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CONSTELLATION SHAPE AS A ROBUST SIGNATURE FOR DIGITAL MOULATION RECOGNITION

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Abstract

Modulation recognition plays a key role in analysis of the intercepted signals by electronic warfare receivers. A hybrid approach for modulation recognition is introducd. This approach consists of two main classification and decision algorithms. The first is a pattern recognition algorithm for reconstruction of the constellation shape as a stable modulation signature of the intercepted signal. The second is a threshold detection logic algorithm for identification of the modulation type of the intercepted signal. These two algorithms are connected through a feature extraction procedure .The complex envelope, which represents both the in phase and quadrature phase components of the received signal after carrier estimation [1,2,11] is utilized as the input of the pattern recognition algorithm. The proposed algorithm shows a robust behavior for identification of single tone digital modulated signals for a relatively low signal to noise ratio (SNR) compared with the ordinary modulation recognition algorithms. Experimental results are shown for various modulation standards including M-ASK, M-PSK, and M-QAM only for M= 8 or 16, received through an AWGN channel and in the presence of carrier recovery errors.

1- Introduction

Vector space representation of digitally modulated signals provides a graphical insight into the underlying signal structure. Constellation representation is obtained by projecting the signal onto an orthogonal vector space the dimensionality of which is determined by the specific modulation type. Two dimension constellations are by far the most common ones with sizes vary from a two point BPSK to the 768 point QAM modulated signals and beyond.

The approach presented in this paper differs from the existing modulation recognition approaches in one fundamental way; Constellation shape, not the signal, is considered as the data to be processed. The premise of the approach is the following: If a modulated signal can be uniquely characterized

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by its constellation it should also be identifiable by the recovered constellation at the receiver. The recovered constellation is of course distorted in a variety of ways depending on the specific receiver structure as well as channel random noise, which disturbs the constellation vertices. Loss of phase lock in a coherent receiver causes a fixed rotation or slowly spinning of the reconstructed constellation vertices. Errors in carrier frequency tracking cause a local spin of individual constellation points. However, the reconstructed constellation built from the received signal will most likely be similar to the original shape .We demonstrate that constellation shape as a global signature, provides a robust, stable and broad means of modulation classification.

Early on, it was recognized that modulation classification is, first and foremost, a classification problem well suited to pattern recognition algorithms [1-4]. The researchers used 8^{th} order moments and normalized matrices to create graphs of signals in terms of moments versus SNR. Modulation types could easily be distinguished at SNRs where the moments had zero slope. However, below some threshold SNR the moments became unstable and the modulation types were not easily determined for BPSK and QPSK the threshold SNR was about 9 dB [3]. In [14], the pattern recognition algorithm used a likelihood function to decide the correct modulation type such that, its reconstructed constellation shape has been more rationally matched to one of reference constellation shapes for different modulation types. Thus, this algorithm needs a training period to know the number of signal states before matching its constellation shape to any modulation type that has this number. Moreover, this classifier operates at 10dB SNR. The current state of the art in modulation classification is the decision theoretic approach using appropriate likelihood functional or approximations [5-10]. The decision theoretic approach depends on extracting some features from the signal of interest. These features included the maximum value of the power spectral density of the instantaneous amplitude, the standard deviation of instantaneous amplitude, standard deviation of instantaneous phase, and standard deviation of instantaneous frequency. The authors also proposed feature parameters based on the expectation of the second, third, and fourth order cumulants at zero lag. Decision theoretic classifier operates at SNR of 15 to 20 dB. The researchers have taken a hybrid approaches. Once the feature set was extracted from the signal of interest, it is fed to an artificial neural network (ANN). A recently reported ANN classifier operates at SNR of 10 to 20 dB with one or two hidden layers of perceptrons [11].

The analysis of most of modulation recognition algorithms showed that there are some common shortcomings reduce the behavior of the modulation recognition algorithms [11]. The first shortcoming is that, assumption of exact knowledge of the carrier frequency. Indeed, the carrier frequency of the intercepted signal is unknown and has some instability. This instability will create a noisy component in the instantaneous phase of the intercepted signal. Consequently, signals having amplitude modulation only may be erroneously classified as signals having both amplitude and phase information. To overcome this problem, we can use one or more of the following solutions: (1) on – line estimation of the carrier frequency, (2) increasing the phase threshold used in isolating phase signals, and (3) using the high order statistics to reduce the effects of noisy phase component. The second shortcoming is that, the ordinary modulation recognition algorithms assume the use of sampling frequency that is synchronized with the carrier frequency. In practice, hostile transmitter generates the carrier frequency whereas the sampling frequency is generated at the interception receiver. Consequently, the two frequencies are not synchronized. Therefore the simulations should be redone as long as the two frequencies being asynchronous with each other. The third shortcoming is that, the use of high sampling frequency that is equal to eight times the carrier frequency. This assumption requires big storage and computation requirements. This shortcoming may be overcomed by the use of band-pass sampling instead of the low pass sampling used in the previous algorithms. It may also be overcomed by the use of key features that may require less storage and computation requirements such as that derived from the complex envelope of the intercepted signal. The fourth shortcoming is that most of the digital modulation recognizers which utilize the pattern recognition approach such as [4] and [14] , require long signal duration and the processing time may be very long: This leads to the use of these algorithms in off-line analysis. Furthermore, some of those recognizers, such as [4], require excessive computer storage to ensure correct modulation recognition. Also, the practical implementation for some of these recognizers, such as [4],[11],and [14] , is excessive complex. However, the work on some of these recognizers attempts to identify digital modulations with a number of levels larger than four.

