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Automatic modulation recognition and classification for digital modulated signals based on ANN algorithms

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***Abstract*—Automatic modulation recognition (AMR) has important role in civil and military applications. Recognition of received signal modulation is intermediate step between signal detection and demodulation; so that in many of communication and military systems AMR considers as a portion of system.**

Nowadays, because of the increasing digital modulations in the civil and military, the recognition of digital modulation has special importance. Normally for AMR, a few features of received signal will be extracted and employed. So choice of appropriate feature has a significant role in increasing the efficiency of AMR. In this paper with choice of suitable features of input modulated signal and with the help of neural network (NN) algorithm, will be begins to recognition and classification of ten modulated signals as follows: 2ASK, 4ASK, 2FSK, 4FSK, 2PSK, 4PSK, 4QAM, 16QAM, 64QAM. Computer simulations implement with characteristic signal to noise in the presence of Gaussian noise -5dB to +20dB. The results show employment of NN algorithm leads to significant considerable in more accurate and faster of recognition type of modulation.

Keywords— Automatic modulation recognition, neural network, feature extraction, classification

I. INTRODUCTION

Automatic modulation recognition is middle step between signal detection and demodulation [1]. This step can recognize modulation type of received signal between the numbers of presupposed modulations. Automatic modulation recognition has important role in civil and military applications [2]. Nowadays due to increasing digital modulations in civil and military applications, digital modulation recognition has particular importance. In general, for automatic modulation recognition, a few feature of received signal will be extracted and employed. Choice of appropriate features has important role in increasing efficiency of recognition. In this paper, with selection of appropriate features for input modulated signals and with the help of multi-layer ANN method will be recognised and separated ten digital modulation include 2ASK، 4ASK، 2FSK،4FSK ،QPSK ،2PSK ،4PSK ،4QAM ، 16QAM and 64QAM also simulation will be accomplished with different SNR (-5dB to +20dB).

In the past due to the limited number of modulation and technological problems, signal modulation detection done by researcher manually. The larger variety of modulation schemes used in telecommunication systems has made the manual recognition too unreliable [3]. With increasing modulation types as well as the scope of their applications, modulation detection by traditional methods, depend on the analyst experience and up to dating someone in this area. The results of this diagnosis could not be trusted. So the researchers of the past decades developed large numbers of signal processing algorithms of AMR (Automatic Modulation Recognition) for various applications. So far, several methods for automatic identification of modulation have been proposed with hypothesis, different advantages and disadvantages. For example, in some methods some or all of received signal parameters such as carrier frequency, symbol rate, etc. are assumed and recognized the type of modulation, while in others, the act of recognition was for the blind (no prior knowledge of received signal parameters) and some essential parameters is performed for signal recognition is estimated. The purpose of this paper is to provide an algorithm that recognizes modulation in the wide range of SNR and for achieving these goals, sub-goals should be provided such as choosing the proper features and appropriate classifiers. Different methods of automatic modulation recognition can be categorized into two broad fields [4]:

1. Decision theoretic approach
2. Pattern recognition or feature extraction approach

In the first method, known as the theory of decision-making, statistical criteria such as similarity estimator or utilize fixed and variable threshold levels is often used to classify the modulations [5]. However, in the second, signal mapping feature space carried out modulation recognition and the benefits of pattern recognition algorithms such as neural networks is employed [6].

