World Academy of Science, Engineering and Technology
International Journal of Electronics and Communication Engineering
Vol:3, No:11, 2009

Modulation Identification Algorithm for Adaptive Demodulator in Software Defined Radios Using Wavelet Transform

P. Prakasam and M. Madheswaran

Open Science Index, Electronics and Communication Engineering Vol:3, No:11, 2009 publications.waset.org/1602.pdf

***Abstract*—**A generalized Digital Modulation Identification algorithm for adaptive demodulator has been developed and presented in this paper. The algorithm developed is verified using wavelet Transform and histogram computation to identify QPSK and QAM with GMSK and M–ary FSK modulations. It has been found that the histogram peaks simplifies the procedure for identification. The simulated results show that the correct modulation identification is possible to a lower bound of 5 dB and 12 dB for GMSK and QPSK respectively. When SNR is above 5 dB the throughput of the proposed algorithm is more than 97.8%. The receiver operating characteristics (ROC) has been computed to measure the performance of the proposed algorithm and the analysis shows that the probability of detection (P_d) drops rapidly when SNR is 5 dB and probability of false alarm (P_f) is smaller than 0.3. The performance of the proposed algorithm has been compared with existing methods and found it will identify all digital modulation schemes with low SNR.

***Keywords*—**Bit Error rate, Receiver Operating Characteristics, Software Defined Radio, Wavelet Transform.

I. Introduction

THE rapid growth in the field of mobile communication in general, Software Defined Radio (SDR) in particular has motivated the research to develop various digital modulation identification algorithms [1]. As the adaptive receiver can communicate with different communication standards like TDMA, CDMA and GSM, the identification of digital modulation type of a signal is to be optimized. Several research groups have developed various modulation identification methods [2-5] in recent past. Jun-Seo Lee et al [2] presented the implementation of M-ary FSK and BPSK demodulators on the DSP (TMS320C6203) board without the conventional complex analog circuits. It has been explained that the power spectral density (PSD) was used to classify M-ary FSK with BPSK. Modulation scheme recognition using the signal envelop method was described by Druckmann et al [3]. Lopatka et al [4] also adopted the approach incorporating fuzzy classification for 4DPSK, 16QAM and FSK schemes. Callaghan et al [5] proposed a signal envelop and zero crossing based modulation recognizer, but the accuracy of the recognizer is highly depending on determination of the exact intercepted signal centre frequency. A pattern recognition approach for both digital and analog recognition was proposed by Jondral [6], which can classify AM, ASK2, SSB, PSK2, FSK2 and FSK4 modulation scheme types. Hellinger distance parameter estimation technique overcomes the degree of noise model distortion, with improved robustness and efficiency [7]. The classifier based on pattern recognitions technique developed by Hero et al [8] used the binary image word spotting problems. This classifier generalizes the moment matrix technique to grey scale images, and the technique is used to discriminate between M-ary PSK and QAM signal space constellations. Aiello et al [9] proposed an artificial neural network (ANN) based classifier which incorporates the pattern recognition techniques. This was implemented using a dedicated DSP and focused on GMSK recognition. Software radio technique for automatic digital modulation scheme recognition was reported by Keith E.Nolan et al [10]. The 8^{th} order statistical moment was used to identify the modulation as either BPSK or QPSK.

The time-frequency analysis concept for non-stationary signal were given due consideration in the past two decade considering the wavelet transforms [11]. Lin and Kuo [12] applied Morlet wavelet to detect the phase changes, and used the likelihood function based on the total number of detected phase changes as a feature to classify M-ary PSK signal. One of the most complex and important identifier was introduced by Liang Hong et al., [13]. They apply the Haar WT and statistical decision theory to the problem of identification of M-ary phase shift keying (MPSK), frequency shift keying (MFSK) and QAM signals without base-band filtering contaminated by additive white Gaussian noise (AWGN). Binary PSK/CPFSK and MSK identification was investigated by Radomir Pavlik [14] and complex Shannon wavelet was applied to identify the above mentioned modulation schemes. This paper was focused primarily on the identification of binary modulation signals under constant envelope class and it fails to identify the non-constant envelop modulation schemes. Automatic Modulation identification (AMI) algorithm [15] was developed to classify QPSK and GMSK signals with simulated Additive White Gaussian Noise (AWGN) channel.

Manuscript received on September 2, 2007.
P. Prakasam is a Research Scholar and he is with Center for Advanced Research, Department of Electronics and Communication Engineering, Muthayammal Engineering College, Rasipuram - 637 408, India. (e-mail: prakasamp@gmail.com).
M. Madheswaran with Center for Advanced Research, Department of Electronics and Communication Engineering, Muthayammal Engineering College, Rasipuram - 637 408, India. (Corresponding Author - Phone: +91-4287-226737; fax: +91-4287-226537; e-mail: madheswaran.dr@gmail.com)

Open Science Index, Electronics and Communication Engineering Vol:3, No:11, 2009 publications.waset.org/1602.pdf

The extracted transient characteristics and histogram peaks were used to identify the modulation scheme.

