Journal of Engineering Science and Technology
Vol. 9, No. 2 (2014) 273 - 285

AUTOMATIC RECOGNITION OF BOTH INTER AND INTRA CLASSES OF DIGITAL MODULATED SIGNALS USING ARTIFICIAL NEURAL NETWORK

JIDE JULIUS POPOOLA

Department of Electrical and Electronic Engineering, Federal University of Technology, P.M.B. 704, Akure, Ondo State, Nigeria
E-mail: jidejulius2001@yahoo.com

Abstract

In radio communication systems, signal modulation format recognition is a significant characteristic used in radio signal monitoring and identification. Over the past few decades, modulation formats have become increasingly complex, which has led to the problem of how to accurately and promptly recognize a modulation format. In addressing these challenges, the development of automatic modulation recognition systems that can classify a radio signal's modulation format has received worldwide attention. Decision-theoretic methods and pattern recognition solutions are the two typical automatic modulation recognition approaches. While decision-theoretic approaches use probabilistic or likelihood functions, pattern recognition uses feature-based methods. This study applies the pattern recognition approach based on statistical parameters, using an artificial neural network to classify five different digital modulation formats. The paper deals with automatic recognition of both inter-and intra-classes of digitally modulated signals in contrast to most of the existing algorithms in literature that deal with either inter-class or intra-class modulation format recognition. The results of this study show that accurate and prompt modulation recognition is possible beyond the lower bound of 5 dB commonly acclaimed in literature. The other significant contribution of this paper is the usage of the Python programming language which reduces computational complexity that characterizes other automatic modulation recognition classifiers developed using the conventional MATLAB neural network toolbox.

Keywords: Automatic modulation recognition, Inter and intra modulation classes, Features extraction key, Artificial neural network.

1. Introduction

Development of algorithms or systems that can automatically recognize radio communication signals has received international attention over the last two decades.

Nomenclatures

a_{cn}(i)	Normalized-centred instantaneous amplitude
a_t	Threshold value
f_s	Sampling frequency
m_a	The mean value of the sample
N	Numbers of samples per segment
$t(\gamma_{\max})$	Threshold value for $\gamma_{\max}$
$t(\sigma_{ap})$	Threshold value for σ_{ap}
$t(\sigma_{dp})$	Threshold value for σ_{dp}
$t(\sigma_{aa})$	Threshold value for σ_{aa}

Greek Symbols

$\gamma_{\max}$	The maximum value of the power spectral density
σ_{aa}	Standard deviation of the absolute value of the normalized centred instantaneous amplitude
σ_{ap}	Standard deviation of the absolute value of the centred non-linear component of the instantaneous phase
σ_{dp}	Standard deviation of the direct value of the centred non-linear component of the direct instantaneous phase
$\phi_{NL}(i)$	Value of the centred non-linear instantaneous phase at time, t

Although the field belongs to non-cooperative communication theory, it has found widespread applications in both cooperative and non-cooperative communication areas such as software-defined radio, cognitive radio, radio spectrum management, interference identification, electronic warfare, threat analysis and electronic surveillance [1-4]. In a non-cooperative environment, the recognition of the transmitting signal is a difficult task since there is no foreknowledge about the features of the signal. This makes modulation format recognition the most significant sorting parameter of the communication signal since all radio systems make use of one modulation format or another. Therefore, ability to correctly recognize the modulation format of the transmitting signal makes the signal detection and tracking easy.

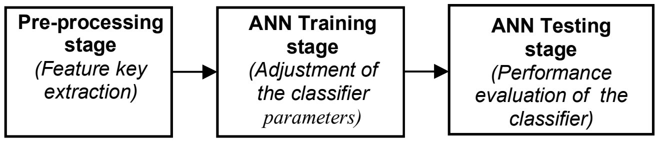
The process of determining the modulation format of a radio signal without foreknowledge of the signal modulation characteristics is known as modulation recognition. There are two approaches to radio signal modulation recognition: automatic and non-automatic. In the non-automatic approach, modulation recognition depends on the operator's interpretation of measured parameters. This approach, as observed by [5], is unpopular because of its slow response rate in hostile environments as well as its success being dependent on the operator's experience. For a fast response, which does not require human involvement, automatic modulation recognition techniques are employed [1]. Automatic modulation recognition of a communication signal is an intermediate step between signal interception and information recovery, which automatically identifies the modulation type of the received signals for further demodulation and other tasks [6] such as radio spectrum management, radio signal confirmation and radio signal interference identification.