Nandi and Azzouz in 1995-1998 [7] [8] [9] introduced some algorithms for automatic modulation recognition and identifying digital signals. This source is the main source of the recently papers. They used nine features based on instantaneous signal information and employed two method contained decision theory and neural network method for separating and claimed that modulation classification including 2ASK, 4ASK, 2PSK, 4PSK, 2FSK and 4FSK when (SNR=15dB) in decision theoretic algorithm. It is found that the overall success rate 94% while in neural network algorithm was 96%. [7]. Wu and et al. [3] in 2010 paid attention to automatic modulation recognition such as 2ASK, 4ASK, 2FSK, 4FSK, BPSK, QPSK, 16QAM and 64QAM, utilized five features based on signal instantaneous information and statistic features. They used feed-forward artificial neural network that be trained for above modulation recognition. They claimed to achieve 98% success rate at 8dB SNR. Hu You-Quang et al. [10] in 2010 used three features from [8] and defined three new features R_a, R_p, R_f. In this source employed decision theoretic approach and utilized wavelet filter for de-noising modulated signal instantaneous information. Simulation has been performed at 5dB and 10dB SNR. In their proposed algorithm, success rate 99% at 10dB SNR and 95% at 5dB SNR. In this source, ANN referred to as useful tools in the classification and the work is postponed. Rada A.El-Khoribi and et al. [11] in 2014 worked on modulation recognition such as 2ASK, 4ASK, FSK, 4FSK, 2PSK, 4PSK, DPSK, 16QAM and used ANN method for signal classification. In this paper, two features γmax, φNL used for signal recognition and also feed-forward network as MLP for classification signal and success rate declared 80% at 10dB and 85% at 20dB SNR.

Although the above approaches are leading to correct functioning but some of them need high SNR value to identify and the others had high complexity to implement software for recognition and classification. A new algorithm that has suggested in this paper for modulation recognition such as 2ASK, 4ASK, 2FSK, 4FSK, QPSK, 2PSK, 4PSK, 4QAM, 16QAM and 64QAM, use 16 features include instantaneous signal information, statistics and spectral features. From these 16 features, 9 features in [7] and 3 features in [10] had been used. It is worth nothing these characteristics are not used combined in different papers just now. Four features will introduce in this paper. By defining the intelligence network features will be more information on effective modulation separation. By selecting these 16 features, simulation results will show that by employing artificial neural network classification methods, feasible to perform well in low SNR. ANN technique is very useful when dealing with classification issues because it has a flexible structure that will implement faced it with ease. In addition, the ANN can be adapted to work with complex signals and it has high learning potential.

Therefore, this article is organized as follows. Section 2 is shown methods for the calculation of instantaneous information and other features is introduced and to extracting signal characteristics. Neural network introduced to identifying and classifying modulations and computer simulations details are given in section 3. In this section performance evaluation of the proposed method are given. Finally Conclusion is shown in section 4.

II. METHODS

The approach used in this article is respectively divided into two general steps:

- First step: Feature extraction
- Second step: Recognition and classification by utilizing neural network

A. *Feature extraction*

The first step in feature extraction is modeling of digital modulated signal to extract signal features. In order to analyze the performance of modulation recognition system, naturally we need signals that they already know the type of modulation. This signal can be used as training data or the testing data; we show a measure of system performance. In this paper, production condition and amounts of signal parameters such as sampling frequency, the carrier frequency is quite similar [7] [10] we choose to allow a fair comparison to be provided in the first phase. The digital modulations to simulate a random bit stream bit rate are 12.5 KHz. The discipline randomly uniform and about each frame containing a different message that matches perfectly with practical applications. Always in real terms as well as in the simulation signals were dealing with discrete samples, so we are forced to sampling operations. Sampling frequency is 1.2 MHz; Default values are shown in table I.

TABLE I. MODULATION PARAMETERS

Parameter	Quantity
Sampling frequency(fs)	1200KHz
Carrier frequency(fc)	150KHz
Symbol rate(rs)	12.5KHz

In most articles, recognition of signal modulated is in the baseband therefore implicitly assumed to know the carrier frequency in all of them. In this study we have produced signals in the band limited. The selected carrier frequency is 150 KHz for all modulation signals that comply with the conditions in [7] [10]. Signals generation has done with MATLAB software and according to mathematical equations as in [11] [12] have been made. 16 different features that have been used in this article that 12 of them are shown in table II.

Two new features are defined in this paper. These features are related to the scope and extent of the imbalance of power spectrum related to frequency and amplitude of signal that can be calculated using equation (1), (2).

$$s = \frac{E(a-\mu)^3}{\sigma^3} \qquad (1)$$

$$s = \frac{E(f-\mu)^3}{\sigma^3} \qquad (2)$$

Another two features are Average value of the instantaneous amplitude $\bar{a}$ and Average value of the instantaneous phase $\bar{\varphi}$.

