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A Novel Technique for Automatic Modulation Classification and Time-Frequency Analysis of Digitally Modulated Signals

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Abstract

Automatic classification of analog and digital modulation signals plays an important role in communication application such as an intelligent demodulator, interference identification and monitoring. 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. This paper presents a new approach for automatic modulation classification for digitally modulated signals. This method utilizes a signal representation known as the modulation model. The modulation model provides a signal representation that is convenient for subsequent analysis, such as estimating modulation parameters. The modulation parameters to be estimated are the carrier frequency, modulation type, and bit rate. The modulation model is formed via autoregressive spectrum modeling. The modulation model uses the instantaneous frequency and bandwidth parameters as obtained from the roots of the autoregressive polynomial. This method is also classifies accurately under low carrier to noise ratio (CNR). This paper is also presents an improved version of S-Transform for time frequency analysis of different digitally modulated signals to observe variations of amplitude, frequency and phase.

Keywords: *Instantaneous Frequency, Bandwidth, Kurtosis, Time-Frequency Analysis*

1. Introduction

The interest in modulation classification has been growing since the late eighties up to date. Previous modulation classification systems have relied on manual identification of signal parameters. Due to the increased activity in the frequency spectrum, manual identification is becoming less practical and automated techniques for modulation classification are becoming desired. Automatic modulation classification (AMC) is an intermediate step between signal detection and demodulation, and plays a key role in various civilian and military applications such as signal confirmation, interference identification, monitoring, spectrum management and surveillance. Implementation of advanced information services and systems for military applications in a crowded electromagnetic spectrum is a challenging task for communication engineers. Friendly signals should be securely transmitted and received, whereas hostile signals must be located, identified and jammed. The spectrum of these signals may range from high frequency (HF) to millimeter frequency band, and their format can vary from simple narrowband modulations to wideband schemes. Under such conditions, advanced techniques are required for real-time signal interception and processing, which are vital for decisions involving electronic warfare operations and other tactical actions. Furthermore, blind recognition of the modulation format of the received signal is an important problem in commercial systems, especially in software defined radio (SDR), which copes with the variety of communication systems. Usually, supplementary information is transmitted to reconfigure the SDR system. Blind techniques can be used with an intelligent receiver, yielding an increase in the transmission efficiency by reducing the overhead. Such applications have emerged the need for flexible intelligent communication systems, where the automatic recognition of the modulation of a detected signal is a major task.

A simplified block diagram of the system model is shown in Figure 1. The design of a modulation classifier essentially involves two steps: signal preprocessing and proper selection of the classification algorithm. Preprocessing tasks may include, but not limited to perform some or all of, noise reduction, estimation of carrier frequency, symbol period, and signal power, equalization, etc. Depending on the classification algorithm chosen in the second step, preprocessing tasks with different levels of accuracy are required; some classification methods require precise estimates, whereas others are less sensitive to the unknown parameters.

Signal interception consists of signal detection followed by estimation of modulation parameters and finally demodulation. A signal of interest (SOI) is generally detected by a spectrum receiver. The frequency band of interest is then further processed to estimate modulation parameters. The modulation parameters considered are the carrier frequency, modulation type and bit rate. The modulation types that are considered are Continuous Wave (CW), Phase Shift Keying (PSK), Frequency Shift Keying (FSK), Amplitude Shift Keying (ASK) and Quadrature Amplitude Modulation (QAM).

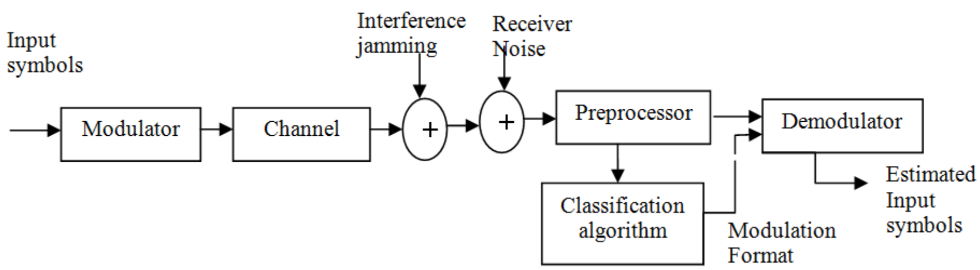

Figure 1. Simplified block diagram

Several methods have been suggested for estimating modulation parameters, *i.e.*, by using statistical moments [2], zero crossing rates [3], and analytical signal representations [4]. This paper uses a modulation model as formed by autoregressive spectrum modeling. The new model allows for an efficient, robust method of estimating modulation parameters.

