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Modulation Classification Based on Statistical Features and Artificial Neural Network

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***Abstract*—Modulation classification has been an interesting topic for many years with many applications in both civil and military fields. In this paper, we propose a feature-based automatic modulation recognition method that is based on the time domain statistical features of the amplitude envelope and the instantaneous phase with an artificial neural network (ANN) classifier. We trained and tested the classifier to classify four different digital modulation schemes: BPSK, QPSK, 16QAM and 64QAM. The classifier performance was compared to one of the feature-based methods in literature and simulation results show that the proposed method performs better especially in lower signal to noise ratios (SNRs). The presented method is also tested with the over-the-air captured signal dataset (RadioML.2018) and gave a maximum of 99% correct classification in high SNRs.**

***Index Terms*—Modulation classification, Modulation recognition, Statistical features, Artificial neural network.**

I. Introduction

For the past two decades, Automatic Modulation Recognition (AMR) has been a challenging topic for research, starting from using it for threat detection and military applications, to nowadays with the expansion of smart systems like cognitive radio and spectrum efficient adaptive modulation systems, where the receiver is able to identify the modulation scheme used with no prior information and with a high classification accuracy.

AMR approaches can be generally categorized into three main methods: the likelihood based (LB), Feature Based (FB), and Deep learning (DL) based approaches. The LB method takes the problem as a multi-hypothesis problem, in which the received signal goes through a maximum likelihood test with every modulation scheme possible in the system. The authors in [1] used the LB method to classify different QAM orders. The LB algorithms tend to give optimum classification accuracy but typically suffer from high computational complexity [2]. FB methods trade the classification accuracy for a reduction in the computational complexity, and hence is more feasible and easier to implement. FB methods include two main steps: feature extraction, where hand-crafted features are extracted from the received signal, and a classifier that identifies the modulation scheme used from the extracted features in the first step. Throughout the years, different types of features and classifiers were used. In [3], the authors used a higher order statistical (HOS) features together with a support vector machine (SVM) classifier to classify PSK and QAM signals, Whereas in [4], the same features were used with a hierarchical polynomial classifier to identify MPSK and MQAM signals as well. Other type of features previously used in the field of AMR include cyclostationary features [5] and Wavelet Transform (WT) coefficients [6]. Different types of classifiers are used for the decision making step including Artificial Neural Networks (ANN), SVM, Naivee Bayes classifiers, decision trees and others. Choosing the type of features to be used in this method mainly depends on the modulation candidates of interest and the type of channel model used in performance evaluation. The DL based approaches use deep neural networks trained on raw signals - IQ samples for example - as an image and use it directly for classification. In [7], the authors proposed a Convolutional Neural Network (CNN) to classify eleven digital and analog modulation schemes. DL methods usually perform better than the previous mentioned methods especially under severe channel effects and large number of modulation candidates, however, they are very computationally complex in training phase.

In this paper, we propose a FB method that extracts expert features from both instantaneous amplitude and phase of the received signal, and then uses a two hidden layer ANN for classification between four different modulation schemes: $M = \{$BPSK, QPSK, 16QAM, 64QAM$\}$.

The rest of the paper is organised as follows: section III discusses the classification method in details, simulation results and comparisons are in section IV followed by conclusions in section V.

II. Proposed Modulation Classifier Method

As mentioned earlier, the feature based classification methods consist of two main parts, starting with feature extraction from the received signal, and then passing the extracted features to a decision maker.

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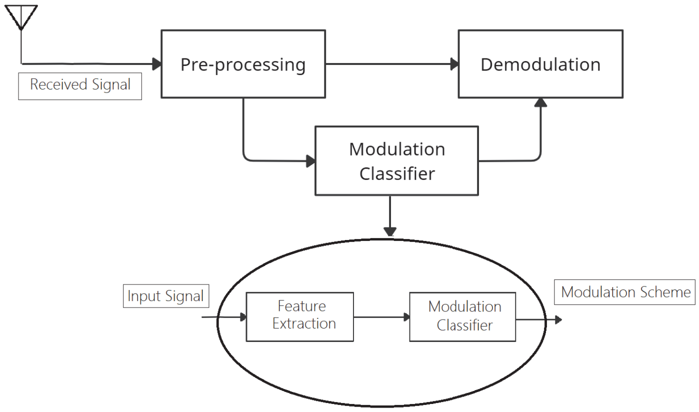

Fig. 1. A block diagram of a receiver that utilizes Automatic Modulation Classification.

In this method, a set of three features is extracted from both the instantaneous amplitude and phase of the received signal, i.e. a total of six features for each received signal sample. The extracted feature set is then passed to an ANN classifier for decision making as shown in Fig. 1.

