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Classification of Digital Modulated Signals Using Linear Discriminant Analysis on Faded Channel

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Abstract: In this paper, modulation classification of digitally modulated signals is done using Linear Discriminant Analysis (LDA) under the influence of additive white guassian noise (AWGN) as well as the channel effect such as fading. The modulations considered for the classification purpose are PSK 2 to 64, FSK 2to 64 and QAM 2 to 64. The channels considered throughout the simulations are AWGN, Rayleigh Flat Fading channel and Rician Flat Fading channel. In Automatic Modulation classification (AMC), digitally modulated signals are classified under the effect of channel noise and fading. Also the classification is done in short interval of time with high probability of success. The features used for modulationclassification are normalized higher order cummulants (HOC) which is extracted from the received signal which is corrupted by AWGN and fading. The LDA classify the received signal in to set of different classes. The performance metric is minimum distance criterion which discriminate the received signal data set into different classes. The performance of the algorithm shows substantial organization of different digital modulated signals. The simulation result also show that LDA algorithm has high classification accuracy at low signal to noise ratio (SNR) on AWGN channel as well as fading channels which are considered. The confusion matrix for PSK 2 to 64, FSK 2 to 64 and QAM 2 to 64 shows the classification performance of the proposed algorithm at SNR of 10dB and 0dB.

Key words: Automatic Modulation Classification (AMC) · Linear Discriminant Analysis (LDA) · Additive White Guassian Noise (AWGN) · Higher Order Cummulants (HOC)

INTRODUCTION

In communication system modulation is one of the basic features. For non-cooperative communication system, identification of signal modulation type is one of the complex issues. In practical communication system, modulation format of the signals is become more diverse to improve the anti-interference ability. Modulation classification is done before demodulation of signal. Modulation classification (MC) has several important applications in commercial sector (interference identification, spectrum management), military domain and in software defines radio (SDR). MC has gain more attention in SDR. For classification of digital modulation signal, MC is used on the front end of SDR. The MC also has applications to cognitive radios (CR). In CR, secondary users are allowed to use the spectrum originally allocated to primary users having constraint to avoid interference from the primary users that secondary user have exact knowledge of the spectrum white spaces. For this reason performance of CR is improve by using reliable MC scheme [1].

Modulation classification is an intermediate step between detection and demodulation of transmitted signal. MC involves two steps: pre-processing of the information signal which is to be transmitted and selection of classification algorithm. To classify the digital modulated signal in the presence of channel noise and various channel effects, MC is used. For classification of signal modulation format various methods have been proposed in literature [2]. The modulation classification method is divided into two approaches [3]: (1) Decision

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theoretic approach based on log likelihood function; (2) Statistical pattern recognition approach based on extraction of features.

The classifiers using Log likelihood function based decision theoretic approach for different modulation schemes are proposed in [4-6]. The approach is usually multi-level classification at lower SNRs, but requires priori knowledge and additional information about the signal such as time domain parameters and higher order spectral components. The decision theoretic approach is optimal solution and computationally complex. In statistical pattern recognition approach also known as feature based (FB) approach, various features of the received signal which is undergo channel noise and effects are extracted and decision is made upon these features. The method based on feature extraction is suboptimal solution, when it is designed properly the performance of the algorithm becomes optimal. The approach is easy to implement and also not computationally complex [7, 8].

The FB approach for classification of modulation are deployed in [9], in which authors present the robust automatic modulation classification algorithm which uses higher order cummulants for estimation of channel and pattern recognition. No priori information is required about the channel. In [10], lower bounds for BPSK and QPSK modulations over an additive white guassian noise channel (AWGN) are presented. The features used are 4^{th} order cummulants. The blind modulation classification in the presence of carrier offset is proposed in [11]. The authors proposed the hierarchical architecture for the 9-class problem. The features utilized in [12, 13] are cyclic features and spectral features and MC is accomplished using the features. A summary of proposed algorithms for MC is in [14], algorithms based on instantaneous amplitude, phase and frequency (time-frequency analysis); algorithm based on the wavelet transform; algorithms based on cummulants and moments (higher order statistics); algorithms based on cyclostationarity properties; and algorithms based on spectral properties.