This paper presents a new method for modulation classification. The following section provides the formulation, which includes a description of the modulation model in addition to its formulation via autoregressive spectrum modeling. The classification algorithm is then described and a flowchart is provided. This section is followed by computer simulation results and the conclusion of this paper.

2. Mathematical Model

This paper utilizes a signal representation known as the modulation model to aid in estimating modulation parameters. The modulation model represents a multicomponent signal as a sum of single component signals in terms of their individual amplitude modulation (AM) and phase modulation (PM) [5]

$$y(t) = \sum_{i=1}^{n} A_i(t)\cos(\omega_i t + \phi_i(t)) \tag{1}$$

where *i* denotes the component, $A_i(t)$ is the signal envelope (AM), and $\Phi_i(t)$ is the instantaneous phase (PM). This parameter only considers constant envelope signals, so the $A_i(t)$ term will be replaced by *A* in subsequent analysis. Since the frequency band of interest is assumed to contain one SOI, the parameter *n* in equation (1) will be equal to one.

The signals that are considered are CW, Binary Phase Shift Keying (BPSK), Quadrature Phase Shift Keying (QPSK), Frequency Shift Keying (FSK), Amplitude Shift Keying (ASK) and Quadrature Amplitude Modulation (QAM). The modulation model for a discrete signal within these categories will appear as

$$y(k) = A\cos(\omega_c k + \phi(k) + \theta) \tag{2}$$

where ω_c is the carrier frequency, θ is the phase at the receiver and

$$\phi(k) = \begin{cases} 0 -------> CW \\ 0, \pi -----> BPSK \\ 0, \pm\frac{\pi}{2}, \pi ---> QPSK \\ \pm\omega_d k ----> BFSK \\ \pm\frac{\omega_d}{2}k, \pm\omega_d k --> QFSK \end{cases} \tag{3}$$

In the above equation, the ω_d represents the frequency deviation for the FSK modulation type.

The modulation model considered here is formed by estimating the instantaneous frequency of the desired signal, which is computed using autoregressive spectrum analysis. Autoregressive spectrum estimation is an alternative to Fourier analysis for obtaining the frequency spectrum of a signal. The method used here for autoregressive spectrum analysis consists of estimating the autocorrelation coefficients followed by an inversion of the autocorrelation matrix. Given an input signal:

$$x(k) = y(k) + n(k) \tag{4}$$

Autoregressive spectrum modeling can be accomplished by solving the following system of equations:

$$\begin{pmatrix} R_{xx(0)} & R_{xx(1)} & \dots & R_{xx(N-1)} \\ R_{xx(1)} & R_{xx(0)} & \dots & R_{xx(N-2)} \\ . & . & & . \\ R_{xx(N-1)} & R_{xx(N-2)} & \dots & R_{xx(0)} \end{pmatrix} \begin{pmatrix} a_1 \\ a_2 \\ . \\ a_n \end{pmatrix} = \begin{pmatrix} R_{xx(1)} \\ R_{xx(2)} \\ . \\ R_{xx(N)} \end{pmatrix} \tag{5}$$

where the autocorrelation estimates $R_{xx(k)}$ are found as:

$$\hat{R}_{xx}(k) = \sum_{n=0}^{M} x(n)x(n+k) \tag{6}$$

The M in the equation (6) represents the number of samples in the analysis frame. In equation (5), the a vector represents the coefficients for the polynomial that best fits the frequency spectrum. The Z-domain expression for this polynomial is:

$$1 - a_1 Z^{-1} - a_2 Z^{-2} - .... - a_N Z^{-N}$$

The roots of this polynomial are related to the spectral peaks and their corresponding bandwidths. This relation is illustrated in Figure 2.

In Figure 2, the angle and magnitude terms, θ_i and M_i respectively, correspond to the frequency and bandwidth for the pole Z_i. The exact result can be obtained from the following equations:

$$F_i = (F_s / 2\pi).\theta_i = (F_s / 2\pi) \tan^{-1}[\mathrm{Im}(Z_i) / \mathrm{Re}(Z_i)] \qquad (7)$$

The quantity F_i provides measure for the Average frequency within the analysis frame. At this point, if the signal is classified as (PSK, CW) sub class, to classify whether the signal is PSK or CW, 'Standard Deviation over Instantaneous frequency' of the signal is used. Because, in case of PSK, a phase change in time domain corresponds to sudden change of frequency in frequency domain. Where as in CW signal there is no phase change as well as frequency change. Therefore 'Standard Deviation over Instantaneous frequency' of PSK is slightly higher than for CW signal.

