Comparison of Digital Modulation Classification Based on Statistical Approaches

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Abstract— **Modulation classification is considered significant in Communication Intelligence (COMINT) applications such as signal interception for defence, civil authority, and surveillance. It is also 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 the type of modulated signals. First of all, Azzouz and Nandi's algorithm has been compared and discussed. As the work is an initial study, only some classical digital modulations have been considered. Many simulations have been carried out and presented for these modulation types by using statistical approaches. Different segments of samples have been considered. Finally, the results have been compared using different windows like Hamming, Gaussian, Bartlett, *etc.***

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]. 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. 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]. The higher order statistics are more preferable because second order statistics suppress the phase information of the signal [6]. The estimation of high order statistics requires long sample sets. As such, it has a high computational complexity.

Several modulation recognition approaches have been established in last two decades [7], [8], [9], [10]. 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 acquaintance about the signal, though the decision rules are simple. But for statistical pattern recognition approaches, the decision rules are complicated [6].

In this paper, 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 appraisals of windows have been taken into consideration. Moreover, different segments of samples have been chosen and the obtained results have been discussed and compared.

II. DIGITAL MODULATION

In this section, the common depiction of modulation signals has been presented [11], [12]. Let $s(t)$ denotes the received signal. For narrow band signals in simplified transmission channels, $s(t)$ can be written as follow:

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

where, $m(t)$ is considered as the modulated signal and $n(t)$ is an Additive White Gaussian Noise (AWGN). The signal part can be described either in quadrature, polar or complex form. Let $c(t)$ denotes the carrier wave signal. It can be written as:

$$c(t) = Acos(2\pi f_c t + \psi_c) \tag{2}$$

where, f_c is the carrier frequency, A is the carrier amplitude and ψ_c is the phase off-set. The information of modulating signals can be sent out by the carrier wave's phase (PSK), frequency (FSK), amplitude (ASK) or a combination (Quadrature Amplitude Modulation). In general, the modulated signal can be written, using the In phase and Quadrature forms as follow:

$$m(t) = p_n(t)cos(2\pi f_c t) - q_n(t)sin(2\pi f_c t) + n(t) \tag{3}$$

here, $p_n(t)$ and $q_n(t)$ are the in phase and quadrature components of $m(t)$ respectively. By setting up complex envelope notations m_e of the modulated signal, it can be written as:

$$m(t) = Re\{m_e(t)exp(j2\pi f_c t)\} \quad (4)$$

here, j is the complex number. The complex envelope $m_e(t)$ can be written as:

$$m_e(t) = p_n(t) + jq_n(t) \quad (5)$$

From the complex envelope, constellations of that signal can be achieved [2]. Constellations can be used to extract lots of modulated signal features [2]. From the above equation it can be seen that carrier frequency is an important feature which must be extracted to distinguish the modulation schemes. The carrier frequency can be well estimated [16]. In this paper, we assume that the carrier frequency has already been estimated.

III. ALGORITHM EVALUATION

The modulation recognitions include converting the analog Radio Frequency (RF) signal to a digital Intermediate Frequency (IF) signal, extracting modulation features and recognizing modulation types [13]. Some classifiers can directly extract the features from the IF signals. But in most cases, a common estimation is essential to convert the IF signal into In phase and Quadrature components and find out modulation features.

The result of modulation type is obtained by using a confusion matrix, which is a table of statistical values achieved for some particular signal to noise ratios (SNR) [3], [13], [14]. This table provides the value of probability of success corresponding to a list of possible modulation types. The probabilities of success versus SNR curves are different for different modulation types. Probability of success can be a performance measurement only, if the two classifiers are developed under similar assumptions [14]. Therefore elementary comparison among dissimilar algorithms should be studied. The modulation recognition procedure requires feature extraction as well as a decision procedure. The task of the front end is the channel equalization and to produce the correct sampled signal representation, before feeding the measurements to the feature extraction system [6]. The features are considered as the input for the decision procedure and most probable modulation type should be the output [6].

IV. 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:

$$p(x|H_i) = \prod_{l=1}^{n} p(X[k]|H_i) \triangleq L(x|H_i) \quad (6)$$

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]. Each measurement, observation, or pattern vector can be written as:

$$x = (X[1], X[2], \ldots, X[n])^T. \quad (7)$$

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].

V. PROBLEM CHARECTERIZATION

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 these approaches, all features are measured all together which should involve a better performance. In this section, Azzouz and Nandi's algorithm is briefly described and emphasized.

