MODULATION CLASSIFICATION USING SPECTRAL FEATURES ON FADING CHANNELS

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ABSTRACT: *Modulation classification plays a key role in demodulation of the received signal for extracting the required information. Modulation classification is a difficult task when there is no information about the received signal (Blind Classification) and especially in presence of multipath fading and white guassian noise. Emerging applications of automatic modulation classification (AMC) in military, civil and cognitive radio (CR) applications leads to the development of various AMC algorithms. The Automatic modulation classification can be achieved by two major approaches, Likelihood based and features based pattern classification approach. In this paper first we have analyze and discourse the merits and demerits of both categories, then we have proposed an algorithm based on spectral features of the modulated signal. The proposed classifier is Multilayer perceptron which is also referred as feed forward back propagation neural network. The channels considered throughout the simulations are additive white guassian noise (AWGN) channel, Rayleigh flat fading and Rician flat fading channel. The considered modulation formats are PAM 2 to 64, PSK 2 to 64, FSK 2 to 64 and QAM 2 to 64. The proposed algorithm will recognize the considered modulation formats with 100% success at 0dB SNR. Tables in the form of confusion matrix and graphs shows correct classification rate for considered modulation formats.*

Key words: Modulation Classification (MC), Cognitive Radio (CR), Additive White Guassian Noise (AWGN), Rayleigh Flat Fading and Rician Flat Fading Channel

1. INTRODUCTION

A signal is modulated by varying on or more of its properties (amplitude, frequency, phase) so that it can be physically transmitted. For successful demodulation at the receiver end the imposed modulation scheme must be known. Automatic modulation classification sometimes also known as blind identification is a process of determining the modulation scheme of the received signal with prior no information and many unknown parameters (signal power, timing, phase offset) of the signal [1-2]. AMC is a difficult task and becomes more challenging in presence of channel noise and multipath fading. Due to its numerous civil and military applications e.g. spectrum surveillance and management, interference identification and military threat evaluation AMC is been the topic of interest for past three decades. Different AMC techniques and algorithms were developed and are still developing for different modulations [3]. The major techniques are being divided into two major categories. Likelihood based (LB) and Pattern or Feature based (FB) classification. LB classification uses the likelihood (probabilistic) behavior of the received signal [4-5]. First likelihood behavior of signal is calculated for all possible modulations then maximum likelihood ratio test against threshold is performed for decision making. LB classification technique provides optimal performance for less number of unknown parameters. With increase in number of unknown parameters the computational complexity also increases resulting in the impracticality of the classifier. The second category of AMC algorithms is Pattern or Feature based classification. Pattern classification can be performed using statistical, template matching or structural methods [6]. Most commonly used method is statistical, in which first unknown parameters are extracted to identify the characteristics (frequency, amplitude, phase and standard deviations) of the signal. After extracting the right set of features they are fed into artificial neural networks (ANN) for classification and the order of modulation [7].

ANN is computing system with a large number of processors based on central neural system of a human. ANN has three layers, input layer, hidden layer and output layer [8]. Each layer has its own functionality. Also it has the ability to learn a behavior and self-organization. An important application of ANN is pattern classification. Back Propagation Algorithm (BPA) is normally used in training of a neural network for classification task (MC). BPA is used in the hidden layer and the main goal of using BPA is to train a neural network in such a way so that it can easily map a set of different inputs to the required output. When the ANN is able to recognize all the outputs and its associated inputs the training is stopped [9]. Although FB classification provides near optimal performance, simplicity and ease of implementation are its plus points over LB classification. A comprehensive analysis of existing AMC techniques shows that either they are less successful at low SNR and multipath fading or they have certain limitations. Also in many experimentations noise and channel models were not considered [10]. Same work using feature based approach in past for classification of (ASK2, ASK4, PSK2, PSK4, FSK2, FSK4) with a success rate of 90% at SNR 10 dB [7]. In [11] author utilizes higher order cummulants for classification of PAM, QAM, and PSK of order 2 to 64 on AWGN channel and linear discriminant analysis (LDA) for classification of most fundamental modulation formats [12].

In this paper, classification of modulation techniques (FSK 2to64, PSK 2to64, PAM 2to64 and QAM 2to64) under the effect of AWGN channel, Rayleigh Flat Fading channel and Rician Flat Fading channel is performed. Features used in this paper are Standard deviation of absolute value of the centered non-linear components of instantaneous phase (σ_{ap}), Standard deviation of direct value of the centered non-linear components of instantaneous phase (σ_{dp}), Standard deviation of absolute value of the normalized centered instantaneous amplitude (σ_{aa}), Standard deviation of absolute value of the normalized centered instantaneous frequency (σ_{af}), Standard deviation of direct value of the normalized centered instantaneous frequency (σ_{fn}), Maximum value of the power spectral density of the normalized centered instantaneous amplitude (γ_{max}). ANN was used as decision classifier and feed forward back propagation algorithm was used in training of the neural network. The theoretical values are also shown for all considered modulation under the effect of considered channel model. The testing of algorithm shows 100% success rate at low SNR's, and the simulation results in form of confusion matrix are also shown.

