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Research Article

Digital Modulation Identification Model Using Wavelet Transform and Statistical Parameters

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A generalized modulation identification scheme is developed and presented. With the help of this scheme, the automatic modulation classification and recognition of wireless communication signals with a priori unknown parameters are possible effectively. The special features of the procedure are the possibility to adapt it dynamically to nearly all modulation types, and the capability to identify. The developed scheme based on wavelet transform and statistical parameters has been used to identify M-ary PSK, M-ary QAM, GMSK, and M-ary FSK modulations. The simulated results show that the correct modulation identification is possible to a lower bound of 5 dB. The identification percentage has been analyzed based on the confusion matrix. When SNR is above 5 dB, the probability of detection of the proposed system is more than 0.968. The performance of the proposed scheme has been compared with existing methods and found it will identify all digital modulation schemes with low SNR.

1. INTRODUCTION

The rapid growth in the field of mobile communication in general, software defined radio (SDR) in particular, has motivated the researchers to develop various digital modulation identification algorithms [1]. As the adaptive receiver in SDR can communicate with different communication standards like TDMA, CDMA, and GSM, the identification of digital modulation type of a signal is to be optimized. The signal identification process is an intermediate step between signal interception and demodulation. In recent past, several research groups have developed various modulation identification methods. An extensive survey of automatic modulation scheme classification was presented in Dobre et al. [2]. The simulation for various methodologies was done and compared. Modulation scheme recognition using the signal envelope method was described by Druckmann et al. [3]. This method achieves better recognition rates at short data records and if the data records are longer, then this method fails to recognize to recognize. Lopatka and Pedzisa [4] 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 was highly dependent on determining the exact intercepted signal center frequency. This recognizer was capable of recognizing carrier wave (CW) and frequency shift keying (FSK) but requires SNR $\geq$ 20 dB for correct modulation scheme recognition. A pattern recognition approach for both digital and analog modulation scheme was proposed by Jondral [6], which can classify AM, ASK2, SSB, PSK2, FSK2, and FSK4 modulation scheme types. The classifier based on pattern recognitions technique to discriminate between M-ary PSK and QAM signal developed and presented by Beran [7] used the binary image word spotting problems. Aiello et al. [8] proposed an artificial neural network-(ANN-) based classifier which incorporates pattern recognition techniques. This classifier had an ability only to identify GMSK modulation scheme. Software radio technique for automatic digital modulation scheme recognition was reported in [9] to classify BPSK and QPSK schemes at lower bound SNR of 9 dB. The 8th-order statistical moment was used to identify the modulation as either BPSK or QPSK. The classification of BPSK, QPSK, 8PSK, 8QAM, and 16QAM was done using a DFT of the phase histogram method, and the analysis was carried out using the maximum likelihood approach in [10]. This method failed to identify the frequency variable digital modulation schemes. These methods are either computationally intensive or require a high signal-to-noise ratio (SNR). The classification of MFSK, MPSK, and QAM was carried out using number of amplitude levels and phase in the carrier of DFT simulation [11], without considering the channel noise.

Ketterer et al. [12] have utilized the time-frequency analysis, that is, wavelet transform (WT), when nonstationary signals were considered. It is reported that the wavelet approach approximates both the signal envelop and frequency content. This has motivated the researchers to effectively utilize the WT approach for estimating the pattern [12–15]. Lin and Kuo [13] 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 MPSK signal. Hong and Ho [14] used the Haar WT and statistical decision theory for identifying identification MPSK, MFSK, and MQAM signals contaminated by additive white Gaussian noise (AWGN). Binary PSK/CPFSK and MSK identification was investigated by Pavlík [15]. The complex Shannon wavelet was applied to identify binary modulation signals under constant envelope scheme and it failed to identify the nonconstant envelop modulation schemes. Automatic modulation identification (AMI) algorithm reported by Prakasam and Madheswaran [16] has been developed to classify QPSK and GMSK signals with additive white Gaussian noise (AWGN) channel. This algorithm failed to identify when SNR is less than 12 dB.

The reported schemes are capable of identifying few modulation schemes with higher SNR. Therefore, an attempt is made to propose a generalized modulation identification model to identify BPSK, QPSK, 8PSK, 16PSK, 2QAM, 4QAM, 8QAM, 16QAM, GMSK, and MFSK modulation schemes under noisy environment with low SNR considering both wavelet transform approach as well as statistical moments.