A. *Deviations in instantaneous properties*

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, γ_{max}. It is given by,

$$\gamma_{max} = \frac{1}{N_s}(max|DFT[a_{cn}[i]]|^2) \quad (8)$$

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

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

$$\sigma_{ap} = \sqrt{\frac{1}{N_s}(\sum \varphi_{NL}^2(i)) - (\frac{1}{N_s}\sum|\varphi_{NL}(i)|)^2} \qquad (9)$$

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

3. The standard deviation of the centered non linear component of the direct instantaneous phase, σ_{dp} is,

$$\sigma_{dp} = \sqrt{\frac{1}{N_s}(\sum \varphi_{NL}^2(i)) - (\frac{1}{N_s}\sum \varphi_{NL}(i))^2} \qquad (10)$$

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

$$P = \frac{P_L - P_U}{P_L + P_U} \qquad (11)$$

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 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, σ_{aa} is,

$$\sigma_{aa} = \sqrt{\frac{1}{N_s}(\sum_{i=1}^{N_s}\sum a_{cn}^2(i) - (\frac{1}{N_s}\sum|a_{cn}(i)|)^2} \qquad (12)$$

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

$$\sigma_{af} = \sqrt{\frac{1}{N_s}(\sum f_N^2(i)) - (\frac{1}{N_s}\lceil f_N(i)\rceil)^2} \qquad (13)$$

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

7. The standard deviation of the normalized centred instantaneous amplitude, σ_a is computed by,

$$\sigma_a = \sqrt{\frac{1}{N_s}(\sum_{i=1}^{N_s}\sum a_{cn}^2(i) - \left(\frac{1}{N_s}\sum_{i=1}^{N_s}|a_{cn}(i)|\right)^2} \qquad (14)$$

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

$$k_a = \frac{E\{a_{cn}^4(i)\}}{\{E\{a_{cn}^2(i)\}\}^2} \qquad (15)$$

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

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

$$k_f = \frac{E\{f_N^4(i)\}}{\{E\{f_N^2(i)\}\}^2} \qquad (16)$$

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 our study.

VI. CLASSIFICATION

Different modulated signals have been generated to study some of the method presented in this paper. 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.

In this section, a Modulation classification scheme for ASK2, ASK4, PSK2, PSK4, FSK2 and FSK4 has been compared. We have chosen Azzouz's two classification parameters to distinguish the classic modulations stated above. These two parameters are γ_{max} and σ_{af}.

The first parameter, γ_{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 γ_{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, Bartlett, Gaussian, *etc*. The maximum power spectral density for different SNR has been taken out using these windows. Fig. 1 and Fig. 2 show γ_{max} for different

SNR using Gaussian window and Bartlett window respectively.

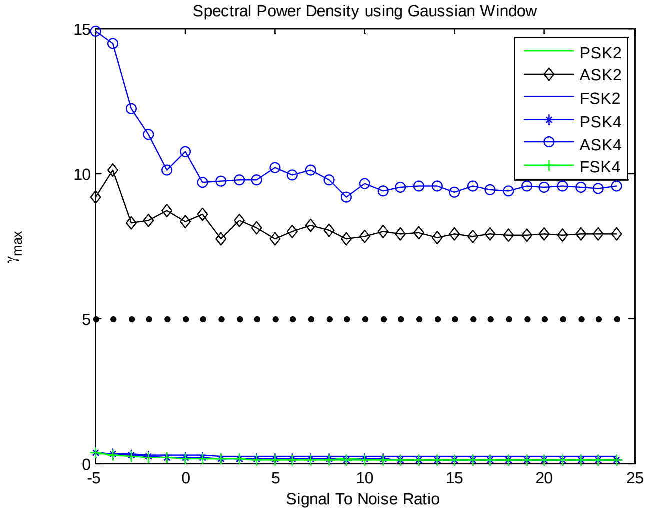

Fig. 1. Maximum Spectral Power Density for different Signal to Noise Ratio using Gaussian window.

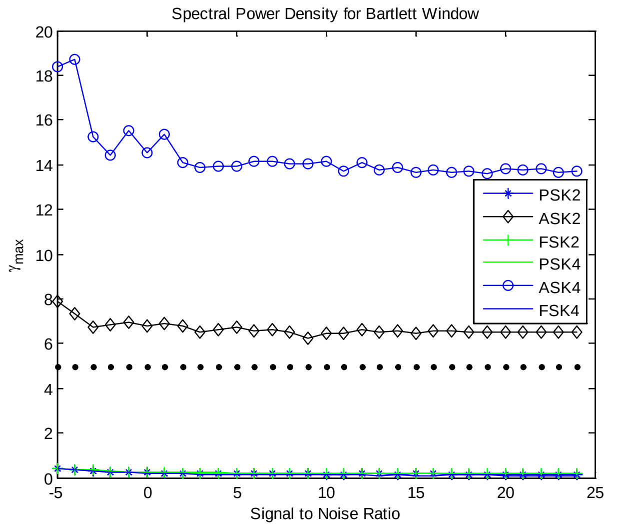

Fig. 2. Maximum Spectral Power Density for different Signal to Noise Ratio using Bartlett window

Fig. 3 represents γ_{max} for different SNR obtained by Hamming window. The threshold value can be varied to some extent for different windows. In all cases, we can separate ASK signals from PSKs and FSKs even for SNR lower than zero.

We have also compared the parameter for different segments of samples. First, we used 1000 samples for each segment. Then we used overlapping, i.e. for the first segment we took first 1000 samples then for the second segment we took 700th to 1700th samples and so on. Fig. 4 represents γ_{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.