This paper proposes the generalized modulation classification algorithm considering the AWGN channel to identify most of the digital modulation schemes. The performance analysis of the proposed algorithm was made and compared with existing algorithms. The throughput analysis was carried out inorder to measure the correct identification capability of the proposed algorithm. The receiver operating characteristics (ROC) and bit error rate (BER) was computed to measure and analyze the performance characteristics of receiver capability.

The remainder of the paper is organized as follows: Section II gives the mathematical modelling of modulation identification method based on decision theory. Section III focuses on generalized modulation identification algorithm for most digital modulation schemes. The results and comparative discussion with existing modulation identification algorithm is presented in section IV. The conclusion of the research paper is presented in section V. The last Section gives the various literatures referred to develop the generalized modulation algorithm.

II. Mathematical Model

Let the received waveform *r(t)* , $0 \le t \le T$ be described as

$$r(t) = s(t) + n(t) \tag{1}$$

where *s(t)* is transmitted signal and *n(t)* is a Additive white Gaussian channel noise. The signal s(t) can be represented in complex form as

$$s(t) = \widetilde{s}(t)e^{f(w_c t+\theta_c)} \tag{2}$$

where ω_c is the carrier frequency and θ_c is the carrier phase.

The analysis technique is required for non-stationary signal, which will analyze the signal frequency with time instants of occurring. The Fourier transform approach gives either the frequency components or time components. The wavelet transform has the special feature of multi-resolution analysis (MRA), which provides the necessary parameters to extract the feature of the modulated signals. The continuous Wavelet Transform of a signal $s(t)$ is defined as [16]

$$CWT(a,\tau) = \int s(t)\psi_a^*(t)dt = \frac{1}{\sqrt{a}}\int s(t)\psi^*\left(\frac{t-\tau}{a}\right)dt \tag{3}$$

where a is the scaling factor and τ is the translation factor. The function $\psi *_\alpha (t)$ is the complex conjugate of mother wavelet. The choice of a mother wavelet depends on its application and commonly used wavelets are Morlet, Haar and Shannon.

Generally, the complex envelope of s(t) in eqn (1) may be expressed for all modulation types as

$$s(t) = \widetilde{s}(t)\exp\big(j\phi(t;a)\big) \tag{4}$$

where $\phi(t;a)$ represents the time-varying phase of the carrier, a represents all possible values of the information sequence $\{a_k\}$, in the case of binary symbols $a_k = \pm 1$. After substitution of eqn (2) with s(t) based on eqn (4) in eqn (3), the resulting integral of $C(a,\tau)$ is of the form of

$$C(a,\tau) = \frac{\widetilde{s}(t)e^{(\phi(.)+\theta_c)}}{j\sqrt{af_c}}\ E_i(n,y) \tag{5}$$

where $E_i(n,y) = \int_1^\infty \exp(-yu/u^n)\,du$ is the exponential integral, $y = -jt(2\pi f - 2\pi f_c)$ and expression (5) does not reduce to a simple form and must be evaluated numerically by taking its absolute value $|C(a,\tau)|$.

A. Classification of GMSK M-ary FSK with PSK and QAM

The normalized histogram generation of Wavelet transformed coefficient is used to classify the GMSK and M-ary FSK (Class 1) with M-ary PSK and M-ary QAM (Class 2) signals. If n_k is the number of occurrence in a particular value then the normalized histogram (probability of occurrence) of a process is given by

$$p(x_i) = \frac{n_k}{n} \tag{6}$$

where n is total number of samples in the particular process. PSK and QAM signal has constant transient characteristics; it has a single peak in its normalized histogram. But the GMSK and M-ary FSK has multi-frequency component, it has multiple peaks in its normalized histogram. Based on the histogram peak, the modulation scheme has been identified.

B. Classification of GMSK with M-ary FSK

The classification of various modulation schemes may be formulated using the statistical parameters such as moments and median. The moment plays the major contribution in non-stationary signal, thus it has been considered for the classification. The n^{th} order moment for $p(x_i)$, where i= 0,1,2,…N-1 is given by

$$\mu_n(x) = \sum_{i=0}^{N-1}(x_i - \mu_1)^n\ p(x_i) \tag{7}$$

where, $\mu_1 = \sum_{i=o}^{N-1} x_i p(x_i)$ is the mean of the statistical process.

The second order moment (variance) of discretized WT can be computed using

$$\mu_2 = E(|C(a,\tau)|^2) - [E(|C(a,\tau)|)]^2 = \frac{1}{N}\sum_{i=0}^{N-1}|Ci(a,\tau)|^2 - [\ \frac{1}{N}\sum_{i=0}^{N-1}|Ci(a,\tau)|]^2 \tag{8}$$

where N is the length of discretized analyzed signal. Then the classification problem can formulated as a binary tree hypothesis-testing problem.