2. 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 an additive white Gaussian channel noise. The signal $s(t)$ can be represented in complex form as

$$s(t) = \tilde{s}(t)e^{j^* f(w_c t+\theta_c)}, \tag{2}$$

where ω_c is the carrier frequency and θ_c is the carrier phase. Generally, the complex envelope of $s(t)$ in (1) may be expressed for all modulation types as

$$s(t) = \tilde{s}(t)\exp\left(j\phi(t;a)\right), \tag{3}$$

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 $a_k = \pm 1$.

The analysis technique is required for nonstationary 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 multiresolution analysis (MRA), which provides the necessary parameters to extract the feature of the modulated signals. The wavelet transform of (3) is given by

$$C(a,\tau) = \frac{\tilde{s}(t)e^{(\phi(\cdot)+\theta_c)}}{j\sqrt{a f_c}}E_i(n,y), \tag{4}$$

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 (4) does not reduce to a simple form and must be evaluated numerically by taking its absolute value $|C(a,\tau)|$.

2.1. Classification of subsystem

The normalized histogram generation of wavelet transformed coefficient is used to classify the Subsystem1 (M-ary PSK and M-ary QAM) with Subsystem2 (GMSK and M-ary FSK). If n_i is the number of occurrence in a particular value then the normalized histogram (probability of occurrence) of a process is given by

$$p(x_i) = \frac{n_i}{n}, \tag{5}$$

where n is total number of samples in the particular process. Subsystem1 signal has constant transient characteristics; they have a single peak in its normalized histogram. But the Subsystem2 signals have multifrequency component, they have multiple peaks in its normalized histogram.

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 nonstationary signal, thus it has been considered for the classification. The nth-order moment for $p(x_i)$, where $i = 0,1,2,\dots,N-1$ is given by

$$\mu_n(x) = \sum_{i=0}^{N-1}(x_i - \mu_1)^n p(x_i), \tag{6}$$

where $\mu_1 = \sum_{i=0}^{N-1} x_i p(x_i)$ is the mean of the statistical process. The second-order moment (variance) of discretized WT can be computed using

$$\begin{aligned}\mu_2 &= E\left(|C(a,\tau)|^2\right) - \left[E\left(|C(a,\tau)|\right)\right]^2\\ &= \frac{1}{N}\sum_{i=0}^{N-1}|Ci(a,\tau)|^2 - \left[\frac{1}{N}\sum_{i=0}^{N-1}\left(|Ci(a,\tau)|\right)\right]^2,\end{aligned} \tag{7}$$

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

Let H_i be the ith modulation format assigned to the received signal, where i is associated with {M-ary PSK, j} and j is with M-ary QAM. The statistical decision needs the probability density function (pdf) of the test statistics conditioned on the assigned digitally modulated signal. Assuming the noise in (1) is AWGN, the wavelet transform coefficient $C(a,\tau)$ has a characteristic of random variables generated from linear combinations of sinusoidal signal and a Gaussian noise. The two conditional Gaussian pdfs allow a threshold setting to decide the M-ary PSK and M-ary QAM, when a certain probability of false identification of both signals is given. The conditional pdf is

$$p\left(\frac{x}{H_i}\right) = \frac{1}{\sqrt{2\pi}\mu_{2,i}} \exp\left(-\frac{\left(x-\mu_{1,i}\right)^2}{\mu_{2,i}^2}\right). \quad (8)$$

Under the hypothesis $H_{\text{M-ary PSK}}$ is true, the probability of M-ary PSK misclassification is simply the probability that $\mu_{1,\text{M-ary PSK}} - x > \mu_{1,\text{M-ary PSK}} - T_1$, that is, $\mu_1 < T_1$. The probability of misclassification error for M-ary PSK is given by

$$P\left(\frac{e}{H_{\text{M-ary PSK}}}\right) = \frac{1}{2}\left(1+\text{ercf}\left(\frac{x-\mu_{1,\text{M-ary PSK}}}{\sqrt{2}\mu_{2,\text{M-ary PSK}}}\right)\right), \quad (9)$$