Automatic modulation recognition (AMR) of digitally modulated signals can generally be divided into two classes: inter-class and intra-class [7]. In inter-class AMR, signals belonging to different modulation formats such as amplitude shift keying (ASK), phase shift keying (PSK) and frequency shift keying (FSK) are distinguished. On the other hand, intra-class AMR refers to distinguishing between modulations of a single class, such as BPSK (binary phase shift keying) and QPSK (quadrature phase shift keying). For both classes of AMR, there exists extensive and diverse literature devoted to the field. Different approaches for recognizing or classifying different modulation formats, as well as usage of different features in extracting signal characteristics under different conditions; make it practically impossible to compare the performance of different methods. However, there are two primary methods which are used in AMR: decision-theoretical (DT) and pattern recognition (PR). The DT methods, according to [8], employ probabilistic or likelihood algorithms that make a decision based on the comparison of a likelihood ratio with a predefined threshold to minimize false decision probability. The advantage of DT method is that its performance is usually optimal [9]. The disadvantages of this method are that it is not robust and highly computational complex [9].

PR methods, on the other hand, employ feature-based algorithms. In PR methods, the modulation classification modules are usually composed of two subsystems [1, 9]. The first is a feature extraction subsystem, which extracts the key features from the incoming signal. Most of the adopted features according to [9] are higher-order statistics including moments and cumulants, and higher-order cyclic cumulants [10]. Other examples of features used in the literature are the correlation between the in-phase and quadrature signal components [8], normalized-centred information contained in instantaneous amplitude, phase and frequency of the incoming signal [1, 11-13] and the variance of the magnitude of the signal wavelet transform after peak removal [14], to mention but a few. The second subsystem of PR is a pattern recognizer subsystem which processes those features to determine the modulation format of the received signal. There are also various classifiers used for modulation recognition, such as support vector machines classifiers [15], decision-tree classifiers [16] and neural network classifiers [1, 11-13].

In contrast to the DT methods, the PR methods are non-optimal, but they are more robust and simple to implement. Most often if PR methods are carefully designed, they can achieve nearly optimal performance [9]. Thus, this paper focuses on the PR modulation recognition. The purpose of the paper is to demonstrate the possibility of recognizing digital modulation signal at signal-to-noise ratio (SNR) values below 5 dB normally considered in the literature.

The organization of the rest parts of the paper are as follows: Section 2, which is the next section, presents in detail the research materials and methods employed in carrying out the study. The section is divided into two sub-sections. The first sub-section provides information on the methodology for the pre-processing block in Fig. 1 using instantaneous amplitude, instantaneous phase and instantaneous frequency of the modulated signal. The second sub-section of the second section provides details information on the second and third blocks of Fig. 1. The simulation results and the performance evaluation of the proposed AMR classifier are presented in Section 3 of the paper. Finally, the paper conclusion is presented in Section 4.



Adapted from: Azzouz and Nandi, 1996 [11]

Fig. 1. Functional Blocks of ANN Automatic Modulation Recognition.

2. Research Material and Methods

In carrying out this study, the proposed AMR classifier employs key features extracted from the instantaneous amplitude, instantaneous phase and instantaneous frequency of the simulated signal as the primary features for the automatic modulation recognition. These features are normalized and then used as input to train a multi-layer perceptron (MLP) developed using the Python programming language rather than the conventional MATLAB neural network toolbox usually used in similar classifiers. Python programming language is used to develop the AMR classifier for this study for two reasons: (i) its usage is less computational complex compared to MATLAB neural network toolbox, (ii) the classifier developed is designed purposely to be coupled with GNU radio developed in Python programming language for further work on cognitive radio technology.

The developed AMR classifier was used for classification of five digital modulation formats (2ASK, 4ASK, 2FSK, BPSK and QPSK) that comprise both inter- and intra-classes of modulation formats. This choice was made as there are few AMR classifiers that analyze both inter-and intra classes of digitally modulated signals in literature.