Open Science Index, Electronics and Communication Engineering Vol:3, No:11, 2009 publications.waset.org/1602.pdf

Let H_i be the i^{th} modulation format is assigned to the received signal, where i is associated with {GMSK, j} and j is with M-ary FSK. The statistical decision needs the probability density function (pdf) of the test statistics conditioned on the assigned digitally modulated signal. Assuming the noise in eqn (1) is AWGN, the Wavelet Transform coefficient C(a,τ) has a characteristic of random variables generated from linear combinations of sinusoidal signal and a Gaussian noise. The probability density function of this process is considered as Gaussian probability density function.

The two conditional Gaussian pdfs allow a threshold setting to decide the GMSK and M-ary FSK, when a certain probability of false identification of both signals is given. The conditional pdf is

$$p(x/Hi)=\frac{1}{\sqrt{2}\,\pi\mu_{2,i}}\exp(-(x-\mu_{1,i})^2/\mu^2{}_{2,i}) \tag{9}$$

Under the hypothesis H_{GMSK} is true, the probability of GMSK misclassification is simply the probability that $\mu_{2,\ GMSK} - x < \mu_{2,\ GMSK} - T_1$, ie, $\mu_2 > T_1$. The probability of misclassification error for GMSK is given by

$$P(e/H_{GMSK})=\int_{T_1}^{\infty}p(x/H_{GMSK})\,dx \tag{10}$$

After the simplification the eqn (10) can be reduced to

$$P(e/H_{GMSK})=\frac{1}{2}\left(1+ercf(\frac{x-\mu_{1,GMSK}}{\sqrt{2}\,\mu_{2,GMSK}}\right) \tag{11}$$

where *ercf()* is defined as $ercf(x)=2/\pi\int_0^x\exp(-t^2)dt$.

Similarly, if it is assumed that the hypothesis $H_{\text{M-ary FSK}}$ is true, the probability of M-ary FSK signal misclassification is simply the probability that $x - \mu_{2,\ GMSK} < T_1 - \mu_{2,\ GMSK}$ ie, $\mu_2 < T_1$. The Probability of misclassification error for M-ary FSK is given by

$$P(e/H_{M-ary\,FSK})=\int_{-\infty}^{T_1}p(x/H_{M-ary\,FSK})\,dx \tag{12}$$

After the simplification the eqn (12) can be reduced to

$$P(e/H_{M-ary\,FSK})=\frac{1}{2}\left(1+ercf(\frac{x-\mu_{1,M-ary\,FSK}}{\sqrt{2}\,\mu_{2,M-ary\,FSK}}\right) \tag{13}$$

where *ercf()* is defined as $ercf(x)=2/\pi\int_0^x\exp(-t^2)dt$.

It is obvious that when the Gaussian noise increases, the variance value of GMSK and M-ary FSK decreases until the point when both the probabilities of misclassification are equal. Thus, $P(e/H_{GMSK}) = P(e/H_{M-ary\,FSK})$ =0.01 and the condition for setting the optimal threshold value T_1 can be obtained by equating Gaussian distribution is zero. Then the related threshold value is obtained as

$$T_1=\frac{\mu_{1,GMSK}\ \mu_{2,M-aryFSK}+\mu_{1,M-aryFSK}\,\mu_{2,GMSK}}{\mu_{2,GMSK}+\mu_{2,M-aryFSK}} \tag{14}$$

Based on the variance (or higher order moment) the classification of GMSK with M-ary FSK can be done.

C. Classification of QPSK with M-ary QAM

The same method described in previous section has been used for setting the related threshold T_2 on the understanding that the sample mean was chosen as the test statistic. Sourced hypotheses are associated with {QPSK, QAM}. Decision making between QPSK and QAM can be done based on the comparison of mean value with threshold T_2. The threshold value T_2 is given by

$$T_2=\frac{\mu_{1,QPSK}\ \mu_{2,QAM}+\mu_{1,QAM}\,\mu_{2,QPSK}}{\mu_{2,QPSK}+\mu_{2,QAM}} \tag{15}$$

Based on the mean and variance (or higher order moment) the classification of QPSK with QAM can be performed.

III. Proposed Modulation Identification Algorithm

The flow graph of the proposed algorithm is shown in Fig.1. The identification of digital modulation schemes have been done by using a common feature and the selection of criterion based on differences. It is clear that the transmission of any signal mainly concentrates in the high frequency components. These high frequency components can be obtained by extracting the coefficients using wavelet transformation. Wavelets are to be selected such a way that it looks similar to the patterns to be localized in the signal. A good approach to find a solution to this problem can be done by searching a function, which would be suitable to approximate both the analyzed signal envelope and frequency content of the signal. The wavelet Transform has been computed and the coefficients are recorded for further processing. These extracted coefficients are used to generate the histogram. Based on the number of peaks, the identifier identifies that the received signal is either M-ary PSK (QPSK) and M-ary QAM or GMSK and M-ary FSK modulated signal. After the major classification the subsystem is classified based on the following decision rules.