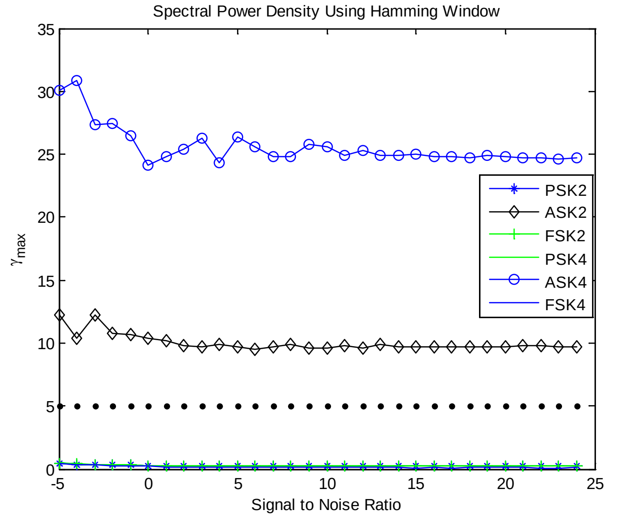

Fig. 3. Maximum Spectral Power Density for different Signal to Noise Ratio using Hamming window

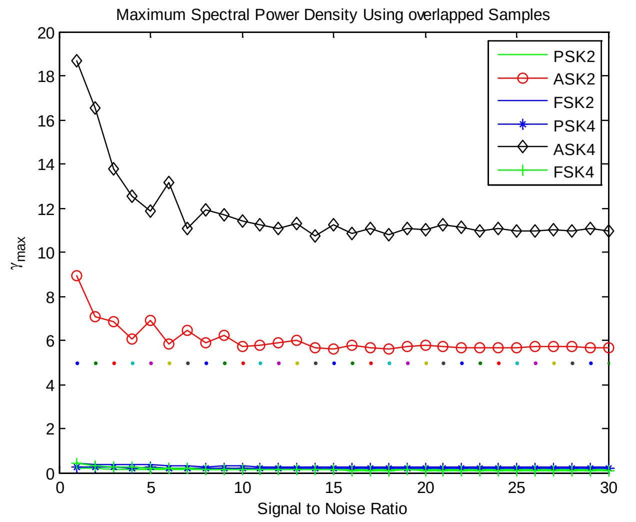

Fig. 4. Maximum Spectral Power Density for different Signal to Noise Ratio using Overlapped Samples.

However, by using the overlapped samples we have achieved almost the same result, as the non overlapped samples.

Now the second step is to distinguish between PSK and FSK signals. 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, σ_{af}, which is the standard deviation of normalized centred instantaneous frequency.

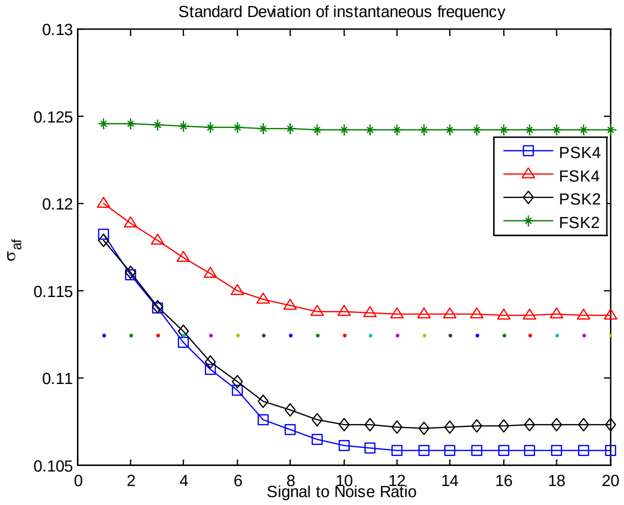

Fig. 5. Standard deviation of normalized centred instantaneous frequency for different Signal to Noise Ratio

First the transmitted signal is passed through by an AWGN channel. Then the received signal's instantaneous frequency has been taken. Finally the standard deviation of the instantaneous frequency has been calculated and it has been plotted with respect to different SNR. From our experiment it has been shown, that σ_{af} can distinguish between PSK and FSK even in the lower signal to noise ratio. For lower SNR, an adaptive threshold should be taken.

In our experimental studies, we have found that Azzouz's two parameter can be used to distinguish ASK, PSK and FSK. For separating ASK from other signals i.e. PSK and FSK, the classification works even when signal to noise ratio is 0. Finally, we can persist 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.

VII. CONCLUSION

In this paper, several features of modulation classification have been studied. The relevant characteristics of communication signals and statistical tools have been presented. A literature review of the previous method was carried out and one of the most well known approaches has been surveyed with more details. Also, the comparison for modulation classification has been emphasized by using statistical process, different estimations of windows and different number of samples. However, only some classic modulations have been considered. Our upcoming works will be focused on the classification of the more complex modulation schemes such as OFDM, TCM *etc*.

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