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# Recognition of Digital Modulated Signals based on Statistical Parameters

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*Abstract*— **Automatic Modulation Recognition is considered significant in Communication Intelligence (COMINT) applications such as signal interception for mobile communication, defence, civil authority, and surveillance. It is also the key for threat analysis. Recently many algorithms have been proposed to distinguish digitally modulated signals. In this paper, we present and evaluate some problems related to automatic recognition of digital modulation. First of all, Azzouz and Nandi's algorithm has been discussed. Some new statistical parameters have been applied on that algorithm. Then a new method has been proposed and presented to recognize Orthogonal frequency Division Multiplex (OFDM) signal, in presence of some other digital modulated signal and Additive White Gaussian Noise (AWGN). Finally, many simulations have been carried out and presented for these modulation types, by using statistical approaches.**

## I. Introduction

Automatic modulation recognition can be used in many civil as well as military applications such as electronic warfare, electronic support measure, spectrum surveillance and management, identification of non license transmitters, *etc* [1], [2], [13], [14]. Modulation types are considered as the signal signature in the field of COMmunication INTelligence (COMINT) [2]. When modulation type is identified, an appropriate demodulator can demodulate the signal to recover the information [2]. Therefore, modulation recognition is an indispensable essential step to retrieve the exact transmitted signal.

Intercepted communication signals have a high degree of uncertainty due to unidentified modulation types and noise [18]. Therefore, many modulation classification algorithms have been established based on statistical methods [3], [4]. The features of the intercepted modulated signals, such as carrier frequency, can be derived from the known statistical characteristics of the signal. Higher order statistics has been studied previously in many communication applications [4], [5].

Several modulation recognition approaches have been established in last two decades [7], [8], [9], [10], [18]. Most of the approaches can be divided into two groups: Maximum likelihood approaches and pattern recognition approaches [4], [6]. In maximum likelihood approaches, the test statistics require advance knowledge about the signal, though the decision rules are simple. But for statistical pattern recognition approaches, the decision rules are complicated [6].

So far, There is a very few attempts to recognize OFDM modulation. OFDM is a promising technique for high data rate wireless communications because it can reduce inter symbol interference (ISI) caused by the fading channel [21], [22]. In this paper, firstly, we have compared a pattern recognition approach based on statistical properties for some classic digital modulations including ASK2 (Amplitude Shift Keying 2), ASK4, PSK2 (Phase Shift Keying 2), PSK4, FSK2 (Frequency Shift Keying 2), FSK4, *etc*. To estimate the statistical features of signals, various types of windows and different segment of samples have been taken into consideration. Then for the second part, OFDM signal has been generated in presence of AWGN. Then a new statistical method has been applied to recognize the OFDM signal from the other digitally modulated signals.

## II. Major Digital Modulation Types

In this section, the major modulation types of interest to our project are outlined. At first, Classic modulations as: ASK (Amplitude Shift Keying), PSK (Phase Shift Keying), QAM (Quadrature Amplitude Modulation), FSK (Frequency Shift Keying) has been considered. Then, we discuss OFDM modulation. The properties of each modulation and the mathematical model of the modulated signals have been developed and discussed.

### *A. Classic Digital Modulations: QAM, PSK, ASK and FSK*

For classic type of modulations, linear ones, the modulating signal can be written:

$$y_n = \sum_k C_k\, \Omega(t - kT) \tag{1}$$

where $C_k$ represents the symbol values, $T$ is symbol duration and $\Omega(t)$ is a simple rectangular shaped window of width $T$. We can write the equation of QAM signal as:

$$m_{QAM}(t) = p_n(t)\cos(2\pi f_c t) - q_n(t)\sin(2\pi f_c t) \tag{2}$$

where $m_{QAM}(t)$ is the modulated signal, $p_n(t)$ and $q_n(t)$ are the in phase and quadrature component of the modulated signal respectively and $f_c$ is the carrier frequency. Here,

$$p_n(t) = \sum_k a_k\, \Omega(t - kT) \tag{3}$$

$$q_n(t) = \sum_k b_k\, \Omega(t - kT) \tag{4}$$

$a_k$ and $b_k$ represents the symbol value for $p_n(t)$ and $q_n(t)$ respectively.

