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Analysis of Digitally Modulated Signals using Instantaneous and Stochastic Features, for Classification

Jaspal Bagga, Neeta Tripathi

Abstract-- **Automatic modulation classification is a procedure performed at the receiver based on the received signal before demodulation when the modulation format is not known to the receiver. AMR is also believed to play an important role in the implementation of Software Defined Radio (SDR) of the 4th-Generation (4G) communication system. The ability to automatically select the correct modulation scheme used in an unknown received signal is a major advantage in a wireless network**

This paper describes one application that exploits the flexibility of a software radio. As compared to the previous work this approach uses stochastic features to distinguish modulated signals for varying Signal to Noise Ratio (SNR). The proposed method is simple effective and robust. It is based on the stochastic features derived from instantaneous features to classify digital modulation signals.. This method is capable of differentiating ASK2, ASK4, FSK2, FSK4, PSK2 and PSK4 signals at the output of a typical high frequency channel with white Gaussian noise, Unlike most other existing methods, proposed method assumes no prior information of the incoming signal (symbol rate, carrier frequency, amplitude etc.). Extensive simulation results demonstrate that this approach is robust in various practical situations in identifying the modulated signals. When SNR is less than 5 dB, the percentage of correct identification is about 97%which increases to almost 100% for SNR 20db.

Key Words- **Digital signals, Modulation Classification, Signal To Noise Ratio, Stochastic features**

I. INTRODUCTION

Modulation scheme is one of the most important characteristics to note in the monitoring activity and identification of radio signals**.** The automatic recognition of the modulation format of a detected signal, the intermediate step between signal detection and demodulation, is a major task of an intelligent receiver, with various civilian and military applications. Obviously, with no knowledge of the transmitted data and many unknown parameters at the receiver, such as the signal power, carrier frequency and phase offsets, timing information, etc., blind identification of the modulation is a difficult task. This becomes even more challenging in real-world scenarios with multipath fading, frequency-selective and time-varying channels. Modulation is the process of varying a periodic waveform, i.e. a tone, in order to use that signal to convey a message. The most fundamental digital modulation techniques are: Amplitude Shift Keying (ASK), Frequency Shift Keying (FSK), Phase Shift Keying (PSK) and Quadrature – Amplitude Modulation (QAM). The QAM modulation is more useful and efficient than the others and is almost applicable for all the progressive modems.

High-level amplitude modulated signals M-ASK M-FSK, M-QAM etc. have an excessive number of symbol status and therefore incline to be disturbed by noise. So it is difficult to identify the high-level amplitude modulated signals at low SNR.

Automatic identification of the digital modulation type of a signal is a rapidly evolving area [1]. The techniques are proposed to distinguish digitally modulated signals such as Quadrature Amplitude Modulation signal, Phase Shift Keying signal and Frequency Shift Keying signal. [2] .The features for identification may be either time based or frequency based. Time domain features may be amplitude, instantaneous frequency or phase of complex envelop of modulated signal In frequency domain power spectrum may be analyzed or parameters such as variance, skewness ,etc may be analyzed. [3-4]. Another approach for digital modulation types identification is to use wavelet transform (WT) [5-6].Artificial neural network approach has been applied to classify identification schemes [7].

The aim of the work is to develop automatic modulation classifier. To achieve this digitally modulated signals are generated using MATLab codes. Instantaneous features such as amplitude phase and frequency are first derived .Stochastic features such as amplitude mean, amplitude mean-square, phase mean are derived from instantaneous features for all set of signal 2ASK, 4ASK, 2PSK, 4PSK 2FSK, 4FSK AND 16 QAM. Five feature vectors are calculated. Feature vectors are plotted and then threshold values are derived to design the classifier to distinguish various modulated signals.

II. LITERATURE REVIEW

Modulation classifiers are generally divided into two categories. The first category is based on decision-theoretic approach while the second on pattern recognition [8]. The decision-theoretic approach is a probabilistic solution based

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Jaspal Bagga Electronics and telecommunication,Shri Shankaracharya College of Engineering and Technology.Bhilai,India.0788-2291606 (e-mail: baggajaspal@gmaill.com).

