ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 8, August 2013

AUTOMATIC MODULATION CLASSIFICATION USING STATISTICAL FEATURES IN FADING ENVIRONMENT

Jaspal Bagga[1], Neeta Tripathi [2]

Associate Professor, (E&TC), HoD (IT), SSTC, Bhilai, India[1]

Professor, Dept. of Electronics & Telecommunication, Principal, SSITM , Bhilai, India[2]

ABSTRACT: Software radio technology is expected to play an important role in the development of Fourth Generation (4G) wireless communication systems. The signal identification process, an intermediate step between signal interception and demodulation, is a major task of an intelligent receiver. Automatic Modulation Classification (AMC) is the process of deciding, based on observations of the received signal, what modulation is being used at the transmitter. Ten Candidate signals 2ASK, 4ASK, 2PSK, 4PSK 2FSK, 4FSK and 16 QAM, GMSK, 64QAM and 256 QAM were generated. Channel conditions were modelled by simulating AWGN and multipath Rayleigh fading effect. Instantaneous features such as amplitude, phase and frequency were first derived. Stochastic features were derived from instantaneous features. Seven key features were used to develop the classifier. Higher order QAM signals such as 64QAM and 256 QAM were classified using higher order statistical parameters such as moments and cumulants. Decision Tree classifier was developed based on threshold values. Overall classification result obtained for SNR=3dB was more than 97 %. The success rate was around 99 % (no fading condition) for SNR=5dB. The developed classifier could classify ten modulated signals under varying channel conditions for SNR as low as -5dB.

Keywords: Digital Modulation; Automatic Modulation Classification; SNR, Decision Tree

I. INTRODUCTION

Automatic Modulation Recognition (AMR) is a procedure performed at the receiver based on the received signal before demodulation when the modulation format is not known to the receiver. The ability to automatically select the correct modulation scheme used in an unknown received signal is a major advantage in a wireless network. Without any knowledge of the transmitted data and many unknown parameters at the receiver, blind identification is a difficult task. Recognition process is even more challenging in real world scenarios with multipath fading, frequency selective, and time varying channels.

The recognizers are divided into two subsets according to methods used in approaching classification problems: Decision-theoretic approach or, Likelihood-Based (LB) approach . Statistical pattern recognition or Feature Based (FB) approach. The decision-theoretic or LB approach is based on likelihood ratio, which is to identify the modulation style of a signal through the maximum likelihood ratio of selecting signals and known signals. The statistical pattern recognition or FB approach is divided into two parts. The first is a feature extraction part and its role is to extract the predefined feature from the received data. The second is a pattern recognition part, whose function is to classify the modulation type of a signal from the extracted features.

Some of the earlier work exists on feature based classification [1-5]. A unified view on modulation classification was presented. The fundamental principle types of features used for classification and algorithm structure were discussed [6-7].A detailed overview on feature based digital modulation techniques has been presented [8]. Many types of features have been used in AMC, e.g., instantaneous amplitude, phase, and frequency [9-11], and wavelet transforms [12-13], higher order moments and higher order cumulants (HOCs) [14-17] and cyclo-stationarity [18]. Several types

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 8, August 2013

of Pattern Recognition (PR) methods have been employed for AMC. PR methods include artificial neural networks [19-21], clustering, support vector machines [12], decision tree [22]. Simulations results were compared for classifier developed using different features [23].

The present work considers classification of ten digitally modulated signals adaptive to Software Defined Radio (SDR) in the presence of AWGN and Multipath fading effect. Hybrid Feature based Decision Tree Classifier has been developed based on threshold values. The classifier is able to classify signals at SNR as low as -5dB.