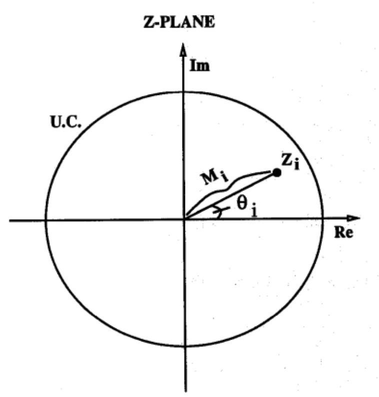

Figure 2. Pole–Frequency relation

Hence, by putting a threshold, incoming signal can be classified as PSK or CW. If the signal is classified as PSK, then it should be further classified as BPSK or QPSK. Higher order statistics are used to classify whether the signal is BPSK or QPSK.

3. Classification Algorithm

3.1 Basic Steps:

The algorithm for performing modulation classification is given by the following steps.

1. The unknown modulated signal's Instantaneous parameters such as Instantaneous frequency and bandwidth are measured using appropriate transformations (autoregressive spectrum modeling).

2. In the first step of classification, kurtosis value is calculated on a given set of samples (typically 4096 samples will be taken for analysis). The kurtosis value will be proportional to amount of amplitude variations.
3. Hence the kurtosis value will be more for amplitude modulated signals and less for frequency and phase modulated signals. So based on a specific threshold value, the signal will be classified as either amplitude modulated (ASK, QAM) or angle modulated (PSK, FSK).
4. If the signal is angle modulated type, then the standard deviation among the instantaneous frequency array is calculated and compared with threshold value to decide whether the signal is PSK or FSK.
5. Since FSK signals will have more abrupt frequency variations when compared to PSK signals, if the standard deviation is above threshold it is classified as FSK type otherwise it is PSK type.
6. If the signal is PSK type, then to find whether it is BPSK or QPSK, frequency domain techniques will be used.
7. The instantaneous amplitude of the signal is squared and for the resulting values, FFT (Fast Fourier Transform) is calculated.
8. If the FFT consists of only a narrow peak, then it is a BPSK signal. If the FFT comes in bell shaped wide curve with multiple peaks then it will be classified as QPSK.
9. Incase if the signal is classified as amplitude modulated type (in step 3), then further thresholds are applied on kurtosis value and standard deviation to classify either as ASK or QAM. The kurtosis value will be higher for ASK signals when compared to QAM signals.

3.2 Higher order statistics

3.2.1 Kurtosis: In probability theory and statistics, kurtosis is a measure of the "peakedness" of the probability distribution of a real-valued random variable. Higher kurtosis means more of the variance is due to infrequent extreme deviations, as opposed to frequent modestly-sized deviations.

The fourth standardized moment is defined as μ_4 / σ^4, where μ_4 is the fourth moment about the mean and σ is the standard deviation. This is sometimes used as the definition of kurtosis in older works, but is not the definition used here. Kurtosis is more commonly defined as the fourth cumulant divided by the square of the variance of the probability distribution,

$$\gamma_2 = \frac{k_4}{k_2^2} = \frac{\mu_4}{\sigma^4} - 3$$

which is known as "excess kurtosis". The "minus 3" at the end of this formula is often explained as a correction to make the kurtosis of the normal distribution equal to zero.

3.2.2 Standard deviation: In probability and statistics, the standard deviation of a probability distribution, random variable, or population or multi set of values is a measure of the spread of its values. It is defined as the square root of the variance. The standard deviation is the root mean square (RMS) deviation of values from their arithmetic mean. For example, in the population {4, 8}, the mean is 6 and the standard deviation is 2. This may be written: {4, 8} ≈ 6±2. In this case 100% of the values in the population are at one standard deviation of the mean.

The standard deviation of a random variable X is defined as:

$$\sigma = \sqrt{E((X - E(X))^2)} = \sqrt{E(X^2) - (E(X))^2}$$

where E(X) is the expected value of X.