The schematic block diagram of the study AMR classifier is shown in Fig.1. The block diagram consists of three blocks: (i) the pre-processing block in which the input feature keys are extracted from all the five signals considered; (ii) the artificial neural network (ANN) training block where the training and learning phase to adjust the classifier parameters are carried out; and (iii) the ANN testing phase to decide the performance of the classifier.

2.1. Pre-processing block methodology

The feature keys for automatic recognition of the modulation format in a PR approach are selected. The selection process involves features that have robust properties sensitive to modulation types and insensitive to variation in SNR of the signal. Since radio signal information characteristics are resident in amplitude, frequency or phase of the signal, the best ways to extract such features is to use information contained in the incoming radio signal instantaneous amplitude, phase and frequency. Four of such feature keys that possess features for reliable recognition of the five modulation formats considered are employed in the study. The choice of these features is a trade-off between minimizing the number of features to reduce the ANN size as well as computational complexity.

The four feature keys used in the study had earlier been used in [11, 12]. They are obtained using Eqs. (1) - (6). The four features are defined as follows:

- $\gamma_{\max}$ is the first feature extraction key employed. It is the maximum value of the power spectral density of the normalized-centred instantaneous amplitude of the intercepted signal segment [11, 12]. It is defined mathematically as:

$$\gamma_{\max} = \frac{\max\left|DFT\left(a_{cn}(i)\right)\right|^2}{N} \tag{1}$$

where N is the numbers of samples per segment, $a_{cn}(i)$ is the value of the normalized-centred instantaneous amplitude at time instant,

$$t = i / f_s \tag{2}$$

and f_s is the sampling frequency. The value of the normalized-centred instantaneous amplitude $a_{cn}(i)$, is defined as:

$$a_{cn}(i) = a_n(i) - 1; \quad a_n(i) = \frac{a(i)}{m_a} \tag{3}$$

where m_a is the mean value of the samples, which is defined as:

$$m_a = (1/N)\sum_{i=1}^{N} a(i) \tag{4}$$

γ_{max} is used to distinguish between signals that have amplitude information (2ASK, 4ASK, BPSK and QPSK) as one subset and signals that have no amplitude information (2FSK) as second subset. The BPSK and QPSK have amplitude information because the band-limitation imposes amplitude information on them especially at the transitions between successive symbols [11]. For the signals with amplitude information, their $\gamma_{\max}$ values will be greater than the threshold value while γ_{max} value for 2FSK without amplitude information is less than the chosen threshold value [9, 10]. This feature, γ_{max}, categorically distinguishes 2FSK from the rest of other signals.

- σ_{ap} is the second feature extraction key employed in this study. It is the standard deviation of the absolute value of the centred non-linear component of the instantaneous phase at time instant, t [11]. It is defined mathematically as:

$$\sigma_{ap} = \sqrt{\frac{1}{C}\left(\sum_{a_n(i) > a_t} \phi_{NL}^2(i)\right) - \left(\frac{1}{C}\sum_{a_n(i) > a_t} \left|\phi_{NL}(i)\right|\right)^2} \tag{5}$$

where $\phi_{NL}(i)$ is the value of the centred non-linear component of the instantaneous phase at time instant, t, C is the number of samples in $\{\phi_{NL}(i)\}$ and a_t is the threshold for $\{a(i)\}$ below which the estimation of instantaneous phase becomes highly noise sensitive.

This feature key is used to distinguish between 2ASK, 4ASK and BPSK as a subset and QPSK as another subset. While 2ASK and 4ASK modulated signals have no absolute phase information by nature, the absolute phase information of BPSK is constant hence making their σ_{ap} values less than the threshold value [11, 12]. On the other hand, QPSK has absolute and direct phase information by nature which makes its σ_{ap} values always greater than the threshold value. Hence, σ_{ap} is used to distinguish between QPSK as a subset and (2ASK, 4ASK and BPSK) as second subset.