If $\mu_1 < T_2$ → QPSK signal
else → M-ary QAM & PSK signals
end
If $\mu_2 > T_1$ → GMSK signal
else → M-ary FSK signal (16)
end.

Open Science Index, Electronics and Communication Engineering Vol:3, No:11, 2009 publications.waset.org/1602.pdf

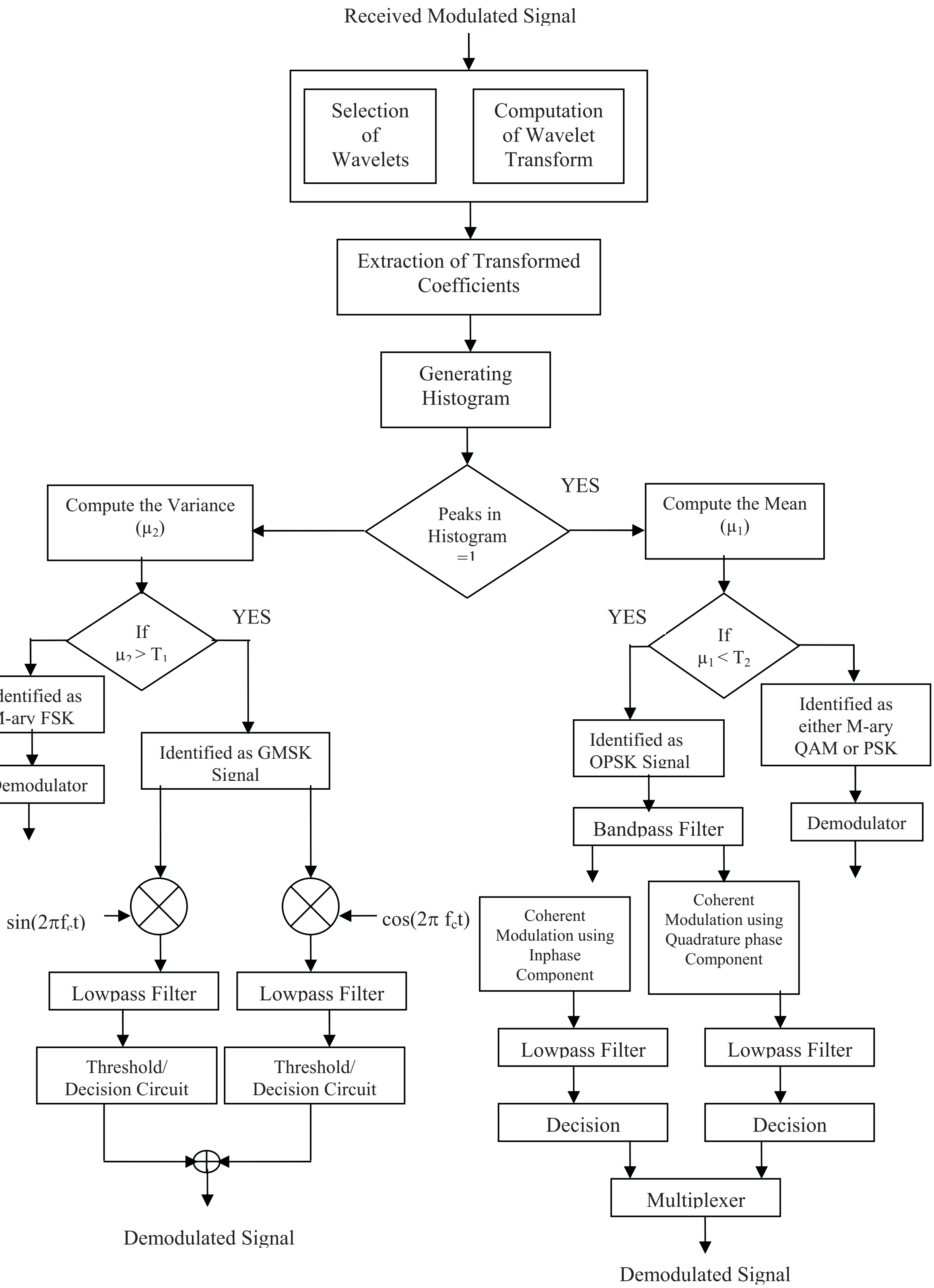

Fig. 1 Flow graph of proposed algorithm

Open Science Index, Electronics and Communication Engineering Vol:3, No:11, 2009 publications.waset.org/1602.pdf

IV. Results and Discussion

The developed algorithm is verified and validated for QPSK and GMSK modulation schemes. The QPSK and GMSK signals were simulated using MATLAB with 200 ensembles input message and the Additive White Gaussian Noise (AWGN) is simulated and added with a transmitting signal as a channel noise. The Wavelet Transform has been applied to extract the transient characteristics of the received signal. The magnitude of Haar wavelet transform for M-ary QAM and QPSK is a constant, but M-ary FSK and GMSK has a multi-step function since the frequency is variable. This common feature made to consider the Haar wavelet as mother wavelet and it is given by [16].