In this paper, we proposed linear discriminant analysis (LDA) as classification algorithm for following digital modulations: PSK2, PSK4, PSK8, PSK16, PSK32, PSK64, FSK2, FSK4, FSK8, FSK16, FSK32, FSK64, QAM2, QAM4, QAM8, QAM 16, QAM 32 and QAM 64. The transmitted signal is corrupted by the AWGN and also undergoes the channel effects. The channels considered throughout the simulations are AWGN channel, Rayleigh Flat Fading channeland Rician Flat Fading channel.

The rest of the paper is organized as follows: Section II represents the system model and feature used for the purpose of classification of modulation techniques such as PSK2 to PSK64, FSK2 to FSK64, QAM2 to QAM64. Section III represents the proposed algorithm in which linear discriminant analysis is used as a classifier and considered modulations are classified. In Section IV, performance of classifier in form of confusion matrix for classification of different modulation schemes are discussed while the whole paper is concluded in Section V.

System Model and Features Used

System Model: The received signal which is singly modulated by amplitude, frequency and phase is represented in eq. 1.

$$x(t) = A(t)\cos(w_c(t)t + \theta_c(t)) + \gamma \tag{1}$$

$$s(t) = A(t)\cos(w_c(t)t + \theta_c(t)) \tag{2}$$

Where x(t) is received signal which is corrupted by white guassian noise (WGN) as well as channel effects. s(t) is original transmitted signal $\gamma(t)$ is WGN. Figure 1 shows the system model for classification of modulation signals.

Higher Order Moments and Cummulants: For classification of modulation signals higher order moments and higher order cummulants are used.Cummulants of 2^{nd}, 4^{th}, 6^{th} and 8^{th} order have the following definitions [2]:

$$C_{20} = E[y^2(n)] = cumm\{y(n), y(n)\} \tag{3}$$

$$C_{21} = E[|y(n)|^2] = cumm\{y(n), y^*(n)\} \tag{4}$$

$$C_{40} = M_{40} - 3M_{20}^{\ 2} = cumm\{y(n), y(n), y(n), y(n)\} \tag{5}$$

$$C_{41} = M_{40} - 3M_{20}M_{21} = cumm\{y(n), y(n), y(n), y^*(n)\} \tag{6}$$

$$\begin{aligned} C_{42} &= M_{42} - |M_{20}|^2 - 2M_{21} \\ &= cumm\{y(n), y(n), y^*(n), y^*(n)\} \end{aligned} \tag{7}$$

$$\begin{aligned} C_{60} &= M_{60} - 15M_{20}M_{40} + 30M_{20}^{\ 3} \\ &= cumm\{y(n), y(n), y(n), y(n), y(n), y(n)\} \end{aligned} \tag{8}$$

$$\begin{aligned} C_{61} &= M_{61} - 5M_{21}M_{40} - 10M_{20}M_{41} + 30M_{20}^{\ 2}M_{21} \\ &= cumm\{y(n), y(n), y(n), y(n), y(n), y^*(n)\} \end{aligned} \tag{9}$$

$$\begin{aligned} C_{62} &= M_{62} - 6M_{20}M_{42} - 8M_{21}M_{41} - M_{22}M_{40} + 6M_{20}^{\ 2}M_{22} + 24M_{21}^{\ 2}M_{22} \\ &= cumm\{y(n), y(n), y(n), y(n), y^*(n), y^*(n)\} \end{aligned} \tag{10}$$

$$\begin{aligned} C_{63} &= M_{63} - 9M_{21}M_{42} + 12M_{21}^{\ 3} - 3M_{20}M_{43} - 3M_{22}M_{41} + 18M_{20}M_{21}M_{22} \\ &= cumm\{y(n), y(n), y(n), y^*(n), y^*(n), y^*(n)\} \end{aligned} \tag{11}$$

$$\begin{aligned} C_{80} &= M_{80} - 35M_{40}^{\ 2} - 28M_{60}M_{20} + 420M_{40}M_{20}^{\ 2} - 630M_{20}^{\ 4} \\ &= cumm\{y(n), y(n), y(n), y(n), y(n), y(n), y(n), y(n)\} \end{aligned} \tag{12}$$