Rest of the paper is organized as follows: Section II presents the system model for classification of modulation techniques. Section III presents proposed features ($\sigma_{ap}, \sigma_{dp}, \sigma_{aa}\ \sigma_{fa}, \sigma_{fn}, \gamma_{max}$) which are extracted from received signal under the effect of noise (AWGN) and considered channel model (Rayleigh Flat Fading, Rician Flat Fading). The theoretical values of features for considered modulations are also shown. In section IV algorithm for classification of modulation formats is presented. Section V discusses the simulation results and section VI concludes the paper.

2. SYSTEM MODEL

The system model indicates three step process of automatic modulation classification using artificial neural network. First the received signal is preprocessed, converting it into required form which may include noise reduction, equalization etc. Preprocessing of signal enhance the overall performance of pattern classification system. After preprocessing of received signal a set of different features are extracted from the received signal which may be corrupted by channel noise or may be undergone some channel effects. After extraction of features, they are fed into decision classifier in which adjustment of classifier is done in training phase and in the testing phase, performance measurement to decide about the modulation type of signal.

There are four basic types of modulation schemes; FSK, PSK, PAM and QAM. Suppose we have a baseband (message) signal $m(t)$ and a carrier signal

$$m_c(t) = A_c \cos(2\pi f_c t + \varphi_c) \tag{1}$$

where A_c is the carrier amplitude and f_c is the carrier frequency and φ_c is carrier phase angle. The baseband and carrier signal are combined at the transmitter by modulator and then it is transmitted. The transmitted signal is $x(t) = m(t) * m_c(t)$ where $m(t)$ is the baseband signal is and $m_c(t)$ is the carrier signal. Modulated signal for frequency shift keying (FSK) is

$$m_{FSK}(t) = \cos\big(2\pi f_c t + \varphi(t)\big) \tag{2}$$

Modulated signal for phase shift keying (PSK) is defined by

$$m_{PSK}(t) = A\cos(2\pi f_c t) + \varphi_i \tag{3}$$

where i = 1, 2, 3...M. In pulse amplitude modulation (PAM), the samples of the baseband signal vary with the amplitude of the carrier in proportion to the sampled values of baseband signal.

$$m_{PAM}(t) = \textstyle\sum_n m(n)p(t-nT) \tag{4}$$

Where m[n] are the pulse amplitude, T is the repetition of pulse interval and 1/T is the symbol rate. Quadrature amplitude modulation (QAM) requires both changing of amplitude and phase of carrier signal and QAM can be achieved by mixing two sine waves that are 90 degree out of phase with each other. By varying only the amplitude of any signal will vary the phase and amplitude of the mixed signal. Let $m_1(t)$ and $m_2(t)$ be the two signals such that $m_1(t) = A\cos(\varphi)$ and $m_2(t) = A\sin(\varphi)$. Modulated signal for QAM is

$$m_{QAM}(t) = m_1(t)\cos(2\pi f_c t) - m_2(t)\sin(2\pi f_c t) \tag{5}$$

The generalized expression for signal received is given by

$$r(n) = s(n) + y(n) \tag{6}$$

where $r(n)$ is complex baseband envelop of received signal, $y(n)$ is the additive white gaussian noise and $s(n)$ is given by

$$s(n) = Ke^{i(2\pi f_o nT + \theta_n)} \sum_{j=-\infty}^{j=\infty} s(l)\, h(nT - jT + \epsilon_T T) \tag{7}$$

where

$s(l)$ = input symbol sequence which is drawn from set of M constellations of known symbols and it is not necessary that symbols are equi-probable

K = amplitude of signal

f_o = frequency offset constant

T = symbol spacing

θ_n = the phase jitter which varies from symbol to symbol

$h(\ldots)$ = channel effects

ϵ_T = the timing jitter

3. SPECTRAL FEATURES

Feature based classification provides better performance over likelihood based for large number of unknown parameters. Many features are under research for this purpose such as power spectral density PSD, SNR, entropy, instantaneous (amplitude, frequency and phase) and statistical measures. At present more than nine different features can be used to recognize different modulations. A common method is to use information contain in instantaneous (amplitude, frequency and phase) of the modulated signal. In this paper we will use standard deviation of normalized signal frequency, phase and amplitude derived from instantaneous amplitude, phase and frequency of the considered (FSK, PSK, PAM, QAM) modulated signals because of the fact that information contents is hidden in signal instantaneous amplitude, phase and frequency [13-14].

σ_{ap} : Standard deviation of absolute value of the centered non-linear components of instantaneous phase

$$\sigma_{ap} = \sqrt{\frac{1}{N_s}\left(\sum \varphi^2{}_{NL}(i)\right) - \left(\frac{1}{N_s}\sum |\varphi_{NL}(i)|\right)^2} \tag{8}$$

where Ns are number of samples in $\sum \varphi_{NL}(i)$ at instant $t = \frac{i}{f_s}$, Nonlinear component of centered instantaneous phase $\varphi_{NL}(i) = \varphi(i) - \varphi_o$ and $\varphi_o = \frac{1}{N_s}\sum_{i=1}^{Ns} \varphi(i)$

σ_{ap} discriminates ASK2, ASK4, PSK2 from PSK4, as ASK2, ASK4 and PSK2 has no absolute phase information, but PSK4 has both absolute and direct phase information. So this feature is used to discriminate between different modulation formats on the basis of information in absolute phase.