$$\psi(t) = \begin{cases} 1, & 0 \le t < \frac{1}{2} \\ -1, & \frac{1}{2} \le t < 1 \end{cases} \tag{17}$$

After extracting the transient characteristics, the coefficients were extracted to generate the histogram. The histogram of M-ary QAM & QPSK and M-ary FSK & GMSK is shown in Fig. 2 and Fig. 3 respectively. These figures show that M-ary QAM & QPSK signals have a single peak in histogram whereas M-ary FSK & GMSK signals have more than one peak in histogram. As the M-ary QAM & QPSK signal has constant transient characteristics, it has a single peak in its histogram. But the M-ary FSK & GMSK have more than single peak because these signals have multistep frequency component. Then the subsystem is classified based on eqn (16). Table I gives the threshold value for each subsystem classification.

Table 1
Threshold Value

Identification Subsystem	Threshold Value
M-ary FSK/GMSK	$T_1 = 1.686$
{M-ary QAM, M-ary PSK} / QPSK	$T_2 = 1.09$

After identification of the modulation scheme demodulation is performed by conventional methods.

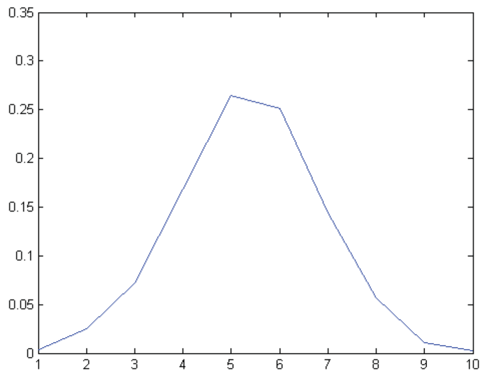

Fig. 2 Histogram of M-ary QAM and QPSK signal

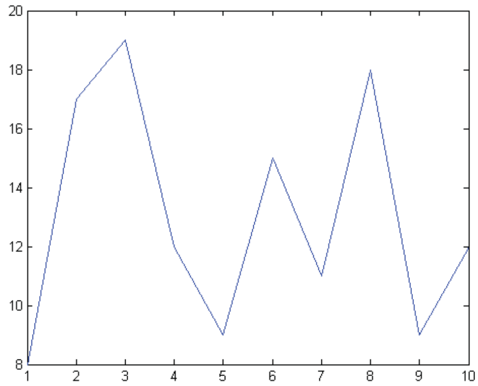

Fig. 3 Histogram for M-ary FSK and GMSK signal

The performance of the proposed algorithm was examined based on the throughput, receiver operating characteristics (ROC) and bit error rate (BER). Table 2 gives the percentage of throughput for the proposed algorithm for QPSK and GMSK signals. The results were the average of 200 independent ensemble runs. It is clear from the Table II that the proposed algorithm has high accuracy. When SNR is greater than 5 dB, the throughput of the proposed algorithm is 97.8% accuracy for both QPSK and GMSK identification.

Table II
Throughput of Proposed Algorithm (%)

SNR (dB)	Input	Output	
		QPSK	GMSK
20	QPSK	100	0
	GMSK	0	100
15	QPSK	100	0
	GMSK	0	100
10	QPSK	99.1	0.9
	GMSK	0	100
6	QPSK	98.2	1.8
	GMSK	0	100
5	QPSK	97.8	2.2
	GMSK	0.9	99.1

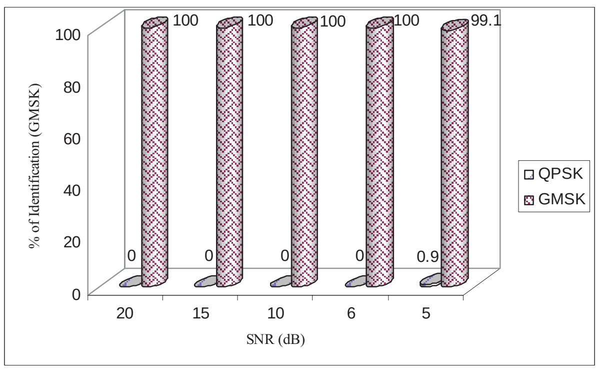

Fig. 4 Percentage of identification of GMSK with SNR

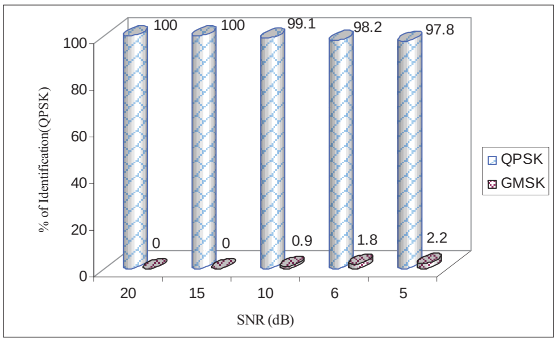

Fig. 5 Percentage of identification of QPSK with various SNR

Fig. 4 and Fig. 5 show the percentage of identification for various SNR of GMSK and QPSK respectively. When SNR is greater than or equal to 5 dB, the percentage of identification for GMSK signal is 99.1% and for QPSK signal is 97.8%. The identifier identifies the correct modulation schemes when SNR is greater than 5 dB for GMSK and 10 dB for QPSK.