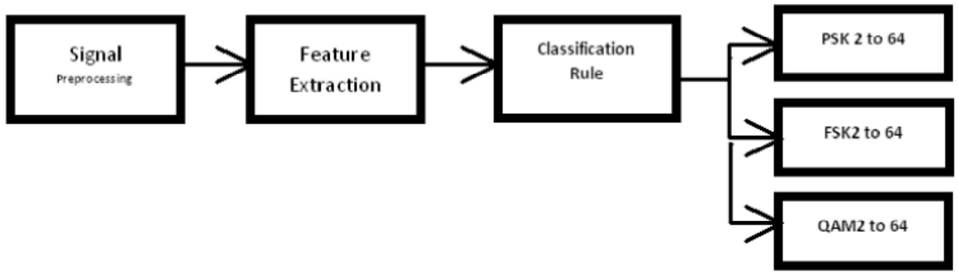

Fig. 1: Modulation Classification System Model

$$C_{84} = M_{84} - 16C_{63}C_{21} + |C_{40}|^2 - 18C_{42}^2 - 72C_{42}C_{21}^2 - 24C_{21}^4$$
$$= cumm\{y(n), y(n), y(n), y(n), y^*(n), y^*(n), y^*(n), y^*(n)\} \quad (13)$$

M_{pq} stands for moments of received signal and it is given by

$$M_{\bar{p}\bar{q}} = E[y(k)^{p-q} y^*(k)^q] \quad (14)$$

Normalized Higher Order Cummulants: The normalized 4th order cummulants $C_{42,x}$ [10]:

$$\hat{C}_{42,x} = C_{42,x}/(C_{21,x})^2 \quad (15)$$

$$\hat{C}_{42,x} = \frac{1}{\beta}\frac{C_{42,y}}{(C_{21,y} - \sigma_g{}^2)^2} \quad (16)$$

$$\beta = \frac{\sum_{k=0}^{L-1} |h(k)|^4}{\left\{\sum_{k=0}^{L-1} h(k)^2\right\}^2} \quad (17)$$

The normalized 6th order cummulants $C_{63,x}$[14]:-

$$\hat{C}_{63,x} = C_{63,x}/(C_{21,x})^3 \quad (18)$$

$$\hat{C}_{63,x} = \frac{1}{\beta}\frac{C_{63,y}}{(C_{21,y} - \sigma_g{}^2)^3} \quad (19)$$

$$\beta = \frac{\sum_{k=0}^{L-1} |h(k)|^6}{\left\{\sum_{k=0}^{L-1} h(k)^2\right\}^2} \quad (20)$$

Feature values based on moments and Cummulants: The features theoretical values used for classification purpose are given in Table1 and Table 2. Table 1 represents the higher order moments and Table 2 represents the higher order cummulants for the selected modulations. The normalized 4th order cummulants and 6th order cummulants values for {BPSK, QPSK}, {FSK2 to 64} and {QAM 2 to 64} modulations are given in Table3.

Table 1: Theoretical Values of Moments of Considered Modulation Types [2]

PSK	PSK2	PSK4	PSK8	PSK16	PSK32	PSK64
M20	1	0	0	0	0	0
M21	1	1	1	1	1	1
M40	1	1	0	0	0	0
M41	1	0	0	0	0	0
M42	1	1	1	1	1	1
M60	1	0	0	0	0	0
M61	1	1	0	0	0	0
M63	1	1	1	1	1	1
M80	1	1	1	0	0	0
M84	1	1	0	1	0	0
QAM	QAM 2	QAM 4	QAM 8	QAM 16	QAM 32	QAM 64
M20	1	0	4	0	0	1
M21	2	0	1	1	0	0
M40	2	1	1	1	0	1
M41	1	0	0	0	0	0
M42	0	7	1.2	1.29	1.32	1.38
M60	0	0	0	0	0	0
M61	1	8	1.18	1.32	1.3	1.29
M63	1	3	1.8	1.96	2	2.22
M80	0.8	0.9	1.5	2.2	2	1.92
M84	1	2.5	2.9	3.12	3.5	3.96
FSK	FSK2	FSK 4	FSK 8	FSK 16	FSK 32	FSK 64
M20	1	0	0	0	0	0
M21	0	0	0	0	0	0
M40	1	0	0	0	0	0
M41	1	0	0	0	0	0
M42	126	126	126	126	126	126
M60	1	0	0	0	0	0
M61	0	0	0	0	0	0
M63	8	8	8	8	8	8
M80	1	0	0	0	0	0
M84	0	0	0	0	0	0