σ_{dp}: Standard deviation of direct value of the centered non-linear components of instantaneous phase

$$\sigma_{dp} = \sqrt{\frac{1}{N_s}\left(\sum \varphi^2_{NL}(i)\right) - \left(\frac{1}{N_s}\sum \varphi_{NL}(i)\right)^2} \qquad (9)$$

$\boldsymbol{\sigma_{dp}}$ discriminate (ASK2, ASK4) from PSK2 on the basis of information in direct phase. (ASK2, ASK4) has no direct phase information where PSK2 has information in direct phase. So this feature is used to discriminate modulation format that have information in direct phase from that which has not direct phase information.

$\boldsymbol{\sigma_{aa}}$**:** Standard deviation of absolute value of the normalized centered instantaneous amplitude

$$\sigma_{aa} = \sqrt{\frac{1}{N_s}\left(\sum_{i=1}^{N_s}\sum A^2_{cn}(i) - \left(\frac{1}{N_s}\sum |A_{cn}(i)|\right)^2\right.} \qquad (10)$$

$A_{cn}(i)$ is normalized centered instantaneous amplitude at time instant $= \frac{i}{f_s}$, $A_{cn}(i) = A_n(i) - 1$ and $A_n(i) = A(i)/m_a$, m_a is average value of instantaneous amplitude over one frame. $m_a = \frac{1}{N_s}\sum_{i=1}^{N_s} A(i)$. This feature is used to distinguish between ASK2 and ASK4. ASK2 has no absolute amplitude information where ASK4 has information present in absolute amplitude.

$\boldsymbol{\sigma_{fa}}$: Standard deviation of absolute value of the normalized centered instantaneous frequency

$$\sigma_{fa} = \sqrt{\frac{1}{N_s}\left(\sum f_n^2(i)\right) - \left(\frac{1}{N_s}\sum |f_n(i)|\right)^2} \qquad (11)$$

Normalized centered instantaneous frequency $f_n(i) = \frac{f_c(i)}{r_s}$, r_s is the symbol rate, $f_c(i) = f_i - m_f$ and $m_f = \frac{1}{N_s}\sum_{i=1}^{N_s} f(i)$ where N_s is symbol rate. σ_{fa} discriminate between FSK2 and FSK4. FSK2 has no absolute frequency information where FSK4 has both absolute and direct frequency information.

$\boldsymbol{\sigma_{fn}}$**:** Standard deviation of direct value of the normalized centered instantaneous frequency

$$\sigma_{fn} = \sqrt{\frac{1}{Ns}\left(\sum f_n^2(i)\right) - \left(\frac{1}{Ns}\sum f_n(i)\right)^2} \qquad (62)$$

$\boldsymbol{\gamma_{max}}$**:** Maximum value of the power spectral density of the normalized centered instantaneous amplitude

$$\gamma_{max} = \frac{1}{Ns}\left(\max|DFT[A_{cn}(i)]|^2\right) \qquad (13)$$

DFT is the Discrete Fourier transform of the modulated signal, γ_{max} uses information of signal's envelope and differentiate modulation format that has amplitude information from that which has no amplitude information(PSD=0). It is used to discriminate FSK2, FSK4 from ASK2, ASK4, PSK2 and PSK4.

Let a signal with sampling rate f_s=4000 is generated and digitally modulated using equation (2). After modulation, Hilbert transform was used for calculating Amplitude, frequency and Phase of that FSK modulated signal. Then these three parameters (Amplitude, Phase and Frequency) used for extraction of the features ($\sigma_{ap}, \sigma_{dp}, \sigma_{aa}$ $\sigma_{fa}, \sigma_{fn}, \gamma_{max}$) from the FSK modulated signal before transmission on the channel. 64. Table 1 shows the theoretical values of considered features for FSK, PSK, PAM and QAM for order 2 to 64.

Table 1: Real theoretical values of considered features for FSK, PSK, PAM and QAM (2-64)