Neeta tripathi, Principal,Shri Shankaracharya institute of Technology and Management,Bhilai,India, (e-mail neeta_31dec @yahoo.com).

on a priori knowledge of probability functions and certain hypotheses [9-10]. On the other hand, the pattern recognition approach is based on extracting some basic characteristics of the signal called features [11-12]. This approach is generally divided into two subsystems: the features extraction subsystem and the classifier subsystem In [13], Wong and Nandi have proposed a method for ADMR using artificial neural networks and genetic algorithms. In their study, they have presented the use of resilient back propagation (RPROP) as a training algorithm for multi-layer perception (MLP) recognizer. However, the second approach is more robust and easier to implement if the proper features set is chosen.. The identification techniques, which had been employed to extract the signal features necessary for digital modulation recognition, include spectral-based feature set [14], higher order cumulants (HOC) [15-16], constellation shape [17], and wavelets transforms [18-20]. In [21], Hong and Ho studied the use of wavelet transform to distinguish among QAM, PSK, and FSK signals. In their work, they have used a wavelet transform to extract the transient characteristics in a digital modulated signal. El-Mahdy and Namazi [22] developed and analyzed different classifiers for M-ary frequency shift keying (M-FSK) signals over a frequency nonselective Rayleigh fading channel. In [23], Pedzisz and Mansour derived and analyzed a new pattern recognition approach for automatic modulation recognition of M-PSK signals in broadband Gaussian noise. This method is based on constellation rotation of the received symbols and fourth-order cumulants of the in-phase distribution of the desired signal.

The most straight forward approach in discriminating different modulation types is using time and /or frequency domain parameters. SNR needs to be considered for modulation classification since noisy signals are more similar to each other. Instantaneous parameters, stochastic features, Higher order Statistics, wavelet transform, are some of the feature extracting techniques.

The paper proposes a simple, effective and robust method based on the stochastic features derived from instantaneous features to classify digital modulation signals.. This method is capable of differentiating ASK2, ASK4, FSK2, FSK4, PSK2 and PSK4 signals at the output of a typical high frequency channel with white Gaussian noise, Unlike most other existing methods, our method assumes no prior information of the incoming signal (symbol rate, carrier frequency, amplitude etc.).

III. MODULATION CLASSIFIER MODEL

A modulation classifier can be described as a system comprising three parts as shown in “Fig.1”

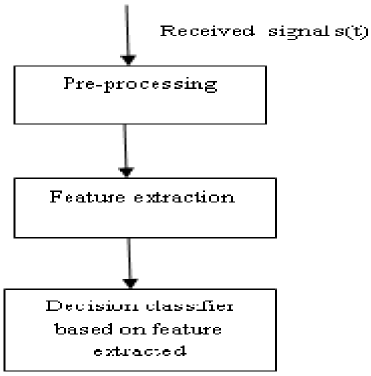

Fig 1. Modulation Classification Model

The work of the pre-processor is increasing the performance of the classifier. The pre-processor removes disturbances from the signal such as interfering signals and increasing the (SNR) and also filtering the received signal, down converting , equalizing, it that compensates for fading on the channel. This is only a preparation for the feature processor which extracts discrimination features of the signal before the classifier makes the decision about the modulation type of the given available data.

The received waveform r (t), $0 \le t \le T$ is described as,

$$r(t) = s(t) + n(t), \ldots\ldots\ldots\ldots \quad (1)$$

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

$$s(t) = s'(t)e^{j * f(\omega ct+ \theta c)}, \ldots\ldots\ldots \quad (2)$$

where ωc, is the carrier frequency and θc is the carrier phase. The complex envelope of s(t) in (1) can be expressed as[14]

For QAM signal:-

$$s'QAM(t) = \sum_{i=1}^{N}(Ai + Bi)\, u_T(t-iT), \ldots\ldots \quad (3)$$

Ai, Bi ∈ {2m-1-M,m=1,2,….,M}.

For PSK signal:-

$$s'PSK(t) = \sqrt{s}\sum_{i=1}^{N} e^{j\varphi i}\, u_T(t-iT), \ldots\ldots \quad (4)$$

φi∈{2π/M(m-1),m=1,2,..,M}.

For FSK signal:-

$$s'FSK(t) = \sqrt{s}\sum_{i=1}^{N} e^{j(\omega_i t + \theta_i)}\, u_T(t-iT \quad (5)$$

$\omega_i \in \{\omega_1, \omega_2, \ldots, \omega_M\}, \theta_i \in \{0, 2\pi\}$

In equation (3), (4), and (5), s is the signal power, N is the number of observed symbols, T is the symbol duration and uT (t) is the standard unit pulse of duration T, the three signals have the same symbol duration. It can be seen from (3)-(5) that symbol changes will give rise to transients in the modulated signals. The transients are created independently in the changes of amplitude, phase and frequency respectively.