The second Criterion to evaluate the performance of the proposed modulation identification algorithm is by computing the receiver operating characteristics (ROC) curves. It is a plot of probability of detection (P_d) as a function of the probability of false alarm (P_f). Probability of false alarm (P_f) is defined as the probability that the receiver decides a target is present when it is not. The probability of detection (P_d) is defined as the probability that the receiver decides a target is present when it is. The probabilities of 200 ensembles are calculated and tabulated at different thresholds and generated curves according to the results. Table III provides the receiver operating characteristics obtained using the proposed algorithm as a function of probability of detection.

TABLE III
RECEIVER OPERATING CHARACTERISTICS (ROC)

SNR = 15 dB		SNR = 10 dB		SNR = 6 dB	
P_{f1}	P_{d1}	P_{f2}	P_{d2}	P_{f3}	P_{d3}
0	1	0	0.91	0	0.3
0.05	1	0.05	0.94	0.05	0.55
0.1	1	0.1	0.96	0.1	0.85
0.2	1	0.2	1	0.2	0.93
0.3	1	0.3	1	0.3	0.98
0.4	1	0.4	1	0.4	1
0.5	1	0.5	1	0.5	1
0.6	1	0.6	1	0.6	1
0.7	1	0.7	1	0.7	1
0.8	1	0.8	1	0.8	1
0.9	1	0.9	1	0.9	1
1	1	1	1	1	1

Fig. 6 shows the ROC curves for the identifier when SNR is equal to15 dB, 10 dB and 6 dB. The performance of the identifier is better if the curve rise faster. When SNR is 15dB, P_{d1} is 100% independent of P_{f1}. When SNR is 10dB and the P_{f2} is 0.1, the P_{d2} between GMSK and QPSK is 0.96. When SNR is 6dB and the P_{f3} is smaller than 0.3 the P_{d3} drops rapidly. This is because the hypothesis of moderate SNR used to obtain the optimum threshold in the decision device will no longer be valid.

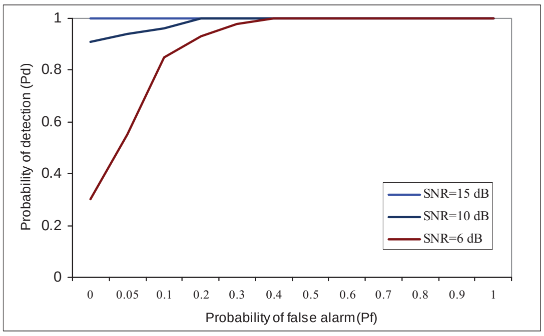

Fig. 6 Receiver Operating Characteristics (ROC) for the Proposed Algorithm

The third criterion to analyze the performance of the proposed system is the bit error rate (BER). Bit error rate has been computed for various Signal-to-Noise (SNR) and it is recorded for the analysis. Table IV represents the BER of the proposed algorithm for various SNR values.

TABLE IV
BIT ERROR RATE FOR THE PROPOSED ALGORITHM

SNR (dB)	Bit Error Rate (BER)	
	QPSK	GMSK
1	0.8350	0.2353
2	0.8024	0.1814
3	0.7565	0.1667
4	0.6751	0.1225
5	0.6013	0.0931
6	0.5942	0.0245
7	0.5207	0.0049
8	0.4634	0.0002
9	0.4041	0
10	0.3768	0
11	0.3273	0
12	0.3051	0
13	0.2612	0
14	0.2064	0
15	0.1012	0
16	0.0023	0
17	0	0

Fig. 7 shows the variation of Bit Error rate (BER) with SNR for the proposed AMI algorithm. This figure shows that the proposed AMI method identifies if lower bound SNR of GMSK 5 dB else it fails to identify the GMSK scheme and also it identifies if lower bound SNR of QPSK is 12 dB else it fails to identify the QPSK scheme.