A. System Model

In this paper, the complex valued received signal (y_n) is given by:

$$y_n = x_n + w_n \tag{1}$$

where x_n is the transmitted symbol that follows the constellation of one of the modulation schemes, and (w_n) is the additive white Gaussian noise (AWGN). The process of classification is then the determination of the used modulation scheme (M_i).

The performance of the classifier is measured by the probability of correct classification P_{CC} which is given by:

$$P_{CC} = P(M = M_i|M_i) \tag{2}$$

B. Feature Extraction

The feature extraction step aims to extract a feature set from the received signal that is sufficient to discriminate between the modulation candidates. In this work, we extracted a set of six features in total from both the amplitude and phase of the received signal. The skewness of the received signal amplitude is also used as an additional seventh feature to improve the classification performance with real captured signals from the RML dataset. The extracted feature set is described in Table I.

For a discrete time signal u_n, these features can be calculated as in [8]:

$$\sigma_u^2 = \frac{1}{N-1}\sum_{n=0}^{N-1}(u_n - \mu_u)^2 \tag{3}$$

TABLE I
EXTRACTED FEATURES.

Feature Symbol	Description
σ_a^2	Variance of received signal amplitude
σ_p^2	Variance of received signal phase
kur_a	Kurtosis of received signal amplitude
kur_p	Kurtosis of received signal phase
H_a	Entropy of received signal amplitude
H_p	Entropy of received signal phase
c_a	Skewness of received signal amplitude

$$k_u = \frac{\sum_{n=1}^{N}(u_n - \mu)^4}{N\sigma^4} \tag{4}$$

$$\mathrm{H}(u) = -\sum_{n=1}^{N}\mathrm{P}(u_n)\log\mathrm{P}(u_n) \tag{5}$$

$$c_u = \frac{\sum_{n=1}^{N}(u_n - \mu)^3}{N\sigma^3} \tag{6}$$

where N is the signal length, μ is the mean of the received signal and σ is the standard deviation.

C. ANN Classifier

An artificial neural network is a mathematical model that aims to simulate the behaviour of biological neural networks. ANNs has been widely used for classification purposes, due to their ability to classify in higher dimensions.

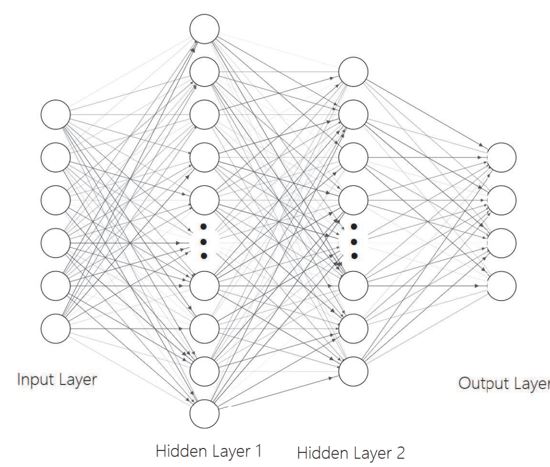

Fig. 2. Artificial neural network architecture.

A neural network is basically composed of different layer, where a layer is a set of neurons, any neural network has an input layer, an output layer and one or more hidden layers. The number of neurons in the input layer is decided by the dimension of the used input, and the number of neurons in the output layer is the number of output classes. The number of hidden layers and hidden neurons is however dependent on the used data, where for each problem there is an optimum number of hidden layers and neurons, below it, the network will not be able to fit, and above it, the network will probably overfit on the training data. Fig. 2 shows a schematic diagram of a neural network. The network performance does depend on other parameters and settings as well, these settings mainly include the activation functions of the neurons in each layer, the training function utilized and the number of epochs. Table III shows the used settings of the proposed network.

TABLE II
CONFIGURATION OF PARAMETERS FOR THE PROPOSED ARTIFICIAL NEURAL NETWORK.

Parameters	**Value**
Number of Hidden Layers	2
No. of Neurons in each Hidden Layer	$\{48,\ 32\}$
Activation Function for each Layer	{'tansig', 'tansig', 'softmax'}
Training Algorithm	Stochastic Gradient Descent
Max. number of Epochs	1000
Max. no. of wrong validation checks	200

III. SIMULATION RESULTS

In this section, we use MATLAB environment to compare the performance -or as we said earlier the probability of correct classification (P_{CC}) of the proposed classifier with different parameters that may vary in the modeled system from section II. These parameters include the signal-to-noise ration (SNR) and the sample length of the tested signal (N). The results are compared to the higher order cumulants (HOC) based classifier from [3]. The proposed classifier is also tested with the over-the-air captured signals dataset RadioML.2018 from [9].

We trained the model on a set of 1000 signals per modulation scheme, i.e., a total of 4000 signals at a signal length (N) of 512 symbols for each SNR value ranging from 0 to 20 in order to compare the performance of the proposed classifier to the method from [3]. The classifier was then tested with a testing set of 300 signals per modulation scheme using Monte Carlo approach with 25 repetition times, each with new generated data stream. Fig. 3 shows the performance of both classifiers with different signal SNRs. We can clearly see that the proposed method outperforms the method from [3] especially in low SNRs, however, both methods give almost the same performance in SNRs higher than 15 dB and eventually converge to the same maximum performance of 98%.