Finally QAM can be expressed as:

$$m_{QAM}(t) = \sum_k A_k \cos(2\pi f_c t + \varphi_k) \tag{5}$$

with $$A_k = \sqrt{a_k^2 + b_k^2} \tag{6}$$

and $$\varphi_k = \arctan\left(\frac{b_k}{a_k}\right) \tag{7}$$

In QAM modulations different states are represented by different amplitude or by different phases. In fact, ASK modulations can be considered as QAM ones if the quadrature components are zeros.

$$m_{ASK}(t) = \sum_k a_k \cos(2\pi f_c t + \varphi_c) \tag{8}$$

where, $\varphi_c$ is the initial carrier phase.
Similarly, PSK can be written as:

$$m_{PSK}(t) = \sum_k \cos(2\pi f_c t + \varphi_k) \tag{9}$$

Two types of FSK modulations can be considered, with continuous and non continuous phase. It can be expressed as:

$$m_{FSK}(t) = \cos(2\pi f_c t + \varphi(t)) \tag{10}$$

Here $\varphi(t)$ depends on the integral over time of the modulating signal [2].

*B. OFDM Modulation:*

In an OFDM scheme, a large number of orthogonal, overlapping, narrow band sub-channels or subcarriers, which are transmitted in parallel, divide the available transmission bandwidth [20], [21]. The separation of the subcarriers is theoretically minimal such that there is a very compact spectral utilization [20].

Multicarrier modulation generates two effects: frequency selective fading and intersymbol interference (ISI) [20].In OFDM technique, as the symbol rate is very low, the symbols are much longer than the channel impulse response [21]. It reduces the ISI effect [19], [22]. The addition of an extra guard interval between consecutive OFDM symbols can reduce the effects of ISI even more [20], [21]. An OFDM symbol consists of a sum of subcarriers that are modulated by using PSK or QAM modulation. If $d_i$ are the complex QAM symbols, $N_s$ is the number of subcarriers, $T$ is the symbol duration and $f_c$ is the carrier frequency, then one OFDM symbol starting at $t = ts$ can be written as [20],

$$s(t) = \sum_{i=-\frac{N_S}{2}}^{\frac{N_S}{2}-1} d_{i+\frac{N_S}{2}}\, exp\left(j2\pi \frac{i}{T}(t - t_s)\right) \tag{11}$$

where, $t_s \leq t \leq t_s + T$.

As $f_c$ is the carrier frequency, the minimum frequency can be calculated from the above equation is:

$$f_{min} = f_c - \frac{N_S - 1}{2T} \tag{12}$$

And the maximum frequency is

$$f_{max} = f_c + \frac{N_S - 1}{2T} \tag{13}$$

Thus the central frequency of the OFDM system can be calculated as:

$$f_{central} = \frac{f_{max} + f_{min}}{2} = \frac{f_c + \frac{N_S-1}{2T} + f_c + \frac{N_S-1}{2T}}{2} = f_c \tag{14}$$

Thus the bandwidth can be written as.

$$W_{OFDM} = f_{max} - f_{min} = f_c + \frac{N_S-1}{2T} - \left(f_c - \frac{N_S-1}{2T}\right) = \frac{N_S}{T} \tag{15}$$

In the OFDM representation defined by (11), the real and imaginary parts correspond to the in phase and quadrature parts of the OFDM signal, which have to be multiplied by a cosine or sine of the desired carrier frequency to produce the final OFDM signal [20], [21]. In practice, it is not necessary that all subcarriers have the same amplitudes and phases. They can be modulated by different amplitudes and phases [20].

## III. REVIEW OF MODULATION CLASSIFICATION

Modulation classification approaches can be divided in basically two groups: Maximum Likelihood approaches and Pattern recognition approaches [6]. Some of the pattern recognition method has been implemented in our paper. In this section we reviewed some of the well known methods.