In this work, we introduce a hybrid approach for single-tone digital signal modulation recognition. The complex envelope, which represents the in-phase and quadrature components of the intercepted signal after frequency estimation [11], is considered as the input data to be processed by modulation recognition algorithm. This in turn overcomes the third shortcoming. The proposed approach consists of two structures which are connected to each other through a feature extraction process. The first structure is the pattern recognition classifier. The function of this classifier is to recover the constellation shape from the complex envelope data of the intercepted signal in short processing time with less complex computation. Thus, this classifier enables the use of the proposed approach in on-line analysis in trial to overcome the fourth shortcoming. All the key features used are extracted only from the graphical positions of the signal states of the recovered constellation shape using the conventional signal processing tools. The second structure is a threshold detection logic classifier. This classifier uses the extracted features to decide about the modulation type of the intercepted signal that has the recovered constellation shape. A detail pictorial representation of the proposed approach is shown in Fig1 in the form of a flowchart.

The rest of the paper is organized as follows: Section II represents the intercepted signal and the corresponding receiver system model. Section III introduces a detail description of our proposed approach. Section IV is dedicated to the simulation for testing and qualifying the performance of the proposed approach where signals generation and the band limitation of both simulated signals and their corrupted noise are considered as a type of realizing the practical situation of real signals and receivers. Section V provides a set of experiments that evaluate the performance of the proposed approach and introduces its capabilities over previous ones. Finally, the paper is conclude in section VI .

2- Signal and system model

Let the envelope of the received signal is given by

$$\tilde{r}(t,\theta_c)=\sum_{k=1}^{N} R_k e^{j(\theta_k+\theta_c)}\, p(t-(k-1)T_s)+R_n(t)e^{j(\theta_n(t))} \qquad (1)$$

where N is the number of observed symbols, R_k is the k^{th} symbol amplitude and θ_k is the corresponding k^{th} symbol phase, T_s is the symbol duration, T $=NT_s$ is the observation interval, θ_c is the carrier phase tracking errors and p(t) is the basic base band unit amplitude pulse which is defined for $0 \le t \le T_s$. Noise is assumed to be white Gaussian with a time varying amplitude $R_n(t)$ and a time varrying phase $\theta_n(t)$. The asynchronous receiver generates the following decision statistics.

$$\tilde{r}_m(\theta_c,\varepsilon)=\tilde{r}_{i,m}(\theta_c,\varepsilon)+j\tilde{r}_{q,m}(\theta_c,\varepsilon)=\int_{(m-1-\varepsilon)T_s}^{(m-\varepsilon)T_s}\tilde{r}(t,\theta_c)\,dt \qquad (2)$$

$$=\int_{(m-1-\varepsilon)T_s}^{(m-\varepsilon)T_s}\sum_{k=1}^{N} R_k e^{j(\theta_k+\theta_c)}\, p(t-(k-1)T_s)+R_n(t)e^{j(\theta_n(t))}\,dt$$

where ε is the timing error of the asynchronous receiver. If that carrier lock error is stable for the duration of integration, equation (2) can be rewritten as:

$$\tilde{r}_m(\theta_c,\varepsilon)=\int_{(m-1-\varepsilon)T_s}^{(m-1)T_s} R_{m-1}(t)e^{j(\theta_{m-1}+\theta_c)}p(t-(m-2)T_s)\,dt+\int_{(m-1)T_s}^{(m-\varepsilon)T_s} R_m(t)e^{j(\theta_m+\theta_c)}p(t-(m-1)T_s$$

$$+\int_{T_s} R_n(t)e^{j\theta_n(t)}\,dt$$

$$=\left[\varepsilon T_s R_{m-1}e^{j\theta_{m-1}}+(1-\varepsilon)T_s R_m e^{j\theta_m}\right]e^{j\theta_c}+noise \qquad (3)$$

where m=1, 2 , ..., N , $0 \le |\varepsilon| \le gT_s$ and g <<1 is the peak symbol timing error as a fraction of the symbol duration.