FSK	Features					
	γ_{max}	σ_{ap}	σ_{dp}	σ_{aa}	σ_{fa}	σ_{fn}
M=2	1509.18	0.075376	0.088643	0.121209	0.066901	0.046635
M=4	17.28	0.057986	0.043193	0.05882	0.009144	0.006813
M=8	93.88	0.049278	0.03716	0.001441	0.00778	0.005875
M=16	515.90	0.113876	0.089539	0.104071	0.019247	0.015851
M=32	5064.68	0.322784	0.214222	0.70927	0.040256	0.025431
M=64	7459.61	0.081873	0.270207	0.21155	0.019277	0.035071
PSK	Features					
	γ_{max}	σ_{ap}	σ_{dp}	σ_{aa}	σ_{fa}	σ_{fn}
M=2	2936.37	0.009466	0.007479	0.016228	0.004818	0.002417
M=4	11245.32	0.120622	0.498344	1.506947	0.001462	0.027942
M=8	14336.72	0.024095	0.322399	0.327786	4.561327	4.589909
M=16	13765.55	0.033166	0.398697	0.063189	1.710944	1.722786
M=32	13230.81	0.039688	0.425937	0.090501	2.178714	2.193964
M=64	13347.93	0.078282	0.430243	0.188842	0.378347	0.394248
PAM	Features					
	γ_{max}	σ_{ap}	σ_{dp}	σ_{aa}	σ_{fa}	σ_{fn}
M=2	2960.66	0.077490	0.047204	0.030303	0.009684	0.004622
M=4	2652.69	0.020219	0.013999	0.064834	0.000756	0.001617
M=8	263.23	0.000373	0.000447	0.011921	0.000681	0.000533
M=16	47.63	0.001820	0.001412	0.002325	0.000286	0.000222
M=32	10.15	0.000477	0.000363	0.001466	0.000075	0.000057
M=64	2.44	0.000037	0.000027	0.001152	0.000006	0.000004
QAM	Features					
	γ_{max}	σ_{ap}	σ_{dp}	σ_{aa}	σ_{fa}	σ_{fn}
M=2	3018.44	0.051966	0.032047	0.046932	0.003606	0.001942
M=4	9284.84	0.046823	0.100495	0.035927	12.15521	12.20237
M=8	7923.54	0.03423	0.630128	0.070858	2.366496	2.383442
M=16	14242.08	0.040641	0.466053	0.195764	4.675667	4.697166
M=32	15156.75	0.093926	0.528192	0.06922	8.642468	8.655034
M=64	14550.60	0.039236	0.504776	0.165473	1.679471	1.697718

Table 2,3,4 shows the spectral features for the considered modulation formats on AWGN channel model, Rayleigh flat fading channel model and Rician flat fading channel model.

4. PROPOSED CLASSIFIER STRUCTURE

The proposed algorithm for classification of several modulation formats are developed using artificial neural network (ANN). The ANN architecture which is used for the classification purpose is a feed-forward back propagation network (FFBPN). The training of algorithm is done using supervised learning. The proposed classifier architecture for classification of considered modulation formats are shown in Fig. 2

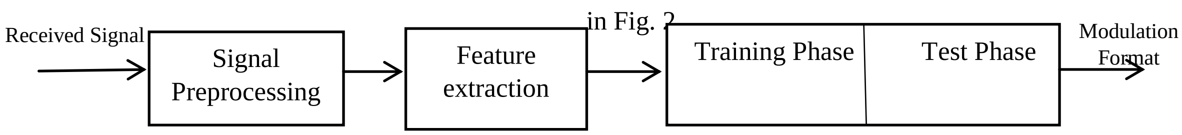

Fig. 1. System Model for Automatic Modulation Classification

Table 2: Spectral features for FSK, PAM, PAM and QAM (2-64) on AWGN channel

FSK	Features					
	γ_{max}	σ_{ap}	σ_{dp}	σ_{aa}	σ_{fa}	σ_{fn}
M=2	9141.23	0.07039	0.524013	0.313731	0.026591	0.046203
M=4	6415.33	0.033842	0.402362	0.125827	0.029873	0.046855
M=8	6709.73	0.037333	0.404321	0.016081	0.034479	0.050834
M=16	7720.15	0.021993	0.423616	0.069606	0.026391	0.041366
M=32	11740.52	0.067073	0.463615	0.490832	0.026315	0.046678
M=64	14051.68	0.051824	0.529343	0.284483	0.031418	0.050532
PSK	Features					
	γ_{max}	σ_{ap}	σ_{dp}	σ_{aa}	σ_{fa}	σ_{fn}
M=2	10287.53	0.045192	0.626967	0.075699	0.031604	0.051864
M=4	16533.30	0.028652	0.552045	0.092758	0.03018	0.051437
M=8	17993.58	0.044413	0.603515	0.020632	0.041494	0.060858
M=16	18163.87	0.047783	0.60082	0.021601	0.037466	0.062706
M=32	17826.98	0.025803	0.6009	0.039804	0.034058	0.06089
M=64	18496.51	0.028079	0.60648	0.322893	0.042337	0.064742
PAM	Features					
	γ_{max}	σ_{ap}	σ_{dp}	σ_{aa}	σ_{fa}	σ_{fn}
M=2	9943.59	0.047165	0.627500	0.053125	0.027954	0.051625
M=4	4233.01	0.081612	0.424497	0.079816	0.028570	0.038637
M=8	443.68	0.006914	0.005375	0.014601	0.000574	0.000460
M=16	77.23	0.001267	0.001029	0.003058	0.000200	0.000163
M=32	17.03	0.001296	0.001011	0.001145	0.000204	0.000159
M=64	4.07	0.000327	0.000253	0.000884	0.000051	0.000040
QAM	Features					
	γ_{max}	σ_{ap}	σ_{dp}	σ_{aa}	σ_{fa}	σ_{fn}
M=2	10417.53	0.042855	0.626881	0.145745	0.031442	0.050195
M=4	15705.58	0.051375	0.543267	0.040471	0.054347	0.080459
M=8	9548.98	0.043320	0.640516	0.192427	0.033598	0.047200
M=16	15220.52	0.042398	0.539814	0.227357	0.048941	0.071457
M=32	15575.79	0.025693	0.552917	0.126005	0.038987	0.062246
M=64	14977.82	0.035123	0.531346	0.196076	0.057755	0.082025