Proposed Algorithm: The features are higher order moments and higher order cummulants extracted from the received signal which may be modulated {PSK 2to 64}, {FSK 2 to 64} and {QAM 2 to 64} are now input to the classifier.The received modulated signals haveundergone different channels such as AWGN channel, Rayleigh flat fading channeland Rician flat fading channel. For classification purpose, Linear discriminant analysis (LDA)

Table 2: Theoretical Values of Cummulants of Considered Modulation Types [2]

PSK	PSK2	PSK4	PSK8	PSK16	PSK32	PSK64
C20	1	0	0	0	0	0
C21	1	1	1	1	1	1
C40	2	1	0	0	0	0
C41	2	0	0	0	0	0
C42	2	1	1	1	1	1
C60	31	4	0	0	0	0
C63	13	4	4	4	4	4
C80	350	35	0	0	0	0
C84	163	34	34	34	34	34
QAM	QAM 2	QAM 4	QAM 8	QAM 16	QAM 32	QAM 64
C20	1	0	4	0	0	0
C21	1	1	1	1	1	1
C40	2	1	1	1	0	1
C41	2	0	1	0	0	0
C42	2	1	1	1	1	1
C60	31	0	0	0	0	0
C63	13	1.96	2.2	2	1.9	1.8
C80	350	13.6	13.5	13	12	11
C84	163	13.6	13.5	13	12	11
FSK	FSK2	FSK 4	FSK 8	FSK 16	FSK 32	FSK 64
C20	0	-1	-1	0	0	0
C21	8	8	8	8	8	8
C40	0	0	0	0	0	0
C41	0	0	0	0	0	0
C42	-2	-2	-2	-2	-2	-2
C60	1223	1028	315	8	29	11
C63	-2923	-2924	-2928	-2929	-2929	-2929
C80	-15572	-10982	-1027	0	-9	-2
C84	284816	284875	285090	285182	285176	285181

Table 3: Theoretical Values of Normalized Cummulants of Considered Modulation Types [15]

	C_{42x}	C_{63x}
BPSK	-2	13
QPSK	-1	4
FSK2	-2	13
FSK 4	-1.3586	7.07
FSK 8	-1.2368	5.22
FSK 16	-1.2113	3.63
FSK 32	-1.2039	2.30
FSK 64	-1.1988	1.536
QAM 2	-2	13
QAM 4	-1	1.96
QAM 8	-1.0011	0.0192
QAM 16	-0.6778	2.08
QAM 32	-0.6876	1.9448
QAM 64	-0.6167	1.7972

is used which is linear classification scheme. LDA works by projecting data into a feature space using a linear mapping and then comparing the result to a centroid for each class. If the data is linearly separable, these schemes work well [3].

Steps for Modulation Classification using LDA [3]:

- Create the two data sets i.e. classes $c_1$and c_2
- Calculate the mean of each data ì$_1$and ì$_2$
- Calculate the weighted mean ì=p_1*ì$_1$+ ì$_2$*p_2
- Calculate the covariance matrix Si of data set and mean of data set.
- Two criterion are as follows:

Criterion 1: Class dependent case

a.inverse (S_i)* S_Bi=1,2,3,......, datasets

Criterion 2: class independent case

b.inverse(Sw)*S_B

Where Sw and S_B are within class scatter matrix and the between class scatter matrix

$$S_W = \sum_{i=1}^{N} S_i$$

$$S_B = \sum_{i=1}^{N} n(m_i - m)(m_i - m)^T$$

- Finding the projection matrix W is equivalent to calculate the eigen values and corresponding eigen vectors of criterion 1 and criterion 2.i.e. $S_b w_i = \lambda_i S_w W_i$

Find the optimum weight vector which corresponds to highest Eigen value.