- σ_{dp} is the third feature extraction key employed in this study. It is the standard deviation of the direct value of the centred non-linear component of the direct instantaneous phase [11]. It is defined mathematically as:

$$\sigma_{dp} = \sqrt{\frac{1}{C}\left(\sum_{a_n(i)>a_t} \phi_{NL}^2(i)\right) - \left(\frac{1}{C}\sum_{a_n(i)>a_t} \phi_{NL}(i)\right)^2} \tag{6}$$

σ_{dp} is used to distinguish between 2ASK and 4ASK signals as one subset and BPSK as another signal. The discrimination is possible because 2ASK and 4ASK signals have no direct phase information; hence their σ_{dp} values are less than the threshold value. On the other hand, BPSK has direct phase information, which makes its σ_{dp} value greater than the threshold value. So, σ_{dp} is used to distinguish between 2ASK and 4ASK as one subset and BPSK as the second subset.

- σ_{aa} is the fourth feature extraction key used in the study. It is the standard deviation of the absolute value of the normalized centred instantaneous amplitude [11]. It is defined as:

$$\sigma_{aa} = \sqrt{\frac{1}{N}\left(\sum_{i=1}^{N} a_{cn}^2(i)\right) - \left(\frac{1}{N}\sum_{i=1}^{N} |a_{cn}(i)|\right)^2} \tag{7}$$

This feature key is used to distinguish between 2ASK and 4ASK. The discrimination is possible because 2ASK has no absolute amplitude information, which makes its σ_{aa} value less than the threshold value. On the other hand, 4ASK signal has an absolute amplitude value which makes its σ_{aa} value greater than the threshold value.

The extracted feature keys ($\gamma_{\max}$, σ_{ap}, σ_{dp} and σ_{aa}) plotted against SNR are shown in Fig. 2 for the five digital modulation formats studied. The decision functional flowchart using the four feature extraction keys is shown in Fig. 3. Normalized values of these feature extraction keys are used as inputs to the ANN classifier developed to classify the signals. ANN is used because of its acclaimed classification capability according to [1] and its ability to automatically and adaptively choose the optimum values for the feature keys thresholds- $t(\gamma_{\max})$, $t(\sigma_{ap})$, $t(\sigma_{dp})$ and $t(\sigma_{aa})$- at each neuron [11]. Details on development of the ANN for the study are presented in next sub-section.

2.2. Development of the proposed AMR classifier

The proposed AMR classifier was developed using an artificial neural network (ANN). ANN is a type of artificial intelligence system that attempts to mimic the way the brain processes and stores information. It works by creating connections between mathematical processing elements, called neurons [17]. There are different forms of ANN architecture.

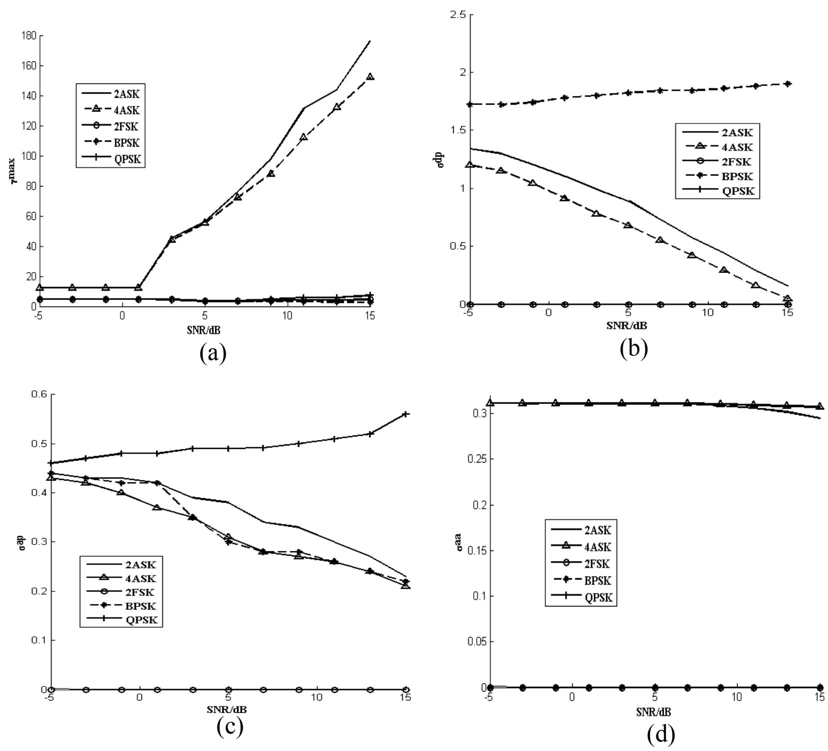


Fig. 2. Variation of (a) γ_{max}, (b) σ_{dp}, (c) σ_{ap} and (d) σ_{aa} with SNR for the Digital Modulated Signals.