*A. Maximum Likelihood Approach*

In the maximum likelihood approach, the classification is analysed as a multiple hypothesis testing problem, where a hypothesis, $H_i$, is arbitrarily assigned to the $i^{th}$ modulation type of m possible types [6]. The ML classifier is established on the conditional probability density function, (pdf), $p(x|H_i)$, $i = 1, 2, \ldots, m$, where x is the observation. If the observation sequence $X[k]$, $k = 1, 2 \ldots, n$ is independent and identically distributed (i.i.d), the likelihood function (LF), $L(x|H_i)$ , can be expressed [6] as:

$$p(x|H_i) = \prod_{l=1}^{n} p(X[k]|H_i) \triangleq L(x|H_i) \tag{16}$$

The ML classifier reports the $j^{th}$ modulation type based on the observation when $L(x|H_j) > L(x|H_i)$ , $j \neq i$ and $j, i = 1, \ldots, m$.

### B. Pattern Recognition Approach

The general pattern recognition system has basically three parts: sensing, feature extraction and decision procedures [15], [16]. Each measurement, observation, or pattern vector can be written as [6]:

$$x = (X[1], X[2], \ldots\ldots, X[n])^T \tag{17}$$

Here the pattern vector describes a characteristic of a pattern or object. The pattern vector could contain redundant information. We should decrease the dimensionality of the pattern space to simplify the computational effort [17]. The decision procedure may have decision functions, distance functions, or neural networks [15].

## IV. PROBLEM CHARACTERIZATION

Azzouz and Nandi proposed nine features for the recognition of classical analog and digital modulations [1], [6]. The features were derived from the signal's power spectral density, instantaneous amplitude, instantaneous frequency and phase. The features were used to classify analog AM, FM, DSB, USB, LSB, and digital ASK2, ASK4, PSK2, PSK4, FSK2, FSK4 [3]. Usually the standard classification of ASK2 and PSK2 is not possible because in most of the cases their constellations are used as an important parameter and for PSK2 and ASK2, constellations are identical [2], [6].

Azzouz and Nandi used two different approaches to classify modulated signals. First approach is a decision theoretic tree classifier where each feature is tested corresponding to a particular threshold value at a time [2]. The success rate of the tree classifier is based on the order of the features tested in these branches. In the second approach, an artificial neural network has been used. In this section, Azzouz and Nandi's algorithm is briefly described.

### A. Features used for recognizing classic modulation types

Nine features have been used in Azzouz and Nandi's method to identify the original modulated signal. These features are described as follows:

1. The maximum value of the spectral power density for normalized centred instantaneous amplitude, $\gamma_{max}$. It is given by,

$$\gamma_{max} = \frac{1}{N_s}(max|DFT[a_{cn}[i]]|^2) \tag{18}$$

here, DFT is the Discrete Fourier Transform of the RF (Radio Frequency) signal, $N_s$ is the number of samples per segment, $a_{cn}$ is the normalized centred instantaneous amplitude and $i = 1,2,\ldots.,N_s$.

2. The standard deviation of the absolute value of the centred non linear component of the instantaneous phase, $\sigma_{ap}$ is,

$$\sigma_{ap} = \sqrt{\frac{1}{N_s}(\sum \varphi_{NL}^2(i)) - (\frac{1}{N_s}\sum|\varphi_{NL}(i)|)^2} \tag{19}$$

here, $\varphi_{NL}$ is the centred non linear component of instantaneous phase. $N_s$ is the number of samples in $\varphi_{NL}$.

3. The standard deviation of the centred non linear component of the direct instantaneous phase, $\sigma_{dp}$ is,

$$\sigma_{dp} = \sqrt{\frac{1}{N_s}(\sum \varphi_{NL}^2(i)) - (\frac{1}{N_s}\sum \varphi_{NL}(i))^2} \tag{20}$$

4. The spectrum symmetry about the carrier frequency, $P$ is given by,

$$P = \frac{P_L - P_U}{P_L + P_U} \tag{21}$$

It is calculated by the difference of the power in the upper and the lower sidebands normalized by the total power. The lower sideband power is, $P_L = \sum_{i=1}^{f_{cn}}|X_c(i)|^2$ and upper sideband power is, $P_U = \sum_{i=1}^{f_{cn}}|X_c(i + f_{cn} + 1)|^2$. $X_c(i)$ is the Discrete Fourier transform of the RF signal and $f_{cn}$ is the sample number corresponding to the carrier frequency.