- Find the transformed data set $y = W^T x$
- Find the minimum distance between transformed data set and test data.

RESULTS

The classification performance of different modulations ({PSK 2 to 64}, {FSK 2 to 64} and {QAM 2 to 64}) in the presence of AWGN channel, Rayleigh flat fading channel and Rician flat fading are simulated here.The higher order moments and higher order cummulants are used as features which are input to the classifier based on LDA. The modulation schemes considered here are divided in three scenarios i.e. and {PSK2, PSK4, PSK8, PSK16, PSK32, PSK64}, {FSK2, FSK4, FSK8, FSK16, FSK32, FSK64} and {QAM2, QAM4, QAM8, QAM16, QAM32, QAM64}. The performance of LDA classifier is evaluated at different SNRs.

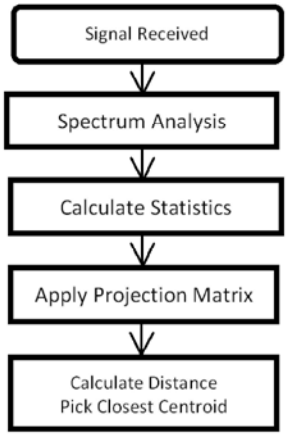

Fig. 2: Flow Chart for Modulation Classification

The flow chart of classifying the modulation schemes are as follows:

First, 30 training signals of 10,000 symbols are generated for the (PSK2, PSK4, PSK8, PSK16, PSK32, PSK64, FSK2, FSK4, FSK8, FSK16, FSK32, FSK64, QAM2, QAM4, QAM8, QAM16, QAM32, QAM64)modulations and higher order moments andcummulants are also calculated for each training signal. After that these parameters are passed to a training function that determines a projection matrix and class centroids. The spectrum of each signal is analyzed by calculating the FFT of first 4096 samples and is also compared with the threshold values estimated in a separate simulation. After that, normalized cummulants are calculate and projected into feature space using the projection matrix. The projected feature are compared to class centroids and closet one is chosen as modulation scheme. The confusion matrix is also saved to analyses the classifier performance for the all considered modulation type [3].

From Table 4 to 9, the classification performance in form of confusion matrix for PSK modulations on AWGN channel, Rayleigh flat fading channel and Rician flat fading channel are shown at SNR of 10dB and 0dB. The average classifier performance in case of AWGN channel is 99.95%, where in case of Rayleigh channel the performance is 91.3% at SNR of 10dB.

From Table 10 to 15, the classification performance in form of confusion matrix for FSK modulations on AWGN channel, Rayleigh flat fading channel and Rician flat fading channel are shown at SNR of 10dB and 0dB. The average classifier performance in case of AWGN channel is 99 %, where in case of Rayleigh channel the performance is 83.4% and in case of Rician channel the performance is 86% at SNR of 0dB. The performance is better in case of Rician channel when comparing with

Table 4: Confusion Matrix for Psk Modulation in Awgn Channel

Average Performance (99.95%)						
1SNR 10dB	2PSK	4PSK	8PSK	16PSK	32PSK	64PSK
2PSK	10000	0	0	0	0	0
4PSK	0	10000	0	0	0	0
8PSK	0	0	10000	0	0	0
16PSK	0	0	3	9992	5	0
32PSK	0	0	0	10	9985	5
64PSK	0	0	0	0	10	9990

Table 5: Confusion Matrix for Psk Modulation in Awgn Channel

Average Performance (99.8%)						
SNR 0dB	2PSK	4PSK	8PSK	16PSK	32PSK	64PSK
2PSK	10000	0	0	0	0	0
4PSK	0	9995	5	0	0	0
8PSK	1	4	9990	5	0	0
16PSK	0	0	3	9981	4	12
32PSK	0	2	8	4	9976	10
64PSK	0	0	10	9	18	9963