The multi-layer feed-forward neural network (MLFFNN) is one of the most widely used forms of neural network architecture. The MLFFNN is capable of modelling the unknown input-output relations of a wide variety of complex systems. The architecture of the MLFFNN classifier used in this study, as shown in Fig. 4, consists of three layers: the input layer of source neurons, one intermediate or hidden layer of computational neurons and the output layer. The number of nodes or neurons in the input and output layers are 4 and 5 respectively corresponding to the independent and dependent variables in the classifier. One hidden layer with 20 processing elements is employed as shown in Fig. 4.

In developing the classifier for the study, the signal data sets were separated into three sets: training, validation, and testing. The training set is used as the primary set of signal data that are applied to the neural network for learning and adaptation. The validation set was used to further refine the neural network development. The testing set was finally used to determine the performance of the neural network.

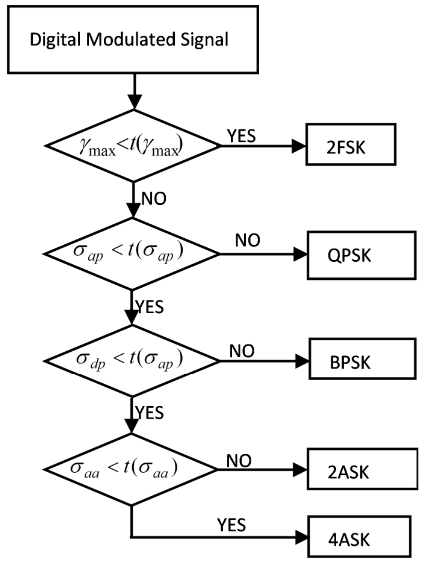


Fig. 3. Functional Flowchart for the Developed Digitally Modulated Classifier.

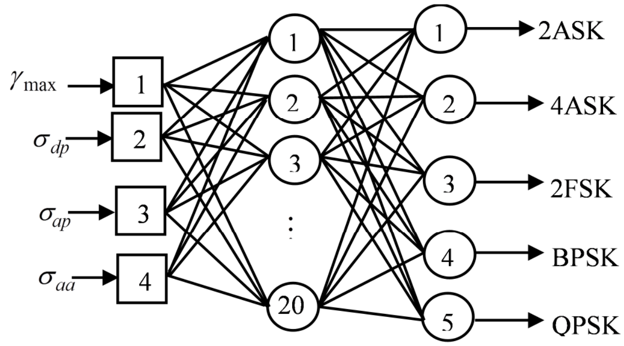


Fig. 4. Architecture of the Developed Automatic Digital Modulation Recognition.

2.2.1. ANN training

The four feature keys extracted in the first sub-section of section two from the digitally modulated signals served as the inputs to the classifier. They are first normalized. The normalization is done for two reasons; (i) to make the training of the network more efficient since the inputs have large differences in magnitude and (ii) because it has been proved experimentally that input normalization significantly improves ANN modulation classifier [11].

A total of 20,000 digitally modulated signals were generated. The signals were divided into three distinct set called training, testing and validation sets. 50% of the signal set was used as training set for the classifier to learn patterns present in the signals. The 4 input neurons or nodes received the ANN inputs and fed them to the hidden layer's neurons and subsequently to the output layer neurons. Each neuron in the classifier was represented by a circle and performed a weighted summation of the inputs, which then passed to a non-linear activation function. The log-sigmoid activation function commonly used in multilayer networks trained by backpropagation algorithm was used in this study. The flow of both feed-forward inputs propagation and backpropagation error during the network training takes place in opposite direction in Fig. 4. Each interconnection in the classifier has a strength that is expressed by weight. The training of the classifier was accomplished by adjusting the interconnection weights according to the learning algorithm. The learning algorithm used in the study is the supervised learning, which incorporates an external teacher so that each output unit is told what its desired response to input signals ought to be. This enables the classifier to change the weight by an amount proportional to the difference between the desired output and the actual output. The adjustment of the classifier parameters continues incrementally until the training data satisfies the desired output, i.e., the mean squared error is minimized.