TABLE II. MATHEMATICAL FORMULA FOR FEATURES

No.	feature	mathematical formula
1	The standard deviation of the centered nonlinear component of the absolute instantaneous phase in a non-weak segment	$\sigma_{ap} = \sqrt{\frac{1}{C}(\sum_{a_n(i)>a_t} \varphi_{NL}^2(i)) - (\frac{1}{C}\sum_{a_n(i)>a_t} \lvert\varphi_{NL}(i)\rvert)^2}$
2	The standard deviation of the centered nonlinear component of the direct (not absolute) instantaneous phase in non-weak segment	$\sigma_{dp} = \sqrt{\frac{1}{C}(\sum_{a_n(i)>a_t} \varphi_{NL}^2(i)) - (\frac{1}{C}\sum_{a_n(i)>a_t} \varphi_{NL}(i))^2}$
3	The standard deviation of the absolute value of the normalized-centered instantaneous amplitude of a signal segment	$\sigma_{aa} = \sqrt{\frac{1}{N_s}(\sum_{i=1}^{Ns} a_{cn}^2(i)) - (\frac{1}{N_s}\sum_{i=1}^{Ns} \lvert a_{cn}(i)\rvert)^2}$ Where , $a_{cn}(i) = \frac{a(i)}{m_a} - 1$ and m_a is the sample mean of a(i)
4	The standard deviation of the absolute value of the normalized-centered instantaneous frequency of a non-weak segment	$\sigma_{af} = \sqrt{\frac{1}{C}(\sum_{a_n(i)>a_t} f_N^2(i)) - (\frac{1}{C}\sum_{a_n(i)>a_t} \lvert f_N(i)\rvert)^2}$
5	The standard deviation of the absolute value of the normalized-centered instantaneous amplitude in the non-weak segment of a signal	$\sigma_a = \sqrt{\frac{1}{C}(\sum_{a_n(i)>a_t} a_{cn}^2(i)) - (\frac{1}{C}\sum_{a_n(i)>a_t} a_{cn}(i))^2}$ where t_{th} the threshold value of the non-weak is signal in and C is the length of non-weak values
6	The kurtosis of the normalized instantaneous amplitude μ_{42}^a	$\mu_{42}^a = \frac{E\{a_{cn}^4(i)\}}{\{E\{a_{cn}^2(i)\}\}^2}$
7	The kurtosis of the normalized instantaneous frequency μ_{42}^f	$\mu_{42}^f = \frac{E\{f_N^4(i)\}}{\{E\{f_N^2(i)\}\}^2}$
8	Ratio of the square of the mean value of the instantaneous amplitude to the variance	$R_a = \frac{m_a^2}{d_a}$ where m_a is the mean value of instantaneous amplitude and d_a is the variance of instantaneous amplitude
9	Ratio of the square of the mean value of the instantaneous phase to the variance of the instantaneous phase	$R_p = \frac{m_p^2}{d_p}$ where m_p is the mean value of the instantaneous phase and d_p is the variance of the instantaneous phase
10	Square of the mean value of the instantaneous frequency to the variance of the instantaneous frequency	$R_f = \frac{m_f^2}{d_f}$ Where m_f is the mean value of the instantaneous frequency and d_f is the variance of instantaneous frequency of the intercepted signal
11	The Maximum Value of Power Spectral Density (PSD) of Normalized-Centered Instantaneous Amplitude	$\gamma_{max} = max\lvert\lvert DFT(a_{cn}(i))\rvert\rvert^2/Ns$
12	Maximum Value of the Spectral Power Density of the normalized-centered instantaneous amplitude	$\gamma_{max} = max\lvert\lvert FFT(f_{cn}(i))\rvert\rvert^2$ where $a_{cn}(i)$ is the value of the normalized-centered instantaneous amplitude at time instantst $=\frac{i}{f_s}$ (i=1,2,…,N_s), defined by $a_{cn}(i) = a_n(i) - 1$ where $a_n(i) = \frac{a(i)}{m_a}$ and m_a is the average value of the instantaneous amplitude over one frame