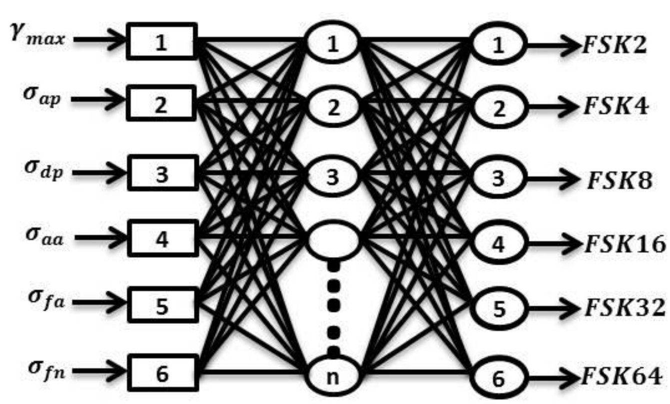

Fig. 2. Proposed Architecture for classification of modulation format

The input data sets are the key features which are extracted from the received signal. The FFBPN have three layers; one is input layer, one is hidden layer one is output layer. At input layer neurons are only used for distribution of extracted features to the hidden layer neurons which are used for the computations. The difference between input layer neurons and hidden layer neurons is that hidden layer neurons perform computations while input layer don't. The output of the hidden layer is input to the output layer. Six neurons are used in input layer as analogous to the number of features extracted from the received signal. Hidden layer carries ten neurons, while six neurons in output layer corresponding to the number of outputs/ modulation formats. Table 5 shows the proposed classifier specifications [15].

Table 3: Spectral features for FSK, PAM, PAM and QAM (2-64) on Rayleigh flat fading channel

FSK	Features					
	γ_{max}	σ_{ap}	σ_{dp}	σ_{aa}	σ_{fa}	σ_{fn}
M=2	47.7140	0.3887	0.4947	1.3405	0.0731	0.0427
M=4	24.4675	0.6223	0.6397	0.8763	0.0931	0.0471
M=8	79.7547	0.6842	0.7655	1.5972	0.1197	0.0584
M=16	72.9445	0.6435	0.4958	1.3039	0.0926	0.0699
M=32	66.5615	0.4086	0.9254	1.7487	0.0597	0.0463
M=64	76.9395	0.6187	0.8103	1.6217	0.0837	0.1053
PSK	Features					
	γ_{max}	σ_{ap}	σ_{dp}	σ_{aa}	σ_{fa}	σ_{fn}
M=2	52.9746	0.6939	0.6459	1.0996	0.2287	0.2333
M=4	163.7582	0.3223	0.5800	2.5087	0.0579	0.0405
M=8	58.7993	0.3308	0.2989	1.5697	0.0371	0.0623
M=16	121.6375	0.6047	0.5578	2.2174	0.0626	0.0582
M=32	50.1168	0.6331	0.5756	1.6571	0.1111	0.1013
M=64	15.2891	0.5202	0.2762	1.0560	0.0209	0.0886
PAM	Features					
	γ_{max}	σ_{ap}	σ_{dp}	σ_{aa}	σ_{fa}	σ_{fn}
M=2	40.2742	0.3569	0.6513	1.1529	0.0644	0.0406
M=4	10.7172	0.4507	0.4786	0.6378	0.0311	0.0569
M=8	4.3633	0.3039	0.2344	0.2988	0.0548	0.0430
M=16	1.2324	0.1069	0.0721	0.1320	0.0136	0.0139
M=32	0.1452	0.0437	0.0338	0.0208	0.0070	0.0054
M=64	2.0621	0.1786	0.1215	0.2355	0.0059	0.0117
QAM	Features					
	γ_{max}	σ_{ap}	σ_{dp}	σ_{aa}	σ_{fa}	σ_{fn}
M=2	146.5183	0.3080	0.7264	2.0132	0.0771	0.0626
M=4	98.2800	0.5775	0.7779	2.4573	0.0449	0.0663
M=8	30.3865	0.3174	0.4589	1.1921	0.0466	0.0644
M=16	51.9916	0.5229	0.4962	1.3900	0.1467	0.1168
M=32	59.6878	0.4794	0.3360	1.7413	0.0908	0.0891
M=64	46.7442	0.3519	0.4712	1.3087	0.0709	0.0435

Training of Algorithm: The input data set and target data set are used to train the proposed classifier until it classifies the modulation formats. The difference between the output value and target value is known as error value, which is back propagated to hidden layer. The feed forward back propagation algorithm is used which involves forward and backward path. In forward path, weights are initialized for training the feed forward network, while in this path weights values are fixed. The error signal is given by

$$e_j = t_j - y_j \qquad (14)$$

Where t is the target response of jth input and y is the output of the network. In second path weights are updated using feed forward back propagation algorithm. The weights are adjusted till then the error signal is minimize in a statistical sense using mean square error criterion.

$$\text{Cost function} = J = \frac{1}{N}\sum_{j=0}^{N}(t_j - y_j)^2 \qquad (15)$$

The training of proposed classifier for the purpose of classification is as follows:

Step1. The input and target vectors are concatenated to represent the Data Matrix.