2.2.2. ANN validation and testing

Thirty percent (30%) of the data set is used as a testing set to evaluate the generalized ability of the trained network. Final check on the performance of the trained network was made using the remaining 20% of the data set as a validating set. The validation signal set is used to minimize over-fitting. The classifier developed was tested with signal data that it had never seen before. It predicts a classification of the signals presented based on the weight it created during training.

3. Results and Discussions

3.1. The study output

The proposed classifier development includes test signal generation and feature keys extraction simulation using MATLAB while the modulation classifier was developed using Python programming language. The developed algorithm is used to recognize 2ASK, 4ASK, 2FSk, BPSK and QPSK which were simulated using MATLAB with additive white Gaussian noise (AWGN) added to the simulated signal as channel noise. The output of the proposed algorithm with varying SNR values starting from - 5 dB to 15 dB are tabulated in Table 1. When the SNR is greater or equal to 5 dB, the percentage of recognition is above 99.0% and the classifier recognizes the correct modulation formats when SNR is even as low as - 5 dB with over 98.0% success rate.

Table 1. Correct Recognition for 2ASK, 4ASK, 2FSK, BPSK and QPSK Signals at: (a) SNR = - 5 dB; (b) SNR = 0 dB; (c) SNR = 5 dB; (d) SNR = 10 dB; and (e) SNR = 15 dB respectively.

Simulated modulated format	Target modulation format recognition (%)					Total missed target (%)
	2ASK	4ASK	2FSK	BPSK	QPSK	
2ASK	98.9	0.7	0.0	0.4	0.0	1.1
4ASK	0.0	99.2	0.0	0.0	0.8	0.8
2FSK	0.0	0.0	99.8	0.0	0.2	0.2
BPSK	0.2	0.0	0.0	99.8	0.0	0.2
QPSK	0.0	0.0	0.3	0.0	99.7	0.3

(a) SNR = -5 dB

Simulated modulated format	Target modulation format recognition (%)					Total missed target (%)
	2ASK	4ASK	2FSK	BPSK	QPSK	
2ASK	98.1	1.9	0.0	0.0	0.0	1.9
4ASK	0.0	99.9	0.0	0.0	0.1	0.1
2FSK	0.0	0.0	99.8	0.0	0.2	0.2
BPSK	0.1	0.0	0.0	99.9	0.0	0.1
QPSK	0.0	0.1	0.1	0.0	99.8	0.2

(b) SNR = 0 dB

Simulated modulated format	Target modulation format recognition (%)					Total missed target (%)
	2ASK	4ASK	2FSK	BPSK	QPSK	
2ASK	99.3	0.7	0.0	0.0	0.0	0.7
4ASK	0.3	99.7	0.0	0.0	0.0	0.3
2FSK	0.0	0.1	99.8	0.1	0.0	0.2
BPSK	0.0	0.0	0.1	99.9	0.0	0.1
QPSK	0.0	0.1	0.0	0.0	99.9	0.1

(c) SNR = 5 dB

Simulated modulated format	Target modulation format recognition (%)					Total missed target (%)
	2ASK	4ASK	2FSK	BPSK	QPSK	
2ASK	99.5	0.5	0.0	0.0	0.0	0.5
4ASK	0.5	99.5	0.0	0.0	0.0	0.5
2FSK	0.0	0.1	99.8	0.1	0.0	0.2
BPSK	0.0	0.0	0.0	99.9	0.0	0.1
QPSK	0.0	0.1	0.0	0.0	99.9	0.1

(d) SNR = 10 dB

Simulated modulated format	Target modulation format recognition (%)					Total missed target (%)
	2ASK	4ASK	2FSK	BPSK	QPSK	
2ASK	99.9	0.1	0.0	0.0	0.0	0.1
4ASK	0.3	99.7	0.0	0.0	0.0	0.3
2FSK	0.0	0.2	99.8	0.0	0.0	0.2
BPSK	0.2	0.0	0.0	99.8	0.0	0.2
QPSK	0.0	0.1	0.2	0.0	99.7	0.3

(e) SNR = 15 dB

Table 2. Percentage Correct Recognition Comparison: Present Work, Method in [18] and Method in [3] at equal SNR = 10 dB.