where ercf() is defined as $\text{ercf}(x) = (2/\pi)\int_0^x \exp(-t^2)dt$. Similarly, if it is assumed that the hypothesis $H_{\text{M-ary QAM}}$ is true, the probability of M-ary QAM signal misclassification is simply the probability that $x-\mu_{1,\text{M-ary PSK}} > T_1-\mu_{2,\text{M-ary PSK}}$, that is, $\mu_1 > T_1$. The probability of misclassification error for M-ary QAM is given by

$$P\left(\frac{e}{H_{\text{M-ary QAM}}}\right) = \frac{1}{2}\left(1+\text{ercf}\left(\frac{x-\mu_{1,\text{M-ary QAM}}}{\sqrt{2}\mu_{2,\text{M-ary QAM}}}\right)\right), \quad (10)$$

where ercf() is defined as $\text{ercf}(x) = (2/\pi)\int_0^x \exp(-t^2)dt$. It is obvious that when the Gaussian noise increases, the mean value of M-ary PSK and M-ary QAM decreases until the point when both the probabilities of misclassification are equal. Thus, $P(e/H_{\text{M-ary PSK}}) = P(e/H_{\text{M-ary QAM}}) = .01$ 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

$$T_1 = \frac{\mu_{1,\text{M-ary PSK}}\,\mu_{2,\text{M-ary QAM}} + \mu_{1,\text{M-ary QAM}}\,\mu_{2,\text{M-ary PSK}}}{\mu_{2,\text{M-ary PSK}} + \mu_{2,\text{M-ary QAM}}}. \quad (11)$$

Based on the mean value the classification of M-ary PSK with M-ary QAM can be done.

2.2. *Classification of M-ary PSK signals*

The method described in earlier has been used for setting the threshold T_{Pr} (where r is varying from $1, 2, 3, \ldots$ to represent 2-ary, 4-ary, 8-ary, etc.) and the further classification of substsem1 can be classified based on second- or higher-order statistical moment. Decision making between BPSK, QPSK, 8PSK, 16PSK, and so on can be carried out based on the comparison of variance value with computed threshold value and for 2PSK and 4PSK is given by

$$T_{P1} = \frac{\mu_{1,2\text{PSK}}\,\mu_{2,4\text{PSK}} + \mu_{1,4\text{PSK}}\,\mu_{2,2\text{PSK}}}{\mu_{2,2\text{PSK}} + \mu_{2,4\text{PSK}}}. \quad (12)$$

Similarly, the threshold value $T_{P2}, T_{P3}, T_{P4}, \ldots$ can be defined using the same procedure.

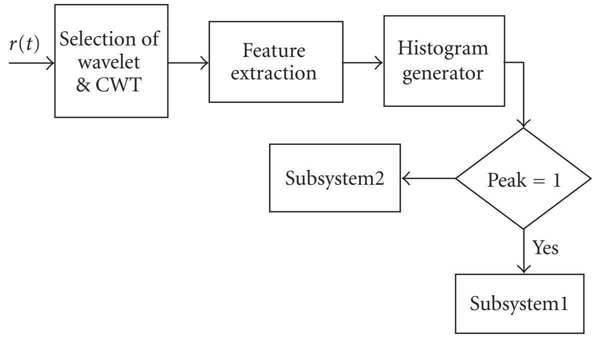

Figure 1: Proposed modulation identification system.

2.3. *Classification of M-ary QAM Signals*

The classification of M-ary QAM has been classified using the same method prescribed in the last section and the comparison of variance value with the threshold is used to classify the subclassification. The threshold value for decision making of 2QAM with 4QAM is given by

$$T_{Q1} = \frac{\mu_{1,2\text{QAM}}\,\mu_{2,4\text{QAM}} + \mu_{1,4\text{QAM}}\,\mu_{2,2\text{QAM}}}{\mu_{2,2\text{QAM}} + \mu_{2,4\text{QAM}}}. \quad (13)$$

Similarly, the threshold value $T_{Q2}, T_{Q3}, T_{Q4}, \ldots$ can be defined using the same procedure.