Step 2. Generated Data are normalized and randomly sorted.

Step 3. The normalized data are partitioned in to training, validation and testing data. The 60% of normalized data are used for the training the neural network. In the training phase the weights are updated until error is minimized. 20% of normalized data are used to validation. In validation, network is able to stop training, before the network over fitted. While for testing the network, 25% of the normalized data are used.

Step 4. Feed forward back propagation neural network (FFBPN) is created. The activation function used are tang-sigmoid (tanh) and (logistic) log-sigmoid.

Table 4: Spectral features for FSK, PAM, PAM and QAM (2-64) on Rician flat fading channel

FSK	Features					
	γ_{max}	σ_{ap}	σ_{dp}	σ_{aa}	σ_{fa}	σ_{fn}
M=2	61.3938	0.5051	0.4201	1.6425	0.0867	0.0985
M=4	13.6235	0.3335	0.5002	0.6549	0.0686	0.0751
M=8	9.6414	0.4220	0.2726	0.4567	0.0877	0.0370
M=16	19.5176	0.5952	0.8790	0.5314	0.0580	0.0795
M=32	32.6621	0.4426	0.5454	1.5053	0.0862	0.0662
M=64	349.9910	0.5184	0.6755	3.9569	0.0889	0.0991
PSK	Features					
	γ_{max}	σ_{ap}	σ_{dp}	σ_{aa}	σ_{fa}	σ_{fn}
M=2	56.0192	0.5836	0.6297	1.2453	0.0885	0.0739
M=4	49.0598	0.3868	0.6755	1.9189	0.0648	0.0406
M=8	51.2956	0.3951	0.5588	1.2376	0.0631	0.0333
M=16	58.3194	0.6384	0.3951	1.4809	0.1461	0.0996
M=32	147.6576	0.5625	0.4879	2.1221	0.0878	0.1194
M=64	30.2520	0.7824	0.3395	0.7814	0.1560	0.1115
PAM	Features					
	γ_{max}	σ_{ap}	σ_{dp}	σ_{aa}	σ_{fa}	σ_{fn}
M=2	57.5370	0.5000	0.7576	1.3848	0.0261	0.0375
M=4	181.5499	0.4641	0.1320	3.4463	0.0957	0.0745
M=8	2.7633	0.1600	0.1223	0.1525	0.0264	0.0201
M=16	1.0964	0.2048	0.1620	0.1717	0.0340	0.0268
M=32	0.7509	0.1587	0.1237	0.1746	0.0275	0.0229
M=64	0.3466	0.0681	0.0524	0.0740	0.0121	0.0095
QAM	Features					
	γ_{max}	σ_{ap}	σ_{dp}	σ_{aa}	σ_{fa}	σ_{fn}
M=2	45.3284	0.2932	0.2235	1.1369	0.0456	0.0395
M=4	141.5396	0.5199	0.6635	2.0916	0.0770	0.0424
M=8	37.9334	0.6737	0.6397	1.2949	0.2441	0.2024
M=16	25.6157	0.3882	0.5893	0.8877	0.1213	0.0909
M=32	75.4700	0.4955	0.4427	2.1962	0.0865	0.0749
M=64	27.8583	0.5431	0.3489	0.8129	0.1140	0.0922

4.2 Testing of Algorithm: The 20% of the normalized data are used to test the network. The performance of classifier is tested for different values of SNR. The net lab is used for simulation of multilayer perceptron based FFBPN.

Table 5: Specifications for the proposed classifier

S. No.	Parameters	Value
1.	neural network architecture	Feed-forward
2.	input layer neurons	6
3.	hidden layer neurons	10
4.	output layer neurons	6
5.	weight-decay Coefficient	0.001
6.	hidden layer Activation function	Logistic
7.	output layer Activation function	Logistic
8.	Iterations	500
9.	Performance Metric	MSE
10.	Learning algorithm	SCG

5. SIMULATION RESULTS

The performance of proposed algorithm is evaluated in this section. The problem of classification of modulation formats considered in this research are divided in four scenarios; {FSK 2 to 64}, {PSK 2 to 64}, {PAM 2 to 64} and {QAM 2 to 64}. The six key features extracted from the received signal which is corrupted by AWGN and undergone through fading effects (Rayleigh flat & Rician flat). The classifier is used are multilayer perceptron which is also referred as FFBPN. The classifier have 6 inputs corresponds to number of feature set and six outputs corresponds to the considered scenario of modulation formats. The feature vectors and target vectors are concatenated to form the data set. The data set is divided in to three portions; 60% used for training while rest 40% are used for validation and testing the proposed algorithm. The performance of proposed are evaluated under the effects of different channel models at SNR of 0dB. The simulation results in the form of confusion matrix show the performance of classification is approximately 100 at SNR of 0dB.