IV. RESULTS AND DISCUSSION

Various digitally modulated signals such as 2ASK, 4ASK, 2PSK, 4PSK, 2FSK, 4FSK, 16QAM are first generated and analyzed with and without noise. The carrier frequency and the sampling frequency has been taken as 10kHz and 200kHz respectively. The symbol rate taken is 600 symbols per second. .Signals are then passed through AWGN channel. The binary data stream for modulation has been obtained from random number generator. Fig 2, Fig 3.Fig 4. show the generation of signals 2ASK , 2FSK and 16 QAM respectfully as an example. Stochastic features such as amplitude mean, amplitude mean-square, phase mean ,frequency mean square are calculated and derived from instantaneous features for all set of signal 2ASK, 4ASK, 2PSK, 4PSK 2FSK, 4FSK and 16 QAM. The feature vectors derived are plotted for SNR varying from 0db to 20 db. Fig5 shows instantaneous amplitude, phase and frequency for 2ASK signal. These instantaneous features are first derived for all modulated signals as the stochastic features derived are based on them. Fig 6 , Fig 7, and Fig 8 show the plot of feature vectors against SNR used to classify signals. In Fig 6 amplitude mean is plotted against SNR .It can be seen that 2ASK ,4ASK and 16 QAM signals can be distinguished for SNR above 4db.Since this feature cannot be used to classify 2FSK,4FSK, 2PSK and 4PSK other features are considered. Fig 7 shows the plot of phase mean square vs. SNR. This shows that this feature can be used to distinguish 2PSK, 4PSK and 16QAM for SNR as low as 0db . Fig 7 shows the plot of frequency mean square vs. SNR .It shows that this feature can be used to differentiate 2FSK and 4FSK for low SNR also. Threshold values are thus derived based on these features .decision tree classifier is developed to classify the modulated signals.