Decision making between GMSK and M-ary FSK can be done based on the comparison of variance value with threshold T_2 and is given by

$$T_2 = \frac{\mu_{1,\text{GMSK}}\,\mu_{2,\text{M-ary FSK}} + \mu_{1,\text{M-ary FSK}}\,\mu_{2,\text{GMSK}}}{\mu_{2,\text{GMSK}} + \mu_{2,\text{M-ary FSK}}}. \quad (14)$$

Based on the mean and variance (or higher-order moment), the classification of M-ary FSK can be performed.

3. DESCRIPTION OF IDENTIFICATION ALGORITHM

The proposed modulation identification scheme is shown in Figure 1. The identification of digital modulation schemes has been done by using a common feature. The feature extraction has been done by extracting the coefficients of the modulated signals using wavelet transform. Wavelets are to be selected such a way that it looks similar to the patterns to be localized in the signal. The wavelet transform has been computed and the extracted coefficients are used to generate the histogram peak. Based on the number of peaks, the identifier identifies that the received signal is either Subsystem1 or Subsystem2 signals.

The further classification of Subsystem1 and 2 is shown in Figures 2 and 3, respectively.

The classification of subsystem is done based on the decision rules as shown in Table 1.

4. RESULTS AND DISCUSSION

The entire system including signal generation, noise addition, reception, feature extraction, and modulation scheme

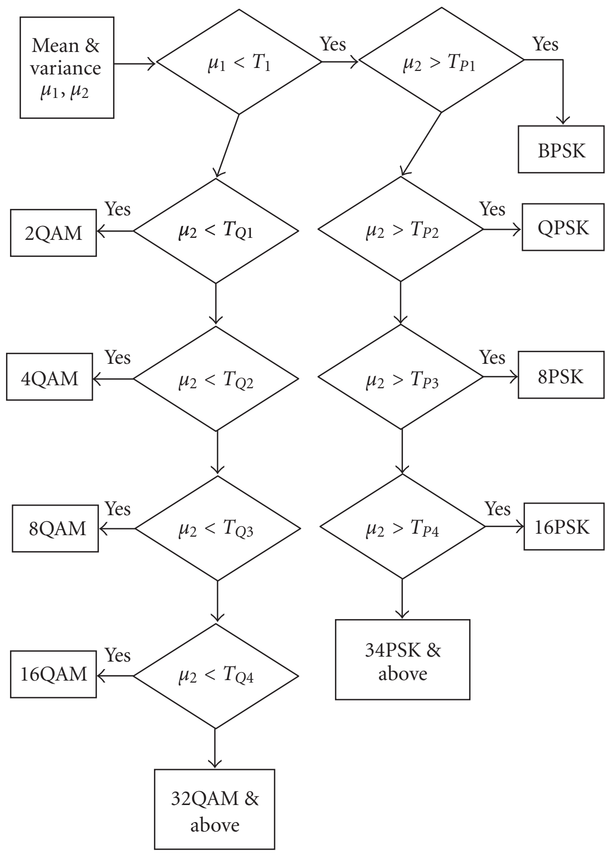

Figure 2: Classification of Subsystem1.

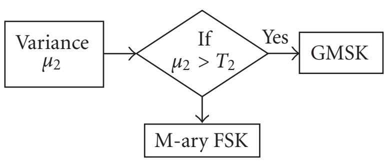

Figure 3: Classification of Subsystem2.

recognition was developed and tested with the software tools of MATLAB. Successful tests were carried out with signals used in the mobile radio systems GSM, CDMA, and UMTS. The developed algorithm is verified for BPSK, QPSK, 8PSK, 16PSK, 2QAM, 4QAM, 8QAM, 16QAM, GMSK, and MFSK modulation schemes. The above specified modulation schemes were simulated using MATLAB with 200 symbols input message and AWGN noise was 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. Because the wavelet transform has a flexible scaling factor, depending upon the SNR of the incoming signal, it will choose the length of the window function. This proposed model has been tested for 1000 individual trials. The effect of sample size plays a major role during the modulation identification process. It is seen from the observation that wavelet transform requires minimum of 6 symbols for better identification. The magnitude of Haar wavelet transform for MQAM and MPSK is a constant, but MFSK and GMSK has a multistep function since the frequency is variable. This common feature made to be considering the Haar wavelet as the mother wavelet and it is given by

$$\psi(t) = \begin{cases} 1, & 0 \le t < \dfrac{1}{2}, \\ -1, & \dfrac{1}{2} \le t < 1. \end{cases} \tag{15}$$

After extracting the transient characteristics, the coefficients were extracted to generate the histogram peak. The histogram of M-ary QAM and M-ary PSK, M-ary FSK and GMSK is shown in Figures 4 and 5, respectively. These figures show as the M-ary QAM and M-ary PSK signal has constant transient characteristics, it has a single peak in its histogram. But the M-ary FSK and GMSK have more than single peak because these signals have multistep frequency component.