In this study, different modulated signals were implemented for six different SNR (-5, 0, 5, 10, 15, 20 dB) and for any amount of noise energy as 200 different data as the input signal are produced. It can be concluded that there will be 12000 different modulations with different values of noise for each type of modulation. Thus, by calculating features of 12000 different modulation can be analyzed separately each type of modulation features.

B. Recognition and classification using ANN

At this step, features are as input into the network in the input layer for classification. The network must have the ability to detect that it belongs to a class suit. This can be achieved by learning network. Learning is a process by which neural network adapts to a stimulus so that after adjusting for proper network parameters, offers a favorable response. In artificial neural networks, rules education is expressed in the form of mathematical equations that educations equations are called. Training ends with the implementation of real output and desirable.

In this paper, a three-layer perceptron learning with error propagation approach is used. Perceptron networks, especially multilayer neural networks are among the most useful. It is able to do a non-linear mapping with arbitrary precision. This is what the main issues discussed engineering and technology as a solution. The network is representative feed-forward networks, and the output is calculated directly from the input without any feedback. In this paper, the MLP have been used with one hidden layer, 120 nodes and shown with 16I-120H-10O. The 'I', 'H' and 'O' display the input, hidden and output layers. Due to the random values mentioned in the first phase, it is necessary, the neural network is repeated several times with different random values to avoid getting stuck in local minima and achieve global minimum.

III. DISCUSSION

The scaled conjugate gradient method is used for learning algorithms in neural network. A total of 10000 sample signals were created randomly for training and testing. Those samples were dividing as: 70% for training and remaining 30% equally is used to test and evaluate network performance.

The number of nodes in the input layer was equal to the number of features used which is 16, and the number of nodes in the output layer was equal to the number of modulation techniques to classify is 10.

Block diagram of a simple neural network is shown in Fig. 1.

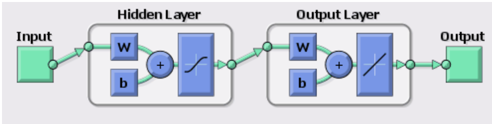

Fig. 1. *simple block diagram of neural network*

To be able to use the nonlinear capabilities of each neuron it can be increased the number of neurons and added capabilities to the neural network. But the excessive number of neurons in fact overshadows the interoperability of the network. So the trade-off exists between increasing the complexity of the system and increasing interoperability. If you want to change the number of neurons in the middle layer of 15 to 300 and evaluate the performance of the neural network, correct diagnosis modulation classes can be considered as a criterion to evaluate performance. The effect of changes in the number of neurons in the middle layer on network performance is shown in Fig. 2.

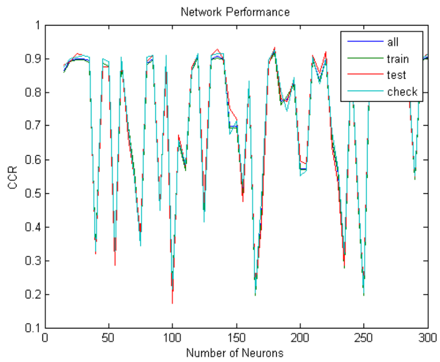

Fig. 2. *effect of the change in the number of neurons on network performance in the middle layer*

According to Fig. 2 seems to be the correct type of modulation for maximum detection occurred at 180 neurons in the middle layer, which is equivalent to 0.9214 for all database have received. But if the number of neurons in the middle layer is reached 120 while prevents the creation of complexity in the system does not cause a significant change in the rate of correct diagnosis. Modulation rate of correct diagnosis for a variety of database with 120 neurons is shown in table III.