Table 6: Confusion Matrix for Psk Modulation in Awgn+ Rician Flat Fading Channel

Average Performance (92.26%)						
SNR 10dB	2PSK	4PSK	8PSK	16PSK	32PSK	64PSK
2PSK	9793	207	0	0	0	0
4PSK	295	9395	290	40	0	0
8PSK	0	111	9639	250	0	0
16PSK	0	190	413	8967	430	0
32PSK	0	0	174	309	9091	426
64PSK	0	0	110	390	1038	8462

Table 7: Confusion Matrix for Psk Modulation in Awgn + Rician Falt Fading Channel

Average Performance (85.28%)						
SNR 0dB	2PSK	4PSK	8PSK	16PSK	32PSK	64PSK
2PSK	9091	909	0	0	0	0
4PSK	210	8998	792	0	0	0
8PSK	0	435	9565	0	0	0
16PSK	0	0	1100	8050	850	0
32PSK	0	0	0	106	7825	2069
64PSK	0	0	0	662	1695	7643

Table 8: Confusion Matrix for Psk Modulation in Awgn + Rayleigh Falt Fading Channel

Average Performance (91.38%)						
SNR 10dB	2PSK	4PSK	8PSK	16PSK	32PSK	64PSK
2PSK	9793	207	0	0	0	0
4PSK	496	9304	200	0	0	0
8PSK	0	185	9625	190	0	0
16PSK	0	9	895	8925	171	0
32PSK	0	0	48	931	8920	101
64PSK	0	0	0	681	994	8325

Table 9: Confusion Matrix for Psk Modulation in Awgn + Rayleigh Falt Fading Channel

Average Performance (84.6%)						
SNR 0dB	2PSK	4PSK	8PSK	16PSK	32PSK	64PSK
2PSK	8990	1010	0	0	0	0
4PSK	1026	8845	129	0	0	0
8PSK	0	04	9991	5	0	0
16PSK	0	243	1678	7940	139	0
32PSK	0	0	0	1931	7710	359
64PSK	0	0	0	621	2099	7280

Table 10: Confusion Matrix for Fsk Modulation in Awgn Channel

Average Performance (99.5%)						
SNR 10dB	2FSK	4FSK	8FSK	16FSK	32FSK	64FSK
2FSK	10000	0	0	0	0	0
4FSK	0	10000	0	0	0	0
8FSK	0	4	9996	0	0	0
16FSK	0	8	31	9961	0	0
32FSK	0	11	22	34	9921	12
64FSK	0	2	11	27	133	9827

Table 11: Confusion Matrix for Fsk Modulation in Awgn Channel

Average Performance (99%)						
SNR 0dB	2FSK	4FSK	8FSK	16FSK	32FSK	64FSK
2FSK	9990	10	0	0	0	0
4FSK	0	10000	0	0	0	0
8FSK	6	8	9986	0	0	0
16FSK	0	8	42	9950	0	0
32FSK	4	15	27	48	9906	0
64FSK	0	0	22	51	241	9686

Table 12: Confusion Matrix for Fsk Modulation in Awgn+ Rician Flat Fading Channel

Average Performance (91%)						
SNR 10dB	2FSK	4FSK	8FSK	16FSK	32FSK	64FSK
2FSK	10000	0	0	0	0	0
4FSK	416	9584	0	0	0	0
8FSK	0	421	9196	383	0	0
16FSK	0	0	921	8942	137	0
32FSK	0	0	0	876	8425	699
64FSK	0	0	0	713	893	8394

Table 13: Confusion Matrix for Fsk Modulation in Awgn + Rician Falt Fading Channel

Average Performance (86%)						
SNR 0dB	2FSK	4FSK	8FSK	16FSK	32FSK	64FSK
2FSK	9847	153	0	0	0	0
4FSK	542	9458	0	0	0	0
8FSK	0	731	8835	434	0	0
16FSK	0	0	889	8510	60	0
32FSK	0	0	0	1349	7765	886
64FSK	0	0	0	1017	1931	7052