Then, each subsystem is further classified based on decision rules shown in Table 1. The next step is the computation of the unknown threshold values. Their computation is derived for the two binary hypotheses test with 0.01 probability of misclassification of each the modulated signal. Based on the misclassification rate condition, the related optimum threshold T_1 has been computed from (11) to classify M-ary PSK and M-ary QAM. Similarly, other related optimum threshold values have been computed using (12),

Table 1: Subsystem classification—decision rule.

Classification system	Decision rules
	If $\mu_1 < T_1 \rightarrow$ M-ary PSK signal
	If $\mu_2 > T_{P1} \rightarrow$ BPSK signal
	else if $\mu_2 > T_{P2} \rightarrow$ QPSK signal
	else if $\mu_2 > T_{P3} \rightarrow$ 8PSK signal
	else if $\mu_2 > T_{P4} \rightarrow$ 16PSK signal
	else $\rightarrow$ 32PSK signal and above
	end
	end
	end
	end
Subsystem1	else $\rightarrow$ M-ary QAM signal
	If $\mu_2 < T_{Q1} \rightarrow$ 2QAM signal
	else if $\mu_2 < T_{Q2} \rightarrow$ 4QAM signal
	else if $\mu_2 < T_{Q3} \rightarrow$ 8QAM signal
	else if $\mu_2 < T_{Q4} \rightarrow$ 16QAM signal
	else $\rightarrow$ 32QAM signal and above
	end
	end
	end
	end
	end
	If $\mu_2 > T_2 \rightarrow$ GMSK signal
Subsystem2	else $\rightarrow$ M-ary FSK signal
	end

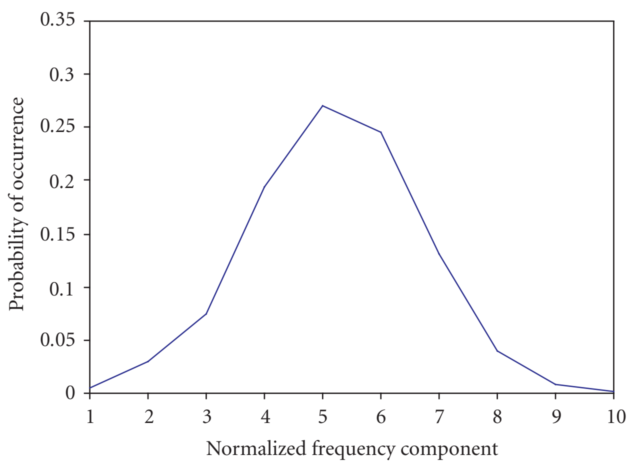

Figure 4: Histogram peak of Subsystem1.

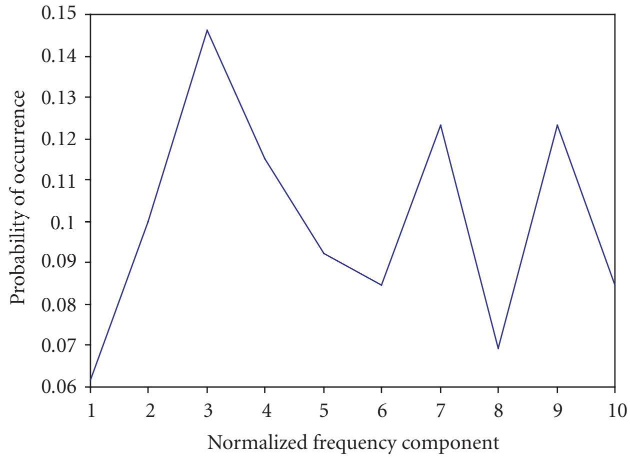

Figure 5: Histogram peak of Subsystem2.