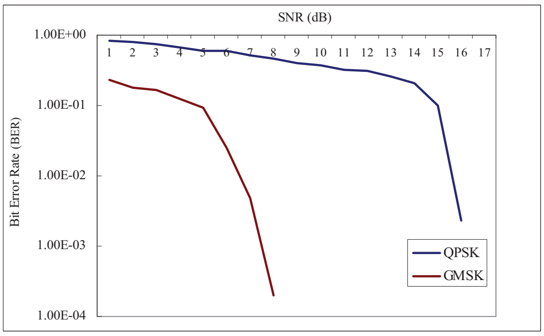

Fig. 7 Variation of Bit Error Rate (BER) with SNR

Open Science Index, Electronics and Communication Engineering Vol:3, No:11, 2009 publications.waset.org/1602.pdf

A. Comparison of Various Classifiers

Performance achieved with several algorithms for classifying various digital modulation schemes is presented in Table V. We consider here the ideal scenario, i.e., no unknown parameters, as well as the scenarios with unknown carrier phase, and unknown carrier phase/ timing offset, respectively. Of course, when higher order modulations are included in the modulation pool, higher SNRs and/or a larger number of symbols are needed to achieve the same performance. From the comparison it is clear that the proposed algorithm is capable of identifying the various modulation schemes with low SNR values.

TABLE V
COMPARISON OF PROPOSED ALGORITHM WITH EXISTING METHODS

Features	Models	Lower bound SNR (dB)
Maximum power spectral density of normalized centered amplitude, standard deviations of normalized amplitude, phase and frequency	Azzouz et al. [1]	12
Fuzzy Classification	Lopatka.J et al. [4]	5
Variance of HWT magnitude and normalized HWT magnitude	Hong et al. [13]	5
Mean and Variance of Complex Shannon WT magnitude	Radomir Pavlik [14]	8
Mean, Variance and Correlation coefficient of the received signal	D. Le Guen et al. [18]	12
DFT of phase PDF	Sapiano et al. [19]	10
Variance of WT magnitude	Ho et al. [20]	6
Fourth- and second-order moments of the received signal	Martret et al. [21]	5
Eighth-order cyclic cumulants of the received signal	Dobre et al. [22]	9
A maximum-likelihood Ratio	J.A. Sills [24]	13
Histogram peaks in WT magnitude and mean & variance of normalized histogram	Proposed algorithm	5

V. CONCLUSION

This paper described a generalized Modulation Identification algorithm to classify the modulation techniques used in SDR. This procedure is capable of identifying any digital modulation schemes. The simulated results using Wavelet transform technique and histogram peak measurement shows that the correct modulation scheme identification is possible even at low channel SNR of 12 dB and 5 dB for QPSK and GMSK respectively. The throughput analysis shows that the percentage of correct modulation identification is higher than 97.8% with 200 ensemble symbols when SNR is not lower than 5 dB. The ROC analysis shows that the probability of detection (P_{d3}) drops rapidly when SNR is 6 dB and probability of false alarm (P_{f3}) is smaller than 0.3. This can be overcome by means of suitable threshold value in the decision devices. The comparisons of the proposed algorithm with existing methods show that the proposed algorithm is capable of identifying the entire digital modulation scheme with low SNR.