5. The standard deviation of the absolute value of the normalized centred instantaneous amplitude, $\sigma_{aa}$ is,

$$\sigma_{aa} = \sqrt{\frac{1}{N_s}(\sum_{i=1}^{N_s}\sum a_{cn}^2(i) - (\frac{1}{N_s}\sum|a_{cn}(i)|)^2} \tag{22}$$

6. The standard deviation of the absolute value of the normalized centred instantaneous frequency, $\sigma_{af}$ is,

$$\sigma_{af} = \sqrt{\frac{1}{N_s}(\sum f_N^2(i)) - (\frac{1}{N_s}[f_N(i)])^2} \tag{23}$$

here, $f_N(i)$ is the normalized centred instantaneous frequency.

7. The standard deviation of the normalized centred instantaneous amplitude, $\sigma_a$ is computed by,

$$\sigma_a = \sqrt{\frac{1}{N_s}(\sum_{i=1}^{N_s}\sum a_{cn}^2(i) - \left(\frac{1}{N_s}\sum_{i=1}^{N_s}|a_{cn}(i)|\right)^2} \tag{24}$$

8. The kurtosis of the normalized centred instantaneous amplitude, $k_a$ is given by,

$$k_a = \frac{E\{a_{cn}^4(i)\}}{\{E\{a_{cn}^2(i)\}\}^2} \tag{25}$$

where, $a_{cn}$ is the normalized-centred instantaneous amplitude.

9. The kurtosis of the normalized centred instantaneous frequency, $k_f$ is given by,

$$k_f = \frac{E\{f_N^4(i)\}}{\{E\{f_N^2(i)\}\}^2} \tag{26}$$

where, $f_N$ is the normalized-centred instantaneous frequency

Statistical parameters depend on number of samples, types of window, width of window *etc.* The impact of these parameters on the overall performance of the algorithm has been considered in the first part of our study.

### B. *New feature proposed for recognizing OFDM*

In this paper, a new feature has been proposed to recognize the OFDM modulation method. We consider, a number of $N_s$ samples of the RF signal $y_r$. The signal is filtered using a FIR (finite Impulse Response) filter. The filtered signal can be written as:

$$y_r[k] = y_{rp}[k] + jy_{rq}[k] \tag{27}$$

where $k = 0,1,2 \ldots\ldots.. Ns - 1$

$$S[w] = DFT(y_r[k]) \tag{28}$$

$$= DFT(y_{rp}[k] + jy_{rq}[k]) \tag{29}$$

$$= real\{S[w]\} + j\ imag\{S[w]\} \tag{30}$$

where, $w = 0,1,2, \ldots\ldots N_s - 1$

and the amplitude of the spectrum is

$$S_a[w] = \sqrt{(real\{S[w]\})^2 + imag\{S[w]\}^2} \tag{31}$$

The key feature which has been chosen for the recognition is

$$X_n = \frac{\max(S_a[w])}{mean\ (S_a[w])} \tag{32}$$

Here, $X_n$ is the key feature for one realization $n$, among $N$ realizations. The mean value of the key feature is

$$X = \frac{1}{N}\sum_{n=1}^{N} X_n \tag{33}$$

## V. CLASSIFICATION OF ASK, PSK AND FSK MODULATION

The digital modulation types produced for simulations are ASK2, ASK4, PSK2, PSK4, FSK2 and FSK4. 1000 samples have been taken for each simulation. The modulating signals have been generated with a relative carrier frequency, $f_c = 1$, and sampling frequency, $f_s = 10$. For simplicity, the symbol duration has been considered $T = 1$ for all the simulations. An Additive White Gaussian Noise (AWGN) has been added to the modulated signal. The signal to noise ratio (SNR) is taken as the ratio of the power of the signal to the power of the noise and it is expressed in decibels.