3.3 Flow chart for modulation classification

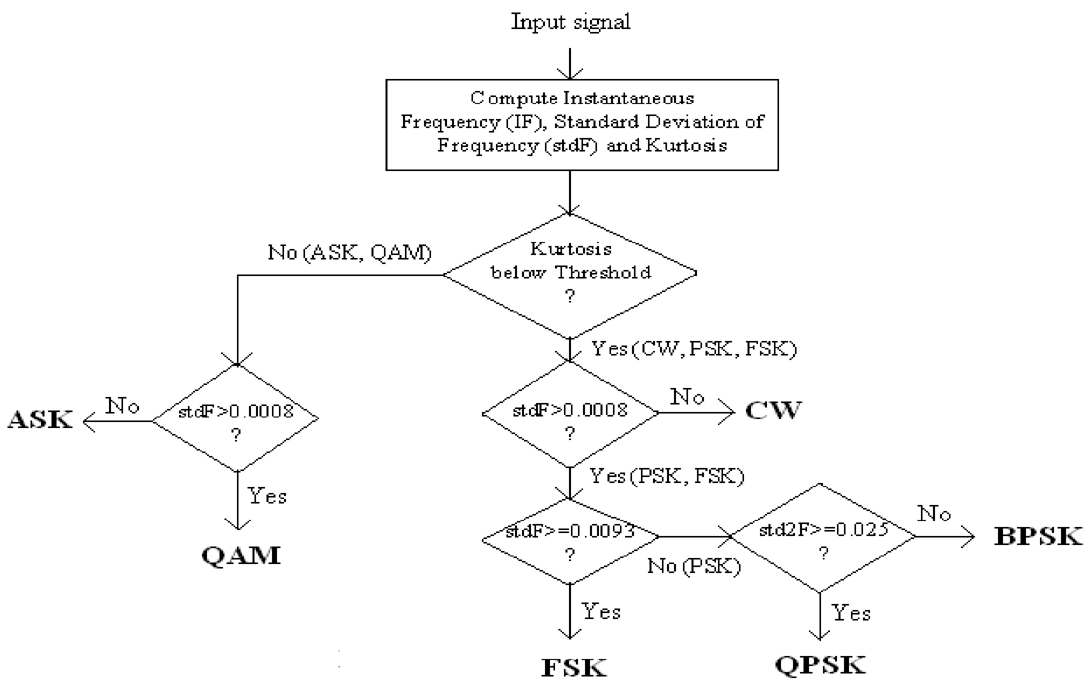

Figure 3. Flow chart for modulation classification

3.4 Classification between (ASK, QAM) / (PSK, FSK, CW) classes

Kurtosis is a measure of how outlier-prone a distribution is. The kurtosis of the normal distribution is 3. Distributions that are more outlier-prone than the normal distribution have kurtosis greater than 3; distributions that are less outlier-prone have kurtosis less than 3. The kurtosis of a distribution is defined as

$$\text{Kurtosis of a given signal element} = \frac{E(X-\mu)^4}{\sigma^4}$$

Where µ is the mean of x, **Σ** is the standard deviation of x, and E(t) represents the expected value of the quantity t. Therefore, as ASK and QAM signals have amplitude differences in their envelopes the value of Kurtosis will be more than for PSK,FSK,CW class of signals where the envelope is constant. Hence, by putting a suitable threshold the incoming unknown signal will be classified into (ASK, QAM) / (PSK, FSK, CW) classes.

If the incoming unknown signal is classified into (PSK, FSK, CW) class, it should be further classified into PSK or FSK or CW.

3.5 Classification between PSK, FSK, CW

The statistical parameter used to classify these modulations is Standard Deviation over Instantaneous Frequency. In FSK, the frequency of modulated signal will change continuously between Mark frequency and Space frequency depending upon the data randomness. Therefore, the instantaneous frequency of FSK will vary continuously. And, hence 'Standard Deviation over Instantaneous frequency' of FSK is more compared to PSK, CW signals where there won't be any frequency change in the signal.

By putting a suitable threshold, incoming signal classified as FSK / PSK, CW sub classes.