REFERENCES

[1] E. E. Azzouz and A. K. Nandi, “Automatic Modulation Recognition of Communication Signals,” *Kluwer Academic Publishers*, 1996.
[2] Enrico Buracchini, CSELT, “The Software Radio Concept,” *IEEE Communication Magazine*, vol 38 no 9, pp 138-143, 2000.
[3] Druckmann. I, Plotkim. E.I, Swamy M.N.S., “Automatic Modulation Type Classification”, *Electrical and Computer Engineering, 1998. IEEE Canadian Conference on*, vol. 1, pp. 65-68, 1998.
[4] Lopatka.J, Pedzisa.M., “Automatic Modulation Classification Using Statistical Moments and a Fuzzy Classifier”, *Signal Processing Procedings, WCCC-ICSP 2000. 5th International Conference on*, vol. 3, pp 1500-1506, 2000.
[5] Callaghan. T.G, Pery. J.L, Tjho. J.K., “Sampling and algorithms aid modulation recoginition”, *Microwave & RF*, 24, (9), pp.117-179, 1995.
[6] Jondral. F., “Foundations of Automatic Modulation Classification”, *ITG – Fachbericht*, 107, pp.201-206, 1989.
[7] Beran.R., “Minimum Hellinger distance Estimates for Parametric Models”, *Annals of Statistics*, vol. 5, pp.445-463, 1977.
[8] Hero. A.O, III, Hadinejad-Mahram.H., “Digital modulation classification using power moment matrices,” *Acoustics, Speech and Signal Processing, 1998. Proceedings of the 1998 IEEE International Conference on*, vol.6, pp.3285-3288, 1998.
[9] Aiello. A, Grimaldi.D, rapuno.s, “GMSK Neural Network based Demodulator”, *Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications, International Workshop on*, pp.2-5, 2001.
[10] Keith E.Nolan, Lida Doyle, Philip Mackenzia, Donald o’Mahory, “Modulation scheme recognition for 4G software Radio Wireless,” *Networks Proceedings of the IASTED International Conference on Signal Processing, Pattern Recognition, and Application,*, pp 25-31, 2002.
[11] Ketterer, H., Jondral, F., Costa, A. H., “Classification of Modulation Modes Using Time-Frequency Methods,” *IEEE International Conference on Acoustics, Speech, and Signal Processing*, vol. 5, 1999.
[12] Y.C. Lin, C.-C. Jay Kuo, “Modulation classification using wavelet transform,” *in Proceedings SPIE*, vol. 2303, pp. 260-271.
[13] Liang Hong K.C. Ho, “Identification of Digital Modulation types using the Wavelet Transform*,” IEEE Conference Proc. MILCOM*, pp. 427-431, 1999.
[14] Radomir Pavlik, “Binary PSK/CPFSK and MSK Bandpass Modulation Identifier Based On The Complex Shannon Wavelet Transform”, *Journal of Electrical Engineering*, vol. 56, no. 3-4, pp. 71–77, 2005.
[15] P.Prakasam and M.Madheswaran, “Automatic Modulation Identification of QPSK and GMSK using Wavelet Transform for Adaptive Demodulator in SDR”, *IEEE Conference Proc. International Conference on Signal Processing, Communications and Networking (IEEE-ICSCN 2007),* MIT, Anna University, Chennai, pp 507-511, February 2007.
[16] Simon Haykin, “Communication Systems,” *Wiley Eastern Limited*, 2005.
[17] Y. T. Chan, “Wavelet Basics,” *Kluwer Academic Publishers*, 1995.
[18] D. Le Guen, A. Mansour, “Automatic Recognition Algorithm for Digitally Modulated Signals,” *Procedings of the IASTED International Conference on Signal Processing, Pattern Recognition & Applications*, pp 32-37, June, 2002.
[19] P. C. Sapiano, J. Martin, and R. Holbeche, ”Classification of PSK signals using the DFT of phase histogram,” *in Conference Proc. ICASSP*, pp. 1868-1871, 1995.
[20] K. C. Ho, W. Prokopiw, and Y. T. Chan, “Modulation identification by the wavelet transform,” *in Conference Proc. IEEE MILCOM*, pp. 886-890, 1995.
[21] C. Martret and D. M. Boiteau, “Modulation classification by means of different order statistical moments,” *in Conference Proc. IEEE MILCOM*, pp. 1387-1391, 1997.
[22] O. A. Dobre, Y. Bar-Ness, and W. Su, “Higher-order cyclic cumulants for high order modulation classification,” *in Conference Proc. IEEE MILCOM*, pp. 112-117, 2003.
[23] Z. Yu, Y. Q. Shi, and W. Su, “M-ary frequency shift keying signal classification based on discrete Fourier transform,” *in Conference Proc. IEEE MILCOM*, pp. 1167-1172, 2003.
[24] J.A. Sills, “Maximum-Likelihood Modulation Classification for PSK/QAM”, *in Conference Proc. IEEE MILCOM*, 1999.

Open Science Index, Electronics and Communication Engineering Vol:3, No:11, 2009 publications.waset.org/1602.pdf

P. Prakasam has born on May 09 1973 and he obtained his BE degree in Electronics and Communication Engineering from Madras University in 1994. He received his M.Tech degree in Advanced Communication Systems from Sastra Deemed University, Tanjore, India. Currently he is doing his Ph.D at Anna University, Chennai, India in Signal Processing in Communication Systems

He is working in Muthayammal Engineering College, Rasipuram, India, as an Assistant Professor in the Department of Electronics and Communication Engineering. Presently he is involved in developing a generalized modulation identification algorithm for adaptive demodulator in software defined radio. He has published more that nine research papers in national and international conferences/journals. His special areas of interest are Signal Processing, Communication Systems and Applications of signal processing in Mobile Communication Systems.

Mr.P. Prakasam is a member of IEEE (USA), life member of ISTE, and VSI (India). He has also coordinated Conferences, AICTE and ISTE sponsored SDP and STTP programme organized by the Department.

M. Madheswaran has born on July 10, 1968 and he received the BE Degree from Madurai Kamaraj University in 1990, ME Degree from Birla Institute of Technology, Mesra, Ranchi, India in 1992, both in Electronics and Communication Engineering. He obtained his PhD degree in Electronics Engineering from the Institute of Technology, Banaras Hindu University, Varanasi, India, in 1999.

At present he is a Principal of Muthayammal Engineering College, Rasipuram, India. He has authored over forty seven research publications in international and national journals and conferences. His areas of interest are theoretical modeling and simulation of high-speed semiconductor devices for integrated optoelectronics application, Bio-optics and Bio-signal Processing.

Dr..M. Madheswaran was awarded the Young Scientist Fellowship (YSF) by the State Council for Science and Technology, TamilNadu, in 1994 and Senior Research Fellowship (SRF) by the Council of Scientific and Industrial Research (CSIR), Government of India in 1996. Also he has received YSF from SERC, Department of Science and Technology, Govt. of India. He is named in Marquis Who's Who in Science and Engineering in the year 2006. He is a life member of IETE, ISTE and IE (India) and also a senior member of IEEE.

Open Science Index, Electronics and Communication Engineering Vol:3, No:11, 2009 publications.waset.org/1602.pdf