Table 2: Threshold value.

System	Modulation schemes	Threshold value
	M-ary QAM/M-ary PSK	$T_1 = 1.09$
	BPSK/Higher MPSK	$T_{P1} = 0.0104$
	QPSK/Higher MPSK	$T_{P2} = 0.0096$
	8PSK/Higher MPSK	$T_{P3} = 0.0091$
Subsystem1	16PSK/Higher MPSK	$T_{P4} = 0.0089$
	2QAM/Higher QAM	$T_{Q1} = 0.0103$
	4QAM/Higher QAM	$T_{Q2} = 0.0109$
	8QAM/Higher QAM	$T_{Q3} = 0.0115$
	16QAM/Higher QAM	$T_{Q4} = 0.0123$
Subsystem2	M-ary FSK/GMSK	$T_2 = 1.686$

(13), and (14) and tabulated in Table 2. After identification of the scheme demodulation is performed by conventional methods.

The performance of the proposed algorithm was examined based on the confusion matrix receiver operating characteristics (ROCs) and bit error rate. For the analysis purpose, the identifier has been tested for 1000 experiments with 200 symbols per experiments. The results obtained from experiments are represented in the form of so-called confusion matrix as shown in Table 3. The left column depicts the modulation schemes fed into the proposed identifier and output modulation schemes indicated in the uppermost row. For an ideal identifier all results, each 100%, are contained in the diagonal matrix elements. The testing was carried out for different SNR starting from 20 dB and the confusion matrix were tabulated at 5 dB for the proposed identifier.

The spread of identification results is caused by the similarity of the waveforms. Most of the nonsuccessfully identified signals were assigned to the reject class REJ. The identification of 8PSK (1.2%) as 16PSK, 8QAM (1.4%) as 16QAM, and GMSK (0.9%) as MFSK is because of the lower SNR, these waveforms are similar in some nature. The numbers of false identification are still moderate for the proposed system.

The second criterion to evaluate the performance of the proposed modulation identification system is by computing the receiver operating characteristics (ROCs) curves. The probabilities of 200 symbols are calculated, tabulated as shown in Table 4, and generated curves according to the results.

Table 3: Confusion matrix for SNR = 5 dB.

Input modulation scheme	Output modulation scheme										
	BPSK	QPSK	8PSK	16PSK	2QAM	4QAM	8QAM	16QAM	GMSK	MFSK	REJ
BPSK	98.6										1.4
QPSK		97.8									2.2
8PSK			97.5	1.2							1.3
16PSK				97.2							2.8
2QAM					100						
4QAM						98.4					1.6
8QAM							97.6	1.4			1.0
16QAM								96.8			3.2
GMSK									99.1	0.9	
MFSK									0.9	98.2	0.9

Table 4: Receiver operating characteristics (ROCs).

SNR = 15 dB		SNR = 10 dB		SNR = 5 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	0.5
0.1	1	0.1	0.96	0.1	0.8
0.2	1	0.2	1	0.2	0.85
0.3	1	0.3	1	0.3	0.9
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

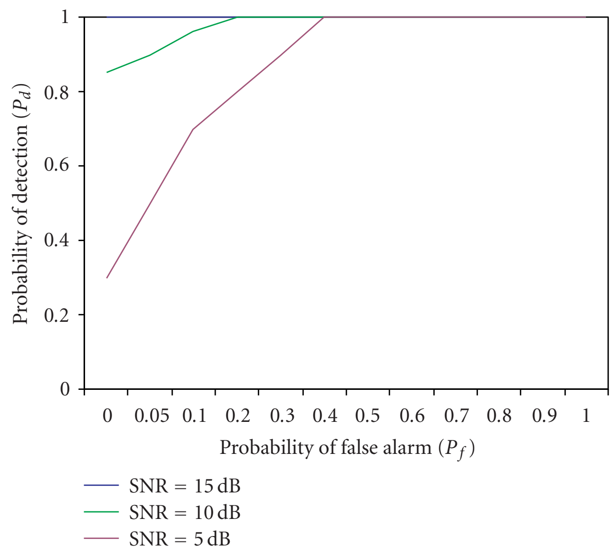

Figure 6: Receiver operating characteristics (ROCs) for the proposed system.