TABLE III. CORRECT MODULATION DETECTION RATE

Modulation recognition rate	Data type
0.9051	Train data
0.9095	Test data
0.9143	Evaluate data
0.9071	Total data

Although it seems with increasing the number of neurons in the middle layer, better identification provided, it should be noted that the increasing in the number of neurons should not negatively affect network interoperability. The result gathered from a variety of relevant databases is summarized in table 2. Error histogram data types of training, testing and evaluation are shown in Fig. 3.

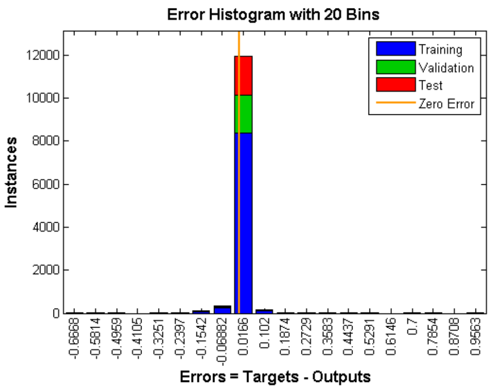

Fig. 3. *error histogram data types of training, testing and evaluating*

As it is clear in Fig. 4, error values rate is in the range of about zero for training, testing and evaluation. The main bar error histogram on the zero line placements indicates the proper functioning of the neural network on proper diagnosis output.
In the following graph is displayed evaluate the best performance according to the epoch.

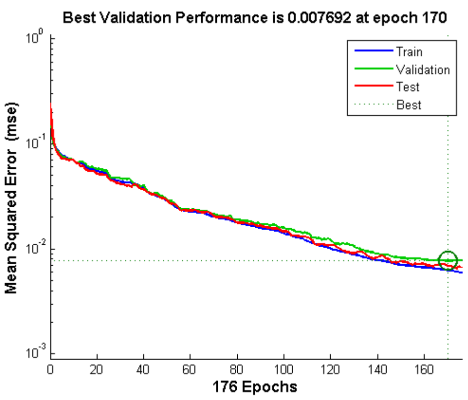

Fig. 4. *the best performance evaluation curve according to the epoch*

The number of passes of the data due to the error rate can specify the time of algorithm suspension. As seen in Fig. 4, in case of passing the entire data 170 times the error learning, testing and evaluation does not vary. So, it seems that by increasing epoch, the error rate is almost constant. Best network performance in the 170 epoch reports performance with 0.007692 error.

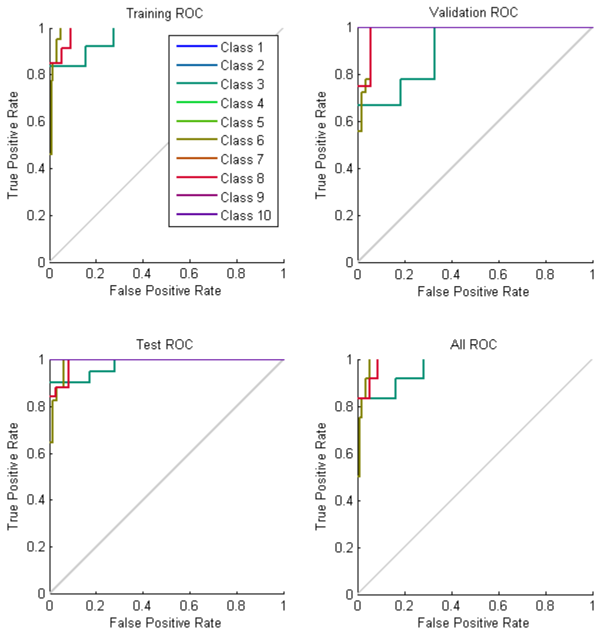

Fig. 5. *correct detection rate curves*

According to the Fig. 5, correct detection rate of output neural network based on objective data reports close to one on training, testing and evaluation values. This shows that the neural network has been able to identify correctly with acceptable rate train, test and evaluation. Detection rate results for all data are shown in Fig. 5. Gradient downward trend due to the increasing number of epoch shows in case of taking epoch higher of 176, significant changes would not be witness in order to reduce the gradient.