3.6 Classification between BPSK/QPSK

Higher order statistics means raising the signal to second power, fourth power, eighth power etc. If the incoming signal is BPSK, raising the signal to second power yields CW signal i.e., modulation of the signal is removed. Because BPSK has only one phase difference which is 180 degrees. After squaring BPSK signal, 180 degree phase difference will become 0 degree phase difference. Therefore, signal lost phase information and became a CW signal. But, if the unknown incoming signal is QPSK, raising the signal to second power does not yield a CW signal. Because, QPSK has 3 phase differences called 90, 180, 270 degrees. Raising the QPSK signal to second power doesn't cause total loss of phase information. It still contains some phase information. Therefore spectrum of squared BPSK will contain only one peak at 2fc frequency. Where f_c is frequency of carrier. But spectrum of squared QPSK will look like a bell shaped one. Hence, variance over spectral data of squared BPSK is far less compared to variance over spectral data of squared QPSK. By putting a suitable threshold over variance of squared signal's spectral data, unknown signal will be classified as BPSK or QPSK.

3.7 Classification between ASK and QAM:

QAM signal will contain both phase and amplitude changes during symbol transition. But ASK will contain only amplitude changes. Therefore Instantaneous frequency of QAM is higher compared to instantaneous frequency of ASK. Consequently Standard Deviation over Instantaneous frequency will be higher for QAM than for ASK. Hence, by putting a threshold over Instantaneous frequency, incoming signal can be classified as ASK or QAM.

4. Improved S-Transform

The ST of a time series $x(t)$ is defined as [1]:

$$s(t, f) = \int_{-\infty}^{\infty} x(\tau) w(t-\tau, f) e^{-2i\pi f\tau} d\tau \tag{8}$$

$$= \int_{-\infty}^{\infty} x(\tau) \frac{1}{\sigma(f)\sqrt{2\pi}} e^{\frac{-(t-\tau)^2}{2\sigma(f)^2}} e^{-2i\pi f\tau} d\tau$$

The standard deviation σ (f) of the window w of the standard S-transform in equation (8) is

$$\sigma(f) = 1/|f| \tag{9}$$

For the modified Gaussian window, we have chosen the standard deviation $\sigma(f)$ to be

$$\sigma(f) = k/(a + b/\sqrt{f}) \tag{10}$$

Where a, b are positive constants, f = signal fundamental frequency and $k \le \sqrt{a^2 + b^2}$. In equation (8), the usually chosen window w is the Gaussian one. Thus, the spread of the original Gaussian function is being varied with frequency to generate the new modified Gaussian window as

$$w(t, f) = \frac{a + b\sqrt{|f|}}{k\sqrt{2\pi}} e^{-\frac{(a+b\sqrt{f})^2 t^2}{2k^2}}, k > 0 \tag{11}$$

In which *f* is the frequency, *t* and τ the time variables and *k*, *b* are scaling factors that control the number of oscillations in the window; a is a constant. When *k* is increased, the window broadens in the time domain and hence frequency resolution is increased in the frequency domain. Again by setting *b=0* and *k=1* we can obtain the Short -Time Fourier Transform explicitly. Thus, an alternative representation for the Generalized S-transform with modified Gaussian window is

$$S(\tau, f) = \int_{-\infty}^{\infty} X(\alpha + f) e^{(-2\pi^2\alpha^2K^2)/(a+b\sqrt{|f|})^2} e^{2i\pi\alpha\tau} d\alpha \tag{12}$$

The discrete version of the S-Transform of a signal is obtained as

$$S[j, n] = \sum_{m=0}^{N-1} X[m+n] e^{(-2\pi^2 m^2 K^2/(a+b\sqrt{|f|})^2)} e^{i\frac{2\pi mj}{N}} \tag{13}$$

5. Simulation Results

The algorithms outlined in the previous sections were tested with MATLAB software. The simulation consisted of a carrier frequency of 25 KHz, whose bit rate or symbol rate is 5 KHz, received through AWGN channel of SNR 15db.The sampling rate was 125 KHz. The time frequency contours using modified S-transform are shown in Figures 4 to 9. Modified S-transform provides excellent detection, visual localization of variations in the modulated signals, *i.e.*, amplitude, frequency and phase.