Table 14: Confusion Matrix for Fsk Modulation in Awgn + Rayleigh Falt Fading Channel

Average Performance (88%)						
SNR 10dB	2FSK	4FSK	8FSK	16FSK	32FSK	64FSK
2FSK	10000	0	0	0	0	0
4FSK	632	9179	189	0	0	0
8FSK	0	645	8924	431	0	0
16FSK	0	0	1116	8795	89	0
32FSK	0	0	69	1721	8210	0
64FSK	0	0	18	381	1891	7710

Table 15: Confusion Matrix for Fsk Modulation in Awgn + Rayleigh Falt Fading Channel

Average Performance (83.4%)						
SNR 0dB	2FSK	4FSK	8FSK	16FSK	32FSK	64FSK
2FSK	9697	303	0	0	0	0
4FSK	518	9079	403	0	0	0
8FSK	0	735	8724	541	0	0
16FSK	0	0	1321	8414	265	0
32FSK	0	0	1987	803	7210	0
64FSK	0	0	58	209	2813	6920

Table 16: Confusion Matrix for Qam Modulation in Awgn Channel

Average Performance (99.95%)						
SNR 10dB	2QAM	4QAM	8QAM	16QAM	32QAM	64QAM
12QAM	10000	0	0	0	0	0
4QAM	0	10000	0	0	0	0
8QAM	0	0	9996	0	0	0
16QAM	0	0	0	9995	3	2
32QAM	0	0	4	4	9990	2
64QAM	0	0	0	6	8	9986

Table 17: Confusion Matrix for Qam Modulation in Awgn Channel

Average Performance (86.7%)						
SNR 0dB	2QAM	4QAM	8QAM	16QAM	32QAM	64QAM
2QAM	10000	0	0	0	0	0
4QAM	5	9990	5	0	0	0
8QAM	0	13	9980	5	2	0
16QAM	0	0	18	7700	1226	1056
32QAM	0	0	25	1400	7540	1035
64QAM	0	0	0	309	2801	6890

Table 18: Confusion Matrix for Qam Modulation in Awgn+ Rician Flat Fading Channel

Average Performance (81%)						
SNR 10dB	2QAM	4QAM	8QAM	16QAM	32QAM	64QAM
2QAM	10000	0	0	0	0	0
4QAM	639	9158	203	0	0	0
8QAM	0	793	8854	353	0	0
16QAM	0	0	1432	7698	870	0
32QAM	0	0	0	1834	6825	1341
64QAM	0	0	0	999	2921	6080

Table 19: Confusion Matrix for Qam Modulation in Awgn + Rician Falt Fading Channel

Average Performance (73%)						
SNR 0dB	2QAM	4QAM	8QAM	16QAM	32QAM	64QAM
2QAM	9700	300	0	0	0	0
4QAM	931	8678	391	0	0	0
8QAM	0	1921	7491	588	0	0
16QAM	0	0	2134	7023	843	0
32QAM	0	0	0	3213	6014	773
64QAM	0	0	0	1032	3921	5047

Table 20: Confusion Matrix for Qam Modulation in Awgn + Rayleigh Falt Fading Channel

Average Performance (77.36%)						
SNR 10dB	2QAM	4QAM	8QAM	16QAM	32QAM	64QAM
2QAM	10000	0	0	0	0	0
4QAM	686	8925	389	0	0	0
8QAM	0	813	8456	731	0	0
16QAM	0	0	1392	7121	1487	0
32QAM	0	0	0	2031	6489	A1480

Rayleigh channel, because it has one line of sight component preserves the spectral component of FSK signals, resulting in high accuracy of classification.

From Table 16 to 21, the confusion matrix for QAM modulations on AWGN channel, Rayleigh flat fading channel and Rician flat fading channel are shown at SNR of 10dB and 0dB. The average classifier performance in case of AWGN channel is 86.7 %, where in case of Rayleigh channel the performance is 69.24% and in case of Rician channel the performance is 73% at SNR of 0dB.