Equation (3) shows that clock recovery error has expanded the integration interval across the adjacent symbol. However, this clock recovery error is not significant for small timing errors and can be absorbed into the constellation model. Carrier phase tracking error has a different effect on the recovered symbols. Clearly, $e^{j\theta_c}$ in (3) introduces a rotation of the symbol. The nature of this rotation varies where θ_c could be fixed for all N symbols, which are needed to make a single reconstruction. This case represents the carrier-non coherent case where, a random constellation rotation occurs each reconstruction iteration as shown in Fig.2-b. On the other hand, θ_c may remain fixed for the symbol duration only; this case is called symbol–non coherent. This leads to random arcing of each constellation vertex about its nominal position as shown in Fig.2-a. This arcing will eventually cause a deformation of the constellation shape once it is reconstructed. The combined effects of phase lock error, clock recovery error and random noise has the net effect of moving each vertex of the reconstructed constellation from its nominal position causing a distortion of the constellation shape.

3- The proposed algorithm

a- Constellation recovery algorithm

The in-phase and qudrature components of the complex envelope data represent the two dimensions, vectors, of the constellation shape which is called the feature space. This feature space will be clustered in order to recover the constellation shape of the intercepted signal. The constellation recovery algorithm divides that feature space into any number of clusters, groups, through a sequence of subdivision processes. The subdivision process divides its input group of data into only two subgroups. The subdivision process calculates the farest two points between a group of N_1 points, feature vectors, that will be divided and considers them as the initial seeds of the required two subgroups. Next, it assigns each of the feature vectors to a seed by minimum distance criteria. The subdivision process produces two separate subgroups of (P_1) and (N_1-P_1) members where (P_1) is the number of points in the first subgroup which is called its size. The second subgroup has a size of (N_1-P_1) members. Each subgroup has its members, points in the feature space, which forms a cluster in that space. The centroid of this cluster represents a signal state on the constellation shape, which is to be recovered. Fig.3 shows noisy intercepted signal constellations of different single tone digital modulated signals at SNR 5 dB. Fig.4 shows those constellations after clustering process. Inadequate selection of the initial prototypes, centers, of the two subgroups, generated from the subdivision process, causes bad clustering. Thus, a problem in clustering process to be considered is the fact that outlier points in a cluster can deviate the center when it is obtained from the cluster average (by averaging each component). Medians can be used in place of averages, although they may throw away good points as well as outliers. We use a type of fuzzy averaging here that puts the center prototype among the more densely situated points by using a weighted average (WFA) [13] and [14]. Fig.5 shows the constellation shapes of Fig.4 after getting the centers of each cluster by using WFA of each cluster.

According to the expected number of the intercepted signal states, the pattern recognition classifier will divide the feature space into this number. The expected number of clusters must be a modulo 2 number larger than the right number of the intercepted signal states. Thus, it is required to use a clustering validity measure in order to know if the clustering is sufficient or not. A clustering process is good if the clusters are relatively compact (packed closely about the center). Let σ_k^2 be the mean square error (variance) of distance between any point , member, $x_k(i)$, of k^{th} cluster and its center ,m_k, $\forall k = 1,2,......,K$ and it can be defined as

$$\sigma_k^2 = \frac{1}{N_k}\sum_{i=1}^{N_k}(x_k(i) - m_k)^2 \qquad (4)$$

where N_k is number of the k^{th} cluster members.

If the values of σ_k^2 are relatively small then the corresponding clusters are compact. Let D_{min} be the minimum distance between all pairs of cluster centers, where center is a single prototype for a cluster. It is desirable for this distance to be larger in which case the clusters are well separated. The initial value of D_{min} is the distance between the first two cluster center points in the feature space for the first time of dividing it. For any pair of clusters, σ_{td} is a measure of their closeness from being far as:

$$\sigma_{td}^2 = \alpha.(\sigma_i^2 + \sigma_j^2) \quad ; \forall\, i \neq j \tag{5}$$

where σ_i^2 and σ_j^2 are the variance of two different clusters and α is a coefficient that controls the resolution of the reconstructed constellation shape. For example, if α =1.25 then the maximum allowable overlap reign between two neighboring clusters is 25%. It is clear that, as α value decreases, the resolution increases. Clearly, the value of α should increase as the signal to noise ratio increases.

An emerging process should be done between any too close pair of cluster centers, seeds, to form a new cluster. The test threshold of closeness of any pair of clusters centers is that, their σ_{td}^2 is less than D_{min}. The center of the new cluster equals to WFA of its members. The emerging process and finding the new center is called the reassignment process. Whenever emerging process done, the number of centers, $\hat{K}$, will be reduced accordingly. Now, the Xie-Beni (XB) cluster validity measure [12]can be used for measuring the performance of clustering process. The smaller this measure is, the better is the clustering and it can be defined as :

$$XB = (\sigma_1^2 + \sigma_2^2 + ...\sigma_K^2)/D_{min} \tag{6}$$

After each emerging process, XB measure is calculated for the new set of clusters.

Thus, we move $\hat{K}$ in the direction that decreases XB until its minimum value is obtained and accept the corresponding $\hat{K}$.