		2ASK	4ASK	2FSK	BPSK	QPSK
Present Work (Popoola 2014)	2ASK	98.9	0.0	0.0	0.0	0.0
	4ASK	0.0	99.2	0.0	0.0	0.0
	2FSK	0.0	0.0	99.8	0.0	0.0
	BPSK	0.0	0.0	0.0	99.8	0.0
	QPSK	0.0	0.0	0.0	0.0	99.7
		2ASK	**4ASK**	**2FSK**	**BPSK**	**QPSK**
Method in [18] (Azzouz and Namdi, 1997)	2ASK	97.0	0.0	0.0	0.0	0.0
	4ASK	0.0	99.8	0.0	0.0	0.0
	2FSK	0.0	0.0	92.5	0.0	0.0
	BPSK	0.0	0.0	0.0	100.0	0.0
	QPSK	0.0	0.0	0.0	0.0	96.3
		2ASK	**4ASK**	**2FSK**	**BPSK**	**QPSK**
Method in [3] (Park et al., 2008)	2ASK	100.0	0.0	0.0	0.0	0.0
	4ASK	0.0	95.5	0.0	0.0	0.0
	2FSK	0.0	0.0	95.75	0.0	0.0
	BPSK	0.0	0.0	0.0	100.0	0.0
	QPSK	0.0	0.0	0.0	0.0	84.25

3.2. Comparison with previous studies

In order to assess the performance of the developed classifier, the results obtained were compared with other classifiers developed and operated under the same conditions. Specifically, classifiers used are characterized by (i) equal value of SNR; (ii) same AWGN channel condition; (iii) capability of recognizing almost the same set of modulation formats, and (iv) absence of any foreknowledge assumption on the signal characteristics of the signals. Table 2 shows the results obtained with the developed classifier and the classifier in [18] and [3]. The 4 feature keys used in this study were used in [18]. The only difference between the present work and [18] is two hidden layers used in [18] while only one hidden layer is used in this study. Excluding BPSK that was 100% recognized in [18] and 99.8% recognized in this study, all other modulation formats (2ASK, 4ASK, 2FSK and QPSK) considered were recognized with high success rates compared with results reported in [18].

A further comparison is reported in Table 2 between the proposed classifier and the classifier presented in [3] using wavelet features and support vector machine classifiers. While all the conditions stated above are fulfilled, the differences between the present work and [3] are the feature keys used and the number of modulations formats considered. Although the proposed classifier presented in this paper works on a fewer range of modulation formats, it achieves results that are similar to other classifiers proposed in literature. Further comparison as reported in Table 2 between the proposed classifier and the classifier presented in [3] shows that the present study produced a better classification of 4ASK, 2FSK and QPSK at over 3.7%, 4.05% and15.45% success rates respectively while [3] out-performed the present work in classifying 2ASK and BPSK with 0.1% and 0.2% success rates respectively. These results show that the present work can compare favourably with previous work in the literature.

4. Conclusions

An overview of classifier for automatic recognition of 5 digitally modulated signals, utilizing an ANN approach without any foreknowledge information about the nature of the signals is presented in this paper. Extensive simulations for the 5 digital modulated signals were carried out to measure the performance of the presented classifier. Sample results are introduced at -5, 0, 5, 10 and 15 dB for the recognition of the considered digitally modulated signals without any prior information. It was found that the ANN classifier developed using the Python programming language instead of the conventional MATLAB neural network toolbox usually described in literature, has successfully recognized all the modulation formats of interest with success rate greater than 98.0% at SNR below 0 dB and success rate greater than 99.0% for SNR greater or equal to 5 dB. These success rates are indications of the work accuracy and statistical feature keys employed. The result of the study as also demonstrates the possibility of correct recognition of digitally modulated signal below 5 dB usually considered in the literature.

Acknowledgment

The authour wishes to acknowledge the financial support of all the sponsors of the University of the Witwatersrand's Centre of Telecommunications Access and Services (CeTAS). The author also acknowledges the financial support received from the Independence Communications Authority of South Africa (ICASA) and the University of the Witwatersrand's Postgraduate Merit Award (PMA) during his PhD programme. Finally, the author thanks Prof. Rex van Olst of School of Electrical and Information Engineering, University of the Witwatersrand, South Africa for his assistance during this study.

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