We have chosen Azzouz's two classification parameters to distinguish the classic modulations stated above. These two parameters are $\gamma_{\max}$ and $\sigma_{af}$.

The first parameter, $\gamma_{\max}$, is the spectral power density of the normalized centred instantaneous amplitude. In Azzouz algorithm, this parameter can be used to divide the modulated signal into two groups.

Our experimental results, as well as many others' results [2] show that $\gamma_{\max}$ is not enough to distinguish the PSK and FSK in lower signal to noise ratio. Therefore, this parameter should be used to distinguish only the ASK signals from others. In this experiment, we have used different windows including Hamming, Gaussian, etc. The maximum power spectral density for different SNR has been taken out using these windows. Fig. 1 and Fig. 2 show $\gamma_{\max}$ for different SNR using Gaussian window and Hamming window respectively.

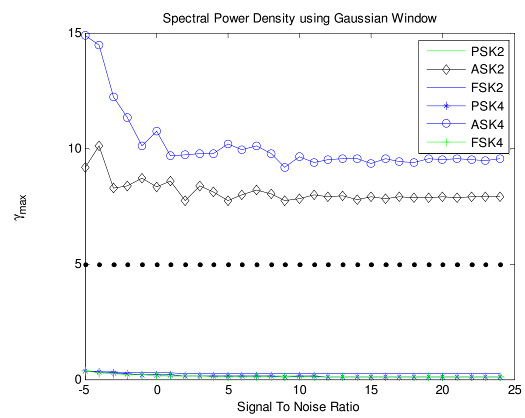


Fig. 1. Maximum Power Spectral Density for different Signal to Noise Ratio using Gaussian window.

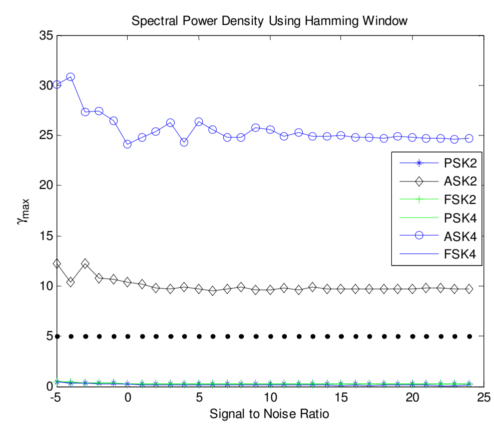


Fig. 2. Maximum Power Spectral Density for different Signal to Noise Ratio using Hamming window.

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The threshold value can be varied to some extent for different windows. In all cases, ASK signals can be separated from PSKs and FSKs even for SNR lower than zero.

Our first study also includes comparison of parameters for different segments of samples. First, 1000 samples were used for each segment. Then 60% overlapping was used. Fig. 3 represents $\gamma_{max}$ for different SNR obtained by overlapped samples. In both cases it has been found that ASK signals can be distinguished from the PSK and FSK signals.

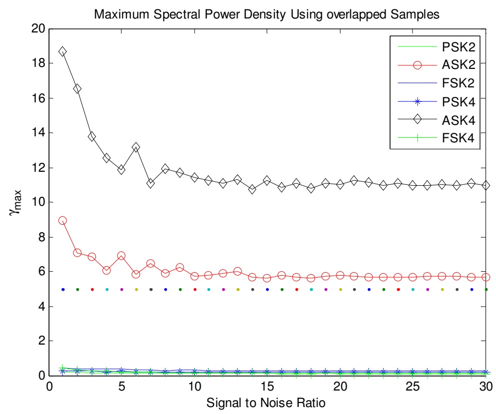


Fig. 3. Maximum Spectral Power Density for different Signal to Noise Ratio using Overlapped Samples.

Then in the next step, PSKs and FSKs have been classified. PSK modulations can be categorized by discontinuous instantaneous phase [2]. Such phase generates a constant instantaneous frequency, but during the time intervals of the phase transition, Dirac impulses appear for the instantaneous frequencies [2]. On the other hand, the instantaneous frequency of FSK can be considered as a sequence of rectangular shaped window [2].This means that PSK and FSK signals have different instantaneous frequency representations. Therefore, we have taken Azouz's parameter, $\sigma_{af}$, which is the standard deviation of normalized centred instantaneous frequency.