For communication signals, it is possible to assume uniform distribution of number of samples, N, which were taken during the observation time, over all the expected number of the intercepted signal states, $\hat{K}$. In other words, assuming the signal states are equiprobable. We use the cluster size, P, as anther cluster validity measure. For noise free environment, P is equal to N / $\hat{K}$. For a noisy environment, we can define the cluster size threshold as:

$$t_p = (1-\beta)\frac{N}{\hat{K}} \tag{7}$$

where β is a fractional number which controls the cluster size. It is clear that, as β value decreases the cluster size increases. The value of β should decrease as the signal to noise ratio increases. The cluster size validity measure is used only the first time of clustering the feature space where empty clusters or any cluster of size less than t_p are eliminated and $\hat{K}$ will be reduced accordingly. Let $\hat{K}_{\text{int}}$ be the initial expected number of the intercepted signal states that was provided to the pattern recognition algorithm and $\hat{K}_{cur}$ is that number after each reduction iteration. The reduction of the chosen number of the expected signal states occurs however due to cluster size validity measure, P, which is used only for the first iteration, or due to XB validity measure calculation after each emerging process.

The pattern recognition algorithm will stop its processing whenever $\hat{K}_{cur}$ does not belong to the integer number interval $\{\hat{K}_{\text{int}} - \frac{\hat{K}_{\text{int}}}{2} + 1\ ,\ \hat{K}_{\text{int}} + \frac{\hat{K}_{\text{int}}}{2}\}$ and restart itself with new $\hat{K}_{\text{int}}$ which is equal to the half of the old $\hat{K}_{\text{int}}$ and so on . Finally, the pattern recognition algorithm will provide a set of $\hat{K}$ centroids which represent the expected signal states of the intercepted signal to the key feature extraction stage of our proposed approach.

b- Decision theoretic algorithm

All the key features extracted from the estimated $\hat{K}$ signal states, the output of pattern recognition algorithm, and will be the input data to decision theoretic algorithm, are derived from two simple conventional qualifying parameters.

The first parameter , $\Delta\phi_{NL}(i)$, is the absolute deviation of the direct value of the non linear component of each phase of the recovered $\hat{K}$ signal states from the mean value of them , ϕ_m , and it is defined as:

$$\Delta\phi_{NL}(i) = |\,\phi_{NL}(i) - \phi_m\,| \quad \forall 1 \le i \le \hat{K} \tag{8}$$

where $\phi_{NL}(i)$ is the value of nonlinear component of ith recovered signal state and ϕ_m is the average value of nonlinear components of $\hat{K}$ signal states phases which is defined as

$$\phi_m = \frac{1}{\hat{K}} \sum_{i=1}^{M} \phi_{NL}(i)\ . \tag{9}$$

The second parameter, $\Delta A_n(i)$, is the absolute deviation of the normalized amplitude of each recovered signal state from the mean value of them , A_m , and it is defined as:

$$\Delta A_n(i) = |\,A_n(i) - A_m\,| \quad \forall 1 \le i \le \hat{K} \tag{10}$$

where $A_n(i)$ is the normalized amplitude of ith estimated signal state and A_m is the average value of $\hat{K}$ signal states normalized amplitudes which is defined as :

$$A_m = \frac{1}{\hat{K}} \sum_{i=1}^{M} A_n(i) \tag{11}$$

In general, each decision rule is applied to a set of modulation types, G, separating it into non-overlapping subsets (A and B) according to :

$$KF \underset{B}{\overset{A}{\gtrless}} x_{opt} \tag{12}$$

where KF is the measured value of the chosen key feature and x_{opt} is the corresponding optimum threshold value. The determination of the optimum key feature threshold, x_{opt}, follows the rule :

$$x_{opt} = \arg\min_x\{ K(x) \} \tag{13}$$

where $K(x) = \frac{P(A(x)/B)}{P(A(x)/A)} + \frac{P(B(x)/A)}{P(B(x)/B)} + [1 - P(A(x)/B) - P(A(x)/A)]$

The implementation of threshold detection logic algorithm for classification and decision requires the determination of the two key features thresholds: $\delta t_{\Delta\varphi_{nl}}$ and $\delta t_{\Delta A_n}$. In this decision theoretic algorithm, the choice of $\Delta\phi_{NL}(i)$ and $\Delta A_n(i)$ key features for single tone digital modulation recognition is based on the following facts: $\Delta A_n(i)$ is used to discriminate between MQAM and MPSK signals as a subset and MASK signals as a second subset. Ideally, MPSK signals have constant instantaneous amplitude. So, $\Delta A_n(i)$ will be zero and $\Delta A_n(i) < \delta t_{\Delta A_n}$. Furthermore, MPSK signals have amplitude variation because the band limitation of those signals imposes amplitude variation especially at the transition between successive symbols. So, this key feature can be used to discriminate between the signals that have amplitude information {MASK and MQAM} over the threshold value, $\delta t_{\Delta A_n}$, and that of limited amplitude variation under this threshold. $\Delta\phi_{NL}(i)$ is used to discriminate between MQAM and MPSK signals where MASK signals have constant instantaneous phase . So, any phase variation of MASK will be less than threshold value $\delta t_{\Delta\phi_{nl}}$. The optimum key features threshold values are chosen to be $\delta t_{\Delta\phi_{nl}} = \frac{2\pi}{\hat{K}}$ and $\delta t_{\Delta A_n} = \frac{A_m}{\hat{K}}$. A detail pictorial representation of the Decision theoretic algorithm is shown in Fig.1