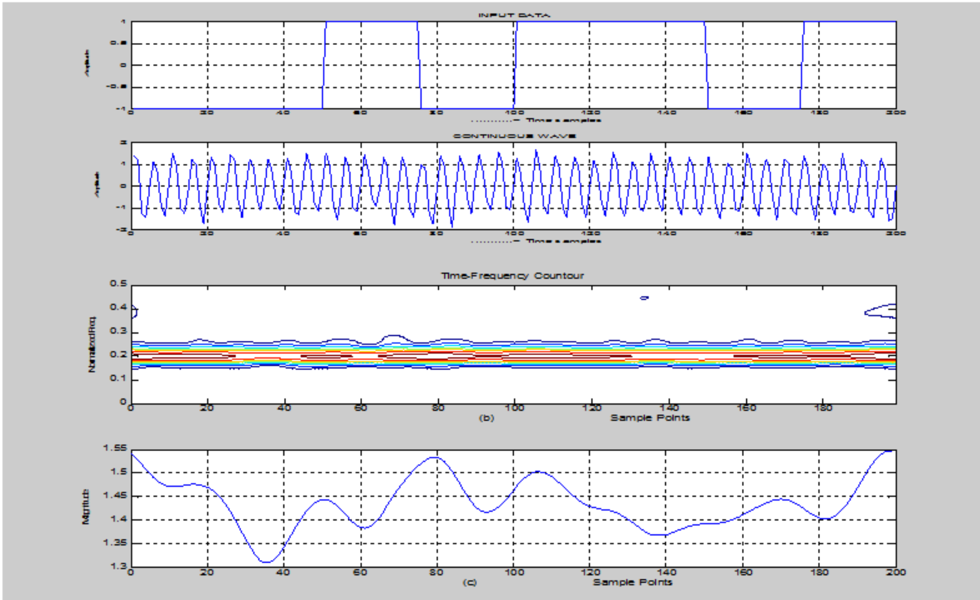

Figure 4. Continuous Signal (no modulation)