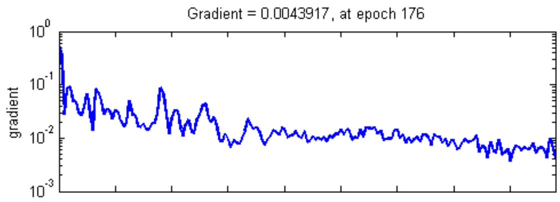

Fig. 6. *gradient rate graph according epoch*

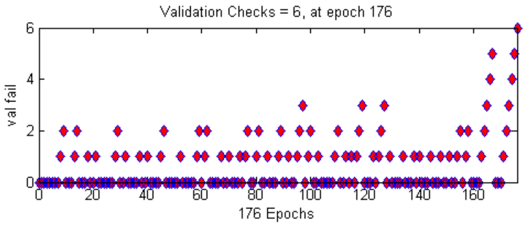

Fig. 7. *performance evaluation recognition*

As shown in Fig. 8, detection rate of network increased gradually with increasing epoch and ha less error, class 6 has been detected well. Correct identification results for different SNR in the presence of 120 neurons in the middle layer are as follows:

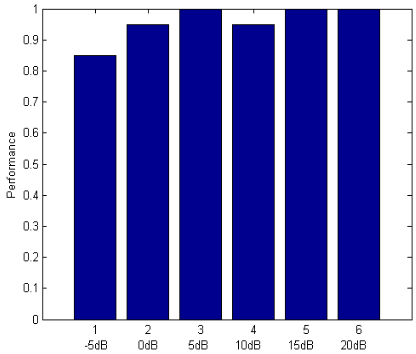

Fig. 8. *correct identification results for different SNR in the presence of 120 neurons in the middle layer*

Results show that although the noise level is less ability to correctly identification is higher, however the correct identification even for modulation pattern of -5dB SNR also shows a value greater than 85%. The comparisons between this article and other that in this study were evaluated are shown in table IV.

TABLE IV. APPROACHES COMPARISON

Approach	Classification Method	Modulation Classes	Success Rate (in different SNR)			
			5dB	10dB	15dB	20dB
Nandi-Azzouz. [8]	Pattern recognition (ANN)	2ASK, 4ASK, 2PSK, 4PSK, 2FSK, 4FSK	-	-	96%	-
	Decision theoretic		-	-	94%	-
Hu. You-qiang et al. [10]	Decision theoretic		95%	99%	-	-
Rada A. Elkhoribi et al. [11]	Pattern recognition (ANN)	2ASK, 4ASK, FSK, 4FSK, 2PSK, 4PSK, DPSK, 16QAM	-	80%	-	85%
Results of Proposed algorithm in this papaer	Pattern recognition (ANN)	2ASK, 4ASK, 2FSK, 4FSK, QPSK, 2PSK, 4PSK, 4QAM, 16QAM , 64QAM	100%	95%	100%	100%

IV. CONCLUSION

Random nature of the signal and the noise causes that modulated signal information has a random nature so the use of computational features to separate different types of modulation could not classify signal alone. This was clear in the study of individual features. Actually you simply use a feature in the presence of noise with different energy levels to classify modulation. So it seems that the simultaneous use of a variety of features related to the amplitude, phase and frequency of modulation signal, better decisions can be made on a variety of modulation. In this regard, neural network with using a variety of modulation characteristics that mentioned may be suitable for modulation classification. The simulation results show that the overall performance of the proposed method even for SNR of -5 dB shows a value greater than 85%. It is important, In this article have achieved success rates for SNR of 0dB, 5 dB, 10 dB, 15 dB and 20dB respectively 98%, 100%, 95%, 100%, 100%. In the proposed algorithm, it is found that the ANN is a better classifier when SNR is low (≤10dB). We offer with defining the new feature such as higher order momentums and cumulants increase capability of classification more modulation with higher M-array. Such methods will be objectives in our future works.

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