CONCLUSION

In this paper, theconsidered modulations such as PSK2, PSK4, PSK8, PSK16, PSK32, PSK64, QAM2, QAM4, QAM8, QAM 16, QAM 32, QAM 64, FSK2, FSK4, FSK8, FSK16, FSK32 and FSK64 are classified using linear discriminant analysis under the effects of AWGN channel, Rayleigh flat fading channel and Rician flat fading channel. The linear classifiers proposed here are very effective in channels that undergo corruption of AWGN and also fading channels for the case of FSK and PSK modulated signals. The simulation shows the classifier performance is approximately 100% at lower SNR. The average performance of classifier for PSK modulations in the presence of AWGN channel is 99.8% at SNR of 0dB, while the performance of classifier in Rayleigh flat fading channel and Rician flat fading channel are approximately 84% and 86% respectively. The classifier performance for QAM signals is 69% in for Rayleigh flat fading channelat low SNRs.

REFERENCES

1. Waqar Aslam, M., Zhechen Zhu and Asoke Kumar Nandi " Automatic Modulation Classification using Combination of Genetic Proramming and KNN", IEEE Transactions on Wireless Communication, 2012.
2. Sajjad Ahmed Ghauri, Ijaz Mansoor Qureshi, Aqdas Naveed Malik, Tanveer Ahmed Cheema "Higher Order Cummulants based Digital Modulation Recognition Scheme",Research Journal of Applied Sciences Engineering and Technology (RJASET), 2013.
3. Sajjad Ahmed Ghauri, Hannan Adeel "Automatic Classification of Digital Modulated Signals using Linear Discriminant Analysis on AWGN Channel" 1st International Conference on Information and Communication Technology Trends (ICICTT), 2-5 September, 2013.
4. Yucek, T. and H. Arslan, 2004. "A novel sub-optimum maximum-likelihood modulation classificationalgorithm for adaptive OFDM systems," in Proc. IEEE Wireless Communications and Networking Conference, 2: 739-744.
5. Panagiotou, P., A. Anastasopoulos and A. Polydoros, 2000. "Likelihood ratio tests for modulation classification," in Proc. IEEE MILCOM, 2: 670-674.
6. Wei, W. and J.M. Mendel, 2000. "Maximum-likelihood classification for digital amplitude-phase modulations," IEEE Trans. Commun., 48(2): 189-193.
7. Marchand, P., C.L. Martret and J.L. Lacoume, 1997. "Classification of linear modulations by a combination of different orders cyclic cummulants," in Proc. IEEE Signal Processing Workshop on Higher-Order Statistics, pp: 47-51.
8. Dobre, O.A., Y. Bar-Ness and W. Su, 2003. "Higher-order cyclic cummulants for high order modulation classification," in Proc. IEEE MILCOM, 1: 112-117.
9. Xi, S. and H.C. Wu, 2006. "Robust automatic modulation classification using cummulant feature in the presence of fading channels", IEEE Wireless Comm. and Networking Conf., Vol 4.
10. Wu, H., M. Saquib and Z. Yun, 2008. "Novel automatic modulation classfication using cummulant features for communications via multipath channels" IEEE transaction in Wireless Communications, 7: 3098-3105.

11. Chaithanya, V. and V.U. Reddy, 2010. “Blind modulation classfication in the presence of carrier frequency offset ”, International conference on signal processing and Communications, pp: 1-5.
12. Lanjun, Q. and Z. Canyan, 2010. “Modualtion classification based on cyclic spectral features and neural network”, International congress on image and Signal Processing, 8: 3601-3605.
13. Wong, M.L.D. and A.K. Nandi, 2004. “Automatic digital modulation recognition using artificail neural network and genetic algorithm”, Signal Process. 84: 351-365.
14. Orlic, V.D. and M.L. Dukic, 20009. “Automatic modulation classification algorithm using higher-order cummulants under real-world channel conditions,” IEEE Communication Letters, 13(12): 917-919.
15. Sajjad Ahmed Ghauri, Ijaz Mansoor Qureshi, Aqdas Naveed Malik and Tanveer Ahmed Cheema “Automatic Digital Modulation Recognition Technique using Higher Order Cummulants on Faded Channels”, Accepted to Publish in Iete Journal of Research.