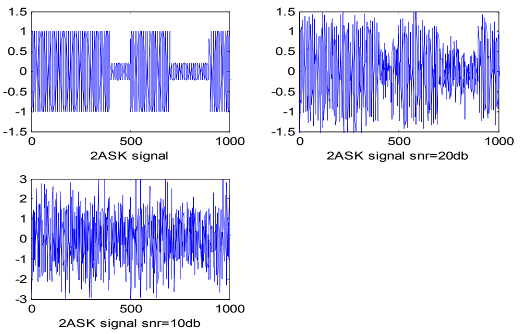

Fig 2. 2ASK signal with and without AWGN noise

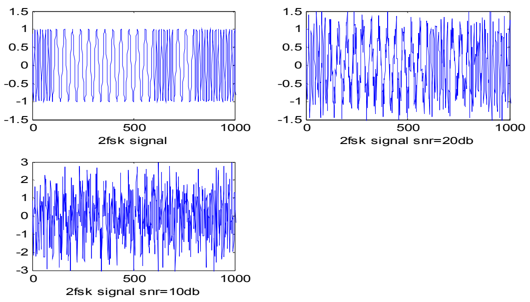

Fig 3. 2FSK signal with and without AWGN noise

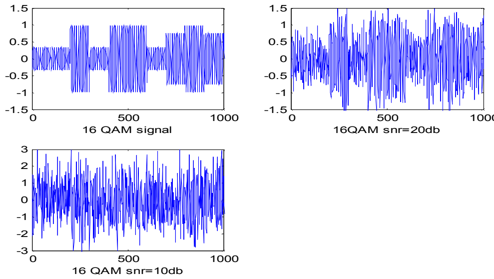

Fig 4.16 QAM signal with and without AWGN noise

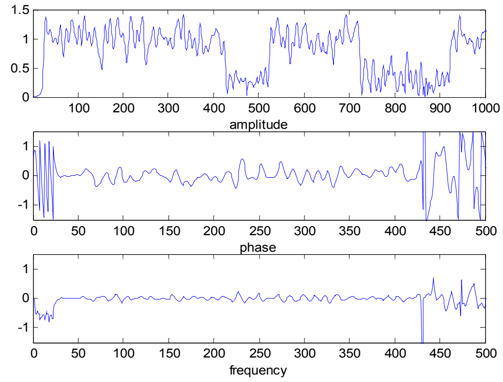

Fig 5.Amplitude, Phase and Frequency plot for 2ask signal

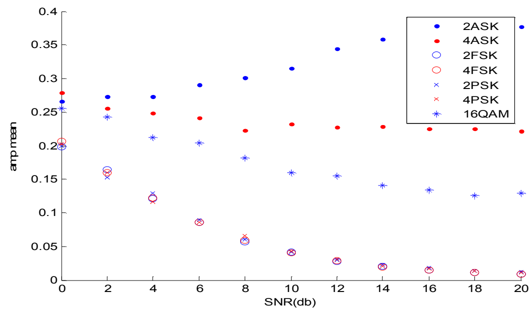

Fig 6. Amplitude mean vs. SNR plot

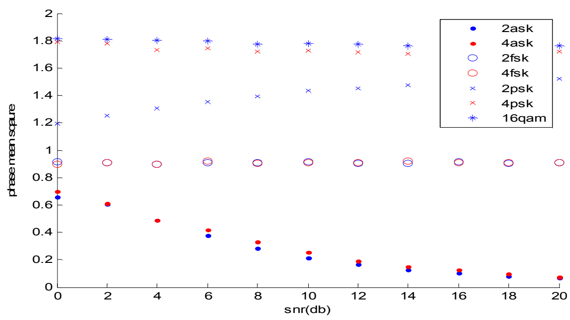

Fig 7. Phase mean square vs SNR plot

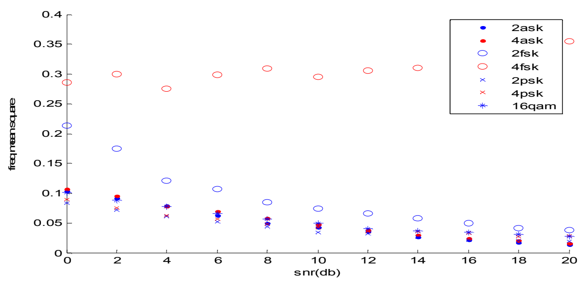

Fig 8. Frequency mean square vs SNR plot

Table I. Percentage of correct classification for SNR =0db

In/out	SNR=0db						
	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK	16QAM
2ASK	96	2	0	0	2	0	0
4ASK	1	96	0	0	1	1	1
2FSK	0	0	97	1	1	0	1
4FSK	0	0	2	98	0	0	0
2PSK	1	1	0	1	97	0	0
4PSK	0	0	0	0	.5	98.5	1
16QAM	0	0	0	0	0	2	98

Table II. Percentage of correct classification for SNR =10db

In/out	SNR=10db						
	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK	16QAM
2ASK	98	0	0	0	1	0	1
4ASK	1	97.5	0	0	.5	1	0
2FSK	0	0	98	1	0	1	0
4FSK	0	0	1	99	0	0	0
2PSK	1	0	0	0	98	1	0
4PSK	0	0	0	0	1	98.5	.5
16QAM	1	1	0	0	0	1	97

Table III. Percentage of correct classification for SNR 20db

In/out	SNR=20db						
	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK	16QAM
2ASK	100	0	0	0	0	0	0
4ASK	0	100	0	0	0	0	0
2FSK	0	0	99	1	0	0	0
4FSK	0	0	2	98	0	0	0
2PSK	0	0	0	0	100	0	0
4PSK	0	0	0	0	0	97	3
16QAM	0	0	0	0	0	2	98

Tables I, II, III show the percentage of correct modulation recognition at SNR 0db, 10 db and 20 db respectively. It can be seen that probability of classification is much higher for SNR =20 db, and also the above results demonstrate that our algorithm can achieve high percentage with low SNR for non-constant envelop signals, while it can still achieve the same performance but with higher SNR for constant envelope signals.

V. CONCLUSION

The developed algorithm for classification is suited for number of modulation schemes employed in SDR; the algorithm developed is used to test for various modulated corrupted signals. The simulated results using stochastic features are analyzed. Decision tree classifier based on features is developed to classify the signals. The developed classifier provides a high probability of correct classification in a short observation interval, for a range of signal-to-noise ratio (SNR) and capable to recognize many different modulations in environments with diverse propagation characteristics. Perfect classification is shown at SNR of 20dB. As the SNR decreases, the rate of successful classifi cation slightly decreases. Experimental results indicates that the proposed method can be effectively used to classify M-ary ASK, M-ary PSK and M-ary FSK. Simulated results show that correct modulation identification is possible for varying SNR.

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Mrs. Jaspal bagga B.E(ET&T),M.Tech(Comp. Tech),MIEI,MISTE---The author is presently working as Sr. Associate Professor in Electronics and Telecom deptt of SSCET Bhilai. She is associated with industry institute partnership cell and has teaching experience of 13 years .She more than 20 papers published in journals and proceedings of national /international conferences. Her area of interest includes analog and digital communication and signal processing.

Dr (Mrs) Neeta Tripathi, B.E. (ET&T),M. Tech. (ET&T),Ph. D.(ET&T) MIE(India), MISTE, is presently working as Principal SSITM Bhilai She has Five year Industrial & Nineteen years Teaching Experience. She has published more than 49 Research Papers in International and National Journal and Conferences. She received one best paper award. She has guided 7 M.Tech. Thesis and guiding 3 Ph. D. research scholars. Her area of research: " Speech processing, Image processing, DSP, Mobile computing".