4-Computer simulation

This section is divided into three subsections. In first subsection, software generation of test signals is discussed. Simulation conditions for the proposed algorithms are presented in the second subsection where the effect of band limitation of the simulated signals is considered. In the third subsection, the band limitation of the simulated noise signal with controlling its SNR points of view is discussed.

a- Single tone digitally modulated signals simulation

The carrier frequency, f_c , the sampling rate , f_s , and the symbol rate , r_s , were assigned the values 150 KHz , 1200 KHz , and 12.5 KHz respectively.

The modulating digital symbol sequence duration is chosen to be 1.707 msec (equivalent to 2048 samples). The simulated signals (MASK , MPSK , MQAM) ,as presented in Table 1, are derived from a general expression :

$$S_k(i)=a_k\ COS\left(\frac{2\pi f_k i}{f_s}+\phi_k\right);\ \forall 1\le i\le N_b\ and\ k=0,1,2,.........\hat{K}-1 \qquad (14)$$

where $\hat{K}$ is the expected number of signal states and N_b is the number of samples per symbol duration, which is equivalent to the ratio between the sampling frequency ,f_s , and the symbol rate , r_s .

Table 1 the simulated signal parameters of various modulation types of interest

modulation type	Instantaneous frequency (f_k)	Instantaneous Amplitude (a_k)	Instantaneous Phase (ϕ_k)
MASK	f_c	{- $\hat{K}$ +1 : 2 : $\hat{K}$ -1 }	Zero or Constant value
MPSK	f_c	Constant value	$k\frac{2\pi}{\hat{K}}$
MQAM	f_c	{- $\hat{K}$ +1 : 2 : $\hat{K}$ -1 }	$k\frac{2\pi}{\hat{K}}$

b- Band limiting of simulated modulated signals

Every communication transmitter has a finite transmission bandwidth. Consequently the transmitted signal is band limited . Therefore, the simulated signals are band limited in order to make them represent more realistic test signals. The modulated signal is band limited to bandwidth B_s which comprises 95% of the total average power. Thus, B_s can be defined by:

$$B_s=\int_{f_c-\frac{B_s}{2}}^{f_c+\frac{B_s}{2}} G_s(f)\ df=0.95\int_{f_c-\frac{B_s}{2}}^{f_c+\frac{B_s}{2}} G_s(f)\ df \qquad (15)$$

where $G_s(f)$ is the power spectral density of the modulated signal S(t).
The analytic expressions of the 95% bandwidth for different types of digital signals are introduced in [11].Bandwidth limitation of the signal was simulated through nulling some of the values of the corresponding FFT sequence and then evaluating the inverse FFT .

c- Noise simulation and SNR adjustment

The procedures for generation of a bandpass complex Gaussian noise sequence comprise the following steps:

(1) Generation of two mutually independent sequences { n_1 and n_2 }each of 2048 independent random numbers uniformly distributed in the interval [0,1].

(2) Calculation of a zero-mean unity-variance sequence{n_5}according to

$$n_3=\sqrt{-2\ln(n_1)}\quad\cos(2\pi n_2) \qquad (16)$$

$$n_4=\sqrt{-2\ln(n_1)}\quad\sin(2\pi n_2) \qquad (17)$$

$$n_5=n_3+j\,n_4 \qquad (18)$$

In order to enhance the quality of the generated Gaussian sequence { n_5 }, its value is normalized as $N_n = (n_5 - \mu) / \sigma$ where μ and σ are respectively the mean and the standard deviation , estimated from much larger sequence.
Usually in practice, the bandwidth of the interception receiver is slightly larger than the signal bandwidth. So, in order to increase the degree of realism of the simulated dative Gaussian noise, it is band-limited to a bandwidth equal to 1.1 times the simulated modulated signal bandwidth. Finally, any desired signal-to-noise ratio (SNR) is adjusted by multiplying the generated noise sequence { N_n } by a coefficient V which is determined from

$$V = \sqrt{\frac{S_p}{N_p}.(10^{-SNR/10})} \tag{19}$$

where SNR is substituted in decibels , the signal mean power is given by:

$$S_p = \frac{1}{N}\sum_{i=1}^{N} S^2(i) \tag{20}$$

and the noise mean power is given by :

$$N_p = \frac{1}{N}\sum_{i=1}^{N} |N_n(i)|^2 \tag{21}$$

d- Performance evaluation:
In this section, we simulate two experiments for performance evaluation of the proposed algorithm. Initially, energy normalization process must be done in order to make the modulation recognition algorithm scale independent and invariant to the channel gain. In first experiment, the performance evaluation of the proposed approach for digital modulation recognition is derived from 400 realizations at 5 and 10 dB SNR for each modulation type of interest (MASK , MPSK , MQAM) with the same control coefficients of the pattern recognition algorithm (β = 0.1and α =1.25). For testing, The generated signals states, M, only equal to 8 and 16 states.

The success rate of identifying the correct modulation type among types of interest is shown in Table 2. It is clear that all types of digital modulations of interest have been correctly classified with 100 % success rate except MPSK (= 92 %). Moreover, all types of digital modulations of interest have been correctly classified with 100 % success rate with the same parameters of pattern recognition algorithm as shown in Table 3 .

Table 2 Estimated success and error rates for the developed approach based on 400 realizations at SNR = 5 dB, β = 0.1, α =1.25, and M=8 or M=16. *

Decided type / Generated type	MASK	MPSK	MQAM
MASK	100 %	0	0
MPSK	0	92%	8 %
MQAM	0	0	100 %

* Entry in row x and column y is the rate of classifying the modulation type x as y

Table 3 Estimated success and error rates for the developed approach based on 400 realizations at SNR = 10 dB, β = 0.1, α =1.25, and M=8 or M=16. *

Decided type / Generated type	MASK	MPSK	MQAM
MASK	100 %	0	0
MPSK	0	100%	0
MQAM	0	0	100 %

* Entry in row x and column y is the rate of classifying the modulation type x as y

In second experiment, We examine the additional impact of carrier phase lock error. This error is random but remains constant for the duration of each symbol. The peak error is assumed to be $\pi/8$ for MQAM, M=8. Thus, the distortion agents are both random noise and carrier phase recovery error. Correct recognition rate versus SNR is shown in Fig.6 where the robustness of the constellation shape recognition paradigm is evident from this plot. Even in the presence of large peak phase error, the classifier achieves performance levels exceeding 90 % at SNR as small as 0 dB. Performance improvement slope vs. SNR is notable. In a span of 5 dB, (-5 dB to 0 dB), correct classification rate increases to 90 % from a low level of 60 %.

5- Conclusion

The aim of this paper is to introduce an approach for digital modulation recognition that uses the shape of the rebuilt constellation as a key signature which is a stable feature of unknown signal and more resilient to channel effects and receiver imperfections. This task is done by using the key features derived from the complex envelope of reconstructed $\hat{K}$ signal states which is the output of a pattern recognition algorithm. It is worth noting that all the suggested key features can be extracted by using the conventional signal processing tools. So, the proposed algorithms can be implemented at extremely low cost and it seems to be suitable for the on line analysis.
Extensive simulations of three digital modulation types have been carried out at different signal to noise ratios. Sample results have been presented at SNR of 5dB and 10 dB only. It is found that the threshold SNR for correct signal classification is about 5 dB. Thus, the proposed modulation recognition algorithm reduces the required SNR to achieve high performance level compared to ordinary modulation recognition algorithms [5-9]. Furthermore, the proposed approach is successful under a carrier phase recovery error up to 45 degrees for 8-QAM signal, which is a fairly large number.

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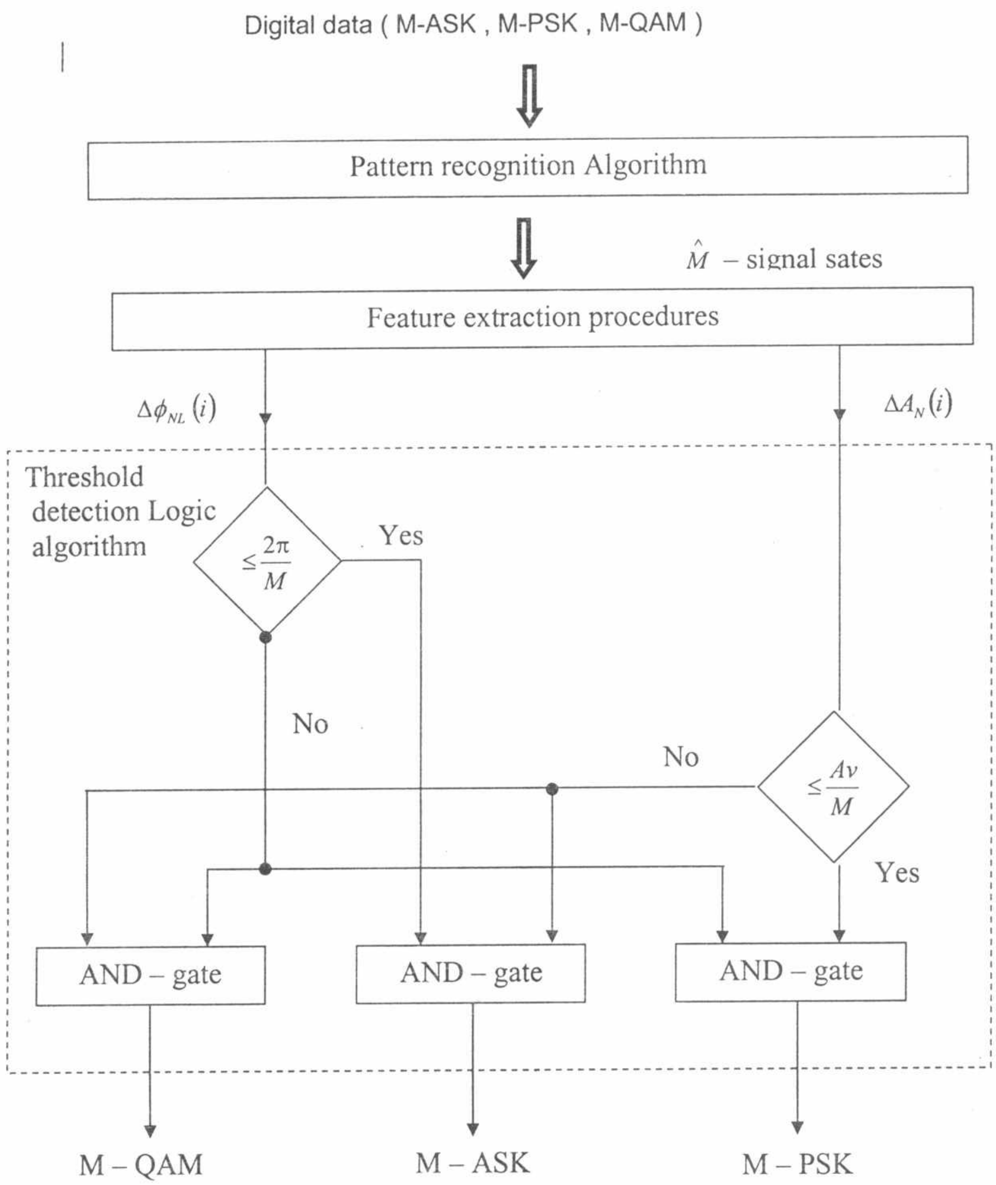
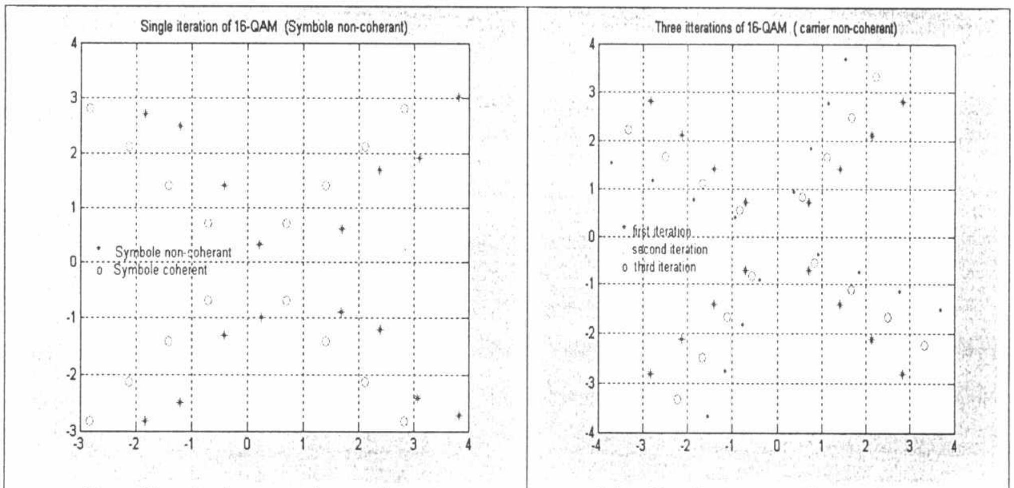
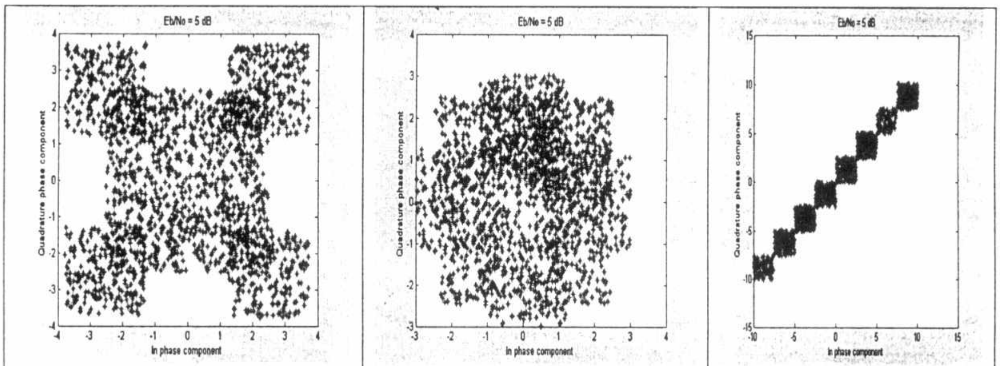


Fig.1 Functional flow chart of the proposed approach



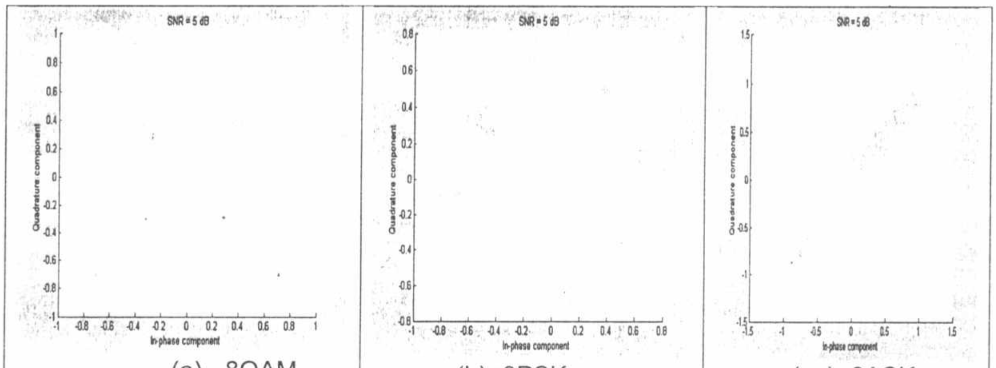
2-a Symbol non-coherent case 2-b Carrier non-coherent case

Fig.2 The effect of Carrier phase tracking error on the constellation shape



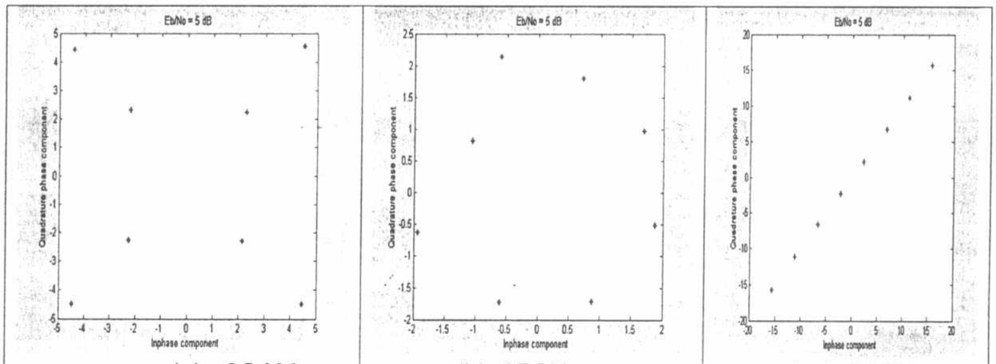
(a)- 8QAM (b)- 8PSK (c)- 8ASK

Fig.3 the constellation of the intercepted signal at low SNR = 5 dB after clustering process



(a)- 8QAM (b)- 8PSK (c)- 8ASK

Fig.4 the constellation of the intercepted signal at low SNR = 5 dB.



(a)- 8QAM (b)- 8PSK (c)- 8ASK

Fig.5 the constellation of the intercepted signal at low SNR = 5 dB after pattern recognition stage.

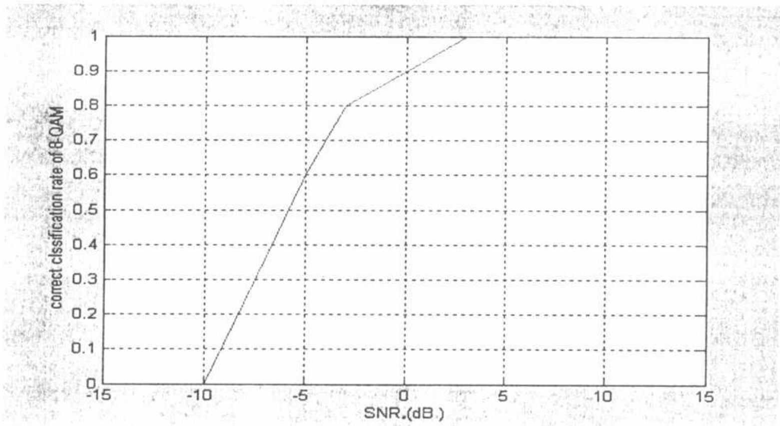


Fig.6 Recognition in the presence of noise and carrier recovery error for 8 QAM signal