The Fig. 3 shows the output result of feed forward back propagation network in case of PSK 2 to 64 modulation format in the presence of AWGN channel model at SNR of 0dB. The subplot shows the FFBPN output pattern, second subplot shows the test output and third one is the error pattern. The training data set is totally different with the test data set and the probability of failure is approximately zero as shown in Fig.. The Fig. also shows that classifier perfectly classifies the considered scenario of modulation format.

Table 6, shows the percentage of correct classification in case of {FSK 2 to 64},{PSK 2to 64},{PAM 2 to 64} and {QAM 2 to 64} under the effect of additive white guassian noise at fixed SNR of 0dB. The performance of classifier in the form of confusion matrix shows the approximately 100% classification. The overall performance of classifier is 99.62% in case of FSK, 99.55% in case of PSK, 99.56% in case of PAM and 99.34% in case of QAM.

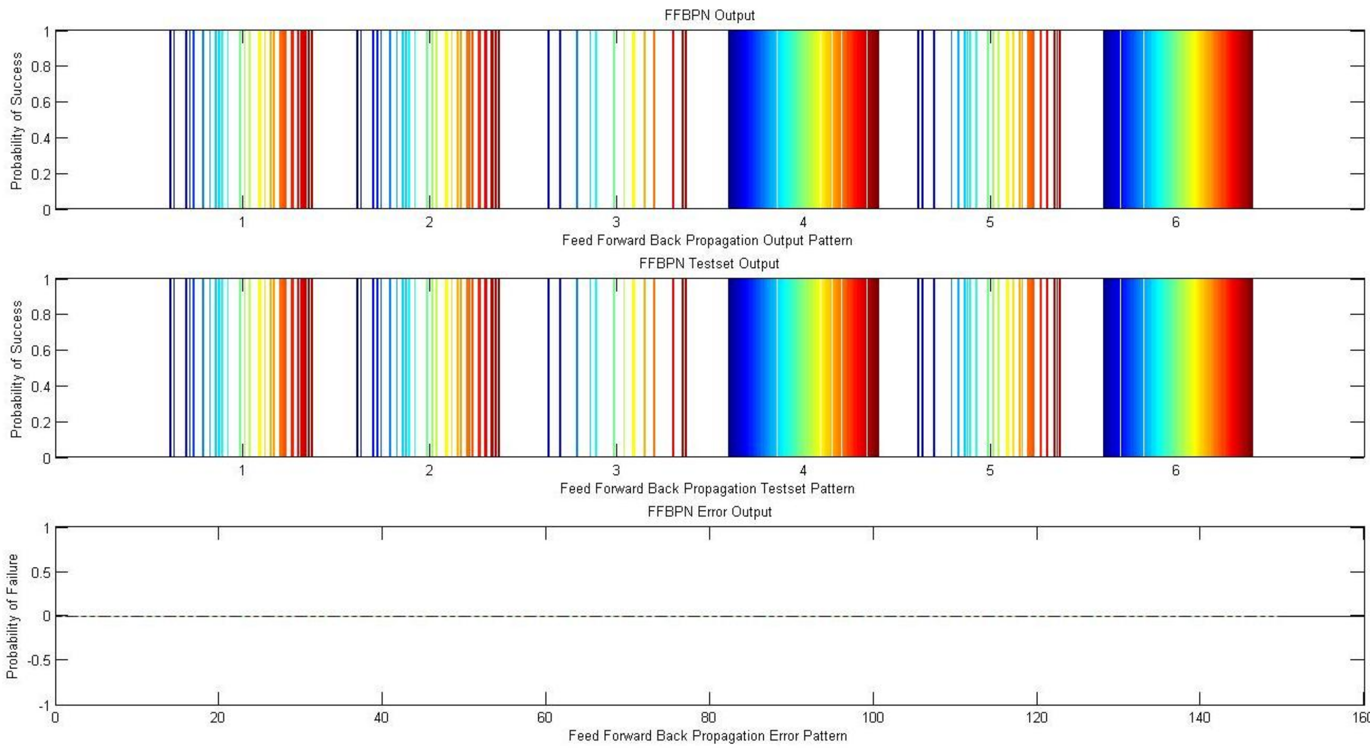

Fig. 3. The FFBPN result for the proposed classifier on AWGN at SNR of 0dB

Table 6: Percentage of correct classification on AWGN channel

FSK	Percentage of Correct Classification in case of FSK on AWGN channel at 0dB SNR					
	M=2	M=4	M=8	M=16	M=32	M=64
M=2	99.61					
M=4		99.92				
M=8			99.99			
M=16				99.94		
M=32					99.54	
M=64						98.76
PSK	Percentage of Correct Classification in case of PSK on AWGN channel at 0dB SNR					
	M=2	M=4	M=8	M=16	M=32	M=64
M=2	99.99					
M=4		99.92				
M=8			99.54			
M=16				98.93		
M=32					99.32	
M=64						99.64
PAM	Percentage of Correct Classification in case of PAM on AWGN channel at 0dB SNR					
	M=2	M=4	M=8	M=16	M=32	M=64
M=2	99.98					
M=4		99.32				
M=8			99.59			
M=16				99.65		
M=32					99.29	
M=64						99.55
QAM	Percentage of Correct Classification in case of QAM on AWGN channel at 0dB SNR					
	M=2	M=4	M=8	M=16	M=32	M=64
M=2	99.99					
M=4		99.64				
M=8			99.87			
M=16				99.29		
M=32					99.13	
M=64						98.12

Table 7: Percentage of correct classification on Rician flat fading channel plus AWGN

FSK	Percentage of Correct Classification in case of FSK on Rician Flat Fading channel at 0dB SNR					
	M=2	M=4	M=8	M=16	M=32	M=64
M=2	98.79					
M=4		98.32				
M=8			97.47			
M=16				98.61		
M=32					97.15	
M=64						98.10
PSK	Percentage of Correct Classification in case of PSK on Rician Flat Fading channel at 0dB SNR					
	M=2	M=4	M=8	M=16	M=32	M=64
M=2	99.18					
M=4		98.12				
M=8			97.83			
M=16				97.95		
M=32					98.53	
M=64						97.31
PAM	Percentage of Correct Classification in case of PAM on Rician Flat Fading channel at 0dB SNR					
	M=2	M=4	M=8	M=16	M=32	M=64
M=2	97.72					
M=4		98.93				
M=8			97.45			
M=16				98.23		
M=32					97.51	
M=64						98.05
QAM	Percentage of Correct Classification in case of QAM on Rician Flat Fading channel at 0dB SNR					
	M=2	M=4	M=8	M=16	M=32	M=64
M=2	99.37					
M=4		99.23				
M=8			98.57			
M=16				98.37		
M=32					97.34	
M=64						97.19