Figure 6 shows the ROC curves for the identifier when SNR is equal to 15 dB, 10 dB, and 5 dB. The performance of the identifier is better if the curve rises faster. When SNR is 15 dB, P_{d1} is 100% independent of P_{f1}. When SNR is 10 dB and the P_{f2} is 0.1, the capability of detection (P_{d2}) is 0.96. When SNR is 5 dB 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.

The third criterion to evaluate the performance of the proposed modulation identification system is the computation of bit error rate. The bit error rate of the proposed model has been computed for various SNR and shown in Figure 7. From the figure, it is found that when SNR increases, the bit error rate decreases. It is also clear that the bit error rate becomes significant for lower SNR values.

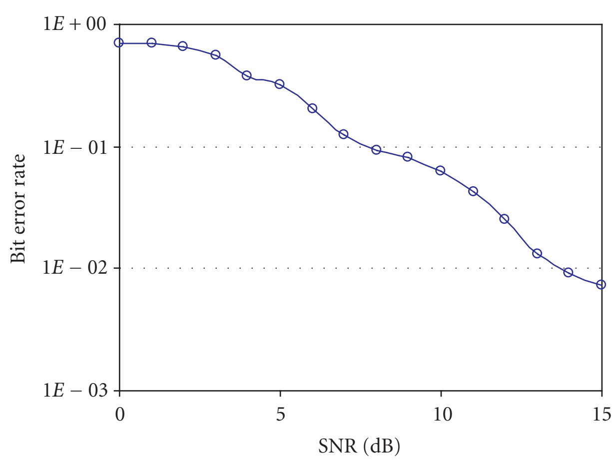

Figure 7: Bit error rate versus SNR.

4.1. Comparison of various methods

Performance of several methods reported for classifying various digital modulation schemes is presented in Table 5.

TABLE 5: Comparison of proposed system with existing methods.

Features	Models	Modulation schemes	Lower bound SNR (dB)	% of identification
Variance of HWT magnitude and normalized HWT magnitude	Hong and Ho [14]	QPSK, 4FSK, 16QAM	5	97%
Mean and Variance of complex Shannon WT magnitude	Pavlík [15]	BPSK, CPFSK, MSK	8	93.1%
Mean, variance, and correlation coefficient of the received signal	Le Guen and Mansour [17]	ASK2, ASK4, PSK2, PSK4, FSK2, FSK4	12	Not mentioned
DFT of phase PDF	Sapiano et al. [18]	BPSK, QPSK, 8PSK	10	92%
Variance of WT magnitude	Ho et al. [19]	BPSK, QPSK, 8PSK, 2FSK, 4FSK, 8FSK, MSK	6	96%
Fourth- and second-order moments of the received signal	Martret and Boiteau [20]	QPSK, 16QAM	5	95%
Eighth-order cyclic cumulants of the received signal	Dobre et al. [21]	BPSK, QPSK, 8PSK, 4ASK, 8ASK, 16QAM, 64QAM, 256QAM	9	95%
Histogram peaks in WT magnitude and mean & variance of normalized histogram	Proposed system	BPSK, QPSK, 8PSK, 16PSK, 2QAM, 4QAM, 8QAM, 16QAM, GMSK, MFSK	5	96.8%

The ideal scenario, that is, no prior information is required about the incoming signal is considered for performance evaluation. Comparison table shows that, model proposed by Hong and Ho [14], Ho et al. [19] and proposed system are capable of identifying modulation schemes with low SNR of 5 dB. Though the % of identification is same for Hong and Ho [14] and proposed model, the present model can identify more number of modulation schemes.

5. CONCLUSION

A generalized modulation identification algorithm is described which is suited for many digital modulation schemes used in SDR. The system was tested with 10 modulation schemes with different SNR. The simulated results using wavelet transform technique and statistical moments measurement show that the correct modulation scheme identification is possible even at low channel SNR of 5 dB. The ROC analysis shows that the percentage of correct modulation identification is higher than 96.8% for 1000 experiments with 200 symbols when SNR is not lower than 5 dB. The comparison with existing methods shows that the proposed system is capable of identifying the entire digital modulation scheme with low SNR.

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