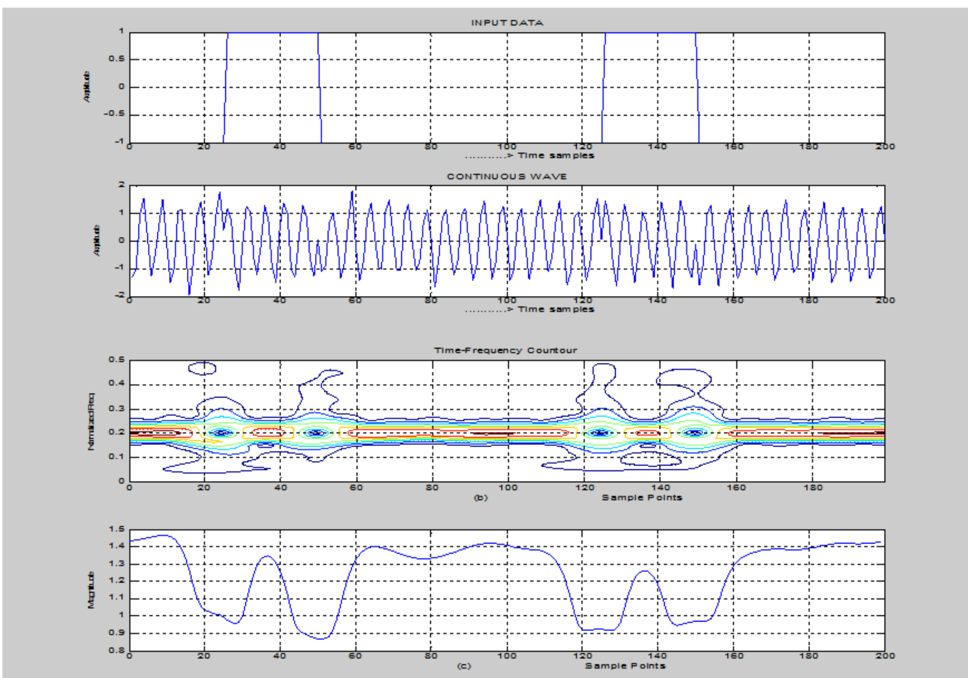

Figure 5. BPSK modulated signal

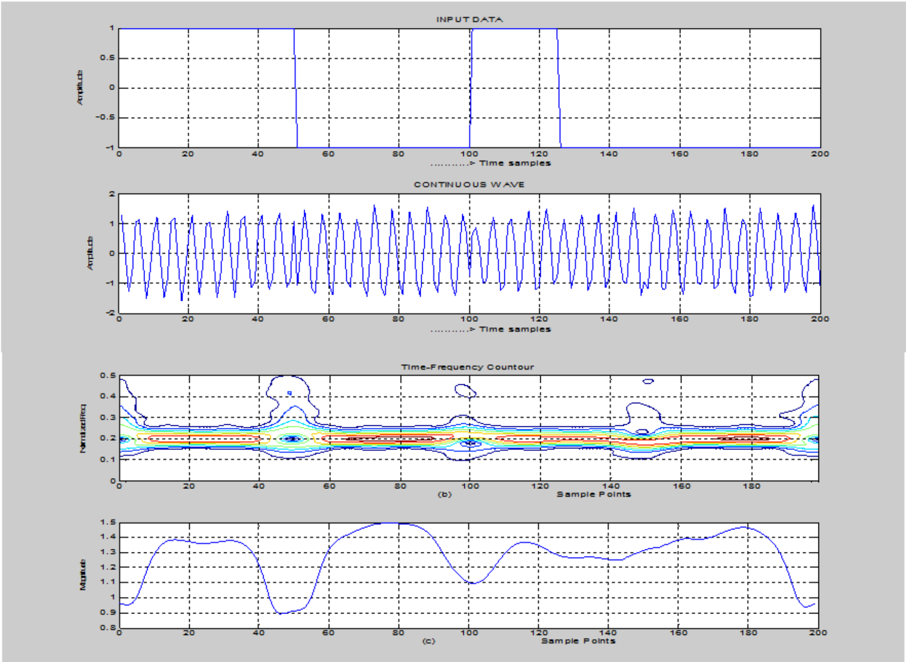

Figure 6. QPSK modulated signal

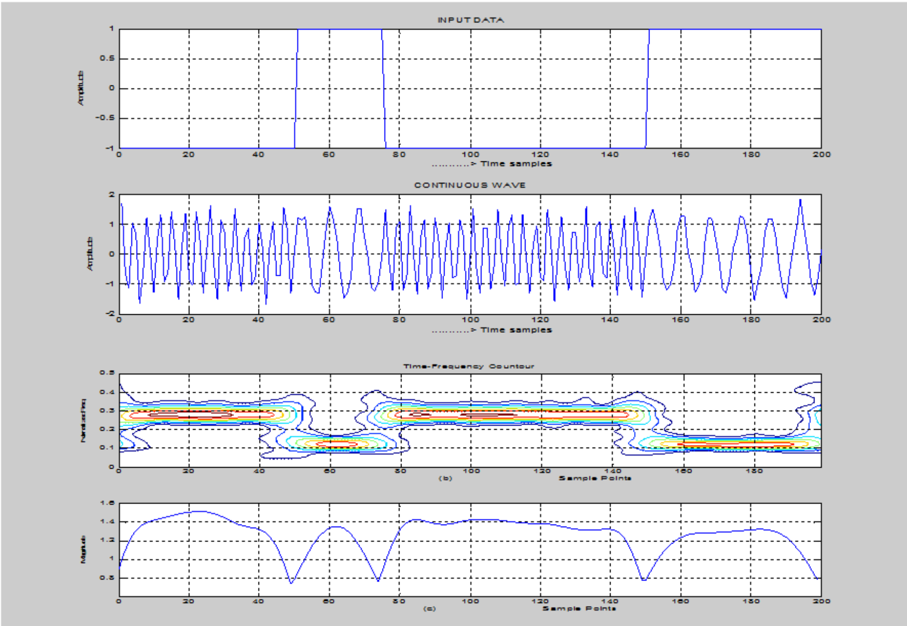

Figure 7. FSK modulated signal

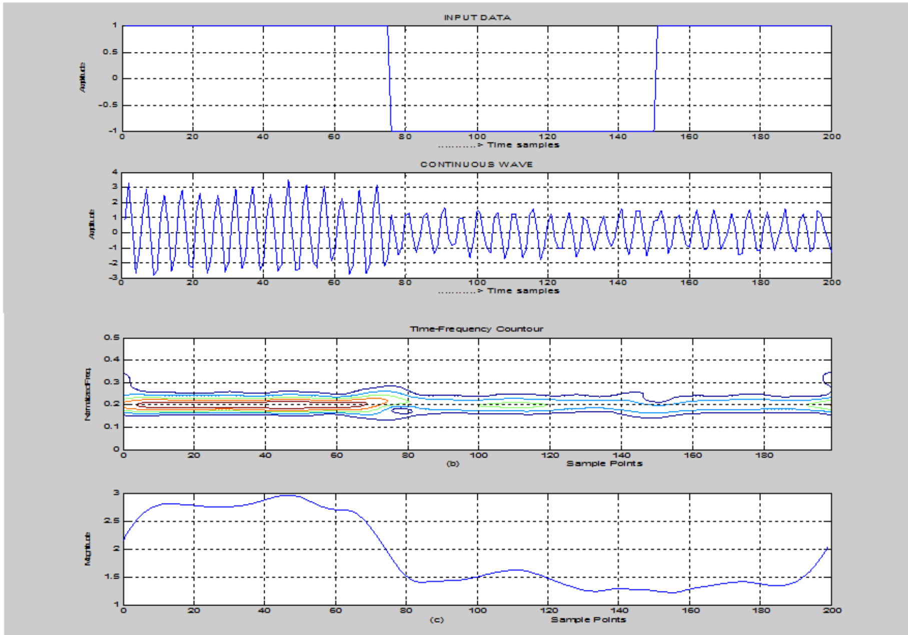

Figure 8. QAM modulated signal

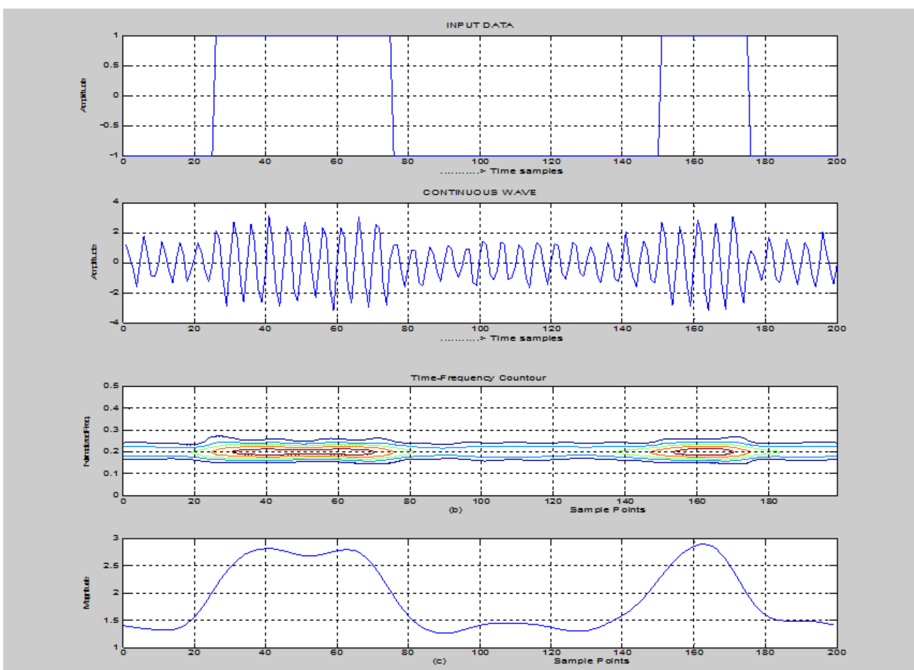

Figure 9. ASK modulated signal

Figures 4-9 show the time-frequency contours of different digitally modulated signals with modified S-transform, and these contours clearly show the nature of modulation is presence. For example Figure 5. (a) represents the input un-modulated digital signal, (b) shows the BPSK modulated signal, (c) represents the normalized time-frequency contour of the BPSK modulated signal. In this we can observe that there is no change in the frequency but at where the phase of the carrier is changed, it tracks that location and by visually shows which type of modulation is present. (d) represents the magnitude-time spectrum obtained by searching rows of ST matrix. Figures 6-9 (a)-(d) show similar plots as in Figures 4 and 5 obtained from ST analysis. Instantaneous frequency and standard deviation of different digital modulation techniques are tabulated is shown in Table 1. These parameters are used to classify different digital modulation techniques.

Table 1. Modulation parameters of different Modulation techniques

S.NO.	Modulation Technique	Instantaneous Frequency(10^4)	Standard Deviation
1	CW	2.79	0.00057
2	BPSK	2.78	0.00180
3	QPSK	2.80	0.00250
4	FSK	2.62	0.08950
5	ASK	2.792	0.00074
6	QAM	2.791	0.00290

6. Conclusion

A new method has been presented for modulation classification of digitally modulated signals. This method uses a modulation model representation of a signal to provide a convenient from for subsequent analysis. The modulation model is formed by estimating the instantaneous frequency and bandwidth using autoregressive spectrum analysis. The new method performed extremely well for input CNRs as low as 15 dB. The S- transform with modified Gaussian window is used in this paper as a powerful analysis tool for detection, visual localization of variations in the digitally modulated non-stationary signal waveforms.

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