The signal length (N) also affects the performance of the classifier, where a robust classifier performance should not drop significantly with reduced available signal length. Table III compares the performance of our proposed classifier to the method from [3] with three different signal lengths in two SNRs. We can see that our proposed method still outperforms the method from [3] in shorter signal lengths even though that both method are relatively robust to the reduction in signal length, however, we can notice that our proposed method performance increases more rapidly to a new maximum of 99% with longer signal length.

TABLE III
A COMPARISON OF AVERAGE PROBABILITY OF CORRECT CLASSIFICATION WITH DIFFERENT SIGNAL LENGTHS.

	Proposed Method		
SNR	$N = 256$	$N = 512$	$N = 1024$
$6dB$	89.29%	92.35%	99.08%
$10dB$	90.77%	95.62%	99.56%
	HOC SVM [3]		
SNR	$N = 256$	$N = 512$	$N = 1024$
$6dB$	81.20%	85.71%	90.91%
$10dB$	86.59%	92.52%	96.30%

We eventually tested our proposed classification method with the publicly available RadioML dataset. The signals in this dataset exhibit different types of well known channel effects including random phase and frequency offsets and doppler effect, and hence, we added the skewness of the received signal amplitude as an additional feature to the

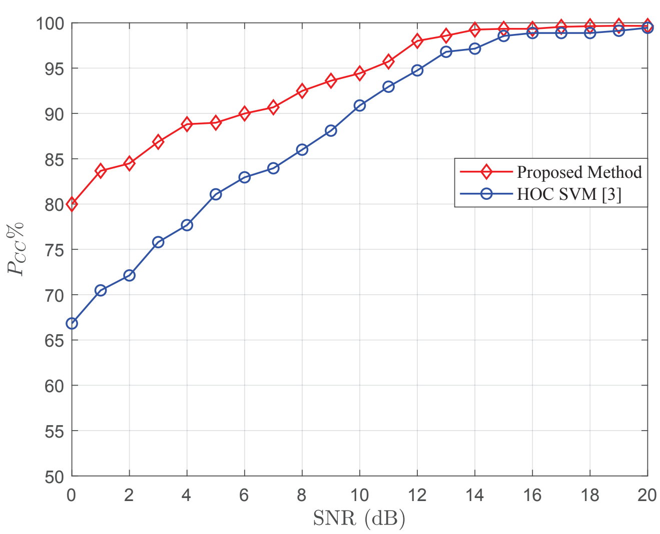

Fig. 3. Comparison of P_{CC} for proposed classifier and [3].

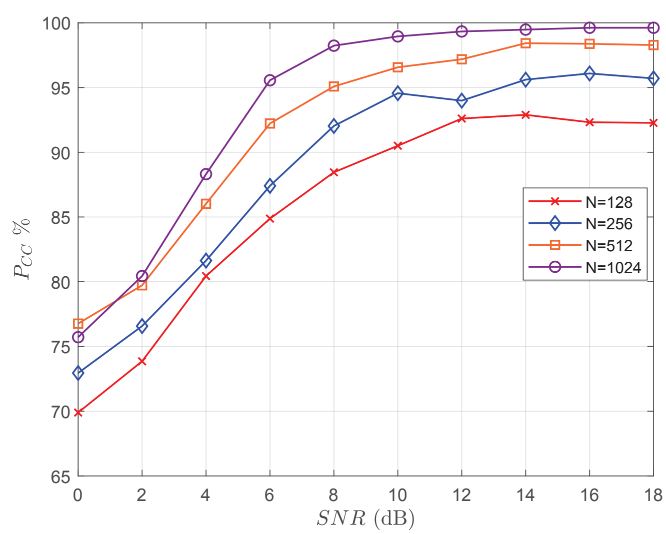

Fig. 4. P_{CC} with SNR in different cases of available signal length.

ones used in the AWGN due to its importance in classifying $QPSK$ and $16QAM$ under these channel impairments. From the dataset, 2048 signals per modulation type per SNR was used with 75% and 25% training and testing split, respectively. Fig. 4 shows the probability of correct classification with signal SNR in different lengths of the tested signal.

IV. Conclusions and Future Work

The proposed method in this article utilizes the statistical features of the amplitude and instantaneous phase of the received signal combined with an ANN classifier to achieve better classification accuracy especially in lower signal-to-noise ratios, with relatively robust performance to reductions in available signal length. And with some modifications, the classifier also performed well with the over-the-air captured signal dataset. Consideration of errors in SNR estimation in the receiver and its effect on the classification performance is a potential theme for future work.

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