22%p~8.24%p. Consequently, even if the number of data is the same, the proposed method can improve the classification performance up to 8.03%p by using the effective feature.

TABLE 6. Difference of classification performance between $\boldsymbol{C_{20}}$ and $\boldsymbol{C_{40}}$ [%p]

SNR	C_{20}	C_{40}
-5 dB	0.59	5.22
0 dB	1.3	8.24
5 dB	0.06	8.09
10 dB	0.02	7.33

IV. Conclusion

In this paper, we have considered the effective features to reduce the computational complexity of the DNN-based AMC and to improve the classification performance. We have evaluated the performance by using the second and the fourth cumulants which were used as the features for the input data. Simulation results show that the proposed method achieves good results by using the effective features that have a large impact on the classification. Also, the classification performance is 92.58% when C_{40} is excluded in an environment with SNR=10 dB, and the performance is 99.02% when C_{20} is excluded in the environment where SNR=5dB. Thus, even if the received signal is better and the same amount of data is used, the classification performance can be improved depending on which features are used. Consequently, we conclude that the elimination of less influential features on the classification and the utilization of more influential features as the input data can improve the classification performance, even in fewer data and low SNR environments. In future work, we will analyze the correlation coefficients for various features.

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