Table 7, shows the percentage of correct classification in case of {FSK 2 to 64},{PSK 2to 64},{PAM 2 to 64} and {QAM 2 to 64} under the effect of Rician flat fading channel plus additive white guassian noise at fixed SNR of 0dB. The performance of classifier in the form of confusion matrix shows the approximately 98% classification. The overall performance of classifier is 98.07% in case of FSK, 98.15% in case of PSK, 97.98% in case of PAM and 98.34% in case of QAM. Table 8, shows the percentage of correct classification under the effect of Rayleigh flat fading channel plus additive white guassian noise at fixed SNR of 0dB. The performance of classifier in the form of confusion matrix shows the approximately 97% classification. The overall performance of classifier is 96.99% in case of FSK, 97.13% in case of PSK, 96.84% in case of PAM and 97.35% in case of QAM.

Table 8: Percentage of correct classification on Rayleigh flat fading channel plus AWGN

FSK	Percentage of Correct Classification in case of FSK on Rayleigh Flat Fading channel at 0dB SNR					
	M=2	M=4	M=8	M=16	M=32	M=64
M=2	96.32					
M=4		97.81				
M=8			97.62			
M=16				96.43		
M=32					96.15	
M=64						97.62
PSK	Percentage of Correct Classification in case of PSK on Rayleigh Flat Fading channel at 0dB SNR					
	M=2	M=4	M=8	M=16	M=32	M=64
M=2	97.40					
M=4		97.93				
M=8			96.23			
M=16				97.11		
M=32					97.02	
M=64						97.13
PAM	Percentage of Correct Classification in case of PAM on Rayleigh Flat Fading channel at 0dB SNR					
	M=2	M=4	M=8	M=16	M=32	M=64
M=2	97.23					
M=4		96.54				
M=8			96.78			
M=16				97.01		
M=32					96.29	
M=64						97.19
QAM	Percentage of Correct Classification in case of QAM on Rayleigh Flat Fading channel at 0dB SNR					
	M=2	M=4	M=8	M=16	M=32	M=64
M=2	98.45					
M=4		98.54				
M=8			96.59			
M=16				96.82		
M=32					96.99	
M=64						96.72

6. CONCLUSION

The classification of digital modulation formats on fading channels is evaluated. The modulation formats considered for the purpose of classification are divided in four scenarios; {FSK 2 to 64}, {PSK 2 to 64}, {PAM 2 to 64} and {QAM 2 to 64}. The features extracted from the received signal are known as spectral features. The spectral features are used as an input to the classifier. The received signals are undergone additive white guassian noise plus Rayleigh flat fading and Rician flat fading channel. The proposed classifier is feed forward back propagation neural network, where the input is key features and outputs are classified modulation formats. The real theoretical values of spectral features are also calculated. The performance of proposed classifier is approximately 99.99 % on AWGN channel, 98% on Rician flat fading channel and 97% on Rayleigh flat fading Channel. The simulation results are also shows that the probability of failure is approximately zero using feed forward back propagation networks.

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