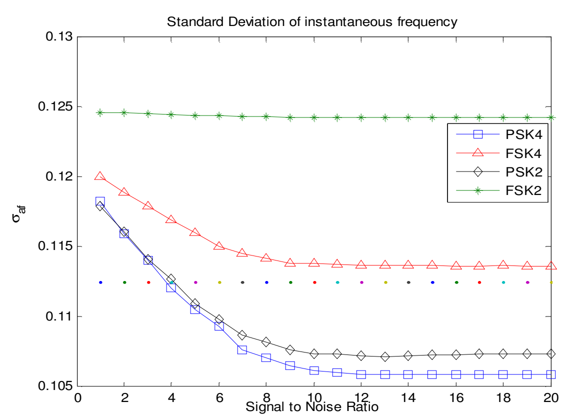


Fig. 4. Standard deviation of normalized centred instantaneous frequency for different Signal to Noise Ratio

It is seen from figure 4, that $\sigma_{af}$ can distinguish between PSK and FSK even in the lower signal to noise ratio.

## VI. CLASSIFICATION OF OFDM MODULATION

Several parameters have been taken into consideration for generating OFDM signal. These parameters are shown in Tab.1.

TABLE I
OFDM PARAMETERS

| OFDM Parameters | Numerical values |
|---|---|
| Number of carriers | 1706 |
| Symbol Duration | 224µs |
| Bandwidth | 7.61 MHz |
| Bit rate | 8Mbps |

OFDM subcarriers are modulated by 4-QAM (Quadrature Amplitude Modulation). The carrier frequency for OFDM subcarriers is 915MHz. An Additive White Gaussian noise was introduced to see the effect of noise on the classification scheme. Two other signals have been generated as well. These are BPSK (Binary Phase Shift Keying) and 4-QAM (Quadrature Amplitude Modulation).The other signals are generated by choosing a carrier frequency of 900 MHz because this is very convenient frequency for mobile communication.

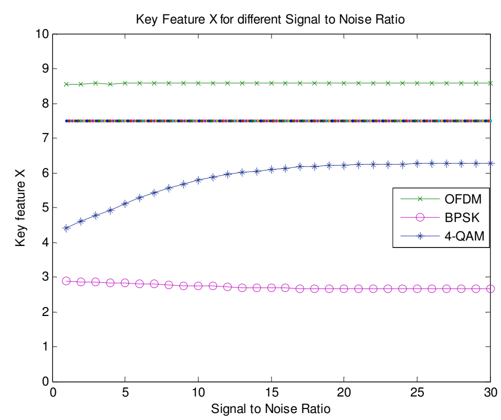


Fig. 5. Mean Value of Key Feature X for different Signal to Noise Ratio

For a particular Signal to Noise Ratio, all signals are generated for 500 times to get values of the key feature $X$. Then the mean value is taken as the final key feature value. Figure 5 shows the key feature $X$ for different Signal to Noise Ratio. It can be shown from this figure that, OFDM signal can be easily separated from the above other two signals i.e. BPSK and 4-QAM.

In our experimental studies, we have found that Azzouz's two parameter can be used to distinguish ASK, PSK and FSK. So, we can say that these two parameters i.e. maximum spectral power density and standard deviation of normalized centred instantaneous frequency are functional to separate classic modulation types. Besides, a new key feature for extracting OFDM has been developed. Simulation result shows that the key feature $X$ is capable to classify OFDM from QAM and BPSK even in the lower signal to noise ratio.

## VII. CONCLUSION

In this paper, a literature review of the previous method for modulation classification has been carried out and one of the most well known approaches has been surveyed with more details. The comparison for modulation classification has been emphasized by using statistical process, different estimations of windows and different number of samples. A new method has been developed to classify OFDM modulation from some other digital modulations in presence of significant amount of noise. Our upcoming works will be focused on developing statistical methods to classify OFDM signal in a more complex environment including delays and mixture of signals.

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