II. SIGNAL MODEL IN AMR

The Modulation Classification model is presented in Fig. 1
The received signal is represented as

$$r_i(t) = s_i(t) + n(t) \qquad (1)$$

Where r_i (t) is the received signal, s_i (t) is the transmitted signal, and n(t) is the additive white Gaussian noise. The discrete expression of received signal in Rayleigh fading environment is given by

$$r_i = \alpha_i s_i + n_i \qquad (2)$$

Where α_i is a Rayleigh random variable, s_i is the signal sequence and n_i is noise

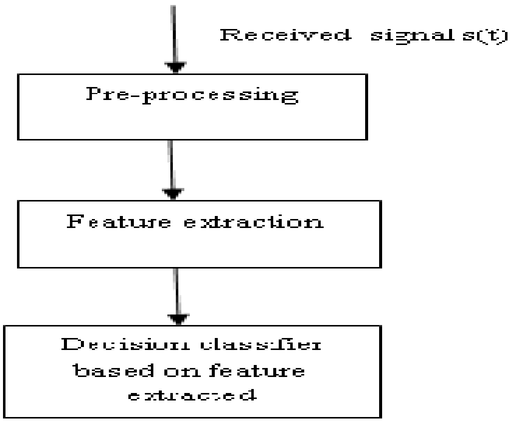

Fig. 1 Modulation Clsssification Model

The model shows three stages:

A. *Preprocessing*
B. *Feature Extraction*
C. *Modulation classification*

A .Preprocessing

The work of the pre-processor is to increase the performance of the classifier. The pre-processor removes disturbances from the signal such as interfering signals thus increasing the (SNR).The preprocessing task carried in this work is signal denoising using wavelet decomposition and blind equalization using Constant Modulus algorithm (CMA) [24].
The algorithm for signal denoising is

i) Wavelet coefficients were calculated.
ii) Detail coefficients were used to estimate noise standard deviation
iii) Global threshold value was selected, which is used for signal denoising.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 8, August 2013

Constant Modulus Algorithm–Fractionally Spaced Equalizer (CMA-FSE) technique was used to undo the channel effect without the knowledge of channel itself. The constant modulus algorithm is a stochastic gradient algorithm designed to force the equalizer weights to keep constant envelope of received signal

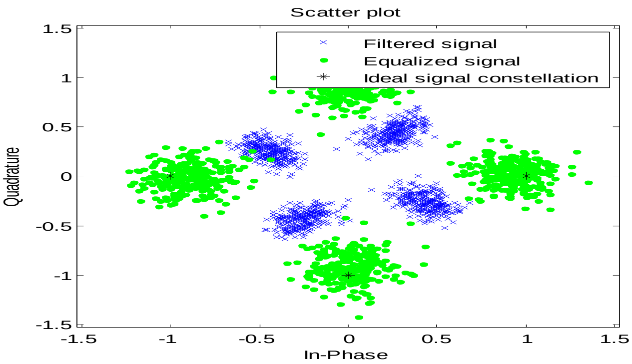

Fig. 2 Constellation plot of 4PSK

In this work the CMA-FSE algorithm was tested on 4PSK, 8PSK, 16QAM, 64QAM and 256QAM. Simulation results proved that this method almost cancels the channel effect in 2PSK, 4PSK, 8PSK, and also 16QAM. The constellation was recoverable also for 64 QAM but not for symbol order beyond 64QAM. Constellation Plot of 4PSK signal is presented in Fig.2. The figure shows ideal, scattered and equalized signal plot. It was observed that effect of noise and fading was more severe on higher order constellation plots.

B. Feature Extraction

Different types of digital signal have different characteristics. Therefore finding the proper features for the recognition of digital signals, particularly in case of higher order and/or nonsquare kinds of digital signal is a serious problem. The key features for modulation classification in pattern recognition approach must be selected. These features should have robust properties which are sensitive with modulation types and insensitive with SNR variation. The Instantaneous features such as amplitude , frequency and phase for complete set of signals were first derived. Stochastic features such as amplitude mean, standard deviation of the absolute value of the normalized- centered instantaneous amplitude standard deviation of the centered non-linear component of the absolute instantaneous phase, the standard deviation of the centered non-linear component of the direct (not absolute) instantaneous phase, the standard deviation of the absolute value of the normalized- centered instantaneous frequency of a signal, as feature vector 1, feature vector 2, feature vector 3, feature vector 4, feature vector 5 respectively were derived from instantaneous features. Higher order moments and cumulants were also calculated. These were used to classify higher order QAM signals. Seven key features were used to develop the classifier.

i) Stochastic features

Five Stochastic features were calculated as follows:

Feature vector 1 is the maximum value of Power Spectral Density (PSD) of normalized-centered instantaneous amplitude [3]

$$\gamma_{max} = \frac{max\,|FFT\,(a_{cn}\,(i))|^2}{N_S} \qquad (3)$$

where Ns is the number of samples, m_a is the sample mean of a(i) and $a_{cn}\,(i) = \frac{a(i)}{m_a} - 1$

This feature classifies PSK modulations as one group, and FSK modulations as another group.

Feature vector 2 is the standard deviation of the absolute value of the normalized- centered instantaneous amplitude of a signal segment

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 8, August 2013

$$\sigma_{aa} = \sqrt{\frac{1}{N_s}\left[\sum_{i=1}^{N_s} a_{cn}^2(i)\right] - \left[\frac{1}{N_s}\sum_{i=1}^{N_s}|a_{cn}(i)|\right]^2} \quad (4)$$

σ_{aa} captures the variation of modulated signal amplitude. Hence, they are used for determining ASK order and to distinguish ASK signals from PSK signals.

Feature vector 3 is the standard deviation of the centered non-linear component of the absolute instantaneous phase

$$\sigma_{ap} = \sqrt{\frac{1}{L}\left[\sum_{a(i)>t_{th}} \varphi_{NL}^2(i)\right] + \left[\frac{1}{L}\sum_{a(i)>t_{th}} \varphi_{NL}^2(i)\right]^2} \quad (5)$$

where t_{th} the threshold value of the non weak is signal in and L is the length of non weak values.
Feature vector 4 is the standard deviation of the centered non-linear component of the direct (not absolute) instantaneous phase

$$\sigma_{dp} = \sqrt{\frac{1}{L}\left[\sum_{a(i)>t_{th}} \varphi_{NL}^2(i)\right] + \left[\frac{1}{L}\sum_{a(i)>t_{th}} \varphi_{NL}^2(i)\right]^2} \quad (6)$$

Feature vector 5 is the standard deviation of the absolute value of the normalized- centered instantaneous frequency of a signal segment

$$\sigma_{af} = \sqrt{\frac{1}{N_s}\left[\sum_{i=1}^{N_s} f_N^2(i)\right] + \left[\frac{1}{N_s}\sum_{i=1}^{N_s}|f_N(i)|\right]^2} \quad (7)$$

ii) Higher Order Statistical Features

Higher order statistical parameters such as Moments and cumulants are used as features to identify distinguishing characteristics of data. Moments are a method of "measuring the shape" of a set of points and cumulants are essentially an alternative method of looking at the moments of a given distribution.

a) Moments

Probability distribution moments are a generalization of the concept of the expected value, and can be used to define the characteristics of a probability density function. The k^{th} moment of a random variable is given by:

$$\mu_k = \int_{-\infty}^{\infty}(s-\mu)^k\ f(s)ds, \quad (8)$$

where μ is the mean of the random variable .The definition for the k^{th} moment for a finite length discrete is given by

$$\mu_k = \sum_{i=1}^{N}(s_i-\mu)^k\ f(s_i) \quad (9)$$

where N is the data length. Here signals are assumed to be zero mean . Equation(9) thus becomes

$$\mu_k = \sum_{i=1}^{N}(s_i)^k\ f(s_i) \quad (10)$$

The auto-moment of the random variable may be defined as

$$E_{s,p+q,p} = E[s^p(s^*)^q] \quad (11)$$

Where p and q represent the number of non conjugated terms and number of the congugated terms, respectively, and p+q is called the moment order. Equation (11) becomes

$$E_{s,2,2} = E[s^2(s^*)^0] = E[s^2] = \mu_2 = {s_i}^2 f(s_i) \quad (12)$$

which is the second moment or the variance of random variable. In a similar way expressions for $E_{s,2,1,}$ $E_{s,4,4}$ $E_{s,8,4}$ were derived. The normalized momemts $E_{s,3,3}$ and $E_{s,4,4}$ are called skewness and kurtosis resp. Skewness is the measure of symmetry of pdf, where as kurtosis is the degree of peakedness (density of peaks) of the pdf.[20]

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 8, August 2013

b) Cumulants

A scalar zero mean random variable has characteristic function given by:

$$\hat{f}(t) = E\{e^{its}\}. \tag{13}$$

Expanding the logarithm of the characteristic function as a Taylor series one obtains

$$\log \hat{f}\,(t) = k_1(t) + \frac{k_2(it)^2}{2} + \cdots + \frac{k_r(it)^r}{r!} + \cdots, \tag{14}$$

Where the constant k_r are called the cumulants . The first three cumulants are identical to first three moments.

Feature Vector 6 E $_{S8,8}$ Eight Order moment

Table 1 Eighth order Statistical Moment of the form a_i+jb_i

$E_{S,8,8}$	$E\,[a^8 + b^8 - 28a^6\,b^2 + 70a^4b^4 - 28a^2b^6]$
$E_{S,8,7}$	$E\,[a^8 - b^8 - 14a^6\,b^2 + 14a^2b^6]$
$E_{S,8,6}$	$E\,[a^8 + b^8 - 4a^6\,b^2 - 10a^4b^4 - 4a^2b^6]$
$E_{S,8,5}$	$E\,[a^8 - b^8 + 2a^6\,b^2 - 2a^2b^6]$
$E_{S,8,4}$	$E\,[a^8 + b^8 + 4a^6\,b^2 + 6a^4b^4 + 4a^2b^6]$

Feature Vector 7 C $_{s,8,8}$ Eighth order cumulant

Table 2 Relation Between Eighth order Cumulant and Moment

$$C_{s,8,8} = E_{s,8,8} - 35E_{s,4,4^2} - 630E_{s,2,2^4} + 420E_{s,2,2^2}E_{s,4,4}$$

Where

$E_{S,8,8}$	$E\,[a^8 + b^8 - 28a^6\,b^2 + 70a^4b^4 - 28a^2b^6]$
$E_{S,4,4}$	$E\,[a^4 + b^4 - 6a^2\,b^2]$
$E_{S,2,2}$	$E\,[a^2 - b^2]$

Calculation of eighth order moment and sixth order cumulant is presented in Table 1 and Table 2 resp. The moment and cumulant were used as features to classify16QAM, 64QAM and 256QAM signal.

C. Modulation Classification

The features to be used for AMR must be selected so that they are sensitive to the modulation types of interest. The classifier shall operate on extracted features and make a decision about the modulation type. Several pattern matching techniques exist as linear classifiers, tree classifiers, neural network based classifiers, hypothesis testing based classifiers and adhoc based classifiers. It was observed that most of the types of classifiers implemented based on various features are decision tree or neural network based and few are Support Vector Machine (SVM) based classifiers.

a) Decision Tree (DT) Classifier

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 8, August 2013

Decision tree methods are one of the basic classification procedures in which decision at each stage is made according to predefined threshold values. In these methods, predefined threshold values are the main parameters affecting the performance of the classifier. In addition, DT methods can be promoted to accommodate more modulations by adding additional decision branches.

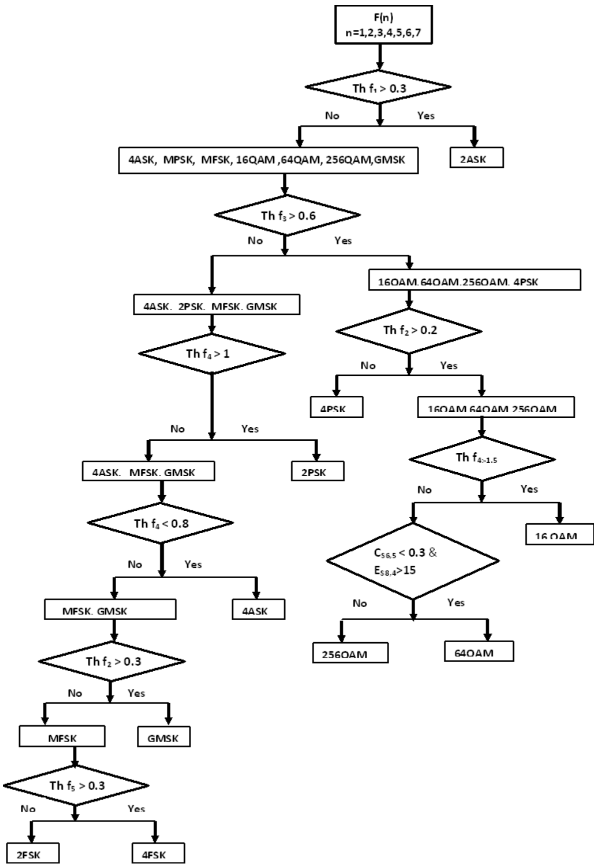

Fig. 3 Decision Tree Classifier

Seven features described above were used as input to the decision tree classifier to distinctly classify the set of modulated signals. The developed Decision tree classifier is presented in Fig 3.Feature vector 1 puts the signals in 2 categories where a threshold value is able to distinguish only 2ASK. To further classify the signals other features were used. Feature vector 3 gives a threshold value which again divides the signals in 2 groups. One group consists of 4PSK and M-QAM and other group has 4ASK, 2PSK, MFSK, GMSK. Similarly threshold values were derived for each feature to clearly classify each category. Since clear distinction could not be achieved for M-QAM signals from stochastic features, moments and cumulants were used to classify them.

III. RESULTS AND DISCUSSION

Various digitally modulated signals such as 2ASK, 4ASK, 2PSK, 4PSK, 2FSK, 4FSK, 16QAM, 64QAM 256QAM and GMSK were first generated. Signals were then passed through AWGN channel and corrupted by simulating multipath Rayleigh fading channel. The carrier frequency taken was f_c = 1000Hz .Total No. of samples taken were 10,000. The binary data stream for modulation has been obtained from random number generator.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 8, August 2013

Random Binary signal was generated for each modulation type for each iteration. Three types of channel conditions were considered. Signals were simulated for 26 values of SNR (-5dB to 20dB) for each channel type. Confusion matrix for each SNR was obtained. Performances of the decision tree classifier were obtained in the form of confusion matrix. Confusion matrix is a matrix providing information about the output of the recognition system for the given modulation type. Table 3 presents confusion matrix obtained for -5 dB SNR, no fading condition.

Input/ Identified as	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK	16QAM	GMSK	64QAM	256QAM
2ASK	92	8								
4ASK	10	90								
2FSK			91	5				4		
4FSK			8	92						
2PSK					100					
4PSK						100				
16QAM						6	94			
GMSK				5			10	85		10
64QAM								8	82	80
256QAM							10		10	

Table 3. Confusion matrix of decision tree classifier (SNR=-5dB) each SNR 100 trials

It can be seen that of 100 trials, 2ASK signal is correctly classified for 92 trials and misclassified for 8 trials. 2PSK and 4PSK signals were 100% correctly classified.2FSK was correctly classified for 91 trials and misclassified as 4FSK and GMSK for five and four trials resp.

Confusion matrix was obtained for various SNR's. Percentage of correct classification for 10 modulated signals for varying SNR(-5 dB to 20 dB) is presented in Table 4. It can be observed that high percentage of results was obtained with selected features even for SNR as low as -5 dB.

Table 4 . Percentage identification results for Decision Tree classifier (No fading, each SNR 100 trials)

SNR/mod signal	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK	16QAM	GMSK	64QAM	256QAM
-5	92	90	91	92	100	100	94	85	82	80
-3	94	92	93	93	100	100	95	95	88	83
0	95	94	96	95	100	100	97	96	91	85
3	96	97	98	98	100	100	100	97	94	90
5	100	100	100	99	100	100	100	98	96	94
10	100	100	100	100	100	100	100	100	100	100
15	100	100	100	100	100	100	100	100	100	100
20	100	100	100	100	100	100	100	100	100	100

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 8, August 2013

Table 5. Overall Percentage of correct classification

SNR/ %Classification	No fading	Low fading	Medium fading	High fading
-5	90.6	89	82	70
-3	93.3	90.4	85.3	74.8
0	94.9	92.3	88	83
3	97	94	91	87.2
5	98.7	96	94	91.6
10	100	100	96.6	94
15	100	100	100	96.5
20	100	100	100	100

Overall classification results of developed decision tree classifier are shown in Table 5. The classification results were observed for various simulation set ups. No fading condition implies classification performance only in presence of AWGN .Low fading condition implies low Doppler shift High fading condition was simulated by taking Doppler shift as high as 100Hz

IV CONCLUSION

It was observed from simulation results that this technique works well even at low SNR. Overall Percentage of correct classification was 97 % for 3dB SNR for no fading condition, i.e. only in presence of AWGN, 94% for low fading 91% for medium fading and 87.2% for severe fading conditions .However the fall in % of correct classification was mainly due to higher order QAM signals which are affected adversely in presence of fading The constellations of 64 QAM and 256 QAM could not be completely recovered even after equalization. 2PSK and 4PSK were 100% correctly classified for -5dB SNR. High percentage of correct classification results were obtained for SNR as low as 0dB and for some signals even as low as -5 dB.

REFERENCES

[1] Weaver ,C.S., Cole, C.A., Krumland, R.B. and Miller, M.L., “The automatic classification of modulation types of Pattern Recognition”, 1969 Technical Report 1829 2, Stanford Electronics Laboratories

[2] Nandi, A.K., and Azzouz, E.E., “Modulation Recognition using Artificial Neural Networks”, Signal Processing , 165-175, 1997

[3] Hsue, S. Z., and Soliman,S. S., “ Automatic modulation recognition of digitally modulated signals”, in Proc. IEEE MILCOM, 645-649, 1989.

[4] Hsue, S. Z. and Soliman, S. S., “Automatic modulation classification using zero crossing”, 1990.

[5] Ketterer, H., Jondral, F., and Costa, A. H., “ Classification of modulation modes using time-frequency methods”, in Proceedings of the IEEE International Conference on Acoustics, 8 Journal of Computer Systems, Networks, and Communications Speech and Signal Processing (ICASSP ’99), , Phoenix, Ariz, USA . vol. 5. 2471– 2474, 1999.

[6] Nagy, P.A.J., “Modulation Classification –A Unified View”, National Defense Research Establishment, Sweden, 1997

[7] Bagga, J., and Tripathi, N., “Modulation Classification: A Survey of Various Techniques”, National Conference AICON CSIT Durg, 6th -8th Feb .2009.

[8] Hazza , A., Shoaib, M., Alshebeili ,S.A. and Fahad ,A. 2013. *An Overview of Feature-Based Methods for Digital Modulation Classification*, 978-1-4673-2821-0/13

[9] Bagga, J.and Tripathi, N. “Analysis of Digitally Modulated Signals using Instantaneous and Stochastic Features, for Classification”, International journal of soft Computing and Engineering”, (IJSCE) ISSN: 2231-2307, Volume-1, Issue-2, 2011

[10] P. Cheol-Sun, J. Won, and N. Sun-Phil, “Automatic Modulation Recognition using Support Vector Machine in Software Radio Applications,” in *Proc. 9th ICACT*, Korea, Feb. 2007, pp. 9-12.

[11] M. L. D. Wong, A. K. Nandi, “Efficacies of Selected Blind Modulation Type Detection Methods for Adaptive OFDM Systems,” *EURASIP JASP*, Article ID 656719, 2009.

[12] Cheol-Sun, P, Jun-Ho, C., Sun-Phil, N., and Won, J., “Automatic Modulation Recognition of Digital Signals using Wavelet Features and SVM”, in *Proc. 10th ICACT*, Phoenix Park, Korea, vol. 1, pp. 387-390, Feb. 2008.

[13] Prakasam, P., and Madheswaran, M., “Digital Modulation Identification Model Using Wavelet Transform and Statistical Parameters,” Journal of Computer Systems, Networks, and Communications, vol. 2008, Article ID 175236, Jan. 2008.

[14] C. Le Martret, Boiteaut, D., “Modulation classification by means of different orders statistical moments”, Nov. 2-4, pp. 256-258, IEEE Military Communication ”, Monterey 1997

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(ISO 3297: 2007 Certified Organization)

Vol. 2, Issue 8, August 2013

[15] Lichun, L., “Comments on signal classification using statistical moments,” IEEE Trans. Commun., vol. 50, pp. 195, 2002
[16] Marchand, P., Martret, C. L., and Lacoume, J. L., “Classification of linear modulations by a combination of different orders cyclic cumulants”, Proc. IEEE Workshop on Higherorder Statistics, 47-51, 1997
[17] Wong, M. L. D., and Nandi, A. K., “Automatic Digital Modulation Recognition Using Spectral And Statistical Features With Multi-Layer Perceptions”, Signal Processing and its Applications, Sixth International, Symposium, Vol. 2, 390-393, 2001.
[18] Dobre, O. A., Abdi, A., Bar-Ness, Y., and Sue,W., “ Cyclostationarity-Based Modulation Classification of Linear Digital Modulations in Flat Fading Channels”, Springer Science andBusiness Media, LLC, 2009.
[19] Khurshid, A. A., Gokhale , A.P., and Kshirsagar, R.V., “Digital Signal Type Identification Using Efficient Identifier And Neural Networks”, Proceedings of SPIT-IEEE Colloquium and International Conference, Mumbai, India, Vol. 1. 27-30, 2007
[20] Hatzichristos, G., and Fargues M.P., “Classification of digital modulation types in Multipath Environments”, Proceedings of the Thirty-Fifth Asilomar Conference on Signals, Systems and Computers, Vol.2, pp. 1494-1498, 2007
[21] Zhang, G. P., “Neural networks for classification: a survey”, IEEE Trans. Syst., Man and Cyber., vol. 30, no. 4, pp. 451-462, 2000.
[22] Chaithanya, V., and Reddy, V. U., “Blind modulation classification in the presence of carrier frequency offset”, Proc2. 8th International Conf. on Signal Processing and Communications, 1-5, July 2010.
[23] Bagga, J., and Tripathi, N., “Study and comparison of various Modulation classification Techniques under Noisy channel Conditions”, International journal of Emerging Technology and Advanced Engineering (IJETAE), Volume 2, Issue 3, March 2012
[24] Babu, R., Kumar, T., “Blind Equalization using Constant Modulus Algorithm and Multi-Modulus Algorithm in Wireless Communication Systems”, International Journal of Computer Applications (0975 – 8887) Vol 1. No. 